Exact and Approximate Solutions for Energy Cost Optimization in Smart Homes

by

Muhammad Raisul Alam

A thesis submitted to the Faculty of Graduate and Postdoctoral Affairs
in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

in

Electrical and Computer Engineering

Carleton University
Ottawa, Ontario

Abstract

This research addresses the energy cost optimization problem in the smart grid from the users' perspective. We first propose a unified model which integrates the partial aspects of previous research in a single cost optimization model. It considers the components which have significant impact on cost optimization, e.g., storage, renewables, microgrid, etc. The model utilizes load and source scheduling, and energy trading strategies for cost optimization. It also addresses the inconvenience created to the users by delaying certain tasks. The model enables Peer-to-Peer (P2P) energy trading among the participating households in the microgrid. In P2P trading, the households determine the microgrid energy price and quantity to minimize the total cost. On the other hand, P2P trading potentially results in an unfair cost distribution among the participating households. We address this unfair cost distribution problem by employing Pareto optimality, ensuring that no households will be worse off to improve the cost of others. However, the optimal solution approach of the unified model is a non-convex Mixed Integer Nonlinear Programming (MINLP) problem. Our results show that, even for small problem sizes, the solution time increases exponentially. Hence, it cannot be utilized to solve practical scenarios. To address this problem, we also propose a bi-linear model which provides an approximate solution within a realistic timeframe. Its complexity is less than the unified model because it works with multiple lower dimensional convex solution spaces. Our results show that the solution time of the bi-linear model is very low (mostly less than a minute) compared to the optimal model. Moreover, for real datasets, 99% of the solutions generated by the bi-linear model are optimal solutions. Finally, we used real datasets of Ottawa to evaluate the impact of renewables and storage in the microgrid. Our results show that P2P energy trading is beneficial if the households have both storage and renewables. In the presence of renewables, increased storage capacity increases cost savings until it reaches a saturation point. Our findings could be helpful for policy makers to design programs and initiatives for the households to accelerate the adoption of storage and renewables in the smart grid.

Acknowledgments

All glory and appreciation to the Almighty Allah - the Beneficent, the most Merciful and the most Compassionate, Who has granted me the opportunity to finish this thesis.

I would like to express my sincere gratitude to my supervisors, Professor Thomas Kunz and Professor Marc St-Hilaire for their excellent support, guidance and suggestions to complete this thesis. I would be delighted to thank them for their invaluable inspiration, kindness and allocation of their precious time for advising me during my research project. Their friendly availability and constant willingness to share their ideas with me regarding my research, in spite of their busy schedule, is sincerely appreciated.

My sincere thanks go to Professor John Chinneck for his guidance and suggestions to my research. I am also grateful to Professor Kevin Cheung for his insightful suggestions to analyze the proposed optimization models. I acknowledge with gratitude Professor Ian Beausoleil-Morrison for providing us the measured residential electric load profiles of Ottawa.

I would like to thank all my colleagues and friends of our lab for providing a relaxed and pleasant research environment. Special thanks go to Ammar, Arifur, Faisal, Jean-Daniel and Yi Li. I cherish all the wonderful time we spent together. My heartfelt appreciation goes to my friends, Adnan Wahid, Mohammad Zulhasnine, Moinul, Riyadh and Shafique, who always stood by me with smile and good wishes. I gratefully acknowledge the support and help of my uncle, Mohammad Noor Kabir, during my stay in Canada.

Last, but not the least, I owe the greatest debt to my parents for not only their never-ending affection, love and patience, but also their encouragement and unconditioned support to me in all my decisions. Their guidance helped me to keep my motivations high throughout my studies. Without the continual support from my parents and siblings, there is no way I would be where I am today. It is my great pleasure to dedicate this thesis to my family.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

2PE	2 Point Estimation
AA	Adaptive Aggressive
AMPL	A Mathematical Programming Language
ApX	Amsterdam Power Exchange
BA	Battery-assisted Appliances
BOS	Balance Of System
CAES	Consumer Automated Energy management System
CDA	Continuous Double Auction
CE	Competitive Equilibrium
CHP	Combined Heat and Power
CP	Convex Programming
DER	Distributed Energy Resource
DG	Distributed Generation
DR	Demand Response
ECS	Energy Consumption Scheduler
EV	Electric Vehicle
FCM	Fuzzy C-Means
FIT	Feed-in Tariff
GA	Genetic Algorithm

HOEP	Hourly Ontario Energy Price
HVAC	Heating, Ventilating, and Air Conditioning
IBR	Inclining Block Rates
IESO	Independent Electricity System Operator
ILP	Integer Linear Programming
IP	Integer Programming
IPM	Interior Point Method
LP	Linear Programming
MA	Model based Appliances
MILP	Mixed Integer Linear Programming
MINLP	Mixed Integer Non-Linear Programming
MPC	Model Predictive Control
NREL	National Renewable Energy Laboratory
NSRDB	National Solar Radiation Database
OEB	Ontario Energy Board
P2P	Peer-to-Peer
PAR	Peak to Average Ratio
PDF	Probability Density Function
PSM	Physical Solar Model
PSO	Particle Swarm Optimization
PV	PhotoVoltaics
QoS	Quality of Service
RB	Risk-Based
RELD	Renewable Energy - Load Disparity

RTP	Real-Time Pricing
SA-IL	Schedule-based Appliances with Interruptible Load
SA-UL	Schedule-based Appliances with Uninterruptible Load
SCP	Sequential Convex Programming
SOC	State Of Charge
TOU	Time Of Use
VPP	Virtual Power Plant
ZI	Zero Intelligence

List of Symbols

$\beta_{k,i}$ — Maximum allowable delay of the i-th appliance of the k-th household.

$BE_{k,h}$ — Positive real variable which represents the energy used from the storage by the k-th household at timeslot h.

C_k — Total cost of the k-th household.

$C_k^{NoTrade}$ — Minimum energy cost of the k-th household in the absence of the microgrid.

CE_k — Energy cost of the k-th household.

CD_k — Disutility cost of the k-th household.

$d_{k,i}$ — Disutility factor of the i-th appliance of the k-th household.

$DS_{k,h}$ — Energy demand or supply of the k-th household at timeslot h without external energy sources (e.g., grid and microgrid).

E_k — Storage efficiency of the k-th household.

$GE_{k,h}$ — Positive real variable which represents the energy drawn from the utility grid by the k-th household at timeslot h.

GP_h — Energy price of the utility grid at timeslot h.

H — Set of timeslots representing the scheduling horizon where $h \in H$ is the h-th timeslot of set H.

I — Set of appliances where $i \in I$ is the i-th appliance of set I.

$IC_{k,h}$ — Boolean variable which represents whether the storage is in charging stage

	or not. $IC_{k,h} = 1$ means the storage of the k-th household is in charging stage at timeslot h.
IE_k	Initial storage energy of the k-th household.
K	Set of households where $k \in K$ is the k-th household of set K.
L_k^{max}	Maximum grid power limit of the k-th household (per timeslot).
$MaxC_k$	Maximum storage capacity of the k-th household.
$ME_{k,h}$	Energy traded with the microgrid by the k-th household at timeslot h. A positive value of $ME_{k,h}$ means the k-th household is a buyer at timeslot h. A negative value means the household is a seller.
$MinC_k$	Minimum storage capacity of the k-th household.
MP_h	A positive real variable which represents the price of the microgrid energy at timeslot h.
$MQ_{k,h}$	Demand (or supply) of the microgrid energy of the k-th household at timeslot h. A positive value represents the minimum energy demand of the household. A negative value represents the maximum amount of energy the household can sell to the microgrid.
N	Number of timeslots.
$p_{k,i}$	Power consumption of the i-th appliance of the k-th household.
$r_{k,i,h}$	Reservation time of an appliance, which represents the time when the scheduler gets a request to start a specific appliance. $r_{k,i,h} = 1$ means that operation of appliance i of the k-th household is requested at timeslot h.
$RE_{k,h}$	Positive real variable which represents the energy used from the renewable sources by the k-th household at timeslot h.
$RQ_{k,h}$	Renewable energy of the k-th household at timeslot h.

$S_{k,i,h}$ Boolean variable which represents the execution time of the appliances. $S_{k,i,h} = 1$ means that appliance i of household k is in operation at timeslot h.

SD_k Self-discharging coefficient of the storage of the k-th household.

$SE_{k,h}$ Positive real variable which represents the stored energy in the storage of the k-th household at timeslot h.

SP_k Required power to charge the storage of the k-th household.

$t_{k,i}$ Duration of the running time of the i-th appliance of the k-th household (measured in timeslots).

$\tau_{k,i}$ End time of the task executed by appliance i at k-th household.

U Set of uninterruptible appliances where $U \subset I$.

$US_{k,i,h}$ Boolean variable which represents the start time of the uninterruptible appliances. $US_{k,i,h} = 1$ means that the uninterruptible appliance i starts at timeslot h in household k.

Chapter 1

Introduction

A smart home is an application of ubiquitous computing that is able to provide context-aware automated or assistive services in the form of ambient intelligence, remote home control, or home automation [1]. It incorporates smartness into the dwellings, provisioning a better control of the home appliances to ensure comfort, safety and security, to improve in-home healthcare services, and to optimize energy cost. A smart home in the smart grid offers an optimized energy management solution in collaboration with the utility and the neighbors. Instead of simply depending on the utility, a smart home can generate its own energy, utilizing solar panels, wind turbines, geothermal plants and other renewable energy sources. Storage devices allow storing surplus and cheap energy to be used when demand is high and/or energy is expensive. The smart homes in a neighborhood may collectively form a microgrid to facilitate Peer-to-Peer (P2P) energy trading among themselves. Energy cost is primarily optimized by rescheduling the appliances when energy is comparatively cheap, provisioning appliance power, interrupting the task execution, scheduling storage usage, and energy trading.

In the smart grid, the user is considered as a prosumer, which means a user not only consumes energy but may also produce it. There are different types of users: home or apartment user, building management authority, hotel management authority, office management authority and those who take the managerial decisions on energy consumption and production. The user may also be a group of cooperative prosumers who collectively agree to exchange information for cost reduction.

This research considers the microgrid as a collection of households which have collectively agreed to trade energy among themselves. In our microgrid model, the end-users are prosumers and the proposed solutions provide microgrid energy price

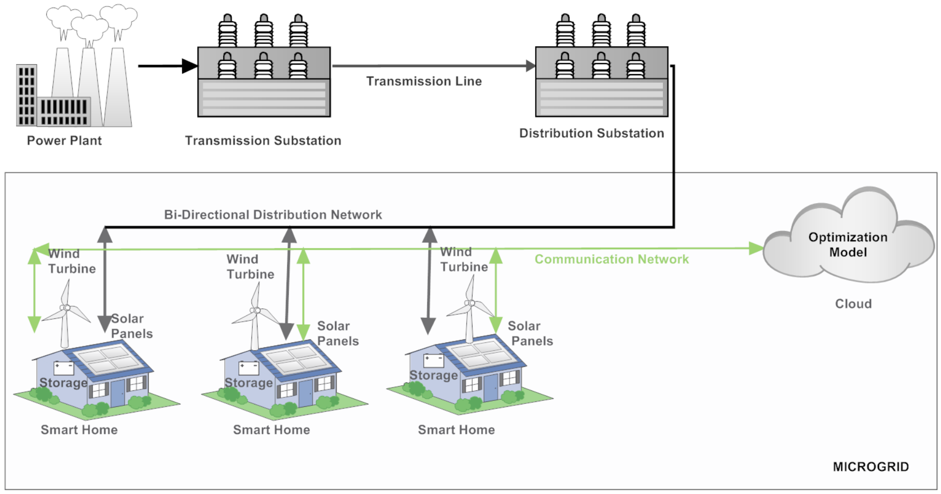

Figure 1.1: Smart Grid Infrastructure.

and energy quantity to optimize energy cost in the microgrid area. The proposed models are developed for a centralized architecture, which requires a central processing unit/center to collect and process the information of all households. Therefore, a cloud infrastructure can be a suitable platform to apply the optimization algorithm to process this huge smart grid data. Figure 1.1 illustrates the smart grid infrastructure. It shows that the smart homes in the microgrid are connected through a bi-directional distribution network. A cloud collects the energy consumption and generation information of the households and process this information by applying the optimization algorithm. The households receive the processed information from the cloud and reschedule their energy sources and loads.

The concept of considering the whole grid as a microgrid depends on how we are defining the grid and the microgrid. Any optimization solution has scalability issues, so considering the whole grid as a microgrid would require to solve the optimization problem for many households at the same time. Based on the current definition of the grid, that could include few hundreds of thousands of households (e.g., all of Ottawa), and is clearly not what we envisioned or think is reasonable.

This research addresses the energy cost optimization problem in smart homes. It explores possible cost saving strategies from the users' point of view. An optimal unified cost optimization model is proposed considering user preferences, appliance characteristics, storage properties, renewable energy generation quantity, and P2P energy trading opportunities within the microgrid. The impact of energy demand, supply, and price on the scheduling of the loads and the sources is studied. In addition, we present a numerical analysis of the optimal solution approach which shows that the time complexity of the model increases exponentially with the increase of the problem size. Hence, aiming for an optimal solution may not be a computationally efficient approach for realistic scenarios. To tackle this issue, we propose an approximate model using bi-linear programming to reduce the computation time. Finally, this research explores the potential of storage, renewables and microgrid on energy cost optimization.

1.1 Research Motivation

Recent advancements of information and communication technology changed the traditional concept of the power grid. The idea of a smart power grid was mainly initiated by the utilities. The first smart grid implementation is credited to ENAL Spa in Italy which initiated the Telegestore project in 2000 [2, 3]. The utility prefers to optimize cost, automate the energy transport and billing systems, and improve the quality of service. Another incentive is that the government promotes the smart grid research because it will have fault detection, tolerance and self-healing features to prevent power blackouts. The northeast blackout of 2003 effected 10 million people in Ontario and 40 million people in eight U.S. states [4]. A smart grid encourages the utilization of renewable energy sources which reduces carbon emission, the primary factor of climate change. For example, the Fort Collins district in Colorado is aiming to reduce its carbon emission by 80 percent by 2030 [5]. To achieve this target, it will deploy rooftop solar PhotoVoltaics (PVs), community supported solar gardens, wind turbines, thermal and electric storage, microgrids, and energy efficiency schemes. The recent Fukushima Daiichi nuclear disaster accelerated the adoption of renewable energy sources to the smart grid [6]. Therefore, the main stake holders in the smart grid, governments, utilities and users, inspired by different motivating factors, are gradually adopting the smart grid technologies as a solution of their own interests.

The success of the smart grid depends to a large degree on the widespread participation of the users. The cost saving potential of smart homes is an excellent motivating factor to involve the users in the smart grid operation. This research addresses the cost saving strategies for the smart homes from the users' perspective.

The previous research identified that optimal rescheduling of the household loads according to the energy price is one of the effective ways of cost minimization [7–21]. It was also reported that optimized utilization of the storage devices (e.g., thermal, electrical) has an impact on energy cost [9, 22–26]. It is evident from the literature that the usage of renewable sources and advanced planning of renewable energy utilization based on the predicted generation quantity reduces energy cost [9, 22–24, 27]. Previous studies claimed that energy trading among the households by forming a microgrid plays an important factor for cost minimization in the smart grid [25, 28–30]. However, most of the existing research failed to provide a comprehensive discussion of smart homes, considering all important possible aspects for cost optimization. Our work combines these potential strategies into a single cost optimization model and analyzes the behavior of the overall system.

1.2 Problem Statement

A smart home has diverse appliances, devices and equipments with different energy consumption profiles. The user has his own preferences for the appliance operations that ensure low energy costs as well as maintain a preferred comfort level. A smart meter acquires price signals advertised by the utility. The renewables show stochastic energy generation profiles correlated to the weather. One or multiple storage devices accumulate cheap and excessive energy to support future energy requirements, avoiding the need to acquire expensive energy from the grid during periods of high prices (for example, at peak hours). However, the usage of such storage devices imposes a cost overhead because of self-discharging and efficiency loss. Any surplus energy can be traded via a microgrid which ensures a collective minimization of energy cost and sometimes maximizes individual profits. P2P energy trading in a microgrid may create an unfair cost distribution problem. In order to deal with all the above smart home features, sophisticated algorithms are required. To that end, this research explores the cost optimization problem in smart homes that involves diverse energy sources, storage and loads constrained by the user preference and the electrical properties of the included components. It also addresses the cost minimization problems associated with P2P energy trading among the participating households in a microgrid. It is a multi-objective cost optimization problem, and a solution with Pareto optimality should be guaranteed. In this multi-objective optimization, Pareto optimality means that no household should be worse off to improve the cost of some other households. However, the our analysis show that the optimal solution approach for the proposed problem is NP-hard. As a result, it is not realistic for the proposed optimization model to be applied in practical applications. Hence, approximate solutions for the proposed problem are more preferable. Therefore, we propose an approximation algorithm to achieve lower computational complexity with a reasonable solution.

1.3 Research Objectives

The main objective of this research is to develop models and algorithms in order to minimize energy cost for smart homes and analyze the behavior of the overall system. More precisely, this research has the following objectives:

- Propose an optimal cost minimization model that unifies the features and components discussed in the previous research. Prior research typically considered a partial problem and therefore failed to address the interdependency between the smart grid components.
- Evaluate the complexity of the proposed unified cost minimization model to see how well it scales and how fast solutions can be found.
- Propose an alternate cost minimization algorithm which is expected to provide reasonable approximate solutions in a realistic timeframe.
- Use real datasets of Ottawa to evaluate the results.
- Evaluate the impact (and interdependency) of storage, renewables and microgrid on energy cost minimization in the smart grid.

1.4 Research Scope

The scope of this research is limited to energy cost optimization for smart homes. Although the utility will benefit from the outcomes of the proposed solution, we do not focus on the problem from the utility's perspective. Smart homes are considered as the center point of the smart grid and the solution has been provided for the greater benefit of the users.

1.5 Our Contributions

We propose an optimal unified energy cost minimization model for smart homes. Energy cost is primarily optimized by rescheduling the appliances when energy is comparatively cheap [7–14], interrupting the task execution [7, 8, 15], scheduling storage usage [9, 22, 23], utilizing renewable energy sources [9, 24, 27] and trading energy [25, 28, 29]. We consider all these features in a single unified model. An optimal unified model is complex in nature because the storage and the microgrid show dual characteristics, i.e., they can act as energy sources and loads. Our work combines all these components with their corresponding electrical characteristics and user preferences into a single model.

In our approach, all households collaboratively determine the microgrid energy price. Most of the energy trading methods reported in the literature focus on individual profit optimization [25, 28–30]. The energy prices estimated by these methods did not consider the impact of energy prices on the total cost in a microgrid area. Our proposed P2P trading strategy considers total cost optimization in a microgrid.

The proposed model ensures Pareto optimality while trading energy via the microgrid. No household will be worse off to improve the cost of others. The previous methods proposed in the literature rarely considered unfair cost distribution issue. There may be some scenarios where an individual household pays more than it used to pay when not participating in microgrid energy trading.

The proposed unified model is an NP-hard problem, which means that using the resulting solution is not practical because the time complexity increases exponentially according to the increase in the problem size. The numerical results illustrate that even small and relatively trivial problems can take hours to solve. In the smart grid, price signals, energy demand and renewable energy generation change frequently within an hour demanding to re-solve the optimization problem with updated information. Therefore, the optimization problem should be solved in a realistic timeframe so that updates can be reflected back to the system to provide an optimized cost. Hence, aiming for an optimal solution may not be a computationally efficient approach for realistic scenarios. We need to trade off the quality of the optimal solution for reduced computation time. Therefore, we propose an approximate model by using bi-linear optimization to reduce the computational complexity of the optimal model. The bi-linear mode is also NP-hard. However, it approximates the non-linear constraints to linear ones to limit the feasible non-convex solution space to a lower dimensional convex region. Therefore, it reduces the solution time. Results show that the solution time of the bi-linear model is very low compared to the optimal model. Moreover, for real datasets, 99% of the solutions generated by the bi-linear model are optimal solutions. Finally, we analyzed the bi-linear solutions and identified that the sub-optimal cost potentially arises when the microgrid price reaches to the boundary limits.

We studied the interdependency of storage, renewables, and microgrid trading. Our results show that the cost benefits show strong correlation, where maximal cost savings are obtained at a saturation point that depends on the household loads, storage capacity and renewable energy generation capacity of an specific microgrid area. Hence, the proposed model could be useful for governments, policy makers and utilities to design programs and incentives for the households to accelerate the adoption of storage and renewables in the microgrid.

1.6 Publications

We achieved our research objectives which are already published in peer-reviewed journals and conferences. The publications discussed the cost saving strategies for smart homes, proposed a simple mathematical model, identified the cost fairness problem, proposed a solution that guarantee Pareto optimality, argued that the time complexity of the optimal unified model is NP-hard, and proposed a bi-linear model for approximate solutions. The publications are listed below and arranged chronologically.

1. Muhammad Raisul Alam, Marc St-Hilaire and Thomas Kunz, "A Bi-Linear Optimization Model for Collaborative Energy Management in Smart Grid", *IEEE Innovative Smart Grid Technologies - Europe (ISGT-Europe 2016)*, Ljubljana, Slovenia, October 2016.

2. Muhammad Raisul Alam, Marc St-Hilaire and Thomas Kunz, "Computational Methods for Residential Energy Cost Optimization in Smart Grids - A Survey", *ACM Computing Surveys*, vol. 49, no. 1, article 2, 34 pages, 2016.

3. Muhammad Raisul Alam, Marc St-Hilaire and Thomas Kunz, "Optimizing Residential Energy Consumption: The Need for Pareto Optimality", *Proceedings of*

the IEEE/CIC International Conference on Communications in China - Workshops on Internet of Things (CIC/ICCC 2014), Shanghai, China, pp. 26-31, October 2014.

4. Muhammad Raisul Alam, Marc St-Hilaire and Thomas Kunz, "A Modular Framework for Cost Optimization in Smart Grid", *Proceedings of the IEEE World Forum on Internet of Things (WF-IoT 2014)*, Seoul, South Korea, pp. 337-340, March 2014.

5. Muhammad Raisul Alam, Marc St-Hilaire and Thomas Kunz, "A Survey on Cost Saving Methods for Smart Grids", *Proceedings of the IEEE International Conference on Smart Energy Grid Engineering (SEGE 2013)*, Oshawa, Canada, pp. 1-7, August 2013 (Third Prize, Student Innovation Competition).

6. Muhammad Raisul Alam, Marc St-Hilaire and Thomas Kunz, "Cost Optimization via Rescheduling in Smart Grids A Linear Programming Approach", *Proceedings of the IEEE International Conference on Smart Energy Grid Engineering (SEGE 2013)*, Oshawa, Canada, pp. 1-6, August 2013.

1.7 Outline of the Thesis

The reminder of this thesis is organized as follows. Chapter 2 explores the cost saving strategies for smart homes available in the literature. Chapter 3 proposes a non-convex Mixed Integer Non-Linear Programming (MINLP) model that unifies the components for cost minimization in smart homes. Chapter 4 evaluates the proposed unified model and analyzes its complexity. Chapter 5 presents a bi-linear model which provides an approximate solution of the proposed problem within a realistic timeframe. Chapter 6 evaluates the performance of the proposed bi-linear model. Chapter 7 analyzes the impact of storage, renewables and microgrid on energy cost minimization. Chapter 8 concludes the thesis, addressing the possible future directions of the research.

Chapter 2

A Review on Energy Cost Optimization

This chapter identifies the components that impact energy cost reduction in smart homes. The previously proposed intelligent optimization methods in the literature are discussed to analyze the underlying component behaviors. The models which are proposed in this thesis are developed based on the factors identified in this chapter.

A user implements cost saving strategies considering the available resources and infrastructure. Figure 2.1 presents an overview of the methods used to minimize energy cost or maximize profit in smart homes. Energy consumption monitoring and manually controlling the electrical appliances according to user preferences and the energy price are basic ways to reduce energy cost [31–33]. The user can visualize the trends of the overall energy consumption and learn ways to shed loads manually by using this information. However, if the user decides to use renewable energy sources, energy storage and microgrid, the overall system will become more complex. In this case, manually controlling the loads and the sources is a tedious task which may not provide optimal cost reduction. As a result, automated intelligent systems or tools are required in order to gain the maximum benefit of the underlying technologies. Our research focuses on the computational methods for energy cost optimization. More specifically, it addresses the energy cost minimization problem by using optimization and trading methods.

The optimization and energy trading methods require the energy price, possible amount of energy consumption and predicted renewable energy generation capacity in advance to plan the optimal load and source scheduling. Therefore, the efficiency of the overall system relies on the prediction accuracy of the energy price, consumption and generation algorithms. In smart homes, prediction tools are used to provide estimates of energy usage [8,31–34], supply [35–37] and energy price [7,16,38]. The scope

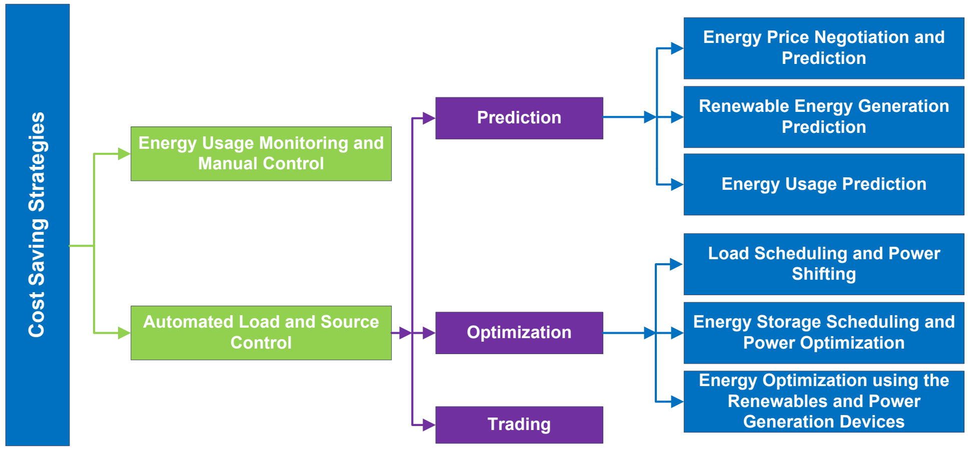

Figure 2.1: Overview of the Cost Saving Strategies for Smart Homes.

of our research is limited to developing cost minimization methods using optimization and trading algorithms. Therefore, we do not explore the prediction methods in this literature review. However, the interested readers could read our survey paper (see reference [39]) which presents a detailed overview of the prediction methods used for energy price, consumption and generation. The remaining portion of this chapter discusses the optimization and energy trading methods which were proposed in the literature for residential energy cost minimization.

It is reported that a Demand Response (DR) program has significant impact on cost reduction [40]. The utility tries to indirectly control the loads in the user premises via DR programs. Vardakas et al. classified the DR methods into three categories as shown in Figure 2.2 [41]. The first category is based on control mechanism, including centralized and distributed control. In the second category, DR methods are classified based on the motivating factors. The price-based and the incentive-based DR methods fall into this category. Finally, the third category is arranged based on the decision variables. Energy consumption can be controlled by scheduling a task operation and energy management, i.e., reducing the power of a load operation. Recently, researchers reported an increased trend of optimization method development for DR programs [41, 42]. In our research, we consider price-based DR methods as the motivating factor. In addition to this, we also used Time Of Use (TOU) rates for energy price to evaluate the scenarios because most utilities use TOU price. The proposed models follow a centralized DR architecture as the control mechanism. The models

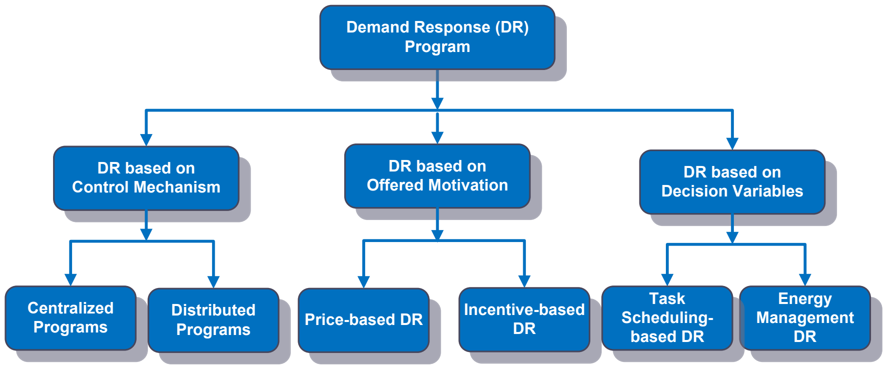

Figure 2.2: A Classification of DR Programs [41].

used the decision variables to implement a task scheduling-based DR program. Hence, scheduling the household loads and the energy sources according to the energy price is the main theme of the proposed cost optimization models.

2.1 Load Scheduling and Power Shifting

This section explores energy cost optimization methods for household loads. The methods are based on two main concepts. The first technique is avoiding an appliance operation when energy is expensive. It could be implemented by delaying an appliance operation. The second technique may be applicable if the appliance operation cannot be delayed. In this case, the algorithms try to operate an appliance at a lower energy consumption level. The following sections review the proposed ideas on cost minimization by rescheduling the appliance operation or operating appliances at lower power levels. The ideas are categorized by the optimization technique used.

2.1.1 Linear Programming

Mohsenian-Rad and Leon-Garcia proposed a Mixed Integer Linear Programming (MILP) model to develop an optimal scheduling method for home appliances [7]. The proposed optimization model is formulated to reduce energy cost as well as waiting cost, which has been defined as disutility. The disutility is modeled as a function of delay and power consumption. The delay cost depends on the user preference, which is adjustable by a control parameter. The model considers the energy price as a function of hourly load. This price function calculates the price from the total power consumed by all appliances at a certain timeslot. The model implemented Inclining Block Rates (IBR) as energy price. In IBR, if the load exceeds a certain threshold level then the price is increased by a fixed value and vice versa. The model also implemented interruptible and uninterruptible appliances. Simulation results showed that the proposed scheduling model and price prediction algorithm significantly reduce the energy cost and peak-to-average energy demand ratios.

Similarly, Bapat et al. proposed Yupik, a system that uses sensing, analytics and optimization to schedule home appliances for cost minimization [8]. An Integer Linear Programing (ILP) model was used to formulate the scheduling problem. The objective function of the proposed ILP model is a function of the energy and the inconvenience costs. If an appliance is deferrable, its operation can be delayed, and if reducible, it can be operated in reduced power states. The inconvenience cost is calculated from the distance between the current time and the preferable earlier time. The model can control uninterruptible and interruptible devices. The authors used CPLEX to solve the ILP. They collected four weeks of energy usage information from a home. The data consists of the usage pattern of a power strip, a musical system, and a TV. The power strip was considered as a virtual device because the connected device was unknown. The authors presented a study of savings and inconvenience cost which is useful to identify different control variables for balancing between comfort and cost savings.

De Angelis et al. proposed an MILP algorithm for optimal task scheduling under dynamic electrical and thermal constraints [9]. The model divided the task into subtasks (e.g., washing machine cycles) and can control the order of consecutive tasks. It can also interrupt the operations of the noisy appliances while the user is sleeping. The model addressed both schedulable and non-schedulable appliances. The heating or cooling load is expressed as a function of thermal resistance of the household. The objective function optimizes the cost using both renewable sources and a storage device. The model considered the electric grid primarily as an energy consumer not as an energy source. If the model does not find any feasible solution, it recalculates the cost by discarding the lowest priority load until the best solution is obtained. The simulated results were evaluated using static and dynamic optimization approaches. The newly added load is considered as an interrupt and the optimizer reschedules the scheduling based on the new scenario. The authors claimed that the overall cost was reduced to almost 50% by using the proposed MILP optimization. However, additional cost optimization is possible by using or storing the grid electricity when the price is lower than the renewable energy production cost. The proposed model did not consider this.

Zhu et al. proposed a demand-side management method using an MILP technique [10]. The appliances are arranged into non-shiftable, time-shiftable and power-shiftable categories according to their power requirement and operational periods. The objective function is defined to minimize the hourly load. The time-shiftable appliances, which may have different power consumption patterns, are controlled by binary vectors. The power-shiftable appliances are limited to operate between maximum and minimum power. Non-shiftable appliances have only one power level that must be maintained during the execution timeslots. The proposed model was evaluated using 7 appliances from 3 categories in an individual household and a small neighborhood area with multiple households to measure the optimal scheduling power requirement. Results showed that the model is able to schedule the optimal operation time for the time-shiftable appliances and optimal power for the power-shiftable appliances while maintaining the power consumption patterns of individual appliance and the user preference. The authors did not consider the disutility caused by delaying the appliance operation by the scheduler. They also did not discuss interruptible and uninterruptible appliances. Although the model focused on hourly load optimization, it can be used for cost optimization by slightly modifying the constraints and the objective function.

Conejo et al. presented an optimization model to minimize energy cost using Linear Programming (LP) [11]. The model proposed a linear consumer utility function which is expressed using a monetary value. Initially, a fixed monetary value (41.5 €/MWh) was used as the consumer utility. The objective function tries to schedule more loads in the time slots which have lower prices than the consumer utility. A significant contribution of this model is that it included the forecasted energy price boundaries (predicted maximum price and other price parameters bounded by minimum and maximum price difference) as the parameters of the objective function. The price bounds (maximum and minimum price) are obtained using the ARIMA model proposed in [43] with 95% confidence level. Results showed that the inclusion of price parameters in the objective function provides 16.22% higher utility (cost savings) than simply using forecasted price in the model. Unlike other models, it does not optimize the energy cost and load for the next 24 hours in advance. It assumed that the energy supplier provides the energy price before the beginning of every hour (10 min in advance) and it computes the load for each hour based on the current price, future load and forecasted price parameters. From the results, it is obvious that the model is scheduling load into lower energy price timeslots. However, it is not clear how the load is delayed for different appliance types, e.g., interruptible vs. uninterruptible devices. The model does not consider the user discomfort that is created by delaying the tasks.

Hubert and Grijalva modeled the Heating, Ventilating, and Air Conditioning (HVAC) system by the law of thermodynamics, which formulated the change in room temperature as a function of HVAC heating rate and rate of losing the heat due to the external weather [13]. The mass of the air in the room and the specific heat of the air are used to measure the heat exchange. The rate of energy change of the HVAC is expressed as a function of temperature difference between the HVAC and the room, specific heat and air flow rate (assumed to be constant). The rate of energy loss due to the external temperature was modeled by temperature difference and thermal resistance. The thermal resistance can be calculated at first based on geometrical properties, and then be improved over time based on both room and outside temperature histories. Constraints were applied to limit the range and the maximum variation rate of the HVAC internal temperature. The authors proposed an optimization system that was formulated as an MILP model. The model did not consider inconvenience cost for delaying an appliance operation. The room temperature is maintained between the user-defined comfort levels which does not create inconvenience.

Marwan et al. developed a DR model to control an air conditioning system for cost minimization [12]. The paper proposed an LP model to calculate the energy cost from the air conditioner power rating and energy price. A constraint was enforced to maintain the room temperature at a comfort level which is modeled using the laws of thermodynamics. The paper investigated the effect of price spikes on the objective function. The energy price was considered as a constant all the time except during the spike periods. The price increases to a certain fixed value when it spikes. Three scenarios were considered to evaluate the proposed model. A system with no price spikes did not show the pre-cooling characteristics of the model. The system with price spikes pre-cooled the room when the energy was cheap. When the model was considered with a certain probability of price spikes, it showed the same pre-cooling properties as the deterministic price spikes scenario. However, the higher the risk of price spikes, the more pre-cooling occurs. Pre-cooling minimizes the total energy cost by reducing energy consumption when the energy is expensive.

2.1.2 Convex Programming

Hovgaard et al. proposed a Convex Programming (CP) method to minimize the total energy cost of a commercial multi-zone refrigerator [16]. The paper used a modified version of Model Predictive Control (MPC) to formulate the cost function. MPC is an advanced process control method which is normally used in process industries such as chemical plants and oil refineries. The objective function minimizes the energy cost and the temperature constraint violation cost. The constraints are convex inequalities which are related to energy usage by the compressor and outdoor and indoor temperatures. The objective function is non-convex and was solved using the Sequential Convex Programming (SCP) method. The SCP method divides the non-convex objective function into a sequence of approximated convex functions. The CVXGEN [44] tool was used to solve these convex quadratic functions. The proposed model showed a clear tendency to apply more cooling when the energy price is cheap and vice versa. The paper compared the proposed model with the thermostat control system. For this purpose, the same system was simulated using conventional thermostat control policies. The conventional thermostat is completely unaware of the energy price so that it cannot be operated according to a DR system. Both models were simulated using one year of historical data. Results showed that the proposed model can reduce cost by 30% compared to a conventional thermostat-based system.

Tsui et al. studied a CP DR optimization model to optimize energy cost in smart homes [15]. The paper categorized the household loads into four groups: i) Schedule-based Appliances with Uninterruptible Load (SA-UL), ii) Schedule-based Appliances with Interruptible Load (SA-IL), iii) Battery-assisted Appliances (BA) and iv) Model-based Appliances (MA). The schedule-based appliances can be delayed. The task may be interruptible or uninterruptible. The battery-assisted appliances have an internal battery which can be used as energy sources. The model-based appliances (e.g., heating system) can be represented by physical models. The schedulable appliances were modeled using binary variables. The authors argued that the usage of binary variables makes the model a convex MINLP problem which is an issue when the solution time is of great concern. To avoid the binary variables, the paper used L1 regularization techniques to transform the model from a convex MINLP to a standard CP problem. The binary variables related to the constraints of SA-IL and SA-UL appliances were relaxed using real numbers and L1 regularization. The objective function uses a quadratic price model and dissatisfaction costs to optimize the total cost of the model. The dissatisfaction function is different for each type of load. For example, the dissatisfaction cost related to the air conditioner is a function of temperature whereas for a battery-assisted appliance, it is related to the operational performance of that appliance. The objective function is convex and the inequality constraints are also convex. Hence, the model was solved by a MATLAB-based convex optimization package called CVX [45]. The paper used an MILP model (which considers only schedulable appliances) as a benchmark to compare the performance of the proposed model. Results showed that the proposed model, most of the time, provides a solution that usually falls within 1% deviation of the optimal solution. The authors argued that even without rounding the relaxed real variables to the nearest binary number, the model finds the same schedule as the binary MILP solution.

2.1.3 Dynamic Programming

Kowahl and Kuh [46] extended the work of Livengood and Larson [47] that proposed a dynamic programming algorithm to optimize cost and maximize user comfort. Dynamic programming is based on mainly six components: stages, states, decisions, decision rules, state transition rules, and cost function. At each stage, the algorithm executes the decisions based on the states. The states are changed based on state transition rules. These rules consider the current states and the decision at the previous stages. The optimal decision at a stage is determined by the potential decisions in that stage, and the current and future stage costs. The authors presented mathematical formulations to model the grid price, indoor temperature, outdoor temperature, load, battery state, and wind speed. The total cost is a function of energy cost and comfort costs. The comfort cost is applicable to the cooling (or heating) device which depends on the indoor temperature. The optimal decision was made for every state using dynamic programming assuming a 24 hour scheduling horizon. The model was then improved by using softmax (a reinforcement learning algorithm) with neighbourhood update model. Instead of discrete states with known transition probabilities, softmax provides solutions to an unknown transition model and infinite number of possible states. Results showed that the softmax approach performs similar and sometimes better than dynamic programming depending on the training time.

2.1.4 Game Theory

Atzeni et al. formulated the load optimization problem using a game-theoretical approach [19]. The paper proposed a non-cooperative game where each active player competes against the others given the energy loads, energy production and storage strategies to minimize energy cost. These individual game strategies impact all users and lead to a Nash equilibrium where all users are unilaterally satisfied. A distributed algorithm based on the proximal decomposition was developed to be executed in the smart meters which allows computing the optimal strategies. The paper presented a simulation study utilizing practical cost functions. Results showed that the resulting demand curve from the optimization had flattened the energy consumption which eventually reduced the energy cost.

Mohsenian-Rad et al. presented a game-theoretic model for load scheduling in smart homes [48]. The proposed architecture requires connectivity among the smart meters of the households to share the hourly load information. Each smart meter is equipped with an automatic Energy Consumption Scheduler (ECS) which interacts automatically with other smart meters by running a distributed algorithm. The proposed distributed algorithm is formulated as an energy consumption game among the users in which each user tries to maximize his payoff by proposing a load schedule. The payoff function ensures Nash equilibrium i.e., all users pay their own minimum cost to the utility. The cost function used in this model is convex, therefore the proposed model is convex. It was solved by using the Interior Point Method (IPM) [49]. Results showed that the proposed model can minimize the energy cost and reduce the Peak to Average Ratio (PAR). However, it did not consider user discomfort created by delaying the appliances. Hence, it cannot impose user delay preference for specific appliances.

2.1.5 Reinforcement Learning

O'Neill et al. proposed a novel algorithm named Consumer Automated Energy management System (CAES) to optimize electricity usage in DR system [50]. The model is developed for a single residence. The system state at a certain time is represented using pending energy backlog, average pending workload, user reservation vector and pricing sequence. For a given energy control policy and system state, CAES calculates the cost from the energy cost and the disutility cost. A control variable is used to maintain the ratio between the monetary cost and the disutility cost. The performance of the system is calculated from the total discounted period cost over an infinite horizon. The model was solved by a Q learning algorithm to minimize the cost. The numerical simulation showed that CAES reduces energy cost by 16% to 40% with respect to a system that does not have any energy price information.

2.1.6 Breadth First Search

Georgievski et al. proposed a system to monitor and control electrical appliances in a building to save energy costs [51]. The model defined the appliance energy requirement constraints by grouping those under five policies: repeat, total, multiple, strict and pattern policy. The repeat policy defines the constraints for an appliance that runs periodically. It depends on the specific time. The total policy limits the total energy consumption of an appliance regardless of the specific time. If a device is required multiple times but does not follow any periodic cycles, then it is defined under the multiple policy. Non-schedulable urgent tasks are considered in the strict policy. The pattern policy defines the power consumption levels of a device according to different internal states. The sleep policy can be enforced on any device when its operation is not required. The system collects the device's usage pattern, renewable energy generation quantity, and grid energy prices from different utilities using a RESTful architecture. The gathered information is processed by a breadth first search optimization algorithm to achieve the optimal cost while maintaining the enforced policies. The system performance was evaluated for four weeks in an office at the University of Groningen. Results showed that the proposed model can save up to 50% of money and 15% of energy. The authors evaluated the inconvenience created by the system by performing a survey on user experiences. The majority of the users were unaware of the experiment. The survey report showed that it created negligible dissatisfaction to the occupants. The proposed model did not consider the preference of the user. It considered only common office appliances, e.g., laptops, computers, printers, etc. for optimization. It did not include the lighting, cooling or heating systems which are significant components for cost saving and might affect visual and thermal comfort.

2.1.7 Summary

Load scheduling and power shifting are the most efficient ways to reduce energy cost in smart homes. The introduction of dynamic energy prices requires frequent and effective human involvement to control the household load, which is not convenient and unlikely to be widely adopted. Failure to ensure the participation of users in load control will ultimately yield an inefficient system. The methods presented in this section provide automated control of the appliances based on energy price and user comfort.

Based on the user preference, the appliances are primarily divided into two types: shiftable and non-shiftable. The non-shiftable appliances cannot be delayed but may be operated at reduced power. Rescheduling is applicable to the shiftable devices which can be delayed to relatively lower energy cost time periods. The delay preference for this type of appliances depends on user comfort. The shiftable appliances can also be operated at reduced power. The user preference related to specific appliances is generally maintained by the constraints.

Based on the power consumption profile, an appliance can be interruptible or uninterruptible. An interruptible device can be turned off in the middle of its operation and resumed later. An uninterruptable appliance must be allowed to continue its operation until the task is finished. Both types of appliances may require different levels of power during the task execution based on internal operational states. These appliance-specific properties are generally enforced by constraints.

Load scheduling and power shifting create discomfort to the user by delaying the task or reducing the task quality (by reducing power). A few methods considered this disutility [7, 8]. Some of the papers considered disutility created by temperature variation [46]. Performing a survey on the participating users is a method to measure this disutility [51]. The survey is more appropriate than other hypothetical assumptions because it is based on human evaluation. These survey results are available at the end of the experiments. The proposed research did not consider how these survey results can be included in the system so that the model will reflect the disutility of the user. Another method to measure disutility is to apply a penalty whenever an appliance operation is delayed or operated at reduced power [7, 8]. The models introduce a disutility cost in addition to the energy cost. The efficiency of this type of model lies on the effective calculation of the disutility cost. The energy cost is a monetary value. Therefore, the disutility cost should be an equivalent monetary value. In economic theory, disutility is expressed using an approximation function. In the proposed models, the disutility is expressed as a function of power or delay or both. However, disutility varies according to users, appliances and situations. To adjust this variation, different user-defined scaling parameters are used for different users and appliances [7]. The previous research rarely considered the situations when no feasible solution of the problem is achievable. De Angelis et al. proposed a solution of the problem by discarding lower priority load [9].

2.2 Energy Storage Scheduling and Power Optimization

Energy storage acts like a load while charging and like a source while discharging. Storage scheduling has a dynamic impact on cost optimization. This section discusses proposed optimization approaches that explicitly included energy storage devices in their formulation.

2.2.1 Linear Programming

De Angelis et al. modeled the energy storage using linear constraints and proposed an MILP model to optimize energy cost [9]. The current storage energy is expressed as a function of the previous stored energy level, the storage efficiency, as well as charging and discharging rates. Several constraints are used to limit the storage capacity, charging rate and discharging rate. The model considered Electric Vehicles (EVs) as energy storage. The paper presented solutions using both static and dynamic optimization approaches. Dynamic optimization re-estimates the optimized cost based on newly added or removed storage (e.g., battery of the EV). Results showed that the model can dynamically update the cost parameter according to the new storage capacity.

Zhang et al. utilized a central electrical storage and a thermal storage for a smart building [22]. The electrical storage is the sum of the storage capacities from each home. Each home can charge or discharge the storage. However, to use the stored energy, the respective home should charge it first. Therefore, each home is assumed to have its own flexible sub-storage and the total storage capacity of the whole building is a predefined constant. Similarly, the central thermal storage had been considered as accumulated sub-thermal storage from each household. The authors proposed an MILP model for smart buildings to optimize energy cost. The electrical storage cannot be charged and discharged simultaneously for the same home. This condition is also true for the thermal storage. The proposed model considered the storage maintenance cost as a cost overhead which is shared by all homes. The model used a 4 kWh_e electrical storage with 95% efficiency and the maintenance cost was 0.5 p/kWh_e (pence per kWh_e). The thermal storage capacity was 6 kWh_{th} with 98% efficiency and the maintenance cost was 0.1 p/kWh_{th} (pence per kWh_{th}). The model was implemented using CPLEX in GAMS. Results showed that the proposed cost optimization model can save 24% to 30% energy cost with cost fairness among the homes.

Hopkins et al. used energy storage to optimize energy cost using an LP model [23]. The proposed cost function considers energy selling, buying and storage loss. A full storage charge and a full storage discharge have been defined as storage cycle and the lifespan of the storage is represented by the number of cycles. The cycle cost is a function of the total cost of the storage and its lifespan in cycles. The inclusion of storage cycles in the cost function not only optimizes the energy cost but also maximizes the battery lifespan. The proposed model was implemented using MATLAB. The model considered eight T105 deep-cycle batteries. Results showed that the surplus energy generated at midday is stored in the battery to be used later when it is more valuable instead of selling it back to the grid. The average daily savings with renewables and the storage was $1.81 and with only the batteries (without renewables), the average daily cost savings was $0.26.

2.2.2 Genetic Algorithm (GA)

Arabali et al. proposed a method to select the optimal storage capacity for the smart grid [24]. The model also optimizes the usage of energy storage according to load and energy sources. The cost function uses the storage capacity with other energy generators to optimize the installation cost. The total capital cost of the storage system is calculated from four components: energy related storage cost, power related storage cost, energy related Balance Of System (BOS) cost and power related BOS cost [52]. Storage charging is formulated as a function of hourly self-discharge rate and round trip efficiency (the ratio between energy recovered and energy input) of the storage. Storage discharging is a function of the hourly self-discharge rate of the storage. The model used a constraint to maintain the energy level of the storage between a given maximum and minimum capacity. A GA-based optimization method was used to estimate the storage capacity considering the load and the energy generated by the renewable sources. Results showed that if wind energy is available, the system requires less storage capacity compared to using only PVs. This is because the wind energy is generated almost every hour of a day. It also showed that increasing the load shifting rate (i.e., the percentage of appliances that are shiftable) decreases the required storage capacity of the system. In this case, energy losses due to storage efficiency and self-discharging are minimized.

2.2.3 Game Theory

Vytelingum et al. proposed a game-theoretic framework to analyze the effect of household storage on the energy price [53]. The paper considered all users in the existing market as agents who try to maximize their own profit. The proposed method tries to determine the Nash equilibrium which leads to optimum costs for each agent considering that the agents behave rationally and have complete information of the market. Initially, each agent computes his own storage strategy that minimizes its cost. Then, it gradually adapts its storage strategy following the trends of the market price. The paper presented an empirical study on the UK energy market. Results showed that the user can save 13% more compared to the current system with no storage. The savings settled at an equilibrium point when 38% of the users adopted storage. At the equilibrium, the average saving of all users was 8.5%. Interestingly, the average saving reduces when more than 38% of the users adopted storage devices in their homes. This is because beyond this equilibrium point, additional storage adds more volatility to already flattened market prices. In this case, a user can save more by not having any storage.

2.2.4 Summary

There are two types of energy storage: electrical storage and thermal storage. The space heating and hot water storage of the household can be considered as thermal storage. The EV battery is considered as electrical storage when it is plugged in. The system looses energy during the energy storing process (e.g., charging, heating). Each type of storage shows a gradual spontaneous energy loss (e.g., self-discharging, temperature loss due to external environment).

Energy storage has great potential to flatten the energy demand curve. In practical scenarios, the energy consumption rate is not the same in different hours of a day. In off-peak hours, energy demand is low and in on-peak hours, energy demand is high. The utility has to ensure the production capability to meet the maximum demand. In smart grid, the utility tries to motivate the users to store energy when demand is low so that it can be used during on-peak hours instead of drawing energy from the grid. As a result, the utility can save the equipment and operational costs which are required to produce more energy at the on-peak hours. However, the impact of an increased utilization of energy storage may create a new trend in energy demand. In this case, an off-peak hour may become an on-peak hour. Also the energy price may then be estimated based on the wrong demand information and may not work as expected. More research is required to analyze the impact of storage on energy demand and on efficient ways to utilize the storage for cost optimization.

Energy storage may have an unintended impact on the smart grid. Sometimes, instead of saving energy cost, storage systems may increase energy cost [53]. In contrast, some research has reported that distributed storage may be more beneficial than distributed generators [54]. The concerned authorities should carefully define the policies related to storage installation in smart grid.

2.3 Energy Optimization using Renewables and Power Generation Devices

This section discusses the impact of renewable energy sources and energy generating devices or technologies (e.g., Combined Heat and Power (CHP) generators, boilers, etc.) on cost optimization.

2.3.1 Genetic Algorithm

Arabali et al. proposed a probabilistic GA-based optimization using the 2 Point Estimation (2PE) method to minimize PV and wind generation installation cost and increase energy usage efficiency [24]. The authors used an HVAC system as the reference load. The 2PE-based analytical method was used to model the stochastic behavior of wind power output, solar power output and load power consumption. Before applying 2PE, 10 years of historical hourly load data, solar irradiance, and wind speed were clustered into 10 groups using Fuzzy C-Means (FCM) clustering. Each cluster comprises of the days with similar 24-h load data, solar irradiance, and wind speed. The model used the Probability Density Functions (PDF) of wind and solar power generation to normalize the parameters of 2PE. A weighted sum of the installation cost of all clusters was used as the fitness function of the GA. The evolutionary algorithm was repeated until the best chromosome had been identified as the optimum solution. The proposed GA algorithm started with an initial population of 200 and continued for 150 generations. The method used 78% crossover and 20% mutation rate. The scenarios were presented with 10%, 20% 30%, 40% and 50% shifting of the deferrable load. Results showed that increased load shifting provides more flexibility and leads to less excess energy generation. The user can use the proposed model to estimate the optimized installation cost of PV, wind turbine and energy storage. The load shifting may introduce inconvenience to the user by setting the room temperature to an uncomfortable level. The model did not consider this inconvenience to the user.

Bilil et al. proposed a multi-objective model to optimize annualized cost when diverse Distributed Generations (DGs) are used to generate energy [27]. The model considered the annualized cost of the DGs as a function of the capital cost, maintenance cost and replacement cost. The objective function also minimizes the Renewable Energy - Load Disparity (RELD) to balance the generation and loads. The proposed model was solved using a genetic algorithm. It had been observed that using both solar panels and wind turbines is obviously better than using the wind turbines alone. It was also reported that the wind generators are more cost effective than the PVs.

2.3.2 Linear Programming

De Angelis et al. addressed the significance of renewable energy sources for cost optimization in smart grids [9]. The proposed model limits the grid energy usage to a certain maximum level. The energy demand was primarily serviced from renewable energy sources. The paper used an MILP model to calculate the optimum energy generation capacity of the renewables considering the given load i.e., it provides an estimate of the capacity of the renewable energy generation devices that is required to be installed at the user's premises for optimal cost savings. It did not consider the dynamic nature of renewable energy sources. The storage capacity in a household has a potential impact on the cost. In this model, if more storage capacity is added, the user can minimize cost by selling surplus energy to the grid. However, it requires an additional capital cost. A model can be developed to address the trade-off between capital cost and daily or monthly profit.

Zhang et al. considered multiple homes in a smart building which share common Distributed Energy Resources (DERs) such as CHP generators and boilers [22]. The building has a CHP generator with a capacity of 4 kW_e and 35% electrical efficiency. It is operated by natural gas at a cost of 2.7p/kWh. The building also has a 24 kW_{th} boiler operated by natural gas. The proposed system is an MILP model that was implemented using CPLEX in GAMS. Their results showed that the CHP was providing constant maximum output of 4 kW most of the time except at night when heat demand is low. The peak demand had been shifted to the night time from evening and the peak demand had been reduced by 7 kW to 32 kW. The results also showed that the proposed cost optimization model saves 24% to 30% of the energy cost by rescheduling the sources and the loads with fairly distributed cost among the homes.

Hopkins et al. proposed an LP model to analyze the impact of DGs on cost optimization [23]. The cost function considers the energy buying cost from the utility, energy selling cost to the utility and storage loss that is calculated from the storage lifespan. The renewable sources have been modeled using an energy balance constraint ensuring that the total generated energy is the same as the total consumed energy. The model considered a 2.24 kW solar system, eight T105 deep-cycle batteries and an Outbreak GTFX2524 inverter. Results showed that with solar panels (without using the storage), the proposed solution can save on average $1.84 per day.

2.3.3 Summary

There are mainly three research challenges related to renewables and energy generating devices. First, a user needs to determine the capacity of the energy sources in advance to be installed in smart homes. The energy price of a renewable source is calculated from the capital cost and the life span of the device. Other energy sources require fuel cost that contribute to the energy prices. The user has to strike a balance where further capital investment does not pay off. If the user decided to become an energy seller, the energy demand and distribution capacity limit the production rate of an individual seller. Research should emphasize more on the capital cost optimization in smart grid. Second, given that a household is equipped with energy sources, the user needs an estimate of the probable energy generation in advance from the renewables. The prediction algorithms are utilized to forecast energy generation of the renewables. If the user optimizes energy consumption knowing the forecasted energy generation from the renewables, it will provide an estimate of how much energy from other sources (e.g., grid, energy generation devices (if any)) will be required. Finally, a combination of different energy sources may result in a more predictable energy generation [27]. The current research trends have not yet identified the most effective combination of different energy sources.

2.4 Energy Trading

Trading energy in the energy market is an effective way to minimize energy cost. It is assumed that users know their own energy demand and expected generation in advance. The energy price and usage preference motivate the user to earn a profit by selling energy in the open energy market. This section discusses the research on effective energy trading methods in smart grids.

2.4.1 Particle Swarm Optimization

Ramachandran et al. proposed a Risk-Based (RB) auction strategy for profit maximization while selling energy to the energy market [28]. The auctioneer agent interacts with a load agent and a DER agent to obtain the bid and ask prices respectively. The risk attitude of the trader (buyer and seller) has been classified into three categories: risk neutral, risk averse and risk seeking attitude. A risk seeking policy means that the trader is looking for high profit which has a lower probability of transaction. A risk averse attitude means that the trader will accept low profit margin but the probability of transaction is high. A risk neutral strategy seeks for a price that maximizes its expected profit. This attitude is represented by a variable called risk factor. The RB auction strategy starts trading by using the risk neutral policy then gradually updates the risk factor based on the current Competitive Equilibrium (CE) price until the bid/ask improvement over the outstanding bid/ask is less than a threshold level. In the experiment, it was found that an agent trades very carefully during the first round because its knowledge was limited. After the first round, the risk factor converged rapidly. The authors used grid energy prices from the Amsterdam Power Exchange (ApX) [55] and assumed energy prices of the renewable energy sources. Results showed that with the aid of a Particle Swarm Optimization (PSO) based algorithm, the energy cost of the utility was reduced by 37%. The users share the benefit of this reduced cost.

Wang et al. developed a PSO-based negotiating agent to facilitate energy trading in smart grids [29]. The utility grid and the smart building were considered as traders which can be buyers and sellers. The PSO optimizer indirectly predicts the opponents' preference based on its previous prices. The proposed optimizer uses a time pressure function which is a function of eagerness to determine the attitude of the agent. Higher eagerness means the agent is willing to complete the transaction by the deadline at any price whereas lower eagerness means the agent is motivated to risk losing the deal for the chance of a better price. Eagerness is a combined effect of long term eagerness and short term eagerness. The short term eagerness function for both the smart building and the utility depends on the previous offers of the opponents. The long term eagerness function of the smart building as a seller depends on the number of recent transactions and the State of Charge (SOC) of the battery. When the smart building is a buyer, the long term eagerness function depends on interruptible loads and comfort levels. Long term eagerness of the utility is a function of the number of successful recent transactions. The simulated results showed that the PSO-based agent in the smart building (buyer) can learn the pattern of the utility (seller) and can mimic the opponent's behavior. The agent saved 17% cost and reduced negotiation time by 9% compared to an agent without learning capability.

2.4.2 Auction

Vytelingum et al. developed a trading agent based on the Continuous Double Auction (CDA) strategy [25]. The CDA allows the buyer and seller to continuously change the energy price during the trading time in a continuously clearing market. The buyer submits two types of orders. One is the inelastic limit order which represents the minimum required energy in the household. The other is the elastic market order which represents optional household demand depending on the market price. The sellers' orders are elastic price-sensitive market orders. The limit order bids offered by the buyers cleared immediately (if that amount of energy is available in the market) by the market because it is an inelastic demand and does not depend on the energy price. When the orderbook (where all bids and asks are recorded) is changed due to a new or improved bid or ask, a market clearing algorithm searches for a possible match where a buying price is more than or equal to a selling price. If a best match is found, a transaction occurs between the buyer and the seller and the market clears the matched ask and bid. The auction occurs a day ahead of the actual consumption. The paper proposed an online balancing policy when the real time demand exceeds beyond the traded market amount or supply drops below it. The proposed mechanism uses the unmatched orders of the orderbook records to rematch the new demand and reduced supply in real time. The paper also considered the cost of using transmission lines (resembles the transportation cost of traditional goods), transmission line constraints and secure transaction policies. The lower bound efficiency of the market was evaluated by a Zero Intelligence (ZI) [56] strategy which uses random bid and ask prices. For this baseline strategy, the market efficiency was 88% to 96%. When the same scenario was simulated with an improved version of an Adaptive Aggressive (AA) [57] strategy, it showed 92% to 99% market efficiency. The authors assumed that the untraded energy would remain on the market to be used at the actual consumption time which may not be true all the time. The seller may decide to increase energy consumption or reduce energy generation because of lower demand. In this case, balancing the real time demand with the day-ahead outdated information may not be feasible.

Ilic el al. described an energy market, named NOBEL [58], to evaluate market-driven demand response of electricity trading [30]. The market facilitates electricity trading in a local network to avoid (or reduce) transportation cost and energy loss. The model utilized a stock exchange model where energy trade time is defined as discrete timeslots. The orders are maintained in an orderbook and a matching algorithm searches for the best match to clear the transaction. Old orders get higher priority over new orders. The orders may have different configurations depending on the user preference. An order may have to be matched partially or fully. A fully matched order should be matched exactly; otherwise it can wait in the orderbook to be matched later if more orders arrive. The matching algorithm may not block the trading if full match orders are waiting in the orderbook. An order may have to be matched immediately which will be cancelled automatically from the market if the matching is unsuccessful. The market was implemented in a Java-based local simulator as well as in an online application server. The trading agent applied the ZI [56] strategy to bid to the market. It randomly bids following a maximum sleep time to facilitate a high-level order matching. The simulator used household load profiles and a renewable energy source with random weather effects as input parameters. Results showed that market efficiency drops when the supply meets the demand and becomes stable if supply exceeds demand, but it never drops below 70%. The minimum matching rate was 75% which means 75% of the total orders were traded in the market.

Recently, a transactive energy framework is proposed to standardize the architecture of transactive control [59]. The term transactive energy refers to techniques for managing the generation, consumption or flow of electric power within an electric power system through the use of economic or market-based constructs while considering grid reliability constraints [59]. Research related to transactive energy mainly considered the underlying architecture to control the energy flow in smart grid [60]. The framework uses auction mechanism for energy trading which are similar to the ones discussed in this section [61].

2.4.3 Game Theory

Capodieci et al. developed a multiagent system to evaluate the energy trading strategy of households [62]. The paper categorized the agents into two types: main agents and auxiliary agents. The main agents are energy producers and consumers e.g., prosumers (buys and sells energy), consumers (buys energy) and Gencos (traditional energy generating companies). The auxiliary agents provide information and mediation to support the behavior of the main agents. The proposed energy trading strategy uses an auction system. All main agents participate at every round in the auction. The authors proposed a learning algorithm based on game theory which predicts the energy price using the previous experiences. The paper reported that a learning algorithm improves the performance of the system.

2.4.4 Summary

From the methodologies discussed above, it is obvious that different types of auctions are the most popular strategies for energy trading in the energy market. The auction strategies could be improved by using algorithms that predict the opponents' behavior. These algorithms use functions which adaptively determine the risk attitude of the users from the previous trading history. The risk attitude of the users could be classified into risk seeking (high profit but higher risk of untraded energy), risk averse (low profit and lower risk of untraded energy) and risk neutral attitudes. The performance of the intelligent algorithms is compared with the ZI auction strategy which is based on random bid and ask prices.

The market orders are classified into two categories based on elasticity: inelastic and elastic orders. The inelastic energy demand must be cleared immediately and it does not depend on the energy prices. The elastic demands are optional energy requirements of the users and could be delayed or discarded based on market prices. An order could be a fully matched order or a partially matched order depending on the users' preferences. A full match order must be matched exactly. A partial match order may be matched with any amount of ask or bid quantity. A matching algorithm clears the transactions based on the matching criteria.

Energy trading takes place in advance before the actual generation. The energy generation on the user side mostly depends on renewable sources that fluctuate with weather conditions. Sometimes, it may not be possible for the seller to supply the traded amount of electricity to the buyer. There may also be some issues related to the quality of the supplied energy in the market. Energy quality refers to an uninterrupted electricity supply with regulated voltage. There should not be any service disruption and the voltage level should maintain the standard level throughout the distribution time. It is not clear how the microgrid will ensure the Quality of Service (QoS) between buyers and sellers and how the current market will deal with any disputes occurring between two trading parties.

2.5 Summary

This chapter explores contemporary cost saving methods for the smart grid from the users perspective. The aim of this chapter is to investigate the potentials of used methods and their interactions. It presents a classification scheme of the proposed algorithms according to their research objectives. It also discusses the research challenges that must be overcome to achieve optimal cost savings in the smart grid.

A smart home in the smart grid offers an optimized energy management solution in collaboration with the utility and the neighbors. The widespread participation of the users plays an important role to achieve the optimal benefit from the smart grid. The users are mostly motivated by the cost saving potential of smart homes.

This survey addresses the cost saving strategies for smart homes from the users perspective. A smart home has diverse appliances, devices and equipment with different energy consumption profiles. Users have their own preferences for the appliance operation to ensure an optimized energy cost as well as maintain a preferred comfort level. The previous research identified that optimal rescheduling of the household loads according to the energy price is one of the effective ways of cost minimization. One or multiple storage devices accumulate cheap and excessive energy to support future energy requirements, avoiding the need to acquire expensive energy from the grid during periods of high prices (for example, at peak loads). However, the usage of such storage devices imposes a cost overhead because of self-discharging and efficiency loss. It was reported that optimized utilization of the storage devices (e.g., thermal, electrical) has an impact on energy cost. Instead of simply depending on the utility, a smart home can generate its own energy utilizing solar panels, wind turbines, geothermal plants and other renewable energy sources. The renewables show stochastic energy generation profiles correlated to the weather. It is evident from the literature that the usage of renewable sources and advanced planning of renewable energy utilization based on the predicted generation quantity reduces energy cost. The smart homes in a neighborhood may collectively form a microgrid to facilitate energy trading among themselves. Previous study claimed that energy trading among the households by forming a microgrid plays an important factor for cost minimization in the smart grid.

Energy cost is primarily optimized by rescheduling the appliances when energy is cheap (energy sources could be grid, microgrid or renewables), provisioning appliance power, interrupting the appliance operation, scheduling storage usage, and energy trading. However, most of the existing research failed to address a comprehensive discussion of smart homes, considering all important possible aspects for cost optimization. Our work combines these potential strategies into a single unified cost optimization model and analyzes the behavior of the overall system. However, in order to deal with all the above smart home features, sophisticated algorithms are required. To that end, this research explores the cost optimization problem in smart homes that involves diverse energy sources, storage, and loads constrained by user preferences and the electrical properties of the participating components. It also addresses the cost minimization problems associated with P2P energy trading among the participating households in the microgrid.

Chapter 3

The Unified Model

This chapter explores the unified residential energy cost optimization problem in the smart grid. We started our research with a simple model, consisting only of appliance properties, user preferences and the utility energy prices, resulting in a MILP problem. The model gradually became more complex with the inclusion of the storage, the renewables and the microgrid. Energy trading in the microgrid requires the model to determine the optimal amount of energy and the optimal energy price. These criteria have been formulated using nonlinear expressions which transformed the model into a non-convex MINLP problem. Energy trading in the microgrid introduces a cost fairness problem among the participating households. As the model was trying to reduce the energy buying cost from the utility for the entire microgrid area, it failed to address the cost optimization for each individual household. It was found that the optimization model using only a single objective function (minimize the sum of the energy costs and the disutility costs for all households in the microgrid) sometimes increases the energy cost of a few households to reduce the cost of others. This unfair cost distribution problem made the model unattractive to the participating parties. To address this problem, the model has been extended to an optimization problem with multiple objective functions that considers individual household energy cost. In multi-objective optimization, we need to ensure Pareto optimality, i.e., no household should be worse off to improve the cost of some other households. This chapter incrementally builds a unified cost optimization model by integrating new components and their corresponding characteristics. It first formulates the complete cost optimization model with the load and the source characteristics, and user preferences. Then, it extends the proposed model to ensure Pareto optimality among the participating households in the microgrid.

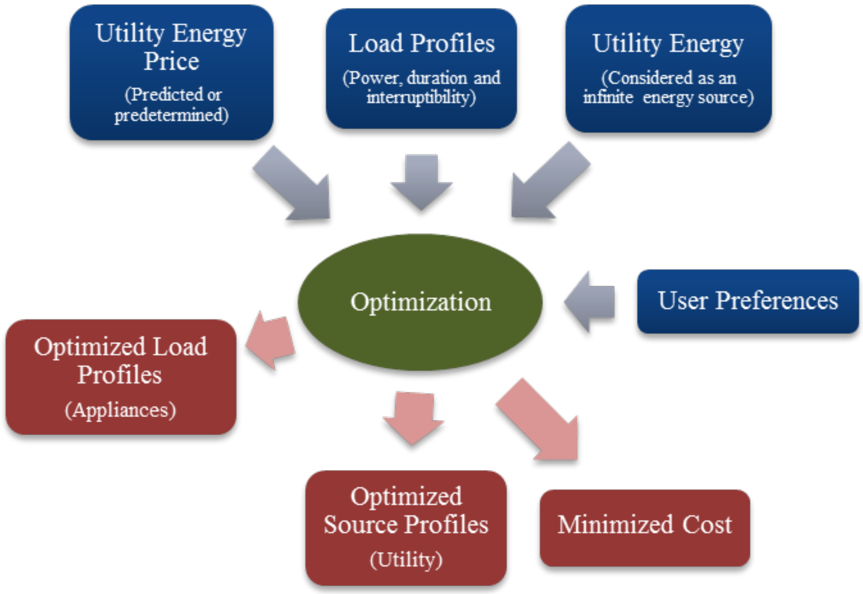

Figure 3.1: A Simple Optimization Framework Considering only the Utility and the Loads.

3.1 Problem Evolution

In this section, we sequentially build a cost optimization model by incrementally adding new components. Household loads are the common components of all models discussed in the literature. These loads can be divided into two categories: elastic and inelastic loads. Elastic loads are re-schedulable and can be delayed (or discarded) based on the energy price. Inelastic loads are non-schedulable and non-deferrable. Both types of loads are further classified into interruptible and uninterruptible loads. An interruptible load or task can be disrupted in the middle of its execution and has to be resumed later. An uninterruptible task must be finished completely once started. The utility is considered as an infinite unidirectional source of electricity.

Our first model considers the traditional electric grid energy flow scenarios where the utility produces energy and the user consumes it. The user behavior will be indirectly controlled by a TOU or a dynamic energy pricing scheme. Figure 3.1 illustrates a framework describing the relationship between the components. In this case, the optimizer will reschedule the loads to minimize energy cost. The elasticity and delay preference of the loads have been implemented by a control variable that imposes a cost if an appliance operation has been delayed.

The smart grid promotes the integration of renewable energy sources. Due to the uncertain generation capacities of most renewable energy sources, the energy generation profile has to be predicted in advance to determine the amount of energy from the renewables. The energy price of the renewables is considered to be 0. We would expect, for a rational residential user, that they would only install renewable energy resources if the per-unit cost falls below the grid price, as they are otherwise acting irrationally. The actual per-unit cost would depend on the amount generated energy over a lifetime. The model allows us to assume a different unit price for renewable energy (in case, we would like to consider the capital and operational cost). By setting the unit price to 0, we assume a best-case scenario, with maximum energy cost reduction potential.

An energy storage can be charged when the energy is cheap, considering the energy demand. Storage charging may introduce a new cost due to the energy loss while charging. This cost is proportional to the efficiency of the storage. Self-discharging is another source of energy loss and imposes additional cost. The stored energy will be utilized in high energy price timeslots. Efficient storage scheduling may result in significant cost reduction because an optimized amount of storage capacity enables the user to avoid high energy price timeslots. Figure 3.2 extends the framework of Figure 3.1 with the renewables and the storage.

One of the key characteristics of the smart grid is that it allows bi-directional energy flow between energy suppliers and energy users. The users are able to trade energy between themselves through a Virtual Power Plant (VPP) or microgrid. It enables the users to earn a profit by selling surplus energy into the microgrid or to minimize cost by buying cheap energy from it.

The framework presented in Figure 3.3 includes the required components to optimize cost from the users' perspective. The energy flow is determined by the energy sources and loads. The source of energy can be either the utility, renewables, storage devices, or the microgrid. The generated energy is consumed by the loads, storage devices and the microgrid. Most of the reviewed research solved a partial problem related to cost minimization in smart grids. These partial problems are part of the unified optimization model as shown in Figure 3.3. The reminder of this chapter formulates this unified optimization framework as a nonlinear optimization problem.

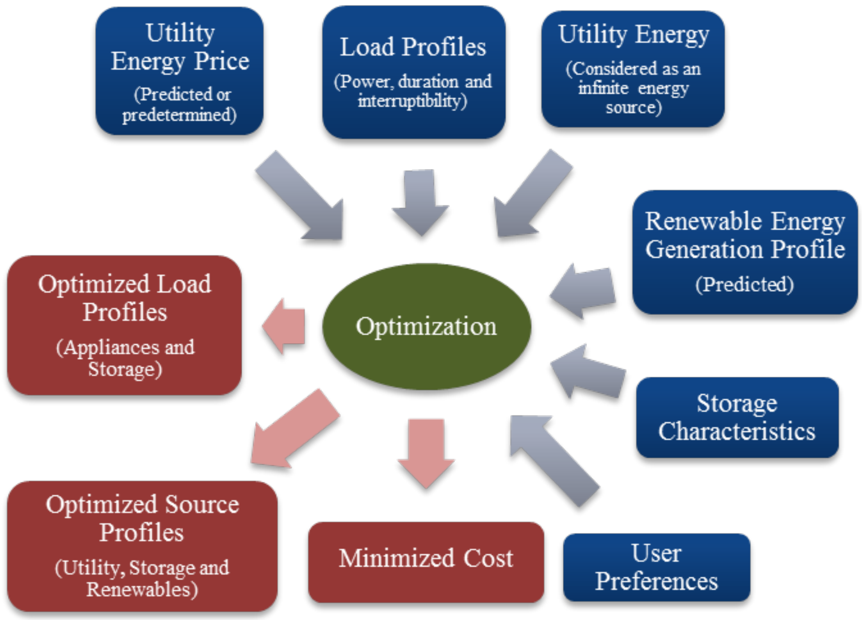

Figure 3.2: An Optimization Framework Covering the Utility, Renewables and Storage Devices.

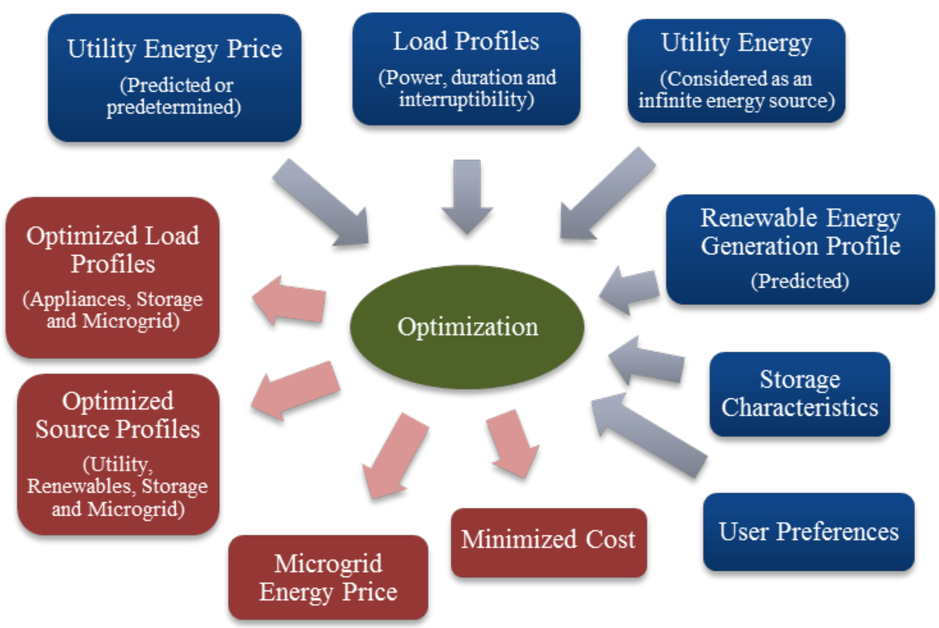

Figure 3.3: The Unified Optimization Framework Including the Utility, Renewables, Storage Devices and Microgrid Trading.

3.2 Problem Definition

Suppose we have several households in a microgrid area which are equipped with a bi-directional distribution network so that they can trade energy between themselves. Every household has access to the utility grid. If the microgrid cannot accommodate the energy demand of a household, the household can buy energy from the utility grid. The utility grid advertises the energy prices which may be based on time or energy demand or any other methods that the utility prefers to use to control the energy consumption.

Different households have different power consumption and generation profiles. A household may be equipped with renewable energy generation devices which have a time-varying energy generation profile based on weather conditions. It has different types of appliances with different power requirements and user preferences. It may also have an energy storage which can store energy to be utilized later. The user can trade energy with other users to minimize energy cost or to generate profit.

The objective is to minimize the cost from the users' perspective. In other words, given a list of appliances that must be used in a given time horizon, we would like to know how users can optimally schedule their energy consumption and energy sources such that the total cost of all users is minimized. It is important to note that the goal is not about load optimization or balancing, which may be useful for the utility to reduce peaks.

A non-convex MINLP model has been developed to optimize the energy cost for the proposed problem. The following notation is used to describe input parameters and decision variables.

3.3 Input Parameters

Sets

- H, set of timeslots representing the scheduling horizon where $h \in H$ is the h-th timeslot of set H.
- I, set of appliances where $i \in I$ is the i-th appliance of set I.
- K, set of households where $k \in K$ is the k-th household of set K.
- U, set of uninterruptible appliances where $U \subset I$.

Constants

- $\beta_{k,i}$, maximum allowable delay of the i-th appliance of the k-th household.
- $d_{k,i}$, disutility factor of the i-th appliance of the k-th household. The disutility related to every appliance is not the same. We can control the delay preference of each appliance by controlling the value of $d_{k,i}$.
- E_k, storage efficiency of the k-th household.
- GP_h, energy price of the utility grid at timeslot h. It is assumed that the electricity price changes at the starting second of a timeslot and stays at the same price until the end of that timeslot.
- IE_k, initial storage energy of the k-th household.
- L_k^{max}, maximum grid power limit of the k-th household imposed by the utility or by the electric fuse (per scheduling timeslot).
- $MaxC_k$, maximum storage capacity of the k-th household.
- $MinC_k$, minimum storage capacity of the k-th household. If the storage energy drops below the minimum level, it reduces the lifespan of the storage.
- N, number of timeslots with fixed duration.
- $p_{k,i}$, power consumption of the i-th appliance of the k-th household.
- $r_{k,i,h}$, reservation time of an appliance, which represents the time when the scheduler gets a request to start a specific appliance. $r_{k,i,h} = 1$ means that operation of appliance i of the k-th household is requested in timeslot h. Alternatively, $r_{k,i,h} = 0$ means that appliance i of the k-th household is not requested in timeslot h. If an appliance gets multiple requests in the same time horizon, it is considered as multiple (virtual) appliances. In this case, the scheduler optimizes the execution time as if it had multiple similar loads and there should be a constraint to ensure that the end time of the previous instance is at or before the start time of the later instance.
- $RQ_{k,h}$, amount of generated renewable energy of the k-th household at timeslot h.

- SD_k, self-discharging coefficient of the storage of the k-th household.
- SP_k, power required to charge the storage of the k-th household.
- $t_{k,i}$, duration of the running time of the i-th appliance of the k-th household (measured in timeslots).

Decision Variables

- $BE_{k,h}$ is a positive real variable which represents the energy used from the storage by the k-th household at timeslot h.
- $GE_{k,h}$ is a positive real variable which represents the energy drawn from the utility grid by the k-th household at timeslot h.
- $IC_{k,h}$ is a Boolean variable which represents whether the storage is in charging stage or not. $IC_{k,h} = 1$ means the storage of household k is in charging stage at timeslot h.
- $ME_{k,h}$ is the energy traded with the microgrid by the k-th household at timeslot h. A positive value of $M_{k,h}$ means the k-th household is a buyer at timeslot h. A negative value means the household is a seller.
- MP_h is a positive real variable which represents the price of the microgrid energy at timeslot h.
- $MQ_{k,h}$ is the demand (or supply) of the microgrid energy of the k-th household at timeslot h. A positive value represents the minimum energy demand of the household. A negative value represents the maximum amount of energy the household can sell to the microgrid.
- $RE_{k,h}$ is a positive real variable which represents the energy used from the renewable sources by the k-th household at timeslot h.
- $SE_{k,h}$ is a positive real variable which represents the stored energy in the storage of the k-th household at timeslot h.
- $S_{k,i,h}$ is a Boolean variable which represents the execution time of the appliances. $S_{k,i,h} = 1$ means that appliance i of household k is in operation at timeslot h.

- $US_{k,i,h}$ is a Boolean variable which represents the start time of the uninterruptible appliances. $US_{k,i,h} = 1$ means that the uninterruptible appliance i starts at timeslot h in household k.
- $\tau_{k,i}$ is the end time of the task executed by appliance i at k-th household. $\tau_{k,i}$ is a positive integer variable that can take values in the following range: $[1, N]$.

3.4 Energy Function

The energy cost of the k-th household, denoted by CE_k, is a function of utility price, the power drawn from the grid, microgrid price and energy traded within the microgrid. This can be expressed in a cost function which is given in Equation 3.1.

$$CE_k = \sum_{h \in H} GP_h \cdot GE_{k,h} + \sum_{h \in H} MP_h \cdot ME_{k,h} \tag{3.1}$$

To optimize the electricity cost in a time horizon, the appliances may be scheduled in timeslots where electricity prices are relatively low. Therefore, to get the optimal savings, CE_k should be minimized.

3.5 Disutility Function

If the scheduler tries to minimize CE_k, it may create discomfort to the user because it may delay the appliances for a long period of time. To consider this discomfort while trying to reduce costs, a disutility function is used to compensate for the inconvenience created by delaying an appliance operation. The disutility function, denoted by CD_k for the k-th household, is expressed in Equation 3.2.

$$CD_k = \sum_{i \in I} d_{k,i} \left(\tau_{k,i} - \left(\sum_{h \in H} r_{k,i,h} \cdot h + t_{k,i} - 1 \right) \right) \tag{3.2}$$

Here, $\sum_{h \in H} r_{k,i,h} \cdot h$ is the reservation timeslot which is calculated from the reservation times. An appliance is reserved only once in the time horizon (which means $\sum_{h \in H} r_{k,i,h} = 1$). Therefore, the multiplication of $r_{k,i,h}$ by the corresponding timeslot will provide the reservation time. Hence, $\sum_{h \in H} r_{k,i,h} \cdot h + t_{k,i} - 1$ represents the end time of the appliance, if it has been started immediately after reservation. Therefore, if we subtract this end time from the scheduled end time $\tau_{k,i}$, we obtain the delay from the reservation time. The disutility factor $d_{k,i}$ is an adjustable coefficient which is defined according to the users' tolerance of delay per appliance. The higher the value of $d_{k,i}$, the more disutility such a delay will generate and to compensate this, the scheduler will reduce the delay.

3.6 The Optimization Model

The total cost of the 1st household is denoted by C_1, the total cost of the 2nd household is denoted by C_2 and so on. In general, the total cost of the k-th household is,

$$C_k = CE_k + CD_k \tag{3.3}$$

The objective is to minimize all cost functions as follows,

$$min\,(C_1, C_2, \ldots, C_k) \tag{3.4}$$

Objective 3.4 is a multi-objective MILP optimization problem which is implemented using a single objective function that minimizes the sum of the energy costs and disutility cost for all households in the microgrid (Equation 3.23 discussed later). Appendix A.2 lists the complete unified optimization model. The optimal solution should satisfy the following constraints.

Energy Balance Constraints

For a specific household, the total energy consumed by all appliances and the storage in a specific timeslot should be the same as the total energy supplied by the grid, renewable sources, microgrid and storage in that timeslot. This relation has been expressed in Equation 3.5.

$$\begin{aligned}\sum_{i \in I} S_{k,i,h} \cdot p_{k,i} + IC_{k,h} \cdot SP_k = GE_{k,h} + BE_{k,h} \\ +RE_{k,h} + ME_{k,h}, (k \in K, h \in H)\end{aligned} \tag{3.5}$$

If the microgrid energy $ME_{k,h}$ is negative, it becomes a load which means the k-th household sells energy to the microgrid during the h-th timeslots. If it is positive, it is an energy source, i.e., the k-th household buys energy from the microgrid during the h-th timeslots. For this constraint, the microgrid can never be both a source and a load at the same time.

Stored Energy Constraints

In the first timeslot, storage energy is measured using Equation 3.6 which is a function of initial energy, charging and discharging at the 1st timeslot, efficiency loss and self-discharging loss.

$$SE_{k,1} = IE_k \cdot SD_k + IC_{k,1} \cdot SP_k \cdot E_k - BE_{k,1}, (k \in K) \tag{3.6}$$

The stored energy in the subsequent timeslots depends on the energy during the immediate previous timeslot, the energy stored in the current timeslot considering the efficiency loss, and the self-discharging loss, which has been expressed in Equation 3.7. Self-discharging only applies to the stored energy from the immediate previous timeslot.

$$SE_{k,h} = IE_{k,h-1} \cdot SD_k + IC_{k,h} \cdot SP_k \cdot E_k - BE_{k,h}, (k \in K, h \in H : h \neq 1) \tag{3.7}$$

Storage Capacity Constraints

A storage must have sufficient energy to act as a source. It should not exceed the maximum storage capacity and should not drop below the minimum energy level. Inequalities 3.8 and 3.9 limit the maximum and minimum stored energy of the storage respectively.

$$SE_{k,h} \leq MaxC_k, (k \in K, h \in H) \tag{3.8}$$

$$SE_{k,h} \geq MinC_k, (k \in K, h \in H) \tag{3.9}$$

Task Duration Constraints

Constraint 3.10 maintains the total duration of a task. It ensures that the sum of all the elements of the scheduling vector of an appliance equals to the duration of that appliance.

$$\sum_{h \in H} S_{k,i,h} = t_{k,i}, (k \in K, h \in H) \tag{3.10}$$

Renewable Energy Availability Constraints

The total energy used from the renewable sources should be less than or equal to the total generated energy by the renewables as expressed in Constraint 3.11.

$$RE_{k,h} \leq RQ_{k,h}, (k \in K, h \in H) \tag{3.11}$$

Reservation Time Constraints

Constraint 3.12 specifies that all executions must start after (or at) the reservation time. Without this constraint, an appliance could be scheduled to run before it has been requested. Here, $\sum_{h\in H} r_{i,h} \cdot h$ refers to the reservation timeslot.

$$\sum_{h\in H} S_{k,i,h} = \sum_{h=\sum_{h\in H} r_{k,i,h}\cdot h}^{N} S_{k,i,h}, (k \in K, i \in I) \tag{3.12}$$

Relationship between the Scheduling Vector and the End Time Constraints

Inequality 3.13 binds $S_{k,i,h}$ with $\tau_{k,i}$. These two decision variables depend on each other: for any appliance, the last execution time should also be the end time. It also implicitly expresses that, for the earliest possible end time, execution time cannot be zero.

$$S_{k,i,h} \cdot h \leq \tau_{k,i}, (k \in K, i \in I, h \in H) \tag{3.13}$$

Maximum Allowable Delay Constraints

Constraint 3.14 imposes that the end time must be before (or at) the user-defined maximum execution time limit.

$$\tau_{k,i} \leq \beta_{k,i}, (k \in K, i \in I) \tag{3.14}$$

Uninterruptibility Constraints

Constraints 3.15 and 3.16 define that if an uninterruptable appliance starts running, it will keep running until it completes its operation. Without these constraints, an uninterruptible appliance may be interrupted.

$$\sum_{d=0}^{t_{k,i}-1} S_{k,i,h+d} - t_{k,i} \geq -t_{k,i}(1 - US_{k,i,h}),$$
$$(k \in K, i \in U, h = [1, N - t_{k,i} + 1]) \tag{3.15}$$
$$\sum_{h=1}^{N-t_{k,i}+1} US_{k,i,h} = 1, (k \in K, i \in U) \tag{3.16}$$

Utility Grid Maximum Power Limit Constraints

Inequality 3.17 limits the load of the utility grid per timeslot to a maximum power limit. Without this constraint, the appliances may be scheduled in such a way that they exceed the maximum grid power limit per household.

$$GE_{k,h} \leq L_k^{max}, (k \in K, h \in H) \tag{3.17}$$

Energy Balance Constraints for Microgrid

Constraint 3.18 imposes that the total energy sold in the microgrid must be equal to the total energy bought from the microgrid.

$$\sum_{k \in K} ME_{k,h} = 0, (h \in H) \tag{3.18}$$

Microgrid Energy Price Constraints

The energy price of the microgrid in a specific timeslot will be greater than or equal to 0 and cannot be greater than the grid energy price (Constraints 3.19 and 3.20).

$$MP_h \geq 0, (h \in H) \tag{3.19}$$
$$MP_h \leq GP_h, (h \in H) \tag{3.20}$$

If the microgrid energy price exceeds the grid price, the household should buy energy from the grid.

Energy Constraints While Trading in Microgrid

The energy surplus or demand is the difference between the total energy consumption and generation in a specific timeslot. Equation 3.21 calculates the amount of energy that is available to trade in the microgrid.

$$\begin{aligned} MQ_{k,h} = \sum_{i \in I} S_{k,i,h} \cdot p_{k,i} + IC_{k,h} \cdot SP_k - GE_{k,h} \\ -RQ_{k,h} - SE_{k,h} - BE_{k,h} + MinC_k, (k \in K, h \in H) \end{aligned} \tag{3.21}$$

If the user is a buyer, Constraint 3.22 defines the minimum energy required by the household from the microgrid. If the user is a seller, this constraint limits the maximum amount of energy that a household can sell to the microgrid.

$$ME_{k,h} \geq MQ_{k,h}, (k \in K, h \in H) \tag{3.22}$$

3.7 Extended Model with Pareto Optimality

The objective function specified in Equation 3.4 is a unified optimization problem that minimizes the sum of the energy cost and the disutility cost of all households in the microgrid. Sometimes an optimal solution will increase the energy cost of a few households to reduce the cost of others. This situation occurs when a household in essence buys more energy than it needs and gives the energy away for cheap to other households. Therefore, the model should ensure Pareto optimality to address the cost fairness problem. We extended the objective function proposed in Equation 3.4 by adding a new function Y defined as the total cost of all households in that microgrid area, which is expressed in Equation 3.23.

$$Y = \sum_{k \in K} \sum_{h \in H} GP_h \cdot GE_{k,h} + \sum_{k \in K} \sum_{i \in I} d_{k,i} \left(\tau_{k,i} - \left(\sum_{h \in H} r_{k,i,h} \cdot h + t_{k,i} - 1 \right) \right) \tag{3.23}$$

Equation 3.23 does not require the cost of energy drawn/supplied from/to the microgrid because in a specific area, the total buying cost from the microgrid equals the total selling profit by all households. Therefore, the microgrid energy price does not have an impact on the total cost. Hence, Y is a linear function that represents the total energy cost drawn from the utility grid by all households and the total disutility because of delayed tasks. The extended multi-objective optimization model is,

$$min\,(Y, C_1, C_2, \ldots, C_k) \tag{3.24}$$

subject to Constraints 3.5 - 3.22. The extended model is solved by using Y as the sole objective function and the remaining objective functions, C_k, are added as inequality constraints. Suppose, for the k-th household, the minimum energy cost in the absence of the microgrid is represented by $C_k^{NoTrade}$. Therefore, the proposed multi-objective optimization problem is defined as:

$$min\ Y \tag{3.25}$$

subject to:

$$C_k \leq C_k^{NoTrade}, (k \in K) \tag{3.26}$$

and all other Constraints 3.5 - 3.22.

The following analysis provides significant information about the model which helps to implement the algorithm practically. The energy cost of a household, $C_k^{NoTrade}$, can be calculated when the household is considered as an isolated household, meaning that the household does not take part in the microgrid trading. Therefore, if we minimize Objective Function 3.25 with respect to Constraints 3.5 - 3.17, the solution will provide us with the maximum energy cost boundary of the specific household when it participates in microgrid. In Equation 3.5, microgrid energy, $ME_{k,h}$, is set to 0. This optimization excludes the microgrid-related constraints because it is calculating the cost of an individual household. Appendix A.1 lists the complete optimization model for single household.

Objective Function 3.25 with Constraints 3.5 - 3.22 and 3.26 provides a Pareto optimal solution of the problem. Due to Constraint 3.26, no household is paying more than what it used to pay before participating in the microgrid. Objective Function 3.25 ensures that the overall cost in that microgrid neighborhood is minimized without causing any of the participating parties to be worse off. Appendix A.3 lists the complete Pareto optimal unified model.

Obviously, there are numerous Pareto optimal solutions that satisfy the above condition. It is possible to generate all Pareto optimal points by iteratively decreasing the value of $C_k^{NoTrade}$. For example, Abounacer et al. proposed a solution approach using the epsilon constraint method that iteratively generates all Pareto optimal solutions [63]. However, it is computationally expensive because the solution time increases exponentially according to the number of households. Zhang et al. proposed a lexicographic minimax method that distributes the cost savings in a proportional fair way among the households. However, it also results in a more complex optimization problem, requiring to solve the problem iteratively in polynomial time [22].

The optimization methods use the forecasted or pre-advertised energy price, predicted consumption and generation information to plan the schedule of the energy sources and the loads for a certain timeframe. Whenever we receive updated information of the forecasted parameters (despite weather forecast, we end up with a cloudy day with less than predicted energy, strong winds generating more energy, etc.), we may have to solve the optimization problem again with the new information.

3.8 Summary

The proposed optimization model has achieved the primary objectives of the research. It does not only consider energy cost optimization but also addresses the inconvenience created to the users by delaying the operation of certain appliances. The constraints, variables and parameters capture the underlying features of the smart grid components, e.g., load characteristics, source behavior and user preferences. The model determines the energy price in the energy market and regulates the demand and supply of microgrid energy. It minimizes the energy cost in a microgrid area as well as ensures Pareto optimality among the participating households while trading energy. The proposed model has unified the partial aspects of the previous research in a single optimization model to attain optimal cost saving profiles for the participating smart homes.

Chapter 4

Performance Analysis - Unified Model

This chapter evaluates the optimal solution approach of the model described in Chapter 3. The proposed model has been implemented in AMPL (A Mathematical Programming Language) [64,65], an algebraic modeling language for describing large-scale complex mathematical optimization problems. We used Couenne 0.5.3 [66] to solve the MINLP models and CPLEX 12.6.1.0 [67] for the MILP models. Couenne is an open source solver which aims at finding the global optima of non-convex MINLPs [66]. Its performance is competitive to other solvers [66]. Couenne implements linearization, bound reduction, and branching methods within a spatial branch-and-bound framework [66]. CPLEX uses primal and dual simplex, and interior-point (barrier) methods to solve linear and quadratic optimization models with continuous and integer variables [68]. The results were collected from a 64 bit Fedora 20 machine which has an Intel Core i7 CPU (2.67 GHz) and 12 GB RAM.

For small problems, we validated the model output by comparing it to the optimal solution that we manually derived. For larger models, we at least ensured that all constraints were met. Also, we varied a number of input parameters in a series of controlled experiments and verified that the model output changed as predicted (see Section 4.1). We are therefore confident that the model accurately captures all relevant constraints.

4.1 Case Studies

The case studies consider simple but complete scenarios to demonstrate the impact of the different components of the model. The scenarios consider 8 timeslots and 2 households. Each household has 2 appliances. The first appliance (App1) is

Table 4.1: Appliance Characteristics

Household	Appliance	Duration (Timeslot)	Power Per Timeslot (kW)	Disutility Factor (¢)	Reservation Timeslot	Max Delay (Timeslot)
Household 1	App1	5	1	0.01	1	8
	App2	2	4	0.01	1	8
Household 2	App1	3	3	0.01	1	8
	App2	4	2	0.01	1	8

Table 4.2: Storage Characteristics

Characteristics	Household 1	Household 2
Initial Energy (kWh)	3	5
Power (kW)	1	2
Max Capacity (kWh)	5	5
Min Capacity (kWh)	3	3
Charging Efficiency	80%	90%
Self-Discharging Rate (Per Timeslot)	1%	1%

interruptible and the second appliance (App2) is uninterruptible. If it is not mentioned explicitly elsewhere, the appliance characteristics are those shown in Table 4.1. The appliances have different duration and power requirements (per timeslot), and all should be scheduled between the first and the last scheduling timeslots, such that they complete by the 8th scheduling timeslot. The maximum power per household that could be drawn from the grid is limited to 20 kW per timeslot.

Each household also has a storage device with characteristics outlined in Table 4.2. The storage devices have a maximum capacity of 5 kWh, should never drop below 3 kWh, have different initial charges, different charging efficiencies, and discharge at a rate of 1% per timeslot. The storage in household 1 can be charged in increments of 1 kW, while the storage in household 2 can only be charged in increments of 2 kW per timeslot.

4.1.1 User Preference

The user uses disutility factors to set his delay preferences for the appliances. The proposed model supports different disutility factors for different appliances depending on the values of $d_{k,i}$. The disutility factor applies an inconvenience cost if the appliance operation is delayed. The higher the value of the disutility factor, the less the model will tolerate appliance execution delay. Figures 4.1 and 4.2 outline the energy consumption profiles and how the appliances are scheduled, given a specific grid energy price profile for household 1. In this example, energy from the grid is relatively cheap early and late in the scheduling period, but very expensive during timeslots 4-7. The figure specifies how much of that available energy is actually drawn upon by indicating which appliance is scheduled to run in that timeslot and whether we charge the storage device. For example, at timeslot 8 in Figure 4.1, both appliances are scheduled to operate, requiring a total of 5 kWh of energy. Based on the figure, all the energy is drawn from the grid, as the grid price in that timeslot is low. In this example, the optimizer determines that it is more efficient to charge the storage with 1 kWh of cheap grid energy in timeslot 1 and with free energy from one of the renewable energy sources in timeslots 4 and 6. App1 (which is interruptible) is scheduled to operate in timeslots 1, 4, 5, 6, and 8, for a total duration of 5 timeslots. App2 (which is uninterruptible) is scheduled to operate in timeslots 7 and 8. It may appear surprising that App1 is scheduled to operate during timeslots with relatively expensive grid energy prices (timeslots 4 to 6), but at these times the appliance is powered from the energy delivered by the renewables, which has a cost of 0. Figure 4.3 shows that the total energy cost to the household is 6.99¢, which is the sum of the total energy cost (6.9¢) and the total disutility cost (0.09¢) of all appliances.

Figure 4.2, likewise, shows the available energy, consumed energy, and its use, for household 1 with higher disutility factors. The only difference between Figure 4.1 and Figure 4.2 is that for all appliances, the disutility factors used in Figure 4.1 are very low (set to 0.01¢) and the disutility factors used in Figure 4.2 are high (set to 5¢). Figure 4.3 shows that the total cost to the household is now 9.57¢, which is only composed of the energy cost. Due to the higher disutility factors, the optimizer did not delay any appliance operation and hence the total disutility cost is 0. The figure shows that the total cost is increased. To comply with the user delay preference for the appliances, the optimizer buys expensive energy from the grid at timeslots 2 and 3, instead of timeslot 8 when grid energy is cheap.

Figures 4.1 and 4.2 show that the user can control the appliance execution delay

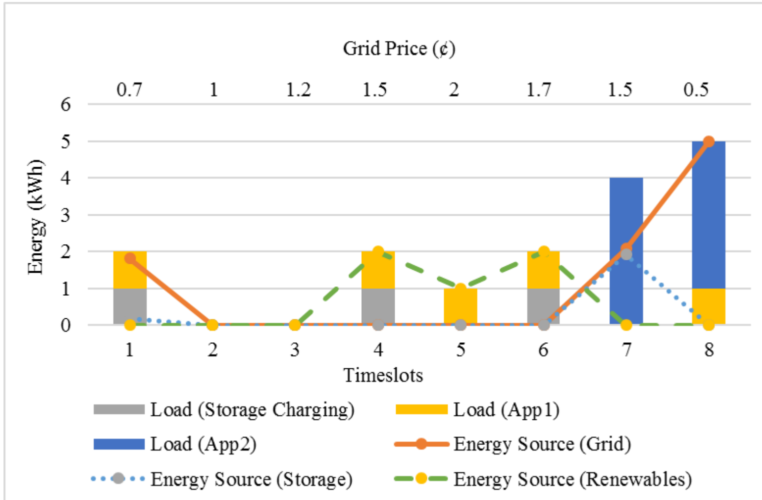

Figure 4.1: Energy Consumption Profile without Microgrid Trading and Low Disutility Factors (Household 1).

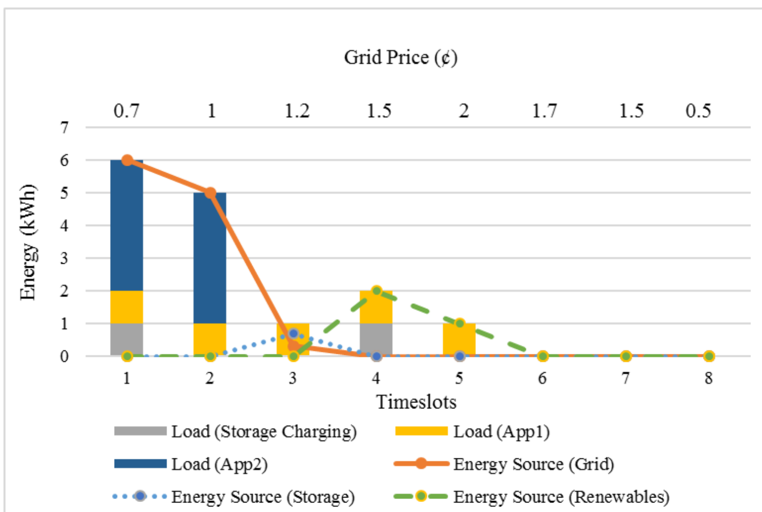

Figure 4.2: Energy Consumption Profile without Microgrid Trading and High Disutility Factors (Household 1).

using the disutility factor for the corresponding appliance. Figure 4.3 shows that if the user desires more comfort by minimizing appliance execution delay, the total cost may increase because the user preferences limit the choices available to the optimizer, resulting in an appliance schedule that is more costly.

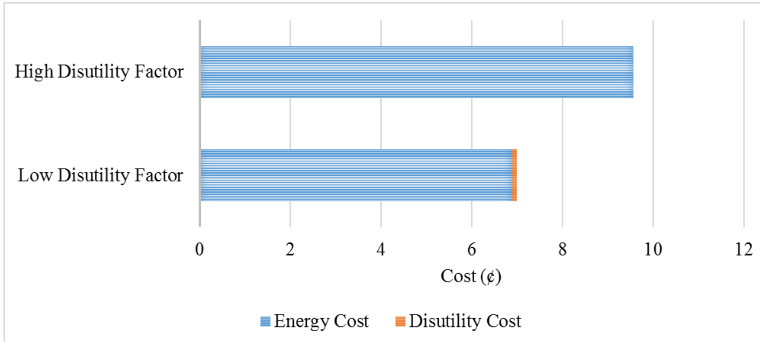

Figure 4.3: Cost Comparison for High and Low Disutility Factors (Household 1).

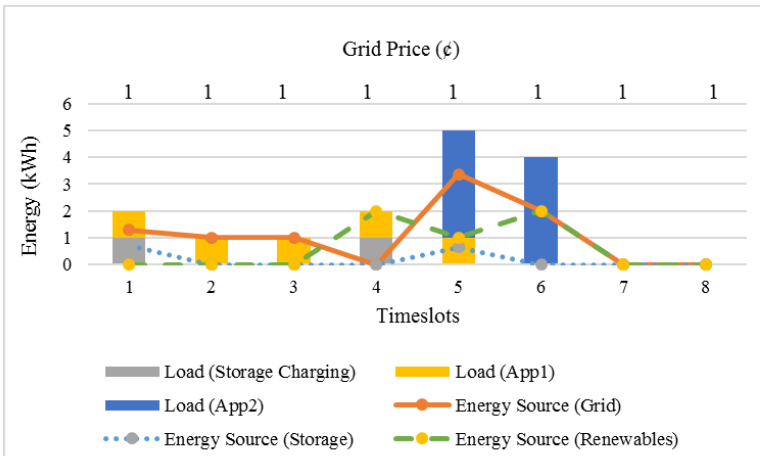

Figure 4.4: Grid Energy Demand with Flat Grid Price Scheme (Household 1).

4.1.2 Demand Response

A DR program is designed to encourage users to change their normal energy consumption patterns in response to changes in energy price. In this section, we first explore the impact of a flat rate electricity price on the load scheduling. Then, we expand the scenario to examine the impact of TOU prices. The Ontario energy board uses TOU electricity prices which vary by time of day, day of the week (weekday or weekend), and season (winter or summer). Finally, we demonstrate the impact of dynamic prices or Real-Time Price (RTP) on the household load. In RTP, the energy price may change hourly and typically depends on the energy demand and supply in a particular time.

Figures 4.4, 4.5 and 4.6 summarize the impact of these three different energy

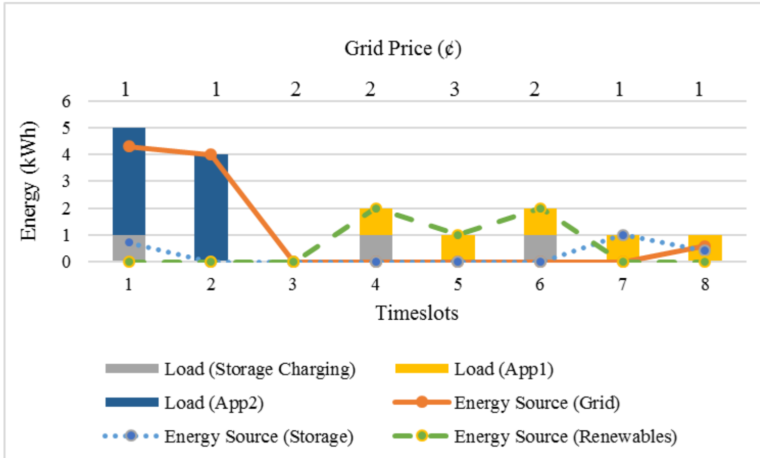

Figure 4.5: Grid Energy Demand with TOU Price Scheme (Household 1).

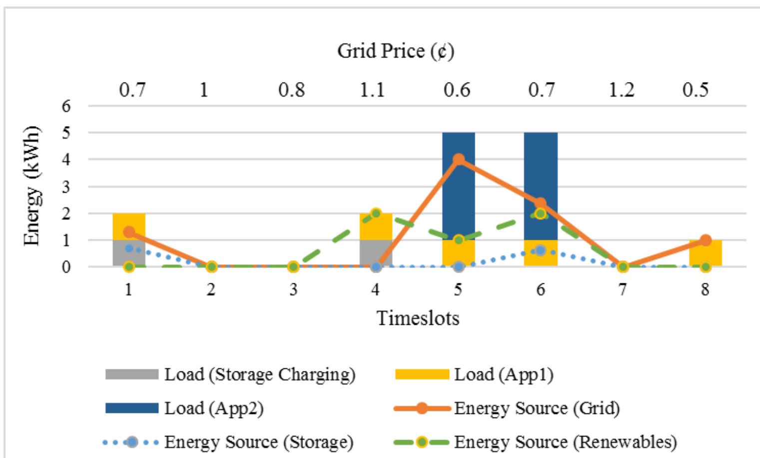

Figure 4.6: Grid Energy Demand with RTP Scheme (Household 1).

price schemes. Figure 4.4 shows the energy drawn from the grid spreads over the time horizon when the grid energy price is flat. The utility has no control over the energy consumption of the user. In this case, the delay of the appliance operation is only controlled by the disutility factors and is impacted by the availability of (free) renewable energy later in the scheduling horizon. Figure 4.5 shows that the scheduler schedules appliances in a way that no energy needs to be drawn from the grid during higher-price periods when the TOU scheme is used. For this scenario, timeslots 1, 2, 7 and 8 are off-peak; timeslot 3, 4 and 6 are mid-peak and timeslot 5 is on-peak. Results show that the household did not buy energy from the grid in mid-peak and on-peak time periods. Figure 4.6 shows how a RTP scheme increases the grid energy demand in lower price timeslots. The grid price is comparatively low in timeslots 1,

Table 4.3: Cost Comparison for Households 1 and 2 in Different Scenarios

Cost	Household 1	Household 2	Total Cost
Cost without Microgrid Trading	6.99¢	7.57¢	14.56¢
Cost with Microgrid Trading	12.65¢	0.09¢	12.74¢
Pareto Optimal Cost with Microgrid Trading	6.87¢	5.86¢	~12.74¢

5, 6 and 8. The household draws energy from the grid during these timeslots.

4.1.3 Pareto Optimality

If we solve the Objective Function 3.25 with Constraints 3.5 - 3.22, excluding Constraint 3.26, it may distribute the cost unfairly between the households. This section describes this problem in more detail and shows how the proposed approach solves this problem by ensuring Pareto optimality.

Cost without Microgrid Trading

Table 4.3 shows the minimum costs of household 1 and household 2 respectively when the households are not participating in microgrid trading. These costs should be the maximum costs when they participate in microgrid trading for cost optimization. The minimum costs for household 1 and household 2 are 6.99¢ and 7.57¢ respectively. Therefore, when these 2 household costs are optimized individually, the total cost is 14.56¢.

Cost with Microgrid Trading

Now, we introduce the microgrid and solve the same optimization problem, but this time also allowing the households to trade energy with each other. Figures 4.7 and 4.8 show the energy consumption profile of the two households. A negative microgrid amount indicates that the household is actually selling energy into the microgrid, whereas a positive value indicates that the household buys that much energy from the microgrid. Compared to the previous solution, summarized in Table 4.3, the total cost of household 1 increases from 6.99¢ to 12.65¢.

As Figures 4.7 and 4.8 show, the two households balance the energy flow in the microgrid: whenever household 1 draws on energy from the microgrid, household

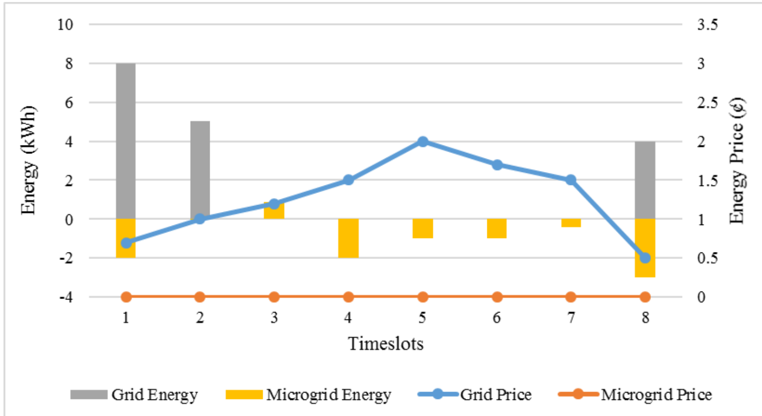

Figure 4.7: Energy Consumption Profile with Microgrid Trading (Household 1).

2 provides that amount into the microgrid and vice versa. Figure 4.8 shows that household 2 does not buy any energy from the grid. Household 1 buys the required energy for household 2 from the grid and sells it for free to household 2 (Figure 4.7). The scenario shows that the energy cost of household 2 is 0 and it increases the cost of household 1 through microgrid energy trading. Overall, the sum of the energy costs for both households decreased from 14.56¢ to 12.74¢. But unless there is a separate mechanism to reimburse household 1 for the additional costs, we do not believe that this solution is a desirable outcome. Trading through the microgrid should improve or at least not worsen each individual household. In other words, we require a Pareto optimal solution, where no household can improve their energy consumption costs further without worsening another household. The optimization problem as outlined above does not deal with this issue, as it only minimizes the total energy costs, irrespective of the impact on individual households.

Therefore, to achieve Pareto optimal costs, we used Constraint 3.26 to solve the unfair cost distribution problem. The constraint defines maximum cost bounds for each household while trading in the microgrid. The maximum cost of each household is the cost that a household pays when it does not participate in microgrid energy trading. This then rules out solutions such as the one presented in Table 4.3 for household 1, whose energy cost increased from 6.99¢ to 12.65¢, which would violate that upper bound. The resulting solution to the unified optimization problem will then be one where each household is no worse off than in the absence of the microgrid,

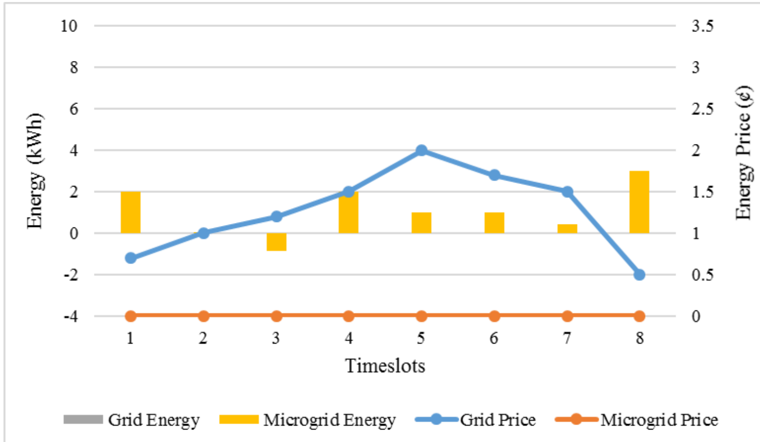

Figure 4.8: Energy Consumption Profile with Microgrid Trading (Household 2).

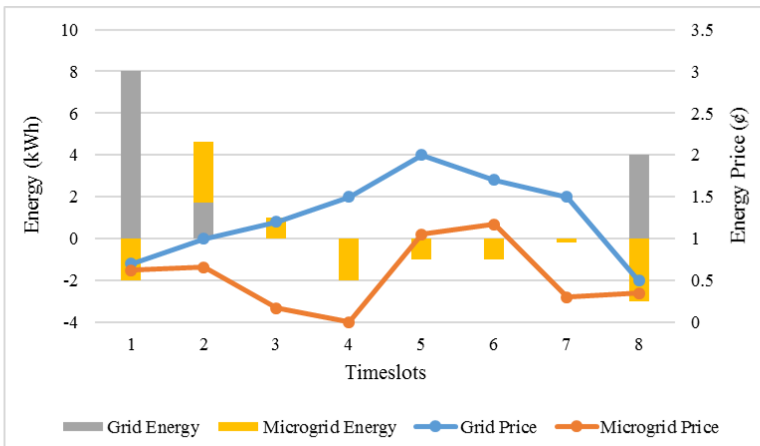

Figure 4.9: Energy Consumption Profile with Microgrid Trading and Pareto Optimality (Household 1).

and no further improvements are possible, representing a Pareto optimal point.

Figures 4.9 and 4.10 show the results when applying this method in the same scenario. As before, trading via the microgrid is balanced, and some timeslots see microgrid prices different from 0 to clear the market (determined by the optimization model). Table 4.3 shows that the energy costs for both households are lower than in the absence of the microgrid. They dropped from 6.99¢ to 6.87¢ for household 1 and from 7.57¢ to 5.86¢ for household 2. The total energy cost for both households is 12.74¢, which is lower than the initial total energy cost of 14.56¢.

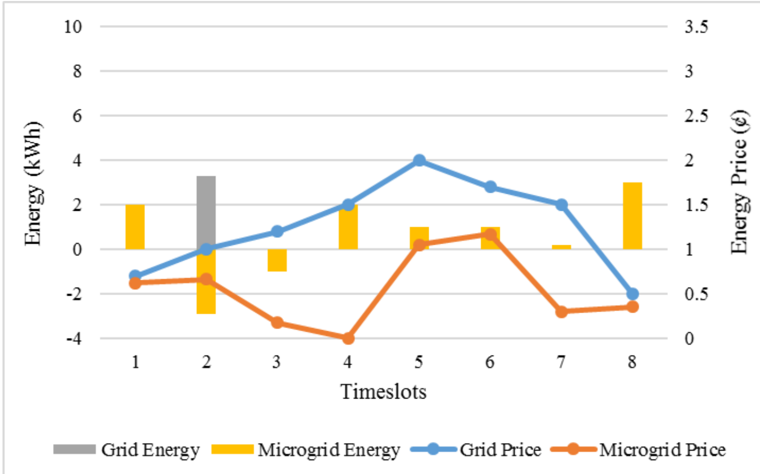

Figure 4.10: Energy Consumption Profile with Microgrid Trading and Pareto Optimality (Household 2).

Table 4.4: Static Parameters

Parameter	Value
Storage Efficiency	90%
Storage Self-Discharging Rate	1%
Storage Initial Energy (kWh)	5
Reservation Time	1st Timeslot
End Time	Last Timeslot
Maximum Power Limit of a Household (kW)	Infinite (200,000)

4.2 Complexity Analysis

The proposed unified MINLP model could be first reduced to a MILP problem in polynomial time then the resulting MILP could be restricted to have only real numbers. Hence, the proposed model reduces to an Integer Programming (IP) problem in polynomial time. Garey and Johnson proved that IP is an NP-hard problem [69]. Even if the variables are restricted to 0, 1 it remains NP-hard [69]. Therefore, the proposed non-convex MINLP model is NP-hard.

In this section, we explored experimentally the impact of the number of appliances, timeslots, and households on the solution time. The simulation environment consists of static and random parameters. All households are considered to have

Table 4.5: Random Parameters

Parameter	Min	Max
Duration of Appliance Operations	1	Total Timeslots
Appliance Power (kW)	0.5	15
Grid Energy Price (¢)	0.1	5
Disutility Factor (¢)	0.01	10
Storage Power (kW)	2	5
Minimum Storage Capacity (kWh)	0	2
Maximum Storage Capacity (kWh)	5	10
Renewable Energy (kWh)	0	10

similar storages, i.e., with the same efficiency and self-discharging rate but different storage capacities. An appliance operation request occurs at the 1st timeslot and it can be executed until the last timeslot. The maximum power limit of a household is set to a large value, e.g., 200,000 kW. Initial storage energy is 5 kWh for all households. The static parameters are specified in Table 4.4. The minimum and maximum bounds for generating random parameters are presented in Table 4.5. The duration of an appliance is uniformly generated between 1 and the total number of timeslots. An appliance consumes energy uniformly distributed between 0.5 and 15 kWh per timeslot. The grid energy price at any timeslot varies uniformly from 0.1¢ to 5¢. The disutility factor of an appliance is randomly selected from any value between 0.01¢ and 10¢. The required storage charging power is generated from a uniform distribution in the range of 2 to 5 kW. The minimum capacity of a storage stays between 0 to 2 kWh and the maximum capacity of a storage is limited between 5 to 10 kWh. The amount of renewable generation is chosen from a range of 0 to 10 kWh per timeslot.

Figure 4.11 shows the relationship between the median solution time and the number of appliances. At least 2 households are required to form a microgrid and 3 timeslots are considered as a minimal number of timeslots for planning purposes. The number of timeslots and households are set to these minimum values. For the same number of appliances, the model was solved for 29 random instances. The bar diagram shows the median solution time and the line diagram shows the percentages of solution instances which exceeded the cut off execution time (8 hours). This means

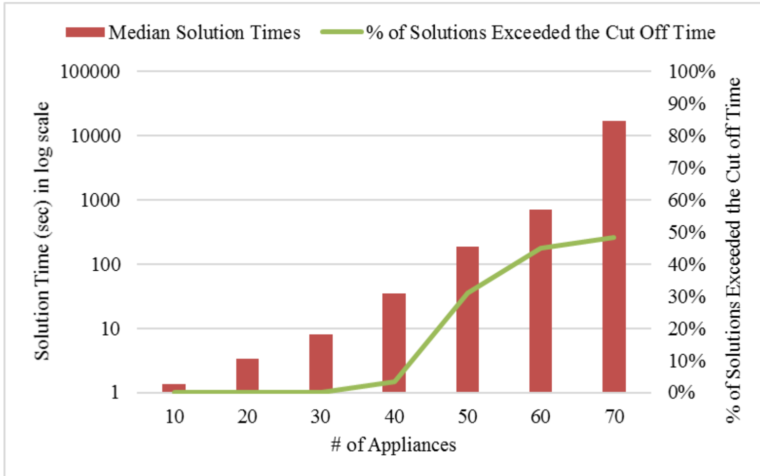

Figure 4.11: Solution Time vs. Number of Appliances.

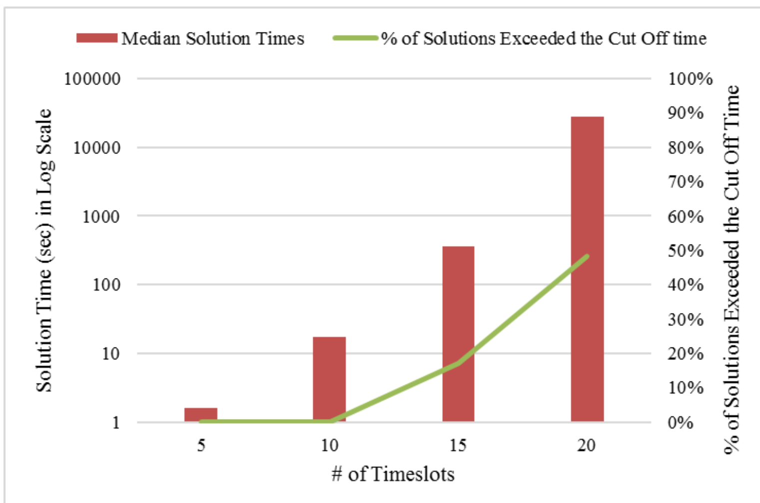

Figure 4.12: Solution Time vs. Number of Timeslots.

that if the optimal solution was not found after 8 hours of computation, the Couenne solver terminates the program. Figure 4.11 shows that for the minimum number of households and timeslots, the median solution times increase exponentially when increasing the number of appliances.

Figure 4.12 illustrates that the median solution time increases exponentially with the number of timeslots for the minimum number of appliances (2 appliances: 1 interruptible and 1 uninterruptible) and the minimum number of households (2 households). For the same number of timeslots, the model was solved for 29 random instances. Finally, Figure 4.13 shows that the time complexity increases exponentially

Figure 4.13: Solution Time vs. Number of Households.

with the number of households for the minimum number of appliances and timeslots. The model was solved for 29 random instances for the same number of households.

4.3 Summary

This chapter identifies the features and characteristics of the proposed optimization model. It describes scenarios showing that the disutility factor controls the actual scheduling delay of the appliances and affects the energy cost. It demonstrates the impact of the energy price on the load and the source scheduling. It explains how the proposed model maintains Pareto optimality among the participating households in the microgrid. The theoretical analysis proves that the proposed non-convex MINLP model is an NP-hard problem. The numerical results illustrate that even for a small problem size, the solution time grows exponentially. In the smart grid, the price signals, the energy demand and the renewable energy generation change frequently, demanding to re-solve the optimization problem with updated information. Therefore, the optimization problem should be solved in a realistic timeframe so that any update could be reflected back to the system to provide an optimized cost. Hence, aiming for an optimal solution for the proposed problem is not a computationally efficient approach for realistic scenarios. We need to trade off the optimal solution for reduced computation time. Therefore, in the next chapter we propose a bi-linear model to achieve approximate solutions which yields near-optimal performance within a lower timeframe.

Chapter 5

The Bi-Linear Model

The unified cost optimization model proposed in Chapter 3 is an NP-hard problem. It means that using the resulting solution is not practical because the solution time increases exponentially according to the increase of the problem size. To deal with this issue, this chapter proposes an approximate model by using bi-linear optimization. The bi-linear model considers the same features as the unified model. However, it approximates the non-linear constraints to linear ones to limit the feasible non-convex solution space to a lower dimensional convex region. Therefore, it reduces the solution time. On the other hand, the bi-linear model does not guarantee an optimal solution because of the relaxation of non-linear constraints.

5.1 The Optimization Model

The proposed bi-linear model breaks down the non-convex MINLP model into multiple MILP models or modules. Each MILP module solves a partial problem and the bi-linear model iteratively achieves an approximate solution. Figure 5.1 explains the relationship between the modules. Module 1 provides the initial values of energy demand and supply to Module 2. Module 2 uses these demand and supply values as constants and determines the microgrid energy price. Module 3 utilizes the microgrid energy price as a constant and determines the amount of energy to be traded in the microgrid. This microgrid energy is used as a constant in Module 2. The bi-linear model iteratively generates the microgrid price (Module 2) and microgrid energy (Module 3) until the termination criterion is satisfied. The program terminates if the cost does not improve more than 0.1% in the last few iterations. Module 3 provides

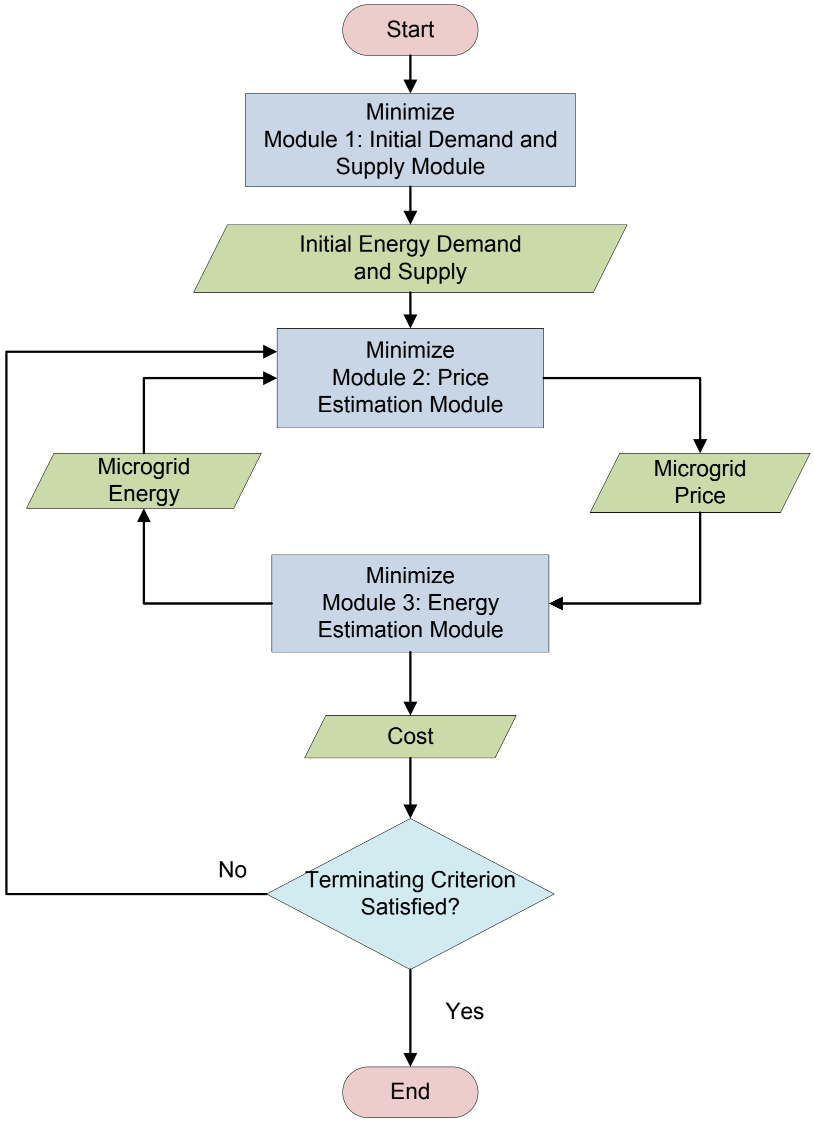

Figure 5.1: The Flow Chart of the Bi-Linear Model.

the final result if the termination criterion is satisfied.

The model proposed in Chapter 3 is extended by introducing or modifying the following variables and constants.

- $DS_{k,h}$ represents the energy demand or supply of household k at timeslot h. A positive value of $DS_{k,h}$ means the k-th household has energy demand at timeslot h. A negative value means the household has surplus energy.

In Module 1, $DS_{k,h}$ is used as a variable and in Module 2, $DS_{k,h}$ is used as a constant. Module 3 use $ME_{k,h}$ instead of $DS_{k,h}$.

MP_h is the microgrid price at timeslot h which has already been introduced in Chapter 3. MP_h is a variable in Module 2 and a constant in Module 3. Module 1 does not require MP_h because this module only considers an individual household when it does not participate in microgrid.

5.1.1 Module 1: Initial Demand and Supply

Module 1 determines energy demand and supply per timeslot of an individual household. It provides the initial demand and supply parameters to the bi-linear model. We introduce the following new constraints to calculate the energy demand or supply in each timeslot of each household.

Demand and Supply Constraints

The energy surplus or demand is the difference between the total energy consumption and total internal energy generation (excluding grid and microgrid) in a specific timeslot of every household. In other words, it represents the net energy demand or supply after utilizing the energy generated by the household energy sources. Constraint 5.1 calculates the amount of energy that is available to trade in the microgrid. Unlike Constraint 3.21, it excludes the energy provided from the grid in calculating the energy demand. Constraint 3.21 calculates the amount of energy that is available to trade in the microgrid which may be sometimes drawn from the grid to reduce energy cost. On the other hand, Constraint 5.1 utilizes the available energy that an individual household possesses and calculates the demand or supply of energy from the external energy sources like grid and microgrid.

$$\begin{aligned} DS_{k,h} = \sum_{i \in I} S_{k,i,h} \cdot p_{k,i} + IC_{k,h} \cdot SP_k - RQ_{k,h} - SE_{k,h} \\ -BE_{k,h} + MinC_k, (k \in K, h \in H) \end{aligned} \tag{5.1}$$

Module 1 calculates the energy cost of a household, $C_k^{NoTrade}$, when it is considered as an isolated household (i.e., the household does not take part in microgrid trading). Therefore, if we minimize Objective 3.25 with respect to Constraints 3.5 - 3.17 and 5.1, the solution provides the maximum cost boundary of the specific household and the energy demand or supply per timeslot. Module 1 excludes the constraints related to the microgrid. In Constraint 3.5, microgrid energy, $ME_{k,h}$, is set to 0. The module calculates the value of variable $DS_{k,h}$ which is used as a constant in Module 2. Appendix A.4 lists the complete Module 1 MILP optimization model.

5.1.2 Module 2: Price Estimation Module

Module 2 determines the microgrid energy price, MP_h, using the constant demand and supply parameter, $DS_{k,h}$, provided by Module 1. The energy must be traded in the microgrid. However, for this specific module, the total energy bought from the microgrid is not always equals to the total energy sold by all households. Hence, the modified cost function is expressed as Z in Equation 5.2.

$$Z = \sum_{k\in K}\sum_{h\in H} GP_h \cdot GE_{k,h} + \sum_{k\in K}\sum_{h\in H} MP_h \cdot DS_{k,h} + \sum_{k\in K}\sum_{i\in I} d_{k,i}\left(\tau_{k,i} - \left(\sum_{h\in H} r_{k,i,h}\cdot h + t_{k,i} - 1\right)\right) \tag{5.2}$$

The quantity of traded energy of each household in the microgrid is a constant. The objective of Module 2 is,

$$min\ Z \tag{5.3}$$

Subject to Constraints 3.6 - 3.17, 3.19, 3.20, 5.4 and 5.5.

Energy Balance Constraints

Constraint 3.5 is modified as Constraint 5.4. For a specific household, the total energy consumed by all appliances, the microgrid and the storage in a specific timeslot should be the same or less than the total energy supplied by the grid, the renewables, the storage, and the microgrid in that timeslot. This relation has been expressed in Constraint 5.4.

$$\sum_{i\in I} S_{k,i,h}\cdot p_{k,i} + IC_{k,h}\cdot SP_k \leq GE_{k,h} + BE_{k,h} + RE_{k,h} + DS_{k,h}, (k \in K, h \in H) \tag{5.4}$$

Pareto Optimality Constraints

Constraint 3.26 has been modified as Constraint 5.5. Constraint 3.26 has a $MP_h \cdot ME_{k,h}$ term where both are variables and $ME_{k,h}$ can have a negative value. Consequently, Constraint 3.26 is a nonlinear function and makes the feasible region of the unified model non-convex. Constraint 5.5 replaces the $ME_{k,h}$ variable with the constant $DS_{k,h}$. Therefore, Constraint 5.5 is a linear function which means that the feasible region is convex.

$$\sum_{h \in H} GP_h \cdot GE_{k,h} + \sum_{h \in H} MP_h \cdot DS_{k,h} + \sum_{i \in I} d_{k,i} \left(\tau_{k,i} - \left(\sum_{h \in H} r_{k,i,h} \cdot h + t_{k,i} - 1 \right) \right) \leq C_k^{NoTrade}, (k \in K) \tag{5.5}$$

Module 2 excludes the constraints related to the microgrid energy because it uses $DS_{k,h}$ as traded energy which is a constant. Appendix A.5 lists the complete Module 2 MILP optimization model. Module 2 calculates the microgrid energy price, MP_h. The value of MP_h is used as a constant in Module 3.

5.1.3 Module 3: Energy Estimation Module

The third module determines the microgrid energy, $ME_{k,h}$, using the constant microgrid price, MP_h, provided by Module 2. The households trade energy in the microgrid. Module 3 considers that MP_h is a constant in Constraint 3.26 which transforms the non-convex feasible region into a convex space.

Objective 3.25, together with Constraints 3.5 - 3.18, 3.21 and 3.22 provides a solution of the problem. The model excludes the constraints related to the microgrid price because microgrid price is a constant. Appendix A.6 lists the complete Module 3 MILP optimization model.

Module 3 provides energy demand and supply of the households to Module 2. The value of variable $ME_{k,h}$ is assigned to the constant $DS_{k,h}$ which is used as an input parameter in Module 2. When the program terminates, Module 3 provides the final solution of the proposed problem.

5.2 Summary

One of the main challenges of our research is to solve the proposed cost optimization problem in a realistic timeframe. The proposed bi-linear model simplifies the computational steps in order to achieve a lower solution time. The next chapter evaluates the performance of the bi-linear model, compared to the unified model.

Chapter 6

Performance Analysis - Bi-Linear Model

This chapter analyzes the performance of the bi-linear model described in Chapter 5. More precisely, we compare the bi-linear model with the optimal model and evaluate its performance. We used both synthetic and real datasets to analyze the results with respect to the solution time and the quality of the solution. The models are implemented in AMPL. We used the same versions of Couenne and CPLEX solvers and the same computer system which we used to collect the results described in Chapter 4.

6.1 Small Scenarios with Synthetic Data

In this section, we used the same dataset as the one described in Section 4.2. The static and random parameters are the same as Table 4.4 and Table 4.5 respectively. The bi-linear model terminates if the cost does not improve more than 0.1% in the last 10 iterations. We solved the unified and the bi-linear models for 492 random scenarios. Among all these scenarios, 111 solutions exceeded the cut off time (set to 8 hr) for the unified model and we did not get any optimal solution for these cases. Therefore, the comparison between the optimal and bi-linear models considers 381 solutions of each model.

Figure 6.1 shows that the median solution times of the bi-linear model are almost constant for any number of appliances. On the contrary, the solution times of the optimal model increase exponentially with the number of appliances. Figures 6.2 and 6.3 demonstrate an exponential increase of the time complexity of both models when the number of timeslots and households increases. The average of the median solution times of the bi-linear model is very low (0.46 sec) compared to the optimal model

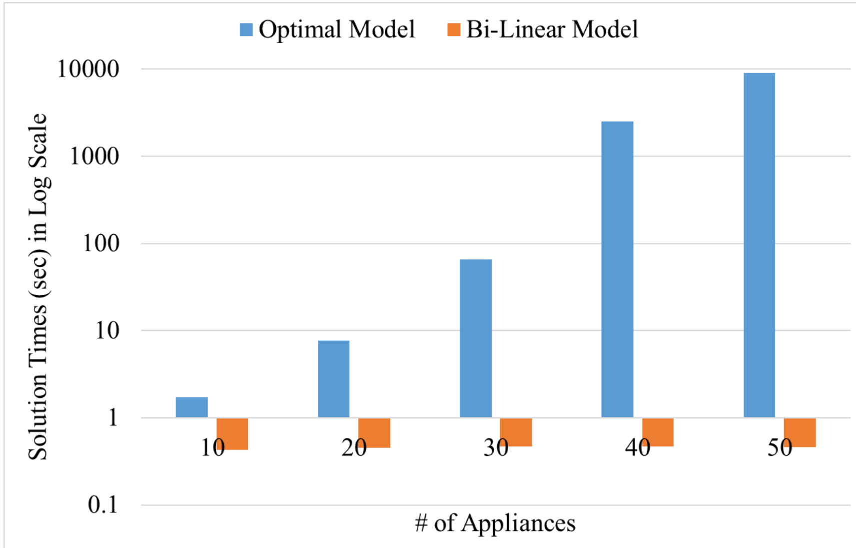

Figure 6.1: Comparison between the Solution Times of the Optimal and the Bi-Linear Models for Different Number of Appliances.

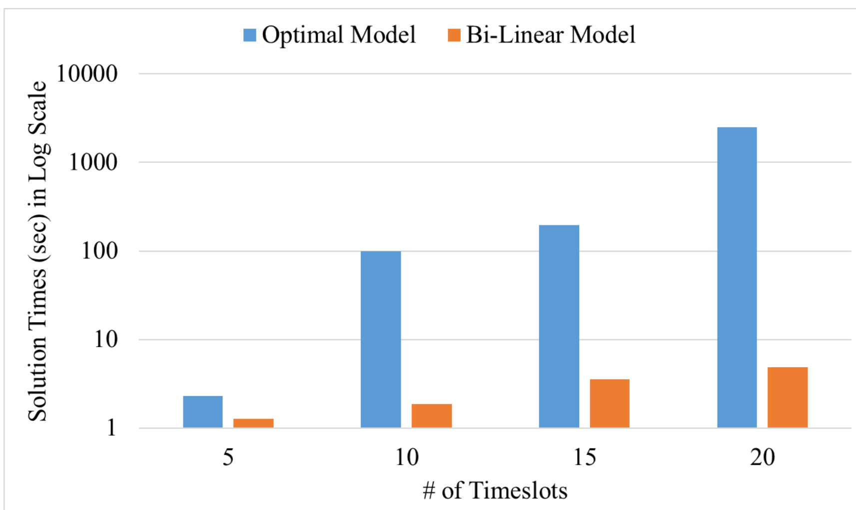

Figure 6.2: Comparison between the Solution Times of the Optimal and the Bi-Linear Models for Different Number of Timeslots.

(2316.05 sec or 38 min). For all scenarios, the maximum median solution time of the bi-linear model is less than 5 sec whereas the maximum median solution time of the optimal model is 7737.86 sec (2 hr and 9 min).

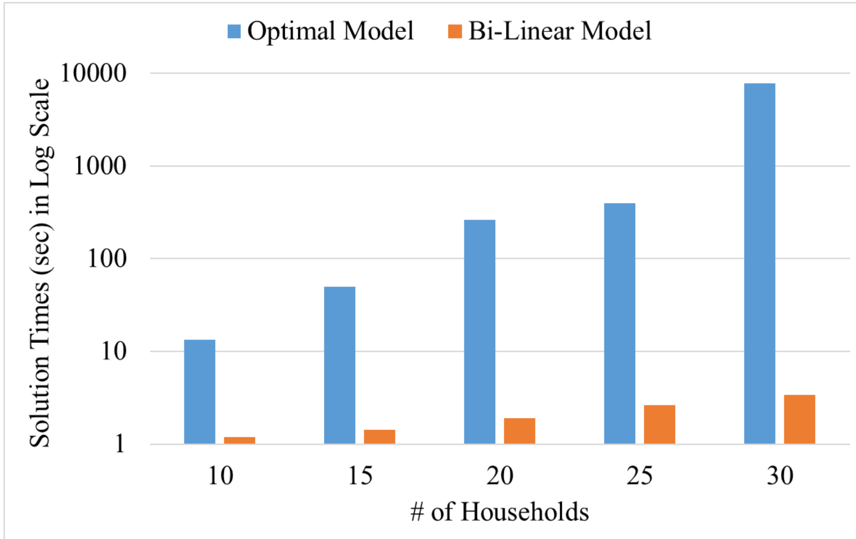

Figure 6.3: Comparison between the Solution Times of the Optimal and the Bi-Linear Models for Different Number of Households.

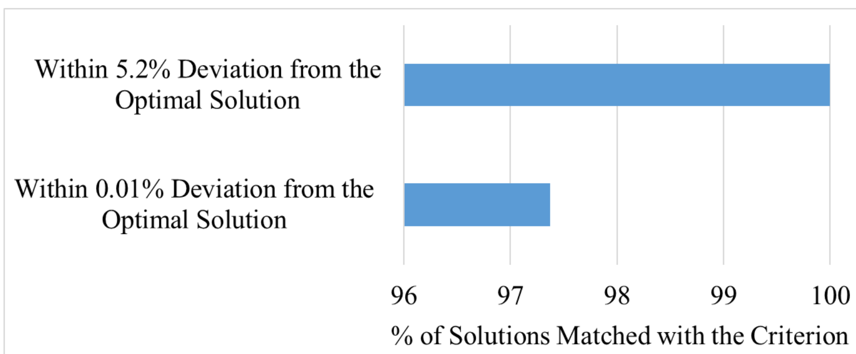

Figure 6.4: Percentage of Bi-Linear Model Solutions Deviating from the Optimal Solutions.

No solver can work with the exact values of the model variables because it is not possible to deal with the exact numerical precision due to memory limitations. Sometimes the solutions are slightly different because of this precision handling issue. Therefore, we consider 0.01% deviation from the optimal solution as an acceptable optimal solution. Figure 6.4 shows that more than 97% of the bi-linear solutions are optimal solutions. The worst deviation from the optimal solution in all 381 cases is 5.2%.

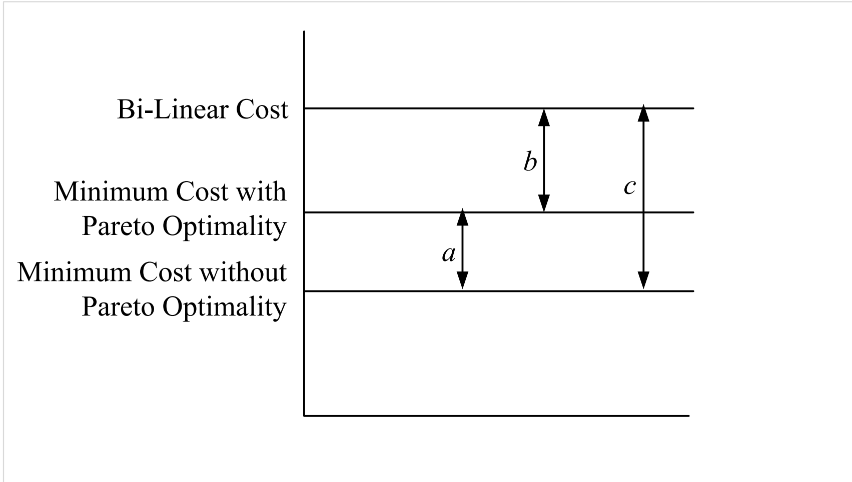

Figure 6.5: Relationship between the Bi-Linear and the Optimal Models with/without Pareto Optimality.

6.2 Large Scenarios with Real Data

The scenarios considered in Section 6.1 are small, compared to any real applications. It may be possible that the bi-linear model achieves optimal solutions in 97% of the cases only for these small problem sizes. Its error rate may increase or decrease if we consider real scenarios. In this section, we compare the optimal and the bi-linear model using large scenarios with real datasets.

The model proposed in Section 3.6 does not consider the Pareto optimality of household costs because it does not include Constraint 3.26. This model is an MILP model because it excludes these non-linear constraints. The solution of this model provides the minimum cost in that microgrid area without ensuring fair cost distribution among the households. We use this minimum cost as the optimal cost to compare with the solutions of the bi-linear model.

The optimal cost of the proposed unified model (Section 3.7) can be equal or greater than the model (Section 3.6) used in this section. The relationships between these costs are expressed in Figure 6.5. The minimum cost which does not consider the Pareto optimality is always equal or less than the minimum cost that considers Pareto optimality. In Figure 6.5, the difference between these 2 costs is represented by a. Instead of comparing the bi-linear model with the proposed optimal model with Pareto optimality (the difference is b), we compare it with the optimal model without Pareto optimality (the difference is c). Here, $c = a + b$ where the value of a is either 0 or a small number. Hence, $c \geq b$.

In the previous section, we compared the bi-linear model with the unified model for small problem sizes. Although it is the best approach to evaluate the performance of an approximate algorithm, it is not practical for our case because we are unable to generate solutions for large scenarios. The proposed approach presents a method to compare the accuracy of the bi-linear model.

6.2.1 Datasets

We first briefly describe the datasets which are used for the experiments. We consider the following criteria while selecting the datasets for our scenarios.

- The datasets were collected in or are applicable to Ottawa.
- Time resolution: 1 hr granularity.
- A description of how the datasets were collected is available. A detailed description is necessary to use the data properly.
- Popularity: Are the datasets accepted by the scientific community and well known?
- Priority is given to datasets which are available from the proper authority, or government institutions.
- Have the datasets been published in peer reviewed journals?

Load Profiles

We used household load datasets collected in Ottawa [70]. In [70], the authors considered 12 households which were selected based on their annual consumption profiles. The electricity bills of the potential participants were examined; some volunteers were selected for the study because their annual electricity consumption were close to the Canadian average, whereas others were selected because they consume below or above the average. Each household contains a maximum of 5 appliances. Table 6.1 shows the appliance type and number in each household. One year temporal consumption data is available for 2009-2010. We used these appliances in our scenarios.

Table 6.1: Number of Loads per Household [70].

Loads	AC	Furnace	Stove	Dishwasher	Dryer	Hot Water
Household 1	1	1	1	1	1	0
Household 2	1	1	0	0	0	0
Household 3	1	1	0	0	0	0
Household 4	1	1	0	0	0	0
Household 5	1	1	0	0	0	0
Household 6	1	1	0	0	0	0
Household 7	1	1	0	0	0	0
Household 8	1	1	0	0	0	0
Household 9	1	1	0	0	0	0
Household 10	1	1	1	0	1	1
Household 11	1	1	0	0	0	0
Household 12	1	1	1	1	1	0

Renewable Energy Generation Profiles

We collected solar irradiance for Ottawa from the National Solar Radiation Database (NSRDB) [71] which is maintained by the National Renewable Energy Laboratory (NREL) [72]. The database is developed using the Physical Solar Model (PSM) [73]. The location information and the PV array configuration are given in Tables 6.2 and 6.3 respectively. We used the PV_LIB MATLAB toolbox [74] developed by Sandia National Laboratories [75] to convert the solar irradiance to DC power. The King Diffuse model (developed by David L. King at Sandia National Laboratory) was used to determine the total diffuse irradiance (sky diffuse and ground reflected irradiance) [76]. We did not consider any DC to AC inverter.

Home Energy Storage Characteristics

We used Tesla Powerwall as the home energy storage. The storage characteristics are given in Table 6.4 [77]. A Powerwall battery can store up to 6.4 kWh and we consider that its energy level should not go below the 40% of the maximum storage capacity (2.56 kWh). The required power to charge the storage is 3.3 kW. Its charging efficiency is 92% and self-discharging rate is approximately 1% per day which is 0.042% per hour. The discharge power of the storage can also be controlled by introducing a continuous variable. In this case, the variable bound should be limited

Table 6.2: Location Information (Ottawa, Canada)

Properties	Value
Latitude	45.41°
Longitude	−75.7°
Elevation	62 m
Local Time Zone	-5

Table 6.3: PV Array Configuration

Properties	Description
PV Module	Suntech STP200S-18/ub-1 Module
Array Tilt Angle	45.41° (Site Latitude)
Array Azimuth	180°(South Facing Array)
Number of Modules in Series	2
Number of Parallel Strings	2

Table 6.4: Characteristics of Tesla Powerwall [77]

Properties	Values
Power	3.3 kW
Efficiency	92%
Self-Discharging Rate	1% per Day (0.042% per Hour)
Minimum Energy Level	2.56 kWh (40% of Max Capacity)
Maximum Energy Level	6.4 kWh

by the maximum and the minimum storage capacity.

Grid Energy Price

We used 4 representative days of 2010 based on seasons (summer and winter) and days of the week (weekend day and weekday) as given in Table 6.5. We used RTP and TOU prices of these days to evaluate our model. Hydro Ottawa uses a TOU price which is set by the Ontario Energy Board (OEB) [78]. Table 6.6 shows TOU energy prices for Ontario, Canada in 2010 [79]. Pagani et al. considered the day ahead price advertised by the wholesale market as the retail energy price for the end user and proposed that this price can be used as RTP [38]. To use this idea in our research, we collected the hourly wholesale energy price advertised by the

Table 6.5: Dates

Date	Description
6-Jan-2010	Winter Weekday
9-Jan-2010	Winter Weekend Day
26-Jun-2010	Summer Weekend Day
30-Jun-2010	Summer Weekday

Table 6.6: TOU Price for Ottawa (2010) [79]

Season	Category	Hours	Price
Winter	Off-Peak	7 pm to 7 am and all day in weekends and holidays	4.4¢/kWh
	Mid-Peak	11 am to 5 pm	8.0¢/kWh
	On-Peak	7 am to 11 am and 5 pm to 7 pm	9.3¢/kWh
Summer	Off-Peak	7 pm to 7 am and all day in weekends and holidays	5.3¢/kWh
	Mid-Peak	7 am to 11 am and 5 pm to 7 pm	8.0¢/kWh
	On-Peak	11 am to 5 pm	9.9¢/kWh

Independent Electricity System Operator (IESO) [80]. The Hourly Ontario Energy Price (HOEP) (Table 6.7) from IESO Historical Reports (2002-present) was used as RTP [81]. IESO is responsible for operating the electricity market and directing the operation of the bulk electrical system in the province of Ontario, Canada. Hydro Ottawa buys energy from IESO [82].

6.2.2 Results

We used different settings of the parameters to generate different scenarios. For household loads, we considered a summer weekday, a summer weekend day, a winter weekday and a winter weekend day load profile. For each of these load profiles, we divided the scenarios based on user preference: economy and comfort. A user may prefer to save cost, which we labeled as economy. We used a low value of the disutility factor (0.001¢ per timeslot) so that the model can tolerate more delay in appliance operation. On the other hand, a user may prefer more comfort. In this setting, the disutility factor is set to a higher value (200¢ per timeslot) so that the model shows reluctance to any delay in appliance operation. If the household has a storage, the scenarios were varied based on the initial storage energy. A household can have minimum storage energy or maximum storage energy at the beginning of a

Table 6.7: RTP (HOEP) for Ottawa (2010) [81]

Hour	06-Jan-10	09-Jan-10	26-Jun-10	30-Jun-10
1	3.10¢	3.44¢	4.02¢	3.52¢
2	2.78¢	4.10¢	3.43¢	3.44¢
3	2.75¢	3.09¢	2.63¢	3.37¢
4	2.73¢	3.18¢	2.44¢	3.45¢
5	2.76¢	3.22¢	2.25¢	3.41¢
6	2.96¢	3.17¢	2.82¢	3.48¢
7	2.82¢	3.19¢	2.42¢	3.37¢
8	4.69¢	3.26¢	3.36¢	3.58¢
9	4.69¢	3.47¢	3.39¢	3.76¢
10	3.49¢	4.79¢	3.59¢	3.93¢
11	3.12¢	4.53¢	3.63¢	3.71¢
12	3.34¢	4.22¢	3.84¢	3.84¢
13	3.15¢	4.51¢	3.86¢	3.85¢
14	3.41¢	3.90¢	3.76¢	3.72¢
15	3.57¢	3.38¢	3.80¢	3.60¢
16	3.78¢	3.19¢	3.63¢	3.60¢
17	4.60¢	3.70¢	3.73¢	3.61¢
18	6.07¢	10.17¢	3.76¢	3.64¢
19	6.61¢	11.13¢	4.25¢	3.60¢
20	5.15¢	5.36¢	4.23¢	3.60¢
21	4.37¢	4.33¢	4.19¢	6.23¢
22	4.18¢	4.66¢	3.74¢	3.72¢
23	3.81¢	4.82¢	3.97¢	3.36¢
24	3.43¢	3.96¢	4.24¢	2.77¢

planning cycle. The parameters were also different for RTP and TOU energy price schemes. Table 6.8 shows a combination of parameters which were considered to generate different scenarios.

The scenarios considered 4 groups of households as shown in Table 6.9. The number of total households increases by 12 in each group. We have load profiles for 12 households [70]. The energy consumption and generation patterns are varied based on the presence of storage and solar panels. The first group has 12 households and these households have no storage and solar panels. The second group has 24 households. This group consists of all the households from the first group plus another set of

Table 6.8: Parameters for the Scenarios

Season	Day of the Week	User Preference	Initial Storage Energy	Grid Energy Price
Summer	Weekday	Economy	Min Energy Level	RTP
				TOU
			Max Energy Level	RTP
				TOU
		Comfort	Min Energy Level	RTP
				TOU
			Max Energy Level	RTP
				TOU
	Weekend Day	Economy	Min Energy Level	RTP
				TOU
			Max Energy Level	RTP
				TOU
		Comfort	Min Energy Level	RTP
				TOU
			Max Energy Level	RTP
				TOU
Winter	Weekday	Economy	Min Energy Level	RTP
				TOU
			Max Energy Level	RTP
				TOU
		Comfort	Min Energy Level	RTP
				TOU
			Max Energy Level	RTP
				TOU
	Weekend Day	Economy	Min Energy Level	RTP
				TOU
			Max Energy Level	RTP
				TOU
		Comfort	Min Energy Level	RTP
				TOU
			Max Energy Level	RTP
				TOU

12 households with storage. The third group has 36 households which includes all households of the second group. It also consists of an additional set of 12 households which installed solar panels on their premises, but have no storage device. Finally, the

Table 6.9: Household Groups based on the Presence of Storage and Solar Panels

# of Households	Descriptions
12	12 households (no storage, no solar panels)
24	12 households (no storage, no solar panels) and 12 households (with storage, no solar panels)
36	12 households (no storage, no solar panels), 12 households (with storage, no solar panels) and 12 households (no storage, with solar panels)
46	12 households (no storage, no solar panels), 12 households (with storage, no solar panels), 12 households (no storage, with solar panels) and 12 households (with storage, with solar panels)

fourth group has 48 households which consists of all households of the third group. This group has an additional set of 12 households which have both storage and solar panels.

There are 32 scenarios for each group of households based on the parameter combinations from Table 6.8. However, for the first group, we cannot vary the initial storage energy level because they do not have storage devices. This group has only 16 scenarios instead of 32. Hence, we generated 112 different scenarios for performance analysis. The bi-linear model terminates if the cost does not improve more than 0.1% in the last 3 iterations. Figure 6.6 shows that the bi-linear model provides optimal solutions for 99% of the scenarios. The remaining 1% is within the bound of 1.8% deviation from the optimal solution. The median solution time is around 4.6 sec for all scenarios. Figure 6.7 shows that the solution times of 90.2% of the scenarios are below 1 min. We found 7.1% of the scenarios that took more than 2 min to solve.

6.3 Result Analysis

6.3.1 Analysis of Local Minima

The bi-linear model sometimes traps into local minima and cannot improve the resulting solution any further. In this section, initially, we present a simple scenario to analyze the conditions under which the model generates sub-optimal solutions. Finally, we generalize the conditions for sub-optimal solutions for large scenarios.

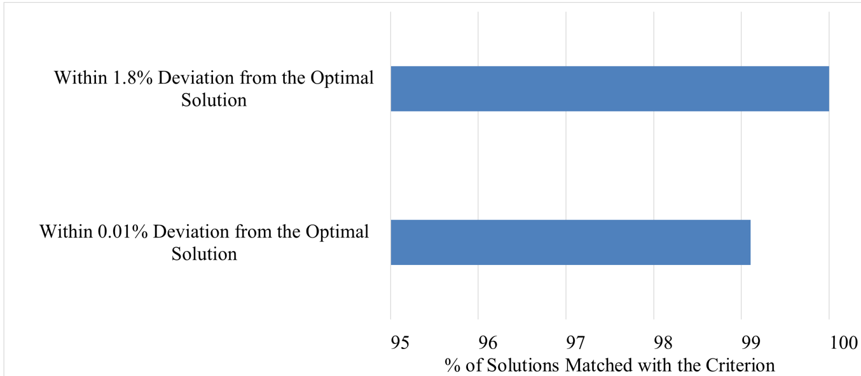

Figure 6.6: Percentage of Bi-Linear Solutions Deviated from the Optimal Solutions (without Pareto Optimality).

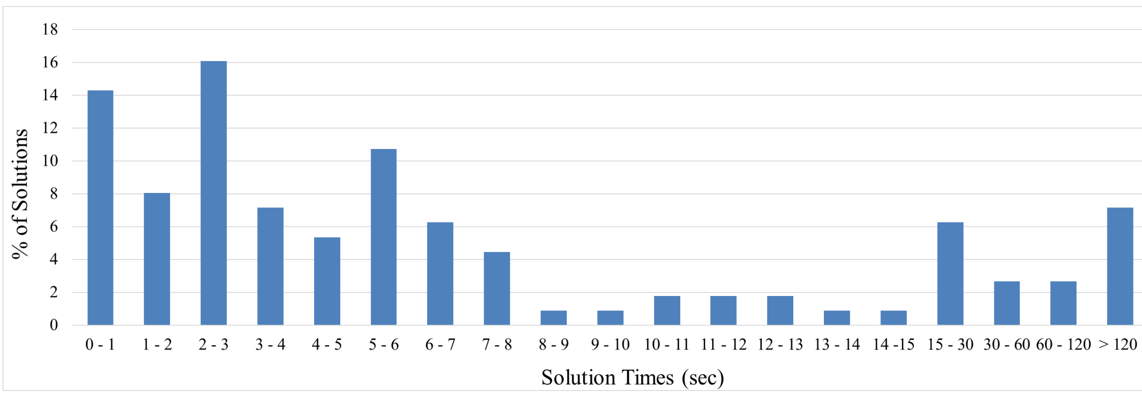

Figure 6.7: Bi-Linear Model Solution Times.

For simplicity, we consider only 2 households, 2 timeslots and 1 appliance. We exclude the renewables and the self-discharging feature of the storage. We do not consider the disutility cost, i.e., all disutility factors are set to 0. The appliance and storage characteristics are shown in Tables 6.10 and 6.11 respectively.

Cost without Microgrid Trading

We use Module 1 of the bi-linear model to generate the household cost when they are not participating in the microgrid energy trading. Tables 6.12 outlines the energy consumption profiles and how the appliances are scheduled, given a specific grid energy price profile (listed below the timeslots) for households 1 and 2. In this example, energy from the grid is cheap at the 1st timeslot but expensive at the last timeslot. The next block in the table specifies what energy is available from the storage. The available storage energy is determined initially by the initial charge

Table 6.10: Appliance Characteristics

Household	Appliance	Duration (Timeslots)	Power (kW)	Disutility Factor (¢)	Reservation Time	Max Delay
Household 1	App1	2	2	0	1	2
Household 2	App1	2	4	0	1	2

Table 6.11: Storage Characteristics

Characteristics	Household 1	Household 2
Initial Energy (kWh)	2	2
Power (kW)	5	3
Max Capacity (kWh)	6	8
Min Capacity (kWh)	2	2
Charging Efficiency	50%	50%
Self-Discharging Rate (per Timeslots)	0%	0%

and then evolves over time to reflect charging/discharging. The fourth block in the table specifies how much of the available energy is actually drawn upon by indicating which appliance is scheduled to run in that timeslot and whether we charge the storage device. For example, the optimization model determines that it is more efficient to charge the storage with 5 kWh of cheap grid energy in timeslot 1 to use this energy at timeslot 2 when energy is expensive (as shown in Table 6.12). The storage has 2 kWh initial energy and after charging it receive 2.5 kWh energy from the grid (because its efficiency is 50%). In this example, at timeslot 1 for household 1, the appliance is scheduled to operate, requiring a total of 2 kWh energy. Based on the block right above, 1.5 kWh energy is drawn from the grid (the remaining 5 kWh of grid energy is used to charge the storage) and 0.5 kWh energy is drawn from the storage (from 4.5 kWh of stored energy after it has been charged). The appliance is scheduled to operate in timeslots 1 and 2, for a total duration of 2 timeslots.

Table 6.12 shows that the minimum costs for household 1 and household 2 are 19.5¢ and 43.5¢ respectively when they are not participating in microgrid trading. These costs should be the maximum costs when they participate in microgrid trading for cost optimization. Therefore, when the 2 households are optimized individually, the total cost is 63¢.

Table 6.12: Cost without Microgrid Trading

Household		Household 1		Household 2	
Timeslot		1	2	1	2
Price	Grid	3.00	9.00	3.00	9.00
Stored Energy (Availability)		4.00	2.00	3.50	2.00
Energy Source	Grid	6.50	0	7.00	2.50
	Storage	0.50	2.00	0	1.50
Load	Storage Charging	1	0	1	0
	App1	1	1	1	1
Total Cost: 63¢		Cost: 19.5¢		Cost: 43.5¢	

Optimal Cost using the Unified Model

Now, we introduce the microgrid and solve the same optimization problem, but this time also allowing the households to trade energy with each other. Tables 6.13 summarizes the results for the 2 households, using the same format as before. We added one line to the price section, as we now also keep track of the prices in the microgrid. The available energy for the microgrid or the energy demand from the microgrid is shown below the stored energy availability section. In addition to this, the actual energy traded through the microgrid is shown between the energy source and the load sections. A negative value of microgrid energy indicates that the household is actually selling energy to the microgrid, whereas a positive value indicates that the household buys that much energy from the microgrid. Compared to the previous solution, the total cost of household 1 decreases from 19.5¢ to 18.14¢ and total cost of household 2 decreases from 43.5¢ to 41.86¢.

Sub-Optimal Cost using the Bi-Linear Model

The bi-linear model also generates an optimal solution for this scenario. However, we can generate a sub-optimal solution by changing the initial microgrid prices which we feed into the model as the starting point. As the starting point, if we use the grid price (which is the maximum limit of the microgrid price) as the microgrid price at the 1st timeslot and if we use 0 (which is the minimum limit of the microgrid price) as the microgrid price at the last timeslot, the bi-linear model traps into a local minimum and cannot improve the solution any further. It generates the same

Table 6.13: Optimal Cost with Microgrid Trading (Unified Model)

Household		Household 1		Household 2	
Timeslot		1	2	1	2
Price	Grid	3.00	9.00	3.00	9.00
	Microgrid	1.22	6.09	1.22	6.09
Stored Energy (Availability)		4.50	2.00	3.50	2.00
Microgrid (Demand/Availability)		-1.32	-1.28	-2.68	1.28
Energy Source	Grid	5.82	0.78	8.18	1.22
	Storage	0	2.50	0	1.50
Microgrid (Source/Load)		1.18	-1.28	-1.18	1.28
Load	Storage Charging	1	0	1	0
	App1	1	1	1	1
Total Cost: 60¢		Cost: 18.14¢		Cost: 41.86¢	

Table 6.14: Sub-Optimal Cost with Microgrid Trading (Bi-Linear Model)

Household		Household 1		Household 2	
Timeslot		1	2	1	2
Price	Grid	3.00	9.00	3.00	9.00
	Microgrid	3.00	0	3.00	0
Stored Energy (Availability)		4.00	2.00	3.50	2.00
Microgrid (Demand/Availability)		-9.00	0	5.50	0
Energy Source	Grid	13.5	0	0	2.50
	Storage	0.50	2	0	1.50
Microgrid (Source/Load)		-7.00	0	7.00	0
Load	Storage Charging	1	0	1	0
	App1	1	1	1	1
Total Cost: 63¢		Cost: 19.5¢		Cost: 43.5¢	

solution in the next few iterations and finally terminates with a solution which is given in Table 6.14.

In Table 6.14, for household 1 at timeslot 1, both microgrid and grid prices are 3¢. It is cost effective to charge the storage with cheap energy at this timeslot to use it at the last timeslot when energy is expensive. In the 1st timeslot, total minimum load is 7 kWh (2 kWh for the appliance and 5 kWh for charging the storage). Household 1 sells 7 kWh of energy to Household 2. Therefore, total load at this timeslot is 14 kWh. This 14 kWh is drawn from the grid and the storage (13.5 kWh from the grid and 0.5 kWh from the storage). Selling energy to the microgrid does not have any impact on the household cost because buying grid energy has the same cost as selling energy to the microgrid. Therefore, the energy cost for household 1 is 19.53¢ for 6.5 kWh energy. At timeslot 2, household 1 does not buy energy from the grid. It uses 2 kWh of energy from the storage. The microgrid price is 0¢ at this timeslot. Hence, buying or selling energy to the microgrid does not impact the household cost (microgrid quantity is set to 0 kWh).

In an iteration, when the microgrid prices are 3¢ and 0¢ (constants) for timeslots 1 and 2 respectively, we get a solution which trades -7 kWh and 0 kWh of energy in the microgrid. This solution provides the maximum cost for Household 1, which is 19.5¢. The microgrid quantity does not have any impact on the energy cost because either the microgrid price is 0¢ or it is the same as the grid price. Therefore, this solution cannot be improved for the given constant microgrid prices.

In the next iteration, when the microgrid quantities are constants (-7 kWh and 0 kWh for timeslots 1 and 2 respectively) the solution cannot be improved either. At timeslot 1, any microgrid price which is less than 3¢ will increase the Household 1 energy cost to more than 19.5¢, which violates the Pareto optimality constraint. For timeslot 2, the microgrid price does not have any impact on energy cost because the households do not trade energy at this timeslot.

A similar explanation is also applicable to household 2. When the microgrid prices are constants (3¢ and 0¢ for timeslots 1 and 2 respectively), total energy cost of this household is the same for any amount of microgrid energy trading. On the other hand, when the microgrid quantities are constants (7 kWh and 0 kWh for timeslots 1 and 2 respectively) any value which is less than 3¢ violates the Pareto optimality constraint for Household 1. For timeslot 2, the microgrid price does not have any impact because it does not trade energy in microgrid.

In an iteration, if the energy price is greater than 0 (at timeslot 2 for both households), we will not trade energy: the only household available to sell into the microgrid is household 1, but it has no energy available (unless it bought some from the grid, but then it would have to sell at least at the grid price to come out ahead).

In addition to this, we analyze the scenarios which generated sub-optimal solutions in Sections 6.1 and 6.2. These are large scenarios and it is hard to identify the exact reasons for sub-optimal solutions. We notice different patterns in the solutions which are mostly related to the boundary values of the microgrid price. Every sub-optimal scenario we found has microgrid energy prices that are higher in adjacent timeslots and the price is either 0 or the same (or at least very close to) as the grid price.

However, scenarios where the grid prices are close to these boundary values do not always result in a sub-optimal solution.

In the proposed bi-linear optimization, the algorithm sets the microgrid prices as constants and determines the microgrid quantities in one module. In the next iteration, it sets the microgrid quantities as constants and determines the microgrid prices. This property of the algorithm sometimes does not allow the solution to be improved to maintain the Pareto optimality constraints in each module. Therefore, we can conclude that the bi-linear method sometimes traps at the local minima because it alternately sets the microgrid price and microgrid quantity as constants.

However, the proposed bi-linear model does not use maximum and minimum values of the grid price as the starting point of the microgrid price. Module 1 of the proposed model generates microgrid prices based on the demand and surplus of energy, which is a dynamic way to determine the microgrid price. Even if, at any stage of the solution, the microgrid price reaches to the boundary values, the bi-linear model can improve it. Our results also support this claim which show that, for real datasets, only 1% of the solutions are sub-optimal solutions.

6.3.2 Impact of Local Minima

In this section, we analyze how a local minimum increases the total cost in a microgrid. To explore the factors, we focus on a specific scenario of our experiments with synthetic data (Section 6.1). The scenario consists of 30 households, 2 appliances and 3 timeslots. The parameters used for this optimization were generated randomly. For this scenario, the optimal cost is 132.79¢ and the sub-optimal cost generated by the bi-linear model is 139.68¢. The sub-optimal cost is 5.2% higher than the optimal cost, the highest error rate in our 381 synthetic scenarios. We use this specific scenario to analyze all the results presented in this section.

There are 2 main reasons for an increase in the cost of the proposed bi-linear model. Firstly, the sub-optimal microgrid price may force the bi-linear model to buy more energy from the grid compared to the optimal solution. Secondly, it may delay an appliance operation compared to the optimal solution. The following discussion presents a detail explanation about how these 2 factors are increasing the cost of the bi-linear model.

Buying More Energy from the Grid

If, in a microgrid area, the households buy more energy from the grid compared to the optimal solution, then the bi-linear model cannot produce the optimal solution. There are 3 main reasons that may impose the solution derived by the bi-linear model to buy more energy from the grid which are discussed as follows.

Energy Loss due to Storage Charging Efficiency

Table 6.15 shows that one of the main reasons for the higher cost in the bi-linear model is that the derived solution unnecessarily charges the storage, which imposes energy loss due to storage charging. The solution charges the storage devices of households 1, 2, 3, 8, 9, 10, 16, 17 and 26. The optimal model never charges any storage in any households. Due to storage charging efficiency, the bi-linear solution lost 3.15 kWh of energy compared to the optimal solution. The households in the bi-linear solution buy this energy at the 1st timeslot from the grid at a price of 1.41¢. Therefore, the bi-linear model incurs additional cost of 3.15 kWh * 1.41¢ = 4.43¢ compared to the optimal solution.

Energy Loss due to Storage Self-Discharging

In a microgrid area, households may buy more energy from the grid if the storage devices lose more energy due to self-discharging. Table 6.15 shows that in the sub-optimal solution, the households lose 0.2 kWh more energy compared to the optimal solution due to self-discharging.

Disutility Cost

The bi-linear solution sometimes delays an appliance operation, which increases the cost due to the disutility cost. Table 6.15 shows that households 4, 20, 21, 23 and 27 increase their cost by 2.35¢ compared to the optimal model.

Table 6.15 shows that the total cost increment due to increased disutility and storage charging is 6.78¢, which is almost the same as the cost difference between the optimal and the bi-linear model (6.89¢). The remaining 0.11¢ cost increase is due to the cost related to self-discharging loss and the precision of the used values (we considered 2 digits after the decimal point). The root cause of this sub-optimal solution is that the bi-linear model does not determine the optimal microgrid price.

Table 6.15: Impact of Local Minima on the Bi-Linear Model Cost

Household	Maximum Cost (¢)	Unified Cost (¢)	Bi-Linear Cost (¢)	Cost Increment in Bi-Linear Model (¢)		Energy Loss due to Self-Discharging (kWh)	
				Due to Storage Charging	Due to Disutility	Unified Model	Bi-Linear Model
1	28.55	24.14	28.55	0.46		0.11	0.16
2	6.67	5.17	6.67	0.64		0.10	0.12
3	14.22	12.34	14.21	0.67		0.11	0.16
4	0.00	-2.81	-3.06		0.06	0.10	0.06
5	2.52	1.04	2.50			0.11	0.10
6	4.52	3.27	4.51			0.11	0.13
7	5.88	4.34	4.01			0.11	0.12
8	13.71	12.01	13.71	0.59		0.10	0.17
9	13.78	10.60	13.78	0.42		0.10	0.16
10	9.32	8.09	9.31	0.41		0.10	0.13
11	0.99	0.02	0.99			0.11	0.11
12	0.00	-3.44	-12.22			0.11	0.08
13	12.53	9.53	12.52			0.10	0.14
14	0.00	-2.62	-5.14			0.09	0.05
15	5.54	4.05	4.53			0.11	0.12
16	13.16	10.66	13.16	0.31		0.10	0.15
17	26.52	22.34	26.51	0.33		0.10	0.17
18	0.00	-2.66	-5.19			0.09	0.05
19	3.28	1.35	3.15			0.10	0.06
20	0.31	-1.68	-5.97		0.31	0.11	0.11
21	7.16	5.64	7.25		0.45	0.11	0.12
22	4.76	3.32	4.71			0.10	0.11
23	4.04	2.11	1.10		0.57	0.10	0.11
24	2.12	-0.07	-2.37			0.11	0.08
25	0.00	-1.59	-4.40			0.11	0.08
26	8.98	7.67	8.98	0.62		0.11	0.14
27	3.77	1.38	1.02		0.96	0.10	0.10
28	3.04	0.85	0.06			0.11	0.09
29	0.00	-1.65	-0.02			0.10	0.06
30	0.88	-0.63	-3.18			0.10	0.11
Total	196.26	132.79	139.68	4.43	2.35	3.15	3.35
	Cost Difference between the Models: 6.89¢			Total Increased Cost in Bi-Linear Model: 6.78¢		Bi-Linear Model Lost 0.2 kWh More Energy	

6.4 Summary

This chapter shows that the accuracy of the bi-linear method is high for a wide range of problem sizes, using both real and synthetic scenarios. Our results show that, for at least 97% of scenarios, the solutions generated by the bi-linear model are optimal solutions. For the sub-optimal solutions, the maximum error rate is 5.2%, i.e., the generated cost is 5.2% more than the optimal cost. The solution time of the bi-linear model is very low (mostly less than a minute) compared to the optimal model. Therefore, based on the results presented in this chapter, we can conclude that the proposed bi-linear model is a better alternative to the unified model considering the accuracy and the solution time. In the next chapter, we use the bi-linear model to evaluate the impact of storage, renewables and microgrid on residential energy cost minimization.

Chapter 7

Case Studies

This chapter presents different case studies to identify the benefits of the microgrid for cost optimization. The demand and response program is an established idea where a dynamic energy price encourages users to reschedule their appliance which ultimately helps to reduce energy cost [7–9, 11, 12, 15, 16, 40, 48, 50]. Therefore, we did not evaluate the impact of dynamic pricing and scheduling on the cost savings. Rather, we evaluate the impact of storage, renewables and microgrid on cost savings. More specifically, we identified the scenarios where P2P energy trading is beneficial and quantified the cost savings based on the availability of renewables and storage.

There are two boundary situations considering cost minimization in a microgrid. If no household has a storage and renewable energy sources, i.e., no energy generation capacity, microgrid trading provides no benefit because in this case there is not sufficient energy to trade. All households, faced with the same grid energy costs, will simply optimize their energy usage locally. On the other hand, if every household generates sufficient energy for their own consumption (in this case, individual household cost is 0), total cost in the microgrid is 0 because no household buys energy from the grid. These two scenarios define the lower and upper bounds of cost savings. In more realistic situations, the cost savings will lie between these two boundaries.

7.1 Datasets

7.1.1 Load Profiles

We used the same realistic datasets for household load profiles that we used previously in Section 6.2.1. The datasets consist of 12 household load profiles of Ottawa.

Table 7.1: List of Households for Case Studies

Household	# of Loads					
	AC	Furnace	Stove	Dishwasher	Dryer	Hot Water
Old Household 1	1	1	1	1 (Never Used)	1	0
Old Household 2	1	1	0	0	0	0
Old Household 10	1	1	1	0	1	1
Old Household 12	1	1	1	1	1	0

Table 7.2: Load Profiles of 40 Households

Date of Load Profile	Old Household 1	Old Household 2	Old Household 10	Old Household 12
June 14	Household 1	Household 2	Household 3	Household 4
June 15	Household 5	Household 6	Household 7	Household 8
June 16	Household 9	Household 10	Household 11	Household 12
June 17	Household 13	Household 14	Household 15	Household 16
June 18	Household 17	Household 18	Household 19	Household 20
June 21	Household 21	Household 22	Household 23	Household 24
June 22	Household 25	Household 26	Household 27	Household 28
June 23	Household 29	Household 30	Household 31	Household 32
June 24	Household 33	Household 34	Household 35	Household 36
June 25	Household 37	Household 38	Household 39	Household 40

We need more households to evaluate more realistic scenarios. For this reason, we consider load profiles of a household on different dates as the load profile of a different household.

Table 7.1 shows the households which are considered for the case studies. Households 2 to 9 and 11 have similar loads: an AC and a Furnace (Table 6.1). Therefore, we used only Household 2 in the case studies as a representative household to represent this group. Both Households 1 and 12 have an AC, a Furnace, a Stove, a Dishwasher and a Dryer (Table 7.1). However, the users of Household 1 never used their Dishwasher. Hence, Household 1 and 12 have different types of loads. Therefore, we considered both households in the case studies. Household 10 has different types of loads (has a hot water tank) than the others, hence it is included in the case studies. Thus, from these 4 household load profiles, and based on 10 different days (10 summer weekdays on June 14 - 25, 2010), we generated load profiles of 40 households as shown in Table 7.2.

Table 7.3: PV Array Configuration

Properties	Small	Medium	Large
PV Module	Suntech STP200S-18/ub-1	Suntech STP200S-18/ub-1	Suntech STP200S-18/ub-1
Array Tilt Angle	45.41° (Site Latitude)	45.41° (Site Latitude)	45.41° (Site Latitude)
Array Azimuth	180° (South Facing Array)	180° (South Facing Array)	180° (South Facing Array)
# of Modules in Series	2	4	8
# of Parallel Strings	2	2	2

Furthermore, the households are arranged in such a way that they are distributed evenly based on the daily energy consumptions as shown in Table 7.2. This balanced distribution is required to reduce the bias of high energy consuming households on the renewables and/or storage penetration rates. It shows that we have 4 new groups of household based on the old households. Each group has similar profiles considering the daily energy consumptions. Appendices B.1 and B.2 show the household energy consumption profiles which are uniformly distributed. Appendix B.3 shows the hourly grid energy consumption by all households.

7.1.2 Renewable Energy Generation Profiles

All case studies considered a historical summer weekday which is June 21, 2010. We used solar irradiance of that day in Ottawa to calculate the amount of generated solar energy. The data source and the modeling tool are the ones we already used in Section 6.2.1.

We used three different types of solar energy generation capacities: small (2 parallel strings, each has 2 modules in series), medium (2 parallel strings, each has 4 modules in series) and large (2 parallel strings, each has 8 modules in series). The configuration of the PV arrays are shown in Table 7.3.

7.1.3 Home Energy Storage Characteristics

We used Tesla Powerwall as the small storage as described in Section 6.2.1. We used similar electrical characteristics of Tesla Powerwall as the characteristics of the

Table 7.4: Storage Characteristics

Properties	Small	Medium	Large
Power	3.3 kW	3.3 kW	3.3 kW
Efficiency	92%	92%	92%
Self-Discharging Rate	1% per Day	1% per Day	1% per Day
Initial Energy	2.56 kWh	5.12 kWh	7.68 kWh
Minimum Energy Level	2.56 kWh	5.12 kWh	7.68 kWh
Maximum Energy Level	6.4 kWh	12.8 kWh	19.2 kWh

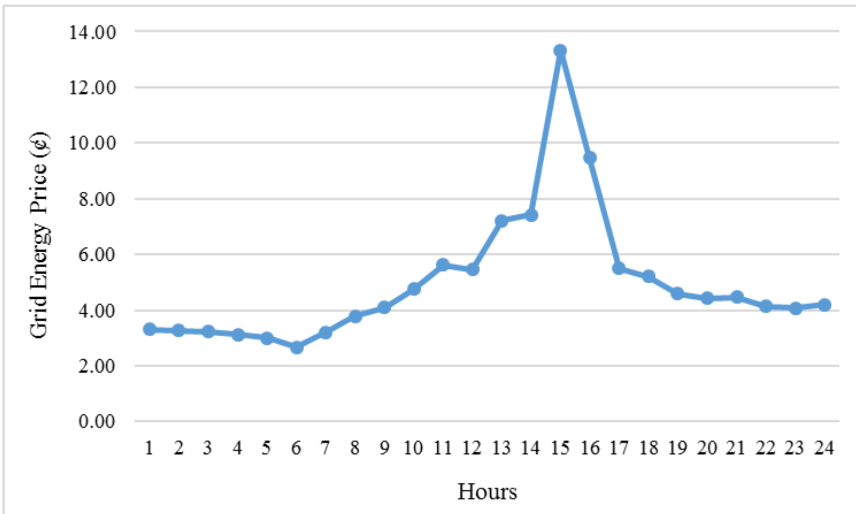

Figure 7.1: Hourly Energy Price (RTP) per kWh [81].

medium and the large storage as shown in Table 7.4. In total we used three different types of storage with different capacities: small (6.4 kWh), medium (12.8 kWh) and large (19.2 kWh).

7.1.4 Grid Energy Price

Instead of using TOU, we used RTP as the energy price because the ultimate goal of the smart grid is to implement a dynamic price scheme. We used the HOEP data as RTP as described in Section 6.2.1. Figure 7.1 shows the considered energy price in Ottawa on June 21, 2010 [81].

7.1.5 Other Parameters

All the datasets considered for the case studies were collected on June 21, 2010 and applied to the households of Ottawa. We consider a 24 hr timeframe with 1 hr time granularity for optimization. We allow higher delay tolerance in appliance operation by using a low disutility factor (0.001¢) and an appliance can be delayed up to the last timeslot. The maximum grid power limit is 100 kW per timeslot per household. The bi-linear model terminates if the cost does not improve more than 0.1% in the last 3 iterations.

7.2 Case Studies

7.2.1 Impact of Storage on Energy Cost

In this section, we evaluate the impact of storage on cost savings based on the storage penetration rate in the microgrid. We increase the number of households with a storage device in the microgrid area from 0% to 100%. We use small, medium and large sizes of storage (Table 7.4) to analyze the impact of storage capacity on cost savings. Each scenario is solved once by the single household model (Appendix A.1) which provides the total cost when the households do not trade energy. In addition, the same scenario is also solved with the bi-linear model which provides the cost when the households participate in microgrid trading. The cost difference between these 2 solutions is used in Figure 7.2 to show the cost savings for energy trading in the microgrid. Each data point in the figure represents a single scenario.

Figure 7.2 shows the relationship between the percentage of households which have a storage (and no renewables) and the saved cost in the microgrid. It shows that cost savings is at a maximum when 20% of the households have an energy storage device (of any size). Beyond that point, cost savings decrease gradually. In the scenario, each household has a minimum storage energy level. This minimum energy level should be maintained because if the level drops below it, it impacts the lifespan of the storage. To maintain the energy level above this minimum energy level, each household needs to charge the storage in the first timeslots even it is not helpful for cost minimization. It imposes energy loss due to storage charging inefficiency and increases the energy cost. Therefore, after a certain point, a higher storage

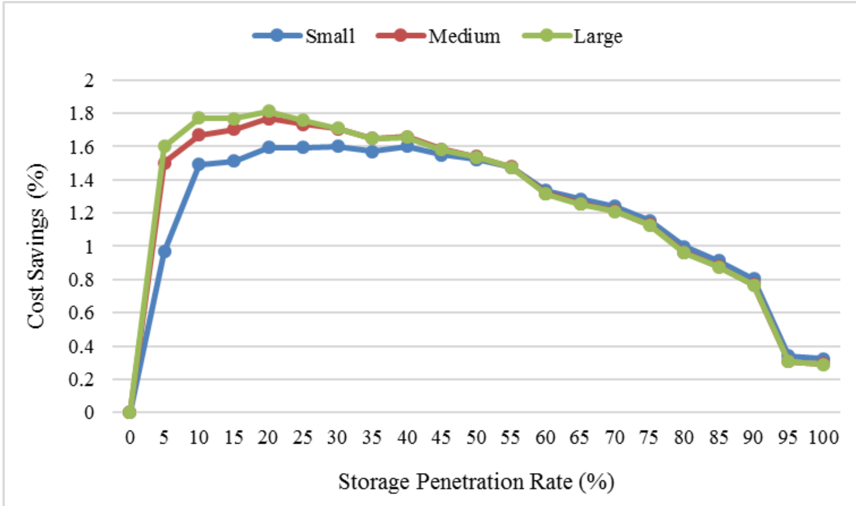

Figure 7.2: Cost Savings vs Storage Penetration Rate.

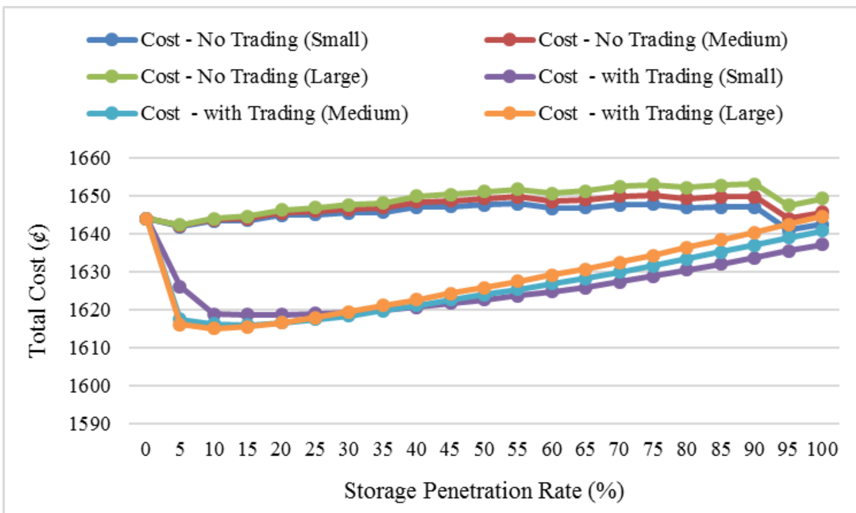

Figure 7.3: Total Cost vs Storage Penetration Rate.

penetration rate does not aid in saving more cost. It is also worth noting the fact that energy savings are small overall, never exceeding 2%. While adding some energy storage to the microgrid overall is beneficial initially, these gains diminish as we add more storage capacity, due to the energy costs incurred by a storage device. It can be concluded that storing grid energy has insignificant impact on cost minimization because the grid energy is not cheap enough to compensate for the energy loss due to charging and self-discharging.

Figure 7.3 shows the relationship between the percentage of households which have a storage and the total cost in the microgrid. It shows that having a storage device may increase the energy cost of individual households because of energy loss due to charging inefficiencies (the cost curves increase with increasing storage penetration rates). In these cases, smaller energy storage imposes less cost overhead. Hence, in the presence of microgrid trading, without renewables, cost savings from having a storage device is not significant. In the next section, we evaluate the scenarios where the households have only renewables without any storage.

7.2.2 Impact of Renewables on Energy Cost

In this section, we evaluate the impact of solar panel penetration rate on energy cost minimization when the households trade energy among themselves. Generally, a storage is also installed with the installation of solar panels. However, to evaluate the impact of only the solar panels, we do not consider any storage in the scenarios in this section. The next section will consider scenarios with both storage and renewables.

For this case study, initially, we gradually increase the percentage of households having solar panels from 0% to 100% and solve the scenarios by the single household model (Appendix A.1) which provides the total cost when the households do not trade energy. Then we solve the same scenarios with the bi-linear model which provides the cost when the households participate in energy trading. The cost difference between these 2 solutions is used in Figure 7.4 to show the impact of renewables on the cost savings in the microgrid. We use 3 different sizes of solar energy generation capacity (Table 7.3) to analyze the results. Each data point in the figure represents a single scenario.

Figure 7.4 shows that cost savings initially increase linearly with the number of households having solar panels (but no energy storage). However, after a saturation point, cost savings decrease gradually except for the small generation capacity. After this point, more solar panels increase energy waste because the generated energy cannot all be used at that moment. Therefore, in this case, energy trading does not aid in saving costs. For the small generation capacity, it shows no energy waste because all generated energy is consumed instantaneously. The surplus energy in a certain timeslot must be traded in the microgrid in that timeslot because the households do not have storage. If the household cannot sell the surplus energy to the microgrid, it cannot minimize the cost further. Therefore, after the saturation point, the difference between the energy cost with microgrid and without microgrid starts decreasing. Compared to the scenarios in the previous section (storage but no

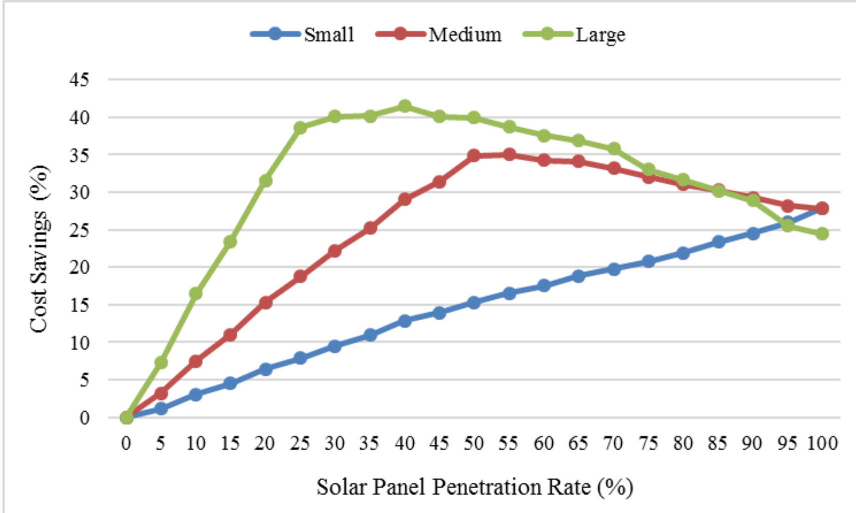

Figure 7.4: Cost Savings vs Solar Panel Penetration Rate.

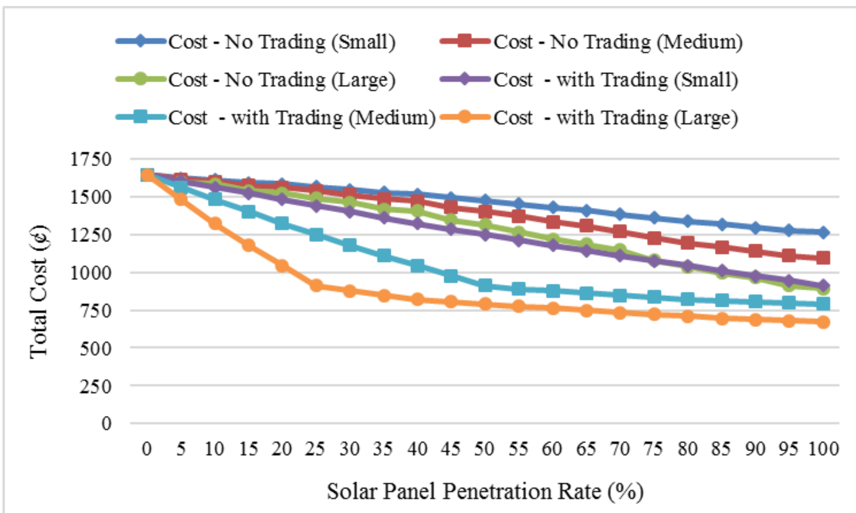

Figure 7.5: Total Cost vs Solar Panel Penetration Rate.

renewables), microgrid trading achieves a significant amount of cost reduction, up to 40% in our scenarios.

Figure 7.5 shows that for individual households, total costs decrease linearly with the number of households having solar panels. For the microgrid, after a saturation point, adding more households with solar panels does not help reducing costs further because of energy waste (for comparatively higher solar energy generation capacity). However, for the same reason, energy waste without energy trading is higher than the

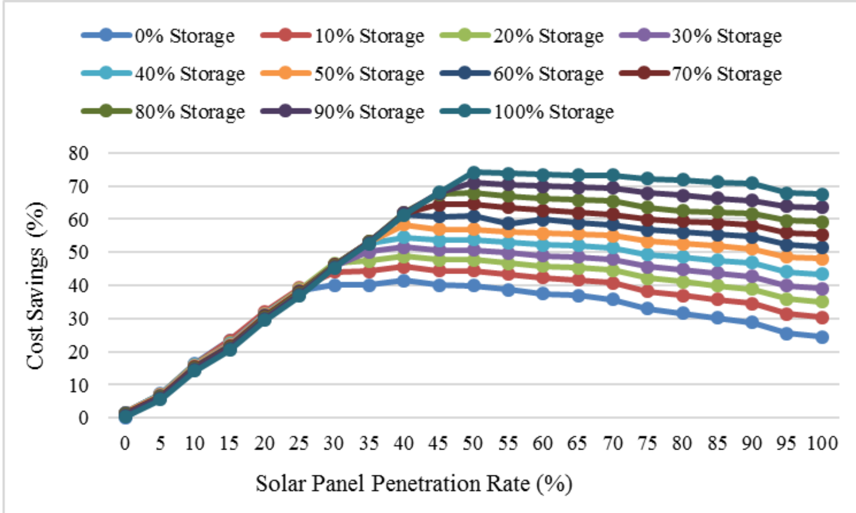

Figure 7.6: Cost Savings vs Storage and Solar Panel Penetration Rate.

energy waste with trading. This is then also reflected in the energy cost.

7.2.3 Impact of Storage and Renewables on Energy Cost

In this section, we evaluate the impact of storage and solar panel penetration rates on cost minimization when the households participate in energy trading. We use small storage and large PV generation capacity for all the scenarios in this section. We increase the percent of households with storage gradually from 0% to 100%. In addition to this, for each penetration rate of the storage, we gradually increase the percent of households having solar panels. We calculated the cost savings using the same procedure discussed in earlier sections.

Figure 7.6 shows that, in the presence of energy trading, storage increases cost savings if the households have solar panels. The savings increase linearly. However, after a saturation point, cost savings decrease because of energy waste. Energy is wasted because the generated energy cannot be used or stored at that moment. Results show that microgrid energy trading can provide up to 74% cost savings when solar panels are used in combination with a storage device.

Figure 7.7 shows that, without trading, total cost decreases linearly with the increase of storage and renewables penetration rates. Figure 7.8 shows that, with

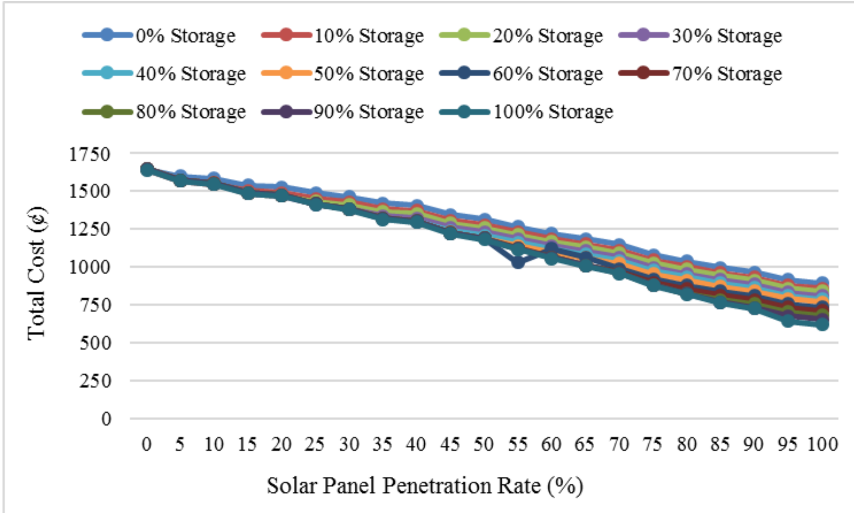

Figure 7.7: Total Cost vs Storage and Solar Panel Penetration Rate (without Microgrid Trading).

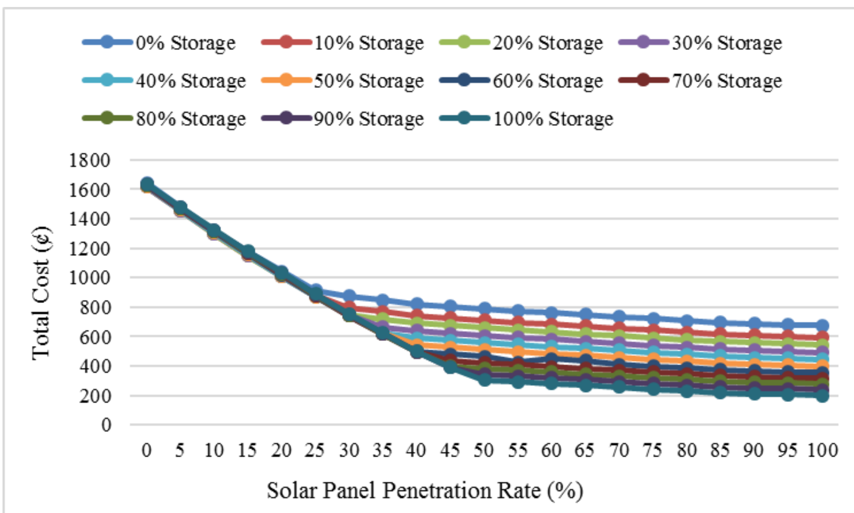

Figure 7.8: Total Cost vs Storage and Solar Panel Penetration Rate (with Microgrid Trading).

trading, total cost decreases linearly for the same reason. However, for this case, after a saturation point, total cost does not decrease significantly because of energy waste. It can be noticed that energy waste without microgrid trading is higher than the energy waste with microgrid trading. It is because energy trading enables the households to trade the energy which would be wasted otherwise.

7.3 Summary

Microgrid energy trading is beneficial when the households have storage and renewables. If the households have only storage without the capability to generate renewable energy, it may not be useful in terms of saving cost. Therefore, if the households have an energy storage, it is recommended to install renewables in their premises. In the presence of renewables, increased storage capacity increases cost savings until it reaches a saturation point. Similar to this, there is a threshold point after which more renewables do not aid in cost savings. From the analysis, it can be concluded that P2P energy trading has significant impact on energy cost minimization. However, the benefits diminish beyond a threshold level, so there is less reason to provide incentives for people to add more solar panels, for example.

Chapter 8

Conclusions and Future Work

8.1 Summary and Contributions

This thesis presents an optimal and an approximate energy cost optimization model from the users' perspective. The proposed models consider the smart homes as the building units of the smart grid. This concept is also applicable to the apartments of a smart building. Therefore, the models can be applied to analyze the behavior of a population (e.g., smart cities, communities, etc.) and characteristics of the components for specific scenarios. As an example, recent advances of home storage technologies imply that the storage may become an integral part of smart cities in the future. The proposed models can be used to analyze the impact of the storage in the smart grid. Similarly, the models can also be used to analyze the impact of renewable energy generation capacity in an area. These models could be utilized to determine the quantity of resources to build a net-zero energy community or building or city. Hence, the proposed models could be useful for governments, policy makers and utilities to predict the users' behavior and conduct a cost-benefit analysis. The contributions of this research are as follows:

8.1.1 The Unified Model

We propose a unified cost optimization model which integrates the partial aspects of previous research within a single cost optimization model. The model utilizes load and source scheduling, and energy trading strategies for cost optimization. It also considers the components which have significant impact on cost optimization, e.g, storage, renewables, microgrid, etc. It does not only consider energy cost minimization but also addresses the inconvenience created to the users by delaying certain tasks. The proposed unified cost optimization model is one of the main contributions of our research.

8.1.2 P2P Energy Trading

The unified model enables P2P energy trading among the participating households in the microgrid. The households determine the microgrid energy price and quantity to minimize the total cost in the microgrid area. Unlike the other models (see Section 2.4), our proposed trading strategy considers the total cost optimization in a microgrid.

8.1.3 Pareto Optimality

One of the issues related to P2P energy trading is that sometimes the households may increase the cost of others to minimize their own cost. We address this unfair cost distribution problem by ensuing Pareto optimality among the participating households in microgrid energy trading. It means that no households will be worse off to improve the cost of others. More specifically, the proposed model ensures that the households' cost when they trade energy in the microgrid is not higher than the cost when they do not participate.

8.1.4 The Bi-Linear Model

The proposed unified model is an NP-hard problem. Our results show that, even for small problem sizes, the solution time increases exponentially. Hence, it cannot be utilized to solve practical scenarios. To address this problem, we propose a bilinear model which provides an approximate solution within a realistic timeframe. It inherits all the features of the unified model but does not guaranty an optimal solution. Our results show that, for real and synthetic datasets, 99% and 97% of the solutions generated by the bi-linear model are optimal solutions respectively. The solution time of the bi-linear model is very low (mostly less than a minute) compared to the optimal model. Therefore, the proposed bi-linear model is a better alternative to the unified model considering the accuracy and the solution time. Finally, we analyzed the bi-linear solutions and identified that the sub-optimal cost potentially arises when the microgrid price reaches to the boundary limits.

8.1.5 Impact of Microgrid

The energy saving strategies of the smart homes can be divided into 2 main categories based on the presence of smart grid infrastructure. The first category includes the scenarios when the smart homes do not use smart grid infrastructure for energy trading. Energy cost can be optimized by controlling the loads, and utilizing the renewables and energy storage. In the second category, a smart home can trade energy with others by utilizing the smart grid infrastructure. P2P energy trading in the microgrid is an additional potential cost saving option of this category.

We considered both categories in our research and compared the solutions with and without the smart grid (microgrid) in Chapter 7. Based on the results presented in Chapter 7, we can conclude that when the smart homes are not linked to the smart grid, the cost savings is low. For example, Figure 7.6 shows that when the smart homes use smart grid infrastructure to trade energy, they can reduce their costs by 74% compared to the scenario when they do not trade energy. For the scenarios presented in the figure, the cost reduction is optimal when 50% of the households have solar panels and 100% of the households have storage.

Our results show that P2P energy trading in the microgrid is beneficial if the households have both storage and renewables. In the presence of renewables, increased storage capacity increases cost savings until it reaches a saturation point. Similar to this, there is a threshold point after which more renewables do not aid in cost savings. Our findings could be helpful for the policy makers to design incentive schemes for cost optimization.

8.2 Limitations and Future Work

The proposed models can be extended or modified to accommodate the following additional features.

8.2.1 Fair Cost Distribution

The unified and the bi-linear models maintain Pareto optimality which ensures that no households will be paying more than what it would pay individually when we allow for microgrid trading. However, it does not ensure that the cost savings will be distributed fairly among the households. In a more practical scenario, the cost savings due to microgrid energy trading should be distributed fairly among the participating households. To implement this, we need to define the policy related to fair cost distribution. It may specify that the household which consumes more energy will get a bigger share of the saved cost or the savings may be evenly distributed among the participating households. It also could be a function of the traded energy by each household: the more energy a household trades, the bigger a share of the saved costs it will receive. This is more logical because the energy cost is minimized because of the traded energy in the microgrid and there will be no benefit if no households trade energy. It will also encourage the households to utilize the microgrid more, which is one of the main objectives to form a microgrid. Once we determine how the saved cost will be distributed fairly among the households, we can change the Pareto optimality constraints of our models to enforce the cost fairness.

8.2.2 Energy Trading Methods

Module 2 of the proposed bi-linear model is a type of auction method which is implemented using an MILP model. However, unlike the auction methods (see Section 2.4.2), instead of determining a market clearing microgrid price which is beneficial only for the individual households, it determines the optimal microgrid price that minimizes the total cost of all households. Module 2 can be modified using the methods used for auction or game theory (see Section 2.4) to determine the competitive market clearing price for individual households. In this situation, the participating households will take the risk of paying a higher cost compared to the cost they would pay when they do not participate. This represents a more realistic scenario which happens in the economic market and hence the previous researchers developed their methods considering it (Section 2.4). However, it may discourage the users to participate in P2P energy trading because the cost savings may not be distributed fairly.

8.2.3 EV Coordination

The proposed cost optimization models coordinate the energy storage in the households. The EVs are considered as energy storage, hence the proposed optimization models can be modified to accommodate EV coordination. To implement this feature, the constraints related to the energy storage (Constraints 3.6 and 3.7) can be modified by using a new parameter or variable to track the energy which is consumed for driving the vehicles. In our models, the stored energy is always available for utilization by the household, or to be traded in the microgrid, which is not true for EVs. The EVs may not be always present in the users' premises. Therefore, the optimization model requires a Boolean variable for all households and timeslots to model the presence of the EVs in the system.

8.2.4 Utility as an Energy Buyer

In the smart grid, the prosumers can send energy to the power grid. In Ontario, the users can sell electricity to the grid through the IESO's Feed-in Tariff (FIT) program [83] (e.g. microFTT [84]). The proposed models can be extended by enabling the households to sell energy to the grid. In our current models, the grid energy variable, $GE_{k,h}$, can take only positive values. If we also consider negative values, the models will allow the households to sell energy to the grid.

8.2.5 Appliance Operating States

In this research, we consider load scheduling for energy cost optimization. However, for some appliances (e.g., space heater, water heater), it is also possible to optimize the energy cost by reducing their operating power. For some appliances (e.g., washing machine), different steps in the operation cycle require different power levels. Our optimization models can be extended by addressing different power levels (discrete and continuous) of these appliances.

8.2.6 Local Minima

In Section 6.3.1, we analyze the scenarios which generated sub-optimal solutions. We notice different patterns in the solutions which are mostly related to the boundary values of the microgrid price. Every sub-optimal scenario we found has microgrid energy prices that are higher in adjacent timeslots and the price is either 0 or the same (or at least very close to) as the grid price. However, scenarios where the grid prices are close to these boundary values do not always result in a sub-optimal solution. There may be some other patterns in the sub-optimal solutions which could be useful to improve the bi-linear model.

8.2.7 Load Optimization

The proposed models can also be utilized, with slight modifications, for load optimization for the utility. The utility is interested in load shaving instead of minimizing the total energy cost over the entire scheduling horizon for all households. That is, the utility tries to minimize the peak demand to flatten the energy demand curve. A minimax optimization model can be used to shave the peak energy demand. The minimax algorithm minimizes the maximum hourly load of all households. Therefore, the objective function of the proposed models can be modified to implement this feature.

List of References

[1] M. R. Alam, M. B. I. Reaz, and M. A. M. Ali, "A review of smart homes - past, present, and future," *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews*, vol. 42, no. 6, pp. 1190–1203, 2012.

[2] S. Rogai, "Enel's metering system and telegestore project," in *National Association of Regulatory Utility Commissioners (NARUC) Conference*, 2006. [Online]. Available: http://www.narucmeetings.org/Presentations/ENEL.pdf

[3] ENEL, "Enel smart grid," 2014. [Online]. Available: http://www.enel.com/en-GB/innovation/smart_grids/

[4] P. Mansbridge, "2003: The great north america blackout," 2003. [Online]. Available: http://www.cbc.ca/archives/categories/economy-business/energy/energy-general/the-great-2003-north-america-blackout.html

[5] J. Kumagai, "The rise of the personal power plant," *IEEE Spectrum*, vol. 51, no. 6, pp. 54–59, 2014.

[6] IEA, "Energy policies of iea countries - germany: 2013 review," 2013. [Online]. Available: http://www.iea.org/countries/membercountries/germany/

[7] A.-H. Mohsenian-Rad and A. Leon-Garcia, "Optimal residential load control with price prediction in real-time electricity pricing environments," *IEEE Transactions on Smart Grid*, vol. 1, no. 2, pp. 120–133, 2010.

[8] T. Bapat, N. Sengupta, S. K. Ghai, V. Arya, Y. B. Shrinivasan, and D. Seetharam, "User-sensitive scheduling of home appliances," in *Proceedings of the 2nd ACM SIGCOMM workshop on Green networking*, ser. GreenNets'11, 2011, pp. 43–48.

[9] F. De Angelis, M. Boaro, D. Fuselli, S. Squartini, F. Piazza, and Q. Wei, "Optimal home energy management under dynamic electrical and thermal constraints," *IEEE Transactions on Industrial Informatics*, vol. 9, no. 3, pp. 1518–1527, 2013.

[10] Z. Zhu, J. Tang, S. Lambotharan, W. H. Chin, and Z. Fan, "An integer linear programming based optimization for home demand-side management in smart grid," in *Proceedings of the IEEE PES Innovative Smart Grid Technologies (ISGT)*, 2012, pp. 1–5.

[11] A. J. Conejo, J. M. Morales, and L. Baringo, "Real-time demand response model," *IEEE Transactions on Smart Grid*, vol. 1, no. 3, pp. 236–242, 2010.

[12] M. Marwan, G. Ledwich, and A. Ghosh, "Smart grid-demand side response model for optimization air conditioning," in *Proceedings of the 22nd Australasian Universities Power Engineering Conference (AUPEC)*, 2012, pp. 1–6.

[13] T. Hubert and S. Grijalva, "Realizing smart grid benefits requires energy optimization algorithms at residential level," in *Proceedings of the Innovative Smart Grid Technologies (ISGT)*, 2011, pp. 1–8.

[14] A. D. Giorgio and F. Liberati, "Near real time load shifting control for residential electricity prosumers under designed and market indexed pricing models," *Applied Energy*, vol. 128, pp. 119 – 132, 2014.

[15] K. M. Tsui and S. C. Chan, "Demand response optimization for smart home scheduling under real-time pricing," *IEEE Transactions on Smart Grid*, vol. 3, no. 4, pp. 1812–1821, 2012.

[16] T. G. Hovgaard, S. Boyd, L. F. S. Larsen, and J. B. Jrgensen, "Nonconvex model predictive control for commercial refrigeration," *International Journal of Control*, vol. 86, no. 8, pp. 1349–1366, 2013.

[17] A. Schroeder, "Modeling storage and demand management in power distribution grids," *Applied Energy*, vol. 88, no. 12, pp. 4700 – 4712, 2011.

[18] J. Yang, L. He, and S. Fu, "An improved PSO-based charging strategy of electric vehicles in electrical distribution grid," *Applied Energy*, vol. 128, pp. 82 – 92, 2014.

[19] I. Atzeni, L. G. Ordonez, G. Scutari, D. P. Palomar, and J. R. Fonollosa, "Demand-side management via distributed energy generation and storage optimization," *IEEE Transactions on Smart Grid*, vol. 4, no. 2, pp. 866–876, 2013.

[20] W. Su and A. Q. Huang, "A game theoretic framework for a next-generation retail electricity market with high penetration of distributed residential electricity suppliers," *Applied Energy*, vol. 119, pp. 341 – 350, 2014.

[21] N. Zhang, Y. Yan, and W. Su, "A game-theoretic economic operation of residential distribution system with high participation of distributed electricity prosumers," *Applied Energy*, vol. 154, pp. 471 – 479, 2015.

[22] D. Zhang, S. Liu, and L. G. Papageorgiou, "Fair cost distribution among smart homes with microgrid," *Energy Conversion and Management*, vol. 80, pp. 498–508, 2014.

[23] M. D. Hopkins, A. Pahwa, and T. Easton, "Intelligent dispatch for distributed renewable resources," *IEEE Transactions on Smart Grid*, vol. 3, no. 2, pp. 1047–1054, 2012.

[24] A. Arabali, M. Ghofrani, M. Etezadi-Amoli, M. S. Fadali, and Y. Baghzouz, "Genetic-algorithm-based optimization approach for energy management," *IEEE Transactions on Power Delivery*, vol. 22, no. 1, pp. 162–170, 2013.

[25] P. Vytelingum, S. D. Ramchurn, T. D. Voice, A. Rogers, and N. R. Jennings, "Trading agents for the smart electricity grid," in *Proceedings of the 9th International Conference on Autonomous Agents and Multiagent Systems*, 2010, pp. 897–904.

[26] R. Arghandeh, J. Woyak, A. Onen, J. Jung, and R. P. Broadwater, "Economic optimal operation of community energy storage systems in competitive energy markets," *Applied Energy*, vol. 135, pp. 71 – 80, 2014.

[27] H. Bilil, G. Aniba, and M. Maaroufi, "Multiobjective optimization of renewable energy penetration rate in power systems," *Energy Procedia*, vol. 50, pp. 368–375, 2014.

[28] B. Ramachandran, S. K. Srivastava, C. S. Edrington, and D. A. Cartes, "An intelligent auction scheme for smart grid market using a hybrid immune algorithm," *IEEE Transactions on Industrial Electronics*, vol. 58, no. 10, pp. 4603–4612, 2011.

[29] Z. Wang and L. Wang, "Intelligent negotiation agent with learning capability for energy trading between building and utility grid," in *Proceedings of the IEEE Innovative Smart Grid Technologies-Asia (ISGT Asia)*, 2012, pp. 1–6.

[30] D. Ilic, P. G. D. Silva, S. Karnouskos, and M. Griesemer, "An energy market for trading electricity in smart grid neighbourhoods," in *Proceedings of the 6th IEEE International Conference on Digital Ecosystems Technologies (DEST)*, 2012, pp. 1–6.

[31] A. Pal, C. Bhaumik, J. Shukla, and S. Kolay, "Energy information gateway for home," in *Proceedings of the 2nd International Conference on Intelligent Systems, Modelling and Simulation (ISMS)*, 2011, pp. 235–240.

[32] M. Jahn, M. Jentsch, C. R. Prause, F. Pramudianto, A. Al-Akkad, and R. Reiners, "The energy aware smart home," in *Proceedings of the 5th International Conference on Future Information Technology (FutureTech)*, 2010, pp. 1–8.

[33] M. Weiss and D. Guinard, "Increasing energy awareness through web-enabled power outlets," in *Proceedings of the 9th International Conference on Mobile and Ubiquitous Multimedia*, 2010, pp. 20:1–20:10.

[34] Y.-G. Cheong, Y.-J. Kim, S. Y. Yoo, H. Lee, S. Lee, S. C. Chae, and H.-J. Choi, "An ontology-based reasoning approach towards energy-aware smart homes," in *Proceedings of the IEEE Consumer Communications and Networking Conference (CCNC)*, 2011, pp. 850–854.

[35] H. Chitsaz, N. Amjady, and H. Zareipour, "Wind power forecast using wavelet neural network trained by improved clonal selection algorithm," *Energy Conversion and Management*, vol. 89, pp. 588 – 598, 2015.

[36] L. Ciabattoni, M. Grisostomi, G. Ippoliti, S. Longhi, and E. Mainardi, "On line solar irradiation forecasting by minimal resource allocating networks," in *20th Mediterranean Conference on Control & Automation (MED)*, 2012, pp. 1506–1511.

[37] Z. Dong, D. Yang, T. Reindl, and W. M. Walsh, "A novel hybrid approach based on self-organizing maps, support vector regression and particle swarm optimization to forecast solar irradiance," *Energy*, vol. 82, pp. 570 – 577, 2015.

[38] G. A. Pagani and M. Aiello, "Generating realistic dynamic prices and services for the smart grid," *IEEE Systems Journal*, vol. 9, no. 1, pp. 191–198, 2015.

[39] M. R. Alam, M. St-Hilaire, and T. Kunz, "Computational methods for residential energy cost optimization in smart grids: A survey," *ACM Computing Surveys*, vol. 49, no. 1, pp. 2:1–2:34, Apr. 2016. [Online]. Available: http://doi.acm.org/10.1145/2897165

[40] P. Siano, "Demand response and smart gridsa survey," *Renewable and Sustainable Energy Reviews*, vol. 30, pp. 461 – 478, 2014.

[41] J. S. Vardakas, N. Zorba, and C. V. Verikoukis, "A survey on demand response programs in smart grids: pricing methods and optimization algorithms," *IEEE Communications Surveys & Tutorials*, vol. 17, no. 1, pp. 152–178, 2015.

[42] F. Shariatzadeh, P. Mandal, and A. K. Srivastava, "Demand response for sustainable energy systems: A review, application and implementation strategy," *Renewable and Sustainable Energy Reviews*, vol. 45, pp. 343 – 350, 2015.

[43] A. J. Conejo, J. Contreras, R. Espinola, and M. A. Plazas, "Forecasting electricity prices for a day-ahead pool-based electric energy market," *International Journal of Forecasting*, vol. 21, no. 3, pp. 435–462, 2005.

[44] J. Mattingley, Y. Wang, and S. Boyd, "Receding horizon control," *IEEE Control Systems*, vol. 31, no. 3, pp. 52–65, 2011.

[45] CVX, "Cvx: Matlab software for disciplined convex programming, version 2.0 beta," 2014. [Online]. Available: http://cvxr.com/cvx

[46] N. Kowahl and A. Kuh, "Micro-scale smart grid optimization," in *Proceedings of the International Joint Conference on Neural Networks (IJCNN)*, 2010, pp. 1–8.

[47] D. Livengood and R. Larson, "The energy box: Locally automated optimal control of residential electricity usage," *Service Science*, vol. 1, no. 1, pp. 1–16, 2009.

[48] A.-H. Mohsenian-Rad, V. W. Wong, J. Jatskevich, R. Schober, and A. Leon-Garcia, "Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid," *Smart Grid, IEEE Transactions on*, vol. 1, no. 3, pp. 320–331, 2010.

[49] S. Boyd and L. Vandenberghe, *Convex optimization.* Cambridge university press, 2004.

[50] D. O'Neill, M. Levorato, A. Goldsmith, and U. Mitra, "Residential demand response using reinforcement learning," in *Proceedings of the 1st IEEE International Conference on Smart Grid Communications (SmartGridComm)*, 2010, pp. 409–414.

[51] I. Georgievski, V. Degeler, G. A. Pagani, T. A. Nguyen, A. Lazovik, and M. Aiello, "Optimizing energy costs for offices connected to the smart grid," *IEEE Transactions on Smart Grid*, vol. 3, no. 4, pp. 2273–2285, 2012.

[52] T. Mosher, "Economic valuation of energy storage coupled with photovoltaics: current technologies and future projections," Master's thesis, Massachusetts Institute of Technology, Cambridge, MA, USA, 2010.

[53] P. Vytelingum, T. D. Voice, S. D. Ramchurn, A. Rogers, and N. R. Jennings, "Agent-based micro-storage management for the smart grid," in *Proceedings of the 9th International Conference on Autonomous Agents and Multiagent Systems*, 2010, pp. 39–46.

[54] P. Poonpun and W. T. Jewell, "Analysis of the cost per kilowatt hour to store electricity," *IEEE Transactions on Energy Conversion*, vol. 23, no. 2, pp. 529–534, 2008.

[55] ApX, 2014. [Online]. Available: https://www.apxgroup.com

[56] D. K. Gode and S. Sunder, "Allocative efficiency of markets with zero-intelligence traders: Market as a partial substitute for individual rationality," *Journal of Political Economy*, vol. 101, no. 1, pp. 119–137, 1993.

[57] P. Vytelingum, D. Cliff, and N. R. Jennings, "Strategic bidding in continuous double auctions," *Artificial Intelligence*, vol. 172, no. 14, pp. 1700–1729, 2008.

[58] NOBEL, 2013. [Online]. Available: http://www.ict-nobel.eu/

[59] GridWise, "Gridwise transactive energy framework version 1.0," 2015. [Online]. Available: http://www.gridwiseac.org/pdfs/te_framework_report_pnnl-22946.pdf

[60] D. J. Hammerstrom et al., "Pacific northwest gridwise testbed demonstration projects," *Part I. Olympic Peninsula Project*, 2007. [Online]. Available: https://www.smartgrid.gov/files/PNNL_GridWise_Testbed_Demo_Projects_Part_I_Olympic_Peninsula_200711.pdf

[61] B. A. Huberman and S. H. Clearwater, "A multi-agent system for controlling building environments." in *ICMAS*, 1995, pp. 171–176.

[62] N. Capodieci, G. A. Pagani, G. Cabri, and M. Aiello, "Smart meter aware domestic energy trading agents," in *Proceedings of the 2011 Workshop on E-energy Market Challenge*. ACM, 2011, pp. 1–10.

[63] R. Abounacer, M. Rekik, and J. Renaud, "An exact solution approach for multi-objective location-transportation problem for disaster response," *Computers and Operations Research*, vol. 41, no. Jan, pp. 83–93, 2014.

[64] R. Fourer, D. M. Gay, and B. W. Kernighan, *AMPL: A modeling language for mathematical programming*, 2nd ed. Cengage Learning, 2002, vol. 2.

[65] AMPL. (2014, Oct). [Online]. Available: http://www.ampl.com

[66] P. Belotti, J. Lee, L. Liberti, F. Margot, and A. Wchter, "Branching and bounds tightening techniques for non-convex minlp," *Optimization Methods & Software*, vol. 24, no. 4-5, pp. 597–634, 2009.

[67] CPLEX, 2016. [Online]. Available: http://www-01.ibm.com/software/commerce/optimization/cplex-optimizer/

[68] CPLEX, 2016. [Online]. Available: http://ampl.com/products/solvers/solvers-we-sell/cplex/

[69] R. G. Michael and S. J. David, *Computers and intractability: a guide to the theory of NP-completeness*, 1st ed. San Francisco: WH Freeman & Co., 1979.

[70] N. Saldanha and I. Beausoleil-Morrison, "Measured end-use electric load profiles for 12 canadian houses at high temporal resolution," *Energy and Buildings*, vol. 49, pp. 519–530, 2012.

[71] NSRDB, 2016. [Online]. Available: https://nsrdb.nrel.gov/

[72] NREL, 2016. [Online]. Available: http://www.nrel.gov/

[73] NSRDB VIEWER, 2016. [Online]. Available: https://nsrdb.nrel.gov/nsrdb-viewer

[74] PV-LIB Toolbox, 2016. [Online]. Available: https://pvpmc.sandia.gov/applications/pv_lib-toolbox/

[75] Sandia National Laboratories, 2016. [Online]. Available: https://pvpmc.sandia.gov/

[76] M. Lave, W. Hayes, A. Pohl, and C. W. Hansen, "Evaluation of global horizontal irradiance to plane-of-array irradiance models at locations across the united states," *IEEE Journal of Photovoltaics*, vol. 5, no. 2, pp. 597–606, March 2015.

[77] Tesla Powerwall, 2016. [Online]. Available: https://www.teslamotors.com/en_CA/POWERWALL

[78] Ontario Energy Board (OEB), 2016. [Online]. Available: http://www.ontarioenergyboard.ca/

[79] OEB TOU Price, 2010. [Online]. Available: http://www.ontarioenergyboard.ca/OEB/Consumers/Electricity/Electricity+Prices/Historical+Electricity+Prices

[80] IESO, 2016. [Online]. Available: http://www.ieso.ca/Pages/Power-Data/default.aspx#price

[81] IESO HOEP, 2010. [Online]. Available: http://www.ieso.ca/Pages/Power-Data/Data-Directory.aspx

[82] List of all registered participants (IESO), 2016. [Online]. Available: http://www.ieso.ca/Pages/Participate/Participants.aspx

[83] Feed-in Tariff (FIT) Program, 2016. [Online]. Available: http://fit.powerauthority.on.ca/

[84] microFIT Program, 2016. [Online]. Available: http://microfit.powerauthority.on.ca/

Appendix A

Optimization Models

A.1 Optimization Model for Single Household

Objective

$$min\ Y \tag{3.25}$$

where,

$$Y = \sum_{k\in K}\sum_{h\in H} GP_h \cdot GE_{k,h} + \sum_{k\in K}\sum_{i\in I} d_{k,i}\left(\tau_{k,i} - \left(\sum_{h\in H} r_{k,i,h} \cdot h + t_{k,i} - 1\right)\right) \tag{3.23}$$

Here, for the k-th household the minimum value of Y is equals to $C_k^{NoTrade}$.

Subject to:

Energy Balance Constraints

$$\sum_{i\in I} S_{k,i,h} \cdot p_{k,i} + IC_{k,h} \cdot SP_k = GE_{k,h} + BE_{k,h} + RE_{k,h}, (k \in K, h \in H) \tag{3.5}$$

Stored Energy Constraints

$$SE_{k,1} = IE_k \cdot SD_k + IC_{k,1} \cdot SP_k \cdot E_k - BE_{k,1}, (k \in K) \tag{3.6}$$

$$SE_{k,h} = IE_{k,h-1} \cdot SD_k + IC_{k,h} \cdot SP_k \cdot E_k - BE_{k,h}, (k \in K, h \in H : h \neq 1) \tag{3.7}$$

Storage Capacity Constraints

$$SE_{k,h} \leq MaxC_k, (k \in K, h \in H) \tag{3.8}$$

$$SE_{k,h} \geq MinC_k, (k \in K, h \in H) \tag{3.9}$$

Task Duration Constraints

$$\sum_{h \in H} S_{k,i,h} = t_{k,i}, (k \in K, h \in H) \tag{3.10}$$

Renewable Energy Availability Constraints

$$RE_{k,h} \leq RQ_{k,h}, (k \in K, h \in H) \tag{3.11}$$

Reservation Time Constraints

$$\sum_{h \in H} S_{k,i,h} = \sum_{h=\sum_{h \in H} r_{k,i,h} \cdot h}^{N} S_{k,i,h}, (k \in K, i \in I) \tag{3.12}$$

Relationship between the Scheduling Vector and the End Time Constraints

$$S_{k,i,h} \cdot h \leq \tau_{k,i}, (k \in K, i \in I, h \in H) \tag{3.13}$$

Maximum Allowable Delay Constraints

$$\tau_{k,i} \leq \beta_{k,i}, (k \in K, i \in I) \tag{3.14}$$

Uninterruptibility Constraints

$$\sum_{d=0}^{t_{k,i}-1} S_{k,i,h+d} - t_{k,i} \geq -t_{k,i}(1 - US_{k,i,h}), (k \in K, i \in U, h = [1, N - t_{k,i} + 1]) \tag{3.15}$$

$$\sum_{h=1}^{N-t_{k,i}+1} US_{k,i,h} = 1, (k \in K, i \in U) \tag{3.16}$$

Utility Grid Max Power Limit Constraints

$$GE_{k,h} \leq L_k^{max}, (k \in K, h \in H) \tag{3.17}$$

A.2 The Unified Model

Objective

$$min(C_1, C_2, \ldots, C_k) \tag{3.4}$$

where,

$$CE_k = \sum_{h \in H} GP_h \cdot GE_{k,h} + \sum_{h \in H} MP_h \cdot ME_{k,h} \tag{3.1}$$

$$CD_k = \sum_{i \in I} d_{k,i} \left(\tau_{k,i} - \left(\sum_{h \in H} r_{k,i,h} \cdot h + t_{k,i} - 1 \right) \right) \tag{3.2}$$

$$C_k = CE_k + CD_k \tag{3.3}$$

Subject to:

Energy Balance Constraints

$$\sum_{i \in I} S_{k,i,h} \cdot p_{k,i} + IC_{k,h} \cdot SP_k = GE_{k,h} + BE_{k,h} + RE_{k,h} + ME_{k,h}, (k \in K, h \in H) \tag{3.5}$$

Stored Energy Constraints

$$SE_{k,1} = IE_k \cdot SD_k + IC_{k,1} \cdot SP_k \cdot E_k - BE_{k,1}, (k \in K) \tag{3.6}$$

$$SE_{k,h} = IE_{k,h-1} \cdot SD_k + IC_{k,h} \cdot SP_k \cdot E_k - BE_{k,h}, (k \in K, h \in H : h \neq 1) \tag{3.7}$$

Storage Capacity Constraints

$$SE_{k,h} \leq MaxC_k, (k \in K, h \in H) \tag{3.8}$$

$$SE_{k,h} \geq MinC_k, (k \in K, h \in H) \tag{3.9}$$

Task Duration Constraints

$$\sum_{h \in H} S_{k,i,h} = t_{k,i}, (k \in K, h \in H) \tag{3.10}$$

Renewable Energy Availability Constraints

$$RE_{k,h} \leq RQ_{k,h}, (k \in K, h \in H) \tag{3.11}$$

Reservation Time Constraints

$$\sum_{h\in H} S_{k,i,h} = \sum_{h=\sum_{h\in H} r_{k,i,h}\cdot h}^{N} S_{k,i,h}, (k \in K, i \in I) \tag{3.12}$$

Relationship between the Scheduling Vector and the End Time Constraints

$$S_{k,i,h} \cdot h \leq \tau_{k,i}, (k \in K, i \in I, h \in H) \tag{3.13}$$

Maximum Allowable Delay Constraints

$$\tau_{k,i} \leq \beta_{k,i}, (k \in K, i \in I) \tag{3.14}$$

Uninterruptibility Constraints

$$\sum_{d=0}^{t_{k,i}-1} S_{k,i,h+d} - t_{k,i} \geq -t_{k,i}(1 - US_{k,i,h}), (k \in K, i \in U, h = [1, N - t_{k,i} + 1]) \tag{3.15}$$

$$\sum_{h=1}^{N-t_{k,i}+1} US_{k,i,h} = 1, (k \in K, i \in U) \tag{3.16}$$

Utility Grid Max Power Limit Constraints

$$GE_{k,h} \leq L_k^{max}, (k \in K, h \in H) \tag{3.17}$$

Energy Balance Constraints for Microgrid

$$\sum_{k\in K} ME_{k,h} = 0, (h \in H) \tag{3.18}$$

Microgrid Energy Price Constraints

$$MP_h \geq 0, (h \in H) \tag{3.19}$$

$$MP_h \leq GP_h, (h \in H) \tag{3.20}$$

Energy Constraints while Trading in Microgrid

$$MQ_{k,h} = \sum_{i \in I} S_{k,i,h} \cdot p_{k,i} + IC_{k,h} \cdot SP_k - GE_{k,h}$$

$$-RQ_{k,h} - SE_{k,h} - BE_{k,h} + MinC_k, (k \in K, h \in H) \quad (3.21)$$

$$ME_{k,h} \geq MQ_{k,h}, (k \in K, h \in H) \quad (3.22)$$

A.3 Extended Unified Model with Pareto Optimality

Objective

$$min\ Y \quad (3.25)$$

where,

$$Y = \sum_{k \in K} \sum_{h \in H} GP_h \cdot GE_{k,h} + \sum_{k \in K} \sum_{i \in I} d_{k,i} \left(\tau_{k,i} - \left(\sum_{h \in H} r_{k,i,h} \cdot h + t_{k,i} - 1 \right) \right) \quad (3.23)$$

Subject to:

Energy Balance Constraints

$$\sum_{i \in I} S_{k,i,h} \cdot p_{k,i} + IC_{k,h} \cdot SP_k = GE_{k,h} + BE_{k,h} + RE_{k,h} + ME_{k,h}, (k \in K, h \in H) \quad (3.5)$$

Stored Energy Constraints

$$SE_{k,1} = IE_k \cdot SD_k + IC_{k,1} \cdot SP_k \cdot E_k - BE_{k,1}, (k \in K) \quad (3.6)$$

$$SE_{k,h} = IE_{k,h-1} \cdot SD_k + IC_{k,h} \cdot SP_k \cdot E_k - BE_{k,h}, (k \in K, h \in H : h \neq 1) \quad (3.7)$$

Storage Capacity Constraints

$$SE_{k,h} \leq MaxC_k, (k \in K, h \in H) \tag{3.8}$$

$$SE_{k,h} \geq MinC_k, (k \in K, h \in H) \tag{3.9}$$

Task Duration Constraints

$$\sum_{h \in H} S_{k,i,h} = t_{k,i}, (k \in K, h \in H) \tag{3.10}$$

Renewable Energy Availability Constraints

$$RE_{k,h} \leq RQ_{k,h}, (k \in K, h \in H) \tag{3.11}$$

Reservation Time Constraints

$$\sum_{h \in H} S_{k,i,h} = \sum_{h=\sum_{h \in H} r_{k,i,h} \cdot h}^{N} S_{k,i,h}, (k \in K, i \in I) \tag{3.12}$$

Relationship between the Scheduling Vector and the End Time Constraints

$$S_{k,i,h} \cdot h \leq \tau_{k,i}, (k \in K, i \in I, h \in H) \tag{3.13}$$

Maximum Allowable Delay Constraints

$$\tau_{k,i} \leq \beta_{k,i}, (k \in K, i \in I) \tag{3.14}$$

Uninterruptibility Constraints

$$\sum_{d=0}^{t_{k,i}-1} S_{k,i,h+d} - t_{k,i} \geq -t_{k,i}(1 - US_{k,i,h}), (k \in K, i \in U, h = [1, N - t_{k,i} + 1]) \tag{3.15}$$

$$\sum_{h=1}^{N-t_{k,i}+1} US_{k,i,h} = 1, (k \in K, i \in U) \tag{3.16}$$

Utility Grid Max Power Limit Constraints

$$GE_{k,h} \leq L_k^{max}, (k \in K, h \in H) \tag{3.17}$$

Energy Balance Constraints for Microgrid

$$\sum_{k \in K} ME_{k,h} = 0, (h \in H) \tag{3.18}$$

Microgrid Energy Price Constraints

$$MP_h \geq 0, (h \in H) \tag{3.19}$$

$$MP_h \leq GP_h, (h \in H) \tag{3.20}$$

Energy Constraints while Trading in Microgrid

$$\begin{aligned} MQ_{k,h} = {} & \sum_{i \in I} S_{k,i,h} \cdot p_{k,i} + IC_{k,h} \cdot SP_k - GE_{k,h} \\ & -RQ_{k,h} - SE_{k,h} - BE_{k,h} + MinC_k, (k \in K, h \in H) \end{aligned} \tag{3.21}$$

$$ME_{k,h} \geq MQ_{k,h}, (k \in K, h \in H) \tag{3.22}$$

Pareto Optimality Constraints

$$C_k \leq C_k^{NoTrade}, (k \in K) \tag{3.26}$$

where,

$$C_k = CE_k + CD_k \tag{3.3}$$

$$CE_k = \sum_{h \in H} GP_h \cdot GE_{k,h} + \sum_{h \in H} MP_h \cdot ME_{k,h} \tag{3.1}$$

$$CD_k = \sum_{i \in I} d_{k,i} \left(\tau_{k,i} - \left(\sum_{h \in H} r_{k,i,h} \cdot h + t_{k,i} - 1 \right) \right) \tag{3.2}$$

A.4 Bi-Linear Model: Module 1

Objective

$$min\ Y \tag{3.25}$$

where,

$$Y = \sum_{k\in K}\sum_{h\in H} GP_h \cdot GE_{k,h} + \sum_{k\in K}\sum_{i\in I} d_{k,i}\left(\tau_{k,i} - \left(\sum_{h\in H} r_{k,i,h}\cdot h + t_{k,i} - 1\right)\right) \tag{3.23}$$

Here, for the k-th household the minimum value of Y is equals to $C_k^{NoTrade}$.

Subject to:

Energy Balance Constraints

$$\sum_{i\in I} S_{k,i,h}\cdot p_{k,i} + IC_{k,h}\cdot SP_k = GE_{k,h} + BE_{k,h} + RE_{k,h}, (k\in K, h\in H) \tag{3.5}$$

Stored Energy Constraints

$$SE_{k,1} = IE_k \cdot SD_k + IC_{k,1}\cdot SP_k \cdot E_k - BE_{k,1}, (k\in K) \tag{3.6}$$

$$SE_{k,h} = IE_{k,h-1}\cdot SD_k + IC_{k,h}\cdot SP_k\cdot E_k - BE_{k,h}, (k\in K, h\in H : h\neq 1) \tag{3.7}$$

Storage Capacity Constraints

$$SE_{k,h} \leq MaxC_k, (k\in K, h\in H) \tag{3.8}$$

$$SE_{k,h} \geq MinC_k, (k\in K, h\in H) \tag{3.9}$$

Task Duration Constraints

$$\sum_{h\in H} S_{k,i,h} = t_{k,i}, (k\in K, h\in H) \tag{3.10}$$

Renewable Energy Availability Constraints

$$RE_{k,h} \leq RQ_{k,h}, (k\in K, h\in H) \tag{3.11}$$

Reservation Time Constraints

$$\sum_{h \in H} S_{k,i,h} = \sum_{h=\sum_{h \in H} r_{k,i,h} \cdot h}^{N} S_{k,i,h}, (k \in K, i \in I) \tag{3.12}$$

Relationship between the Scheduling Vector and the End Time Constraints

$$S_{k,i,h} \cdot h \leq \tau_{k,i}, (k \in K, i \in I, h \in H) \tag{3.13}$$

Maximum Allowable Delay Constraints

$$\tau_{k,i} \leq \beta_{k,i}, (k \in K, i \in I) \tag{3.14}$$

Uninterruptibility Constraints

$$\sum_{d=0}^{t_{k,i}-1} S_{k,i,h+d} - t_{k,i} \geq -t_{k,i}(1 - US_{k,i,h}), (k \in K, i \in U, h = [1, N - t_{k,i} + 1]) \tag{3.15}$$

$$\sum_{h=1}^{N-t_{k,i}+1} US_{k,i,h} = 1, (k \in K, i \in U) \tag{3.16}$$

Utility Grid Max Power Limit Constraints

$$GE_{k,h} \leq L_k^{max}, (k \in K, h \in H) \tag{3.17}$$

Demand and Supply Constraints

$$DS_{k,h} = \sum_{i \in I} S_{k,i,h} \cdot p_{k,i} + IC_{k,h} \cdot SP_k - RQ_{k,h} - SE_{k,h} - BE_{k,h} + MinC_k, (k \in K, h \in H) \tag{5.1}$$

A.5 Bi-Linear Model: Module 2

Objective

$$min\ Z \tag{5.3}$$

where,

$$Z = \sum_{k\in K}\sum_{h\in H} GP_h \cdot GE_{k,h} + \sum_{k\in K}\sum_{h\in H} MP_h \cdot DS_{k,h} + \sum_{k\in K}\sum_{i\in I} d_{k,i}\left(\tau_{k,i} - \left(\sum_{h\in H} r_{k,i,h} \cdot h + t_{k,i} - 1\right)\right) \tag{5.2}$$

Subject to:

Energy Balance Constraints

$$\sum_{i\in I} S_{k,i,h} \cdot p_{k,i} + IC_{k,h} \cdot SP_k \leq GE_{k,h} + BE_{k,h} + RE_{k,h} + DS_{k,h}, (k \in K, h \in H) \tag{5.4}$$

Stored Energy Constraints

$$SE_{k,1} = IE_k \cdot SD_k + IC_{k,1} \cdot SP_k \cdot E_k - BE_{k,1}, (k \in K) \tag{3.6}$$

$$SE_{k,h} = IE_{k,h-1} \cdot SD_k + IC_{k,h} \cdot SP_k \cdot E_k - BE_{k,h}, (k \in K, h \in H : h \neq 1) \tag{3.7}$$

Storage Capacity Constraints

$$SE_{k,h} \leq MaxC_k, (k \in K, h \in H) \tag{3.8}$$

$$SE_{k,h} \geq MinC_k, (k \in K, h \in H) \tag{3.9}$$

Task Duration Constraints

$$\sum_{h\in H} S_{k,i,h} = t_{k,i}, (k \in K, h \in H) \tag{3.10}$$

Renewable Energy Availability Constraints

$$RE_{k,h} \leq RQ_{k,h}, (k \in K, h \in H) \tag{3.11}$$

Reservation Time Constraints

$$\sum_{h \in H} S_{k,i,h} = \sum_{h=\sum_{h \in H} r_{k,i,h} \cdot h}^{N} S_{k,i,h}, (k \in K, i \in I) \tag{3.12}$$

Relationship between the Scheduling Vector and the End Time Constraints

$$S_{k,i,h} \cdot h \leq \tau_{k,i}, (k \in K, i \in I, h \in H) \tag{3.13}$$

Maximum Allowable Delay Constraints

$$\tau_{k,i} \leq \beta_{k,i}, (k \in K, i \in I) \tag{3.14}$$

Uninterruptibility Constraints

$$\sum_{d=0}^{t_{k,i}-1} S_{k,i,h+d} - t_{k,i} \geq -t_{k,i}(1 - US_{k,i,h}), (k \in K, i \in U, h = [1, N - t_{k,i} + 1]) \tag{3.15}$$

$$\sum_{h=1}^{N-t_{k,i}+1} US_{k,i,h} = 1, (k \in K, i \in U) \tag{3.16}$$

Utility Grid Max Power Limit Constraints

$$GE_{k,h} \leq L_k^{max}, (k \in K, h \in H) \tag{3.17}$$

Microgrid Energy Price Constraints

$$MP_h \geq 0, (h \in H) \tag{3.19}$$

$$MP_h \leq GP_h, (h \in H) \tag{3.20}$$

Pareto Optimality Constraints

$$\sum_{h \in H} GP_h \cdot GE_{k,h} + \sum_{h \in H} MP_h \cdot DS_{k,h} + \sum_{i \in I} d_{k,i} \left(\tau_{k,i} - \left(\sum_{h \in H} r_{k,i,h} \cdot h + t_{k,i} - 1 \right) \right) \leq C_k^{NoTrade}, (k \in K) \tag{5.5}$$

A.6 Bi-Linear Model: Module 3

Objective

$$min\ Y \tag{3.25}$$

where,

$$Y = \sum_{k\in K}\sum_{h\in H} GP_h \cdot GE_{k,h} + \sum_{k\in K}\sum_{i\in I} d_{k,i}\left(\tau_{k,i} - \left(\sum_{h\in H} r_{k,i,h}\cdot h + t_{k,i} - 1\right)\right) \tag{3.23}$$

Subject to:

Energy Balance Constraints

$$\sum_{i\in I} S_{k,i,h}\cdot p_{k,i} + IC_{k,h}\cdot SP_k = GE_{k,h} + BE_{k,h} + RE_{k,h} + ME_{k,h}, (k\in K, h\in H) \tag{3.5}$$

Stored Energy Constraints

$$SE_{k,1} = IE_k \cdot SD_k + IC_{k,1}\cdot SP_k \cdot E_k - BE_{k,1}, (k\in K) \tag{3.6}$$

$$SE_{k,h} = IE_{k,h-1}\cdot SD_k + IC_{k,h}\cdot SP_k\cdot E_k - BE_{k,h}, (k\in K, h\in H : h\neq 1) \tag{3.7}$$

Storage Capacity Constraints

$$SE_{k,h} \leq MaxC_k, (k\in K, h\in H) \tag{3.8}$$

$$SE_{k,h} \geq MinC_k, (k\in K, h\in H) \tag{3.9}$$

Task Duration Constraints

$$\sum_{h\in H} S_{k,i,h} = t_{k,i}, (k\in K, h\in H) \tag{3.10}$$

Renewable Energy Availability Constraints

$$RE_{k,h} \leq RQ_{k,h}, (k\in K, h\in H) \tag{3.11}$$

Reservation Time Constraints

$$\sum_{h \in H} S_{k,i,h} = \sum_{h=\sum_{h \in H} r_{k,i,h} \cdot h}^{N} S_{k,i,h}, (k \in K, i \in I) \tag{3.12}$$

Relationship between the Scheduling Vector and the End Time Constraints

$$S_{k,i,h} \cdot h \leq \tau_{k,i}, (k \in K, i \in I, h \in H) \tag{3.13}$$

Maximum Allowable Delay Constraints

$$\tau_{k,i} \leq \beta_{k,i}, (k \in K, i \in I) \tag{3.14}$$

Uninterruptibility Constraints

$$\sum_{d=0}^{t_{k,i}-1} S_{k,i,h+d} - t_{k,i} \geq -t_{k,i}(1 - US_{k,i,h}), (k \in K, i \in U, h = [1, N - t_{k,i} + 1]) \tag{3.15}$$

$$\sum_{h=1}^{N-t_{k,i}+1} US_{k,i,h} = 1, (k \in K, i \in U) \tag{3.16}$$

Utility Grid Max Power Limit Constraints

$$GE_{k,h} \leq L_k^{max}, (k \in K, h \in H) \tag{3.17}$$

Energy Balance Constraints for Microgrid

$$\sum_{k \in K} ME_{k,h} = 0, (h \in H) \tag{3.18}$$

Energy Constraints while Trading in Microgrid

$$\begin{aligned} MQ_{k,h} = \sum_{i \in I} S_{k,i,h} \cdot p_{k,i} + IC_{k,h} \cdot SP_k - GE_{k,h} \\ -RQ_{k,h} - SE_{k,h} - BE_{k,h} + MinC_k, (k \in K, h \in H) \end{aligned} \tag{3.21}$$

$$ME_{k,h} \geq MQ_{k,h}, (k \in K, h \in H) \tag{3.22}$$

Pareto Optimality Constraints

$$C_k \leq C_k^{NoTrade}, (k \in K) \tag{3.26}$$

where,

$$C_k = CE_k + CD_k \tag{3.3}$$

$$CE_k = \sum_{h \in H} GP_h \cdot GE_{k,h} + \sum_{h \in H} MP_h \cdot ME_{k,h} \tag{3.1}$$

$$CD_k = \sum_{i \in I} d_{k,i} \left(\tau_{k,i} - \left(\sum_{h \in H} r_{k,i,h} \cdot h + t_{k,i} - 1 \right) \right) \tag{3.2}$$

Appendix B

Household Energy Consumption

This appendix presents additional information on the household load profiles which we used in the case studies described in Chapter 7. These load profiles were used as the input parameters of the bi-linear model to evaluate the impact of storage and renewables while trading energy in the microgrid.

B.1 Energy Consumption Profiles

Figure B.1 shows the energy consumption profiles of the households. It shows that we have 40 different load profiles of 40 households. We noticed that some users prefer to run their appliances at off-peak hours to reduce energy cost. Some households have only 2 appliances which are continuous load. These households normally have a flat energy consumption profiles with different amount of daily consumptions.

B.2 Daily Energy Consumption

Figure B.2 shows that the households are arranged uniformly for the case studies based on their daily energy consumption profiles.

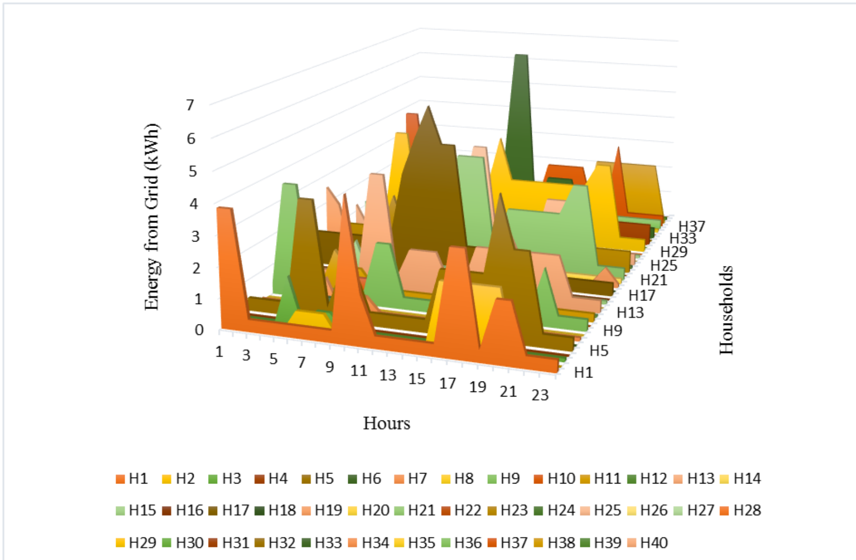

Figure B.1: Energy Drawn from the Grid by the Households.

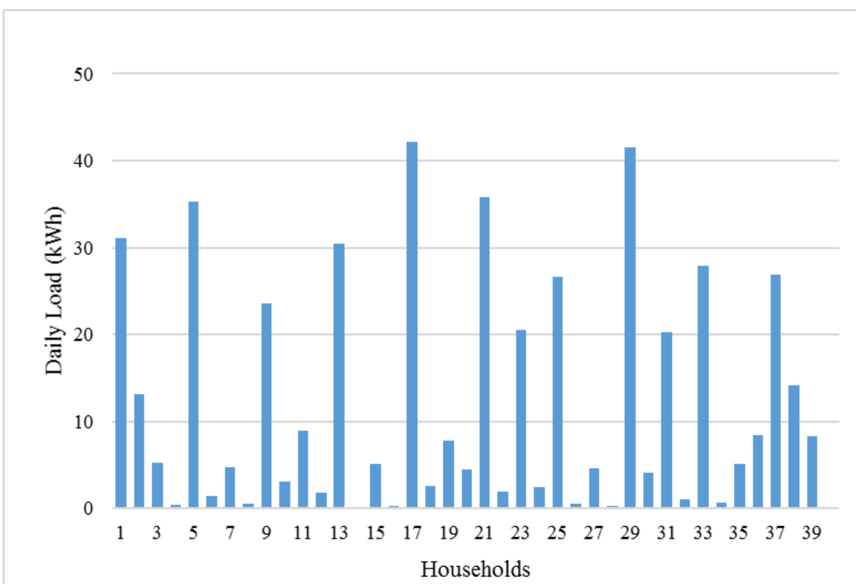

Figure B.2: Daily Load per Household.

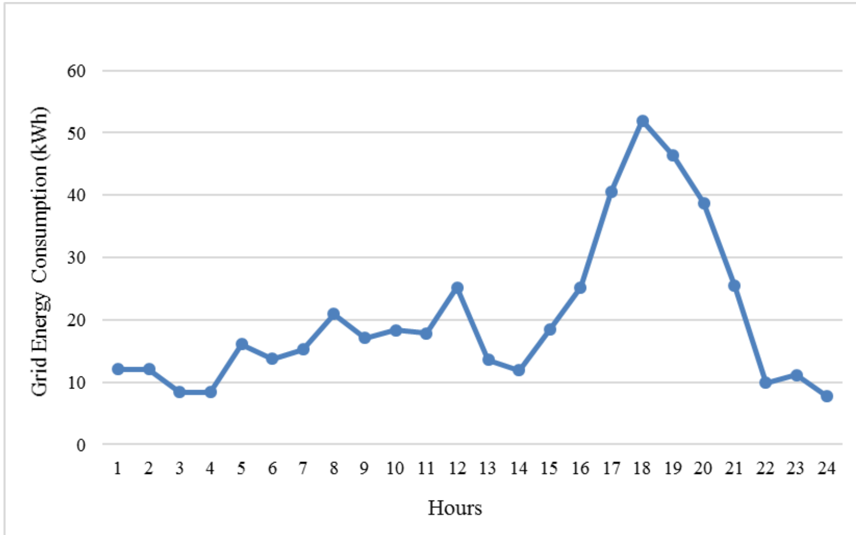

Figure B.3: Hourly Energy Consumption by All Households.

B.3 Hourly Energy Consumption

Figure B.3 shows hourly energy consumption by all households. It shows a peak in the evening as expected. It also shows a lower energy demand at night and in the early morning. At other times of the day, energy demand falls between these two boundaries.