Optimal Coordination of Home Energy Management Systems in a Distribution Grid

by

Omar Alrumayh

A thesis
presented to the University of Waterloo
in fulfillment of the
thesis requirement for the degree of
Master of Science
in
Electrical and Computer Engineering

Waterloo, Ontario, Canada, 2016

© Omar Alrumayh 2016

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

Involving end-users in Demand Side Management (DSM) programs with home energy management systems (HEMS) is an important requirement in realizing a smart grid. One of the main advantages of smart grids is the presence of advanced communication technologies that facilitate grid operators and local distribution companies (LDCs) to communicate directly with customers. Thus, there is a need to evaluate the potential impact of the application of Demand Response (DR) programs on both customers and utilities.

The thesis presents a comprehensive mathematical model of an HEMS including the interrelationships between various entities such as the rooftop solar photovoltaic panel (PV) with its associated battery, energy storage device (ESD), and the LDC. The HEMS comprises a set of essential household appliances such as refrigerator, water heater, washer and dryer, and lighting system. The thesis also presents the application of model predictive control (MPC) on an HEMS model in order to arrive at the optimal operational decisions when the inputs are subject to variations. Case studies have been carried out to illustrate the advantages of applying the MPC approach on HEMS. The results show an improvement in the HEMS operation which can potentially lead to an increase in the customers' revenue from selling the generated and stored energy to the LDC.

The thesis further proposes the formulation of a bi-level optimization framework wherein multiple HEMSs simultaneously optimize their respective energy consumption profiles, while the LDC aggregates the controllable demand from each HEMS to optimize its operational performance. A coordination scheme between multiple HEMS and the LDC is proposed to determine the optimal DR signals for each HEMS. The results show that the proposed approach helps regulate the total load profile of the LDC in addition to bringing about significant improvements in the voltage profile at each bus. However, it was noted that the customers would incur a slight increase in their daily energy cost.

Acknowledgements

All praises are due to Allah for helping me to complete this work and for everything. All praises are due to Allah for giving me the ability to overcome the challenges during my graduate studies and different life stages.

I would like to express my deepest gratitude and appreciation to my supervisor Professor Kankar Bhattacharya for his continuous guidance, support, patience, and encouragement throughout my Master's degree studies at University of Waterloo. It has been my greatest honor to complete my Master's degree studies and Prof.Kankar's supervision.

I would like also to greatly thank Professor Claudio Caizares and Dr. Tarek Abdelgalil for serving as members of my thesis committee. Their valuable comments, effort ,and encouragement in reviewing this thesis are highly appreciated.

Special thanks to the Ministry of Higher Education, Saudi Arabia and Qassim University. Also, I would like to thank the Saudi Arabian Cultural Bureau in Canada for their financial and academic support, special thanks for my academic advisor Saly Michael.

I wish to express my deepest and sincere gratitude to my mother (Rogeah), my father (Nasser), and my siblings for believing in me, praying for me, and supporting me during my whole life.

I would like to thank my friends: Talal Alharbi, Nizar Alsharif, Walied Alharbi, Badr Lami, Hisham Alharbi, Abdulaziz Almutairi, Abdullah & Omar Bin Humayd, Omar Hafez, Hisham Abduljabbar, Rayed Al-Yousef, Omar Alghamdi, Mohammed Aldaej, Ibrahim Almohanna, and Abdulaziz Alaskar for their support, sincerity, and encouragement during my stay in Canada.

Special thanks are extended to my friends in Canada and Saudi Arabia, who make my life colorful and enjoyable.

Dedication

To my wonderful Mother, Rogeah, To my Wonderful Father, Nasser
To my Lovely Brothers and Sisters
for their endless love and support

Table of Contents

List of Tables viii

List of Figures ix

Nomenclature xi

1 Introduction 1

1.1 Motivation 1

1.2 Literature Review 3

1.2.1 The Smart Grid and Demand Side Management 3

1.2.2 Home Energy Management System 5

1.3 Research Objectives 7

1.4 Outline of the Thesis 8

2 Background Review 9

2.1 Smart Grid 9

2.2 Demand Side Management and Demand Response 10

2.3 Home Energy Management Systems and Mathematical Model 11

2.3.1 Objective Function 12

2.3.2 Operational Constraints of the Household Appliances 12

2.3.3 Operational Constraints of The Household Devices 20

2.4 Model Predictive Control 21

2.5 Summary 22

3 Model Predictive Control Based Home Energy Management System 23

3.1 Introduction . . . 23

3.2 Modified Home Energy Management System: Mathematical Model . . . 23

3.2.1 Objective Functions . . . 25

3.2.2 The Modified Operational Constraints . . . 26

3.2.3 Initial Settings of the HEMS Model . . . 29

3.2.4 Model Predictive Control . . . 29

3.3 Case Studies and Results . . . 31

3.3.1 Case Studies . . . 31

3.3.2 Results . . . 34

3.4 Summary . . . 40

4 Optimal Coordination of Home Energy Management System for Demand Response Provisions 41

4.1 Introduction . . . 41

4.2 Proposed Framework and Mathematical Models . . . 41

4.2.1 Coordination of Multiple HEMS and LDC . . . 41

4.2.2 Home Energy Management Systems . . . 44

4.2.3 LDC Operations Model . . . 45

4.3 Results and Discussions . . . 47

4.4 Summary . . . 53

5 Conclusions 57

5.1 Summary . . . 57

5.2 Contributions of the Thesis . . . 58

5.3 Future Work . . . 59

References 60

List of Tables

3.1 Parameters of the HEMS Model 29
3.2 Summary of Case Studies 32
3.3 Energy Consumption of Household Appliances 36
3.4 Energy Interchanges between Two Entities 36

4.1 Energy Consumption of House #1,080 50
4.2 Energy Interchanges between Entities in House #1,080 50
4.3 LDC Load Profile Characteristics 52

List of Figures

2.1 Overview of Home Energy Management System (HEMS) Structure 12

3.1 Comprehensive Representation of HEMS 24
3.2 Schematic for Model Predictive Control of HEMS 30
3.3 Flow Process of MPC Based HEMS. 31
3.4 Actual and Forecasted Outdoor Temperature 33
3.5 Actual and Forecasted Activity Level 33
3.6 Actual and Forecasted RTP 34
3.7 OFF-Peak Comparison between Case 2 and Case 3 at Time Interval 64 . . 35
3.8 ON-Peak Comparison between Case 2 and Case 3 at Time Interval 58 . . 35
3.9 Energy Level of PV Battery vis-a-vis RTP 37
3.10 Energy Level of ESD vis-a-vis RTP 38
3.11 Refrigerator Operation vis-a-vis RTP 38
3.12 Water Heater Operation vis-a-vis RTP 39
3.13 AC Operation vis-a-vis RTP 39

4.1 Schematic of Coordination between HEMS and LDC. 42
4.2 Coordination of Multiple HEMS and the LDC. 43
4.3 Layout of 33-Bus Feeder System. 48
4.4 Number of Houses at Each Bus. 49
4.5 DR Required at Each Iteration. 49

4.6 Optimal Load Profile for House #1,080. 51
4.7 Optimal Temperature Profile inside Refrigerator in House #1,080. 52
4.8 Optimal Indoor Temperature Profile in House #1,080. 53
4.9 Optimal Energy Level of PV Battery in House #1,080. 54
4.10 Optimal ESD Energy Level in House #1,080. 54
4.11 Total Power Received by LDC from Residential Customers. 55
4.12 Power Imported from External Grid over Substation. 55
4.13 Average Voltage at Each Bus before and after Convergence. 56

Nomenclature

Indices and Sets

h	Index for household.
i	Index for household appliances.
j,k	Index for bus.
t	Index for time.
z	Index for zones inside a house.
$\mathcal{A}$	Set of household appliances.
$\mathcal{H}$	Set of households.
$\mathcal{N}$	Set of system buses.
$\mathcal{T}$	Set of time intervals.

Parameters

$AL(t)$	Activity level inside a house.
E_i^{min}, E_i^{max}	Minimum and maximum energy level of $i \in \{ESD,\ BPV\}$, kWh.
EOT_i	Early operation time of appliance $i \in \{DW,W,DRY,PMP,STV\}$.
$G_{j,k}$	Conductance of feeder between bus j and k.
G_i	Heat rate of device $i \in \{HT,WH\}$.

K_t	Price elasticity associated with the illumination inside a house $i \in \{HT, WH\}$.
LOT_i	Late operation time of appliance $i \in \{DW, W, DRY, PMP, STV\}$.
L_z^{out}	Natural illumination in zone z.
L_z^{min}	Minimum illumination in zone z.
MUT_i	Minimum uptime of appliance $i \in \{AC, HT, DW, W, DRY, PMP, STV\}$.
MDT_i	Minimum downtime of appliance $i \in \{AC, HT, DW, W, DRY, PMP, STV\}$.
MST_i	Maximum successive operation time of appliance $i \in \{DW, W, DRY, PMP, STV\}$.
$P_{C_q,h}^{max}$, $P_{D_q,h}^{max}$	Maximum charging/discharging power of q in house h, kW.
$P_{D_0,h}$	Connected load at time t in house h, kW.
$P_h^{max}(t)$	House h maximum demand at time t, kW.
$\widehat{P}_h^{max}(t)$	Updated house h maximum demand at time t, kW.
$P_{i,h}$	Rated power of appliance i in house h, kW.
$P_{LI_{z,h}}$	Rated power of the lighting system LI_z in zone z in house h, kW.
$P_j^d(t)$	Active power drawn by residential loads at bus j at time t, $p.u.$
$P_j^{Imp}(t)$	Total power purchased by LDC from residential loads at bus j at time t, $p.u.$
$P_{PV,h}(t)$	PV panel generation at time t in house h, kW.
$Q_j^d(t)$	Reactive power drawn by residential loads at bus j at time t, $p.u.$
ROT_i	Required operation time of appliance $i \in \{DW, W, DRY, PMP, STV\}$.
$Y_{j,k}$	Magnitude of admittance matrix element.
β_i	Cooling/Warming effect associated with OFF state of device $i \in \{AC, HT, FR, WH\}$.

α_i	Cooling/Warming effect associated with ON state of device $i \in \{AC, HT, FR, WH\}$.
η_1, η_2	Charging/discharging efficiency.
ρ^{GAS}	Gas price, $\$/m^3$.
$\rho^{RTP}(t)$	Real time price, $\$/kWh$.
ρ^{SEL}	Residential customers selling price to the LDC, $\$/kWh$.
ρ_i	Effect of the difference between inside and outside temperature on the inside temperature of device $i \in \{AC, HT, FR, WH\}$.
γ_i	Cooling/Warming effect associated with OFF state of device $i \in \{FR, WH\}$.
τ	Length of the time interval.
$\theta_{in}^{min}(t), \theta_{in}^{max}(t)$	Minimum and maximum allowable temperature inside a house.
θ_{out}	Ambient temperature.
$\theta_{j,k}$	Angle of complex Y-bus matrix element.

Variables

$E_{i,h}(t)$	Energy level of $i \in \{ESD,\ BPV\}$ at time t in house h, kWh.
$L_z(t)$	Illumination level at time t in zone z. t in house h, kW.
$P_{C_{BPV},h}(t)$	Total charging power from BPV at time t in house h, kW.
$P_{D_{BPV},h}(t)$	Total discharged power from BPV at time t in house h, kW.
$P_{i,h}^{H}(t)$	Discharging power from device $i \in \{ESD,\ BPV\}$ to house at time t in house h, kW.
$P_{i,h}^{LDC}(t)$	Discharging power from device $i \in \{ESD, BPV\}$ to LDC at time t in house h, kW.
$P_j^g(t)$	Active power drawn from substation at bus j and time t, $p.u.$

$P_j^{DR}(t)$	Active power to be minimized at bus j and time t, $p.u.$
$P_{LDC,h}^{i}(t)$	Charging power drawn by device $i \in \{ESD,\ BPV\}$ at time t in house h, kW.
$P_{LDC,h}^{H}(t)$	Delivered power by LDC to meet the house demand at time t in house h, kW.
$P_{LDC,h}^{BPV}(t)$	Total charging power drawn by BPV at time t in house h, kW.
$P_{PV,h}^{BPV}(t)$	Generated power by PV solar panel used to charge the PV battery (BPV) at time.
$P_{PV,h}^{H}(t)$	Generated power by PV solar panel consumed by household appliances at time t in house h, kW.
$P_{PV,h}^{LDC}(t)$	Generated power by PV solar panel sold to LDC at time t in house h, kW.
$Q_j^g(t)$	Reactive power drawn from substation at bus j and time t, $p.u.$
$S_{C_i,h}(t)$	Binary charging status of $i \in \{ESD,\ BPV\}$ at time t in house h, ON/OFF.
$S_{D_i,h}(t)$	Binary discharging status of $i \in \{ESD,\ BPV\}$ at time t in house h, ON/OFF.
$S_{i,h}(t)$	Binary status of device i at time t in house h, ON/OFF.
$V_j(t)$	Voltage at bus j at time t, $p.u.$
$\delta_j(t)$	Voltage angle at bus j at time t, $p.u.$
$\theta_{in}(t)$	Temperature inside a house.

List of Abbreviations

DSM	Demand Side Management
DR	Demand Response
LDC	Local Distribution Company
DLC	Direct Load Control
RTP	Real Time Price
TOU	Time of Use
HEMS	Home Energy Management System
HVAC	Heating, ventilation and air conditioning
ESD	Energy storage devices
PV	Photovoltaic
MPC	Model Predictive Control
DLC	Direct Load Control
PSO	Particle Swarm Optimization
MIP	Mixed integer programming
MILP	Mixed integer linear programming
MINLP	Mixed integer non-linear programming
OPF	Optimal Power Flow
DERs	Distributed energy resources
PEVs	Plug-in electric vehicles

Chapter 1

Introduction

1.1 Motivation

There has been a growing concern on the availability of energy resources in the long run while the global energy demand increases continuously. According to [1], the world energy consumption is expected to increase 30% over the next 15 years. Consequently, there will be a need for sufficient generation to meet the demand, by either increasing the generation capacity or using the current capacity efficiently, or both.

The provision of additional generation using traditional fossil fuel based energy sources impacts the environment. According to the United Environment Protection Agency, one of the main sources of greenhouse gas emissions is electricity generation using fossil fuels such as coal, and natural gas, which accounted for approximately 30% of the total emissions of USA in 2013 [2]. The integration of renewable energy resources can limit the production of greenhouse gas emissions.

In addition to the provision of environmentally friendly energy resources, the efficient use of electrical energy can reduce the peak demand of the utility. A study carried out by the Council of Energy Ministers Demand Side Management (DSM) Working Group to evaluate the potential of DSM in Canada shows that up to 10% reduction in the total energy demand by 2025 is possible [3]. In order to achieve this goal, the utilities need to improve their traditional grid capabilities by deploying advanced communication technologies with customers and hence facilitate to improve grid security, reliability, and sustainability, and the transition to a smart grid.

Smart grids also facilitate the implementation of Demand Response (DR) programs which encourage end-users to reduce or change their electricity consumption patterns in

response to a price or grid condition signal, which can also reduce their monthly energy cost. At the demand side, the installation of smart meters can provide more information about a customer's behavior to the Local Distribution Company (LDC), which can be very helpful to the LDC in order to balance the system. To support the change of the traditional grid in Ontario, Canada, Hydro One Inc. has installed more than 1.3 million smart meters at the residential level [4]. From the customer's point view, smart meters provide significant information to them, such as their current consumption and the associated prices, whereby they can change their consumption based on the price signals received from their LDC; hence, the customers should efficiently respond to these signals in order to optimize their energy consumption.

Home Energy Management Systems (HEMS) are being developed by vendors in response to the developments in smart grids such as the introduction of smart meters and Real Time Price (RTP). These Home Energy Management System (HEMS) seek to optimize the operation of household appliances to meet the customers' objectives and preferences. However, the uncertainty associated with solar irradiation in Photovoltaic (PV) systems, and volatility of RTP, for example, can render the HEMS optimal decisions as sub-optimal, under such varying conditions. As a result, there is a need to tackle the impact of uncertainty associated with some related aspects of HEMS. At the distribution level, it is also important to evaluate the DR of residential customers in the presence of the HEMS.

In the context of smart grids, customers have started considering various energy self-supply options as well, such as roof top solar PV panels, battery energy storage, etc. With smart meters and advanced metering infrastructure, the customers can not only draw power from the LDC but can also serve as supply resources, thus rendering them as smart energy hubs. The penetration of HEMS seeks to improve the operation of such energy hubs considering customers' objectives and preferences.

It is important to evaluate a customer's response considering such variations in the electricity price and other signals, and the impact on LDC operation. Consequently, the present research examines the role of residential customers' response to the LDC's signals considering the uncertainty associated with different input parameters related to the HEMS. In addition, there is a need to develop an understanding of the customers' behavior, which can increase the efficient use of energy resources and decrease the uncertainty in the load prediction.

1.2 Literature Review

The purpose of this section is to review the relevant literature pertaining to the topics and issues discussed in this thesis including smart grids, DSM and DR, and HEMS.

1.2.1 The Smart Grid and Demand Side Management

According to The US Department of Energy, "Think of the smart grid as the internet brought to our electric system. Devices such as wind turbines, plug-in hybrid electric vehicles (PHEVs) and solar arrays are not part of the smart grid. Rather, the smart grid encompasses the technology that enables to integrate, interface with and intelligently control these innovations and others" [5]. The deficiencies of traditional grids plays an important role in the movement toward smart grids, and involve some environmental and financial issues such as greenhouse gas emissions and electricity prices, respectively [6]. One of the main features in smart grids is the provision for information and communication technologies. From the LDC's prospective, the installation of smart meters can provide real-time energy consumption readings, facilitate two-way communication with end-users, and support the integration of renewable resources and Energy storage devices (ESD) [7]. The provision of two-way communication between the LDC and end-users also facilitates the implementation of DSM and DR programs, which are being implemented in different customer sectors such as industrial, commercial, and residential loads.

One of the options in DSM programs is the Direct Load Control (DLC) program, which allows the LDC to turn OFF an appliance, such as Heating, ventilation and air conditioning (HVAC) or water heater, to handle an emergency event in the system [8]. This program is commonly applied to residential and commercial customers. In [9], the provision of aggregated regulation services using DLC of electric water heater is investigated while considering the customers' comfort level. The results indicate a possibility of valuable revenue for the LDC. Another study is carried out to evaluate the potential of DLC of aggregated HVAC units to provide a load balancing service [10]. The study shows a promising increase in the revenue of the electricity provider. In [11], a DLC algorithm is proposed to control a group of air-conditioning loads based on a least enthalpy estimation approach to estimate the thermal comfort level of customers and to optimize the operation of the appliance. A study in [12] proposes a DLC algorithm to control a large number of residential and commercial air-conditioning systems integrated as a virtual power plant to achieve a significant load reduction. Such a framework can allow aggregators to bid in electricity markets by offering a certain level of load reduction.

The authors in [13] propose a Mixed integer non-linear programming (MINLP) model to manage the energy consumption of electrolytic process industries by minimizing the energy cost and peak load by shifting and rescheduling the load. The study reports a significant reduction of up to 19% in peak demand and around 3% energy cost reduction under Time of Use (TOU) price scheme.

Interruptible loads play an important role in the context of reliability and security of electricity systems. An Optimal Power Flow (OPF) based interruptible load management scheme is proposed in [14] to address several problems associated with optimal load curtailment with short-term and long-term price discounts. Another work in [15] proposes a real time interruptible tariff mechanism to determine the optimal incentive rate to be provided to a customer. Fuzzy dynamic programming is used in [16] to optimize the curtailment schedule of interruptible loads, while in [17] a Mixed integer programming (MIP) based unit commitment is proposed considering probabilistic spinning reserve and interruptible load as operating reserve, to coordinate the operation of energy and reserve facilities.

TOU tariff and RTP are price-based DR programs, whereby the end-users do not have a fixed price over the day. Many studies are being carried out to evaluate the effectiveness of dynamic pricing schemes on the consumption behavior of residential customers. According to [18], significant savings in total energy cost and reduction in peak load of the utility can be achieved by implementation of dynamic pricing schemes. However, the implementation of such a dynamic DR program requires efficient response from the end-users. In [19], an optimization based automated DR controller is proposed to control the response of residential customers to the fluctuation in electricity prices.

The DR of residential customers to a demand charge imposed by an LDC in Norway is examined in [20]. The demand charge is considered during the peak hours' energy-use in winter; furthermore, the customers are not aware of their consumption level, and when the demand charge is being imposed. The results show a reduction in the average demand by 5% with a maximum reduction up to 9% at hour 8 in the morning; however, the authors state that the savings could be more significant by increasing the awareness of the end-users about their consumption level and when the demand charge is being imposed.

From the above brief review, it is noted that there is a need to provide an efficient automated energy management system to residential customers in order to enhance their responsiveness to the price signals sent by the LDC.

1.2.2 Home Energy Management System

In recent years, several researchers have reported their works on the mathematical modeling of an HEMS that optimizes the operation of household appliances.

An early example is presented in [21]. The study proposes a DLC of air-conditioning system utilizing a multi-pass dynamic programming method in order to generate a control schedule of the air-conditioning system, whereby a reduction in the peak load and energy cost can be achieved. Another study presents a physical load model of HVAC to evaluate its ability to contribute in DR programs such as DLC [22]. Recently, a study proposes a DLC of residential air-conditioning system to evaluate its capability to provide ancillary services; a pilot program with 2000 households equipped with air-conditioning control is discussed [23].

A mathematical model of an HEMS is presented in [24] that considers the minimization of both electricity cost and the waiting time of appliances' operation. A weighted average price prediction filter is used to estimate the RTP. The results show a significant reduction in energy use of the customer as well as in the peak-to-average ratio. A Particle Swarm Optimization (PSO) based residential decision support tool is presented in [25] to schedule the household appliances and associated Distributed energy resources (DERs), to maximize the net benefit of a customer [26]; in addition, a significant reduction in the energy cost for the customer is noted.

Another work in [27] proposes a dynamic DR controller for residential HVAC systems based on the fluctuation in the RTP. The authors emphasize that the flexibility in thermal comfort level of the customers could decrease their electricity cost and the peak load by implementing the dynamic DR controller of the HVAC.

In [28], the authors propose an ESD controller to coordinate the operation of residential PV and ESD to minimize the peak load and energy cost taking advantage of the fluctuations in electricity prices. A forecasting method is proposed to predict the PV generation and energy demand, whereby the ESD controller could help to achieve peak load shaving.

An adaptive neuro-fuzzy learning framework is used in [29] to optimize the operation schedule of household appliances based on many factors such as the customer's behavior and the electricity price, minimizing the peak load or re-scheduling the energy consumption of aggregated residential customers.

An MIP based consumption scheduling algorithm is proposed in [30] to minimize the peak load and energy use of a customer by maximizing the usage of the generated power from the local renewable energy sources. A non-cooperative game theoretic algorithm is used to coordinate the household appliances of the customer.

A comprehensive Mixed integer linear programming (MILP) model is proposed in [31] to optimize the household appliances schedule, which can be incorporated into automated residential energy controllers. The mathematical model includes most of the household appliances in addition to ESD and PV panels. The values of the model parameters are determined from practical tests, and the model is implemented on a household in Ontario, and the results show a significant reduction in both energy cost and peak demand while maintaining the customer preferences.

Several recent studies have been reported that consider the uncertainty associated with the external parameters of the HEMS. A real-time scheduling of household appliances by HEMS is presented in [32]. A conditional value-at-risk approach is used to take into account the trade-off between the estimated energy cost and the risk of being exposed to uncertainties associated with RTP and other parameters.

An energy efficient stochastic scheduling algorithm is proposed in [33] to optimize the household appliances operation under RTP considering the uncertainty in PV generation. The proposed approach shows significant savings in the energy cost of a household.

Another work in [34] presents an HEMS with solar assisted thermal load, including HVAC and water heater, to minimize the energy cost while maintaining the thermal comfort level of customers. A two-stage stochastic model is proposed to reduce the impact of uncertainty in RTP and PV power generation.

In [35], an appliance commitment algorithm is developed to optimize the operation schedules of residential water heater so as to meet the customer's objective, considering the uncertainty associated with RTP and water consumption. Furthermore, a two-step appliance commitment algorithm is formulated to re-schedule the appliance operations to reduce the impact of uncertainty associated with RTP and hot water usage of the customer. An MILP model is proposed [5] to optimize the energy consumption and operation of different energy resources, considering the customer's thermal comfort level.

A Model Predictive Control (MPC) based appliance scheduling of an automated residential building energy management controller is proposed in [36]. The thermal appliances are modeled as thermal mass of the building and are included as thermal constraints in the mathematical model. The proposed approach results in significant reduction in the electricity cost of the customer. In addition, the study presents an evaluation of the impact of the customer preferences on the amount of energy cost saving.

A stochastic dynamic programming based approach is proposed in [37] to minimize the energy cost of a customer, small and medium loads, under RTP. The uncertainty associated with energy consumption of the customer is considered. Another study proposes a Markov

decision process based scheduling of power consumption considering the uncertainty in electricity prices [38].

Many recent studies have been carried out to investigate the impact of residential DR on the electricity system. A residential DR program, operated by a load service entity, is integrated into an OPF model to evaluate the impact of DR on the distribution network [39]. In addition, a distributed DR scheme is proposed to avoid the centralized control approach, in order to protect the customers' privacy.

In [40], the authors emphasize that automated residential DR to reschedule the operation of flexible appliances in order to exploit low values of RTP can lead to a peak rebound in the LDC's load profile. Consequently, they propose different approaches to solve the problem of peak rebound such as flat price or house-wise RTPs at late hours in a day.

Another study in [41] proposes a coordinated approach to DR in order to reduce the peak rebounds. The objective is to flatten the load profile of the LDC while considering minimization of the customer's energy cost. Two hierarchical stages are formulated- in the first stage, individuals optimize their appliances' operation schedules minimizing their electricity cost, individually. In the second stage, the LDC can reschedule their appliances' operation in order to flatten the load profile.

1.3 Research Objectives

The specific objective of this research includes studying the impact of uncertainty associated with external parameters of the HEMS in addition to the coordination of multiple HEMSs and the LDC. The research objectives are listed below:

- Propose a comprehensive architecture of the HEMS considering ESD and PV panel in the residence and including appliance models. Consequently, develop a comprehensive interrelationship representation between the LDC and different entities (ESD, PV panel, and its associated battery) within the customer's household. The framework will help to better understand the impact of each entity on the HEMS.

- Improve the mathematical optimization model of the HEMS presented in [31] by appropriate representation of ESD and PV panel battery related constraints.

- Examine the impact of uncertainty in forecasted inputs such as weather, activity level inside the house, and RTP, on the optimal decisions of the HEMS. Thereafter, use an MPC based approach to solve the HEMS model to mitigate the impact of uncertainties in forecasted data.

- Assess the impact of the DR of multiple HEMS on the LDC operation system by formulating a mathematical framework for the optimal coordination of multiple HEMS and LDC. Formulate a bi-level optimization framework to coordinate a large number of HEMS with the LDC in order to evaluate the role of the customers in providing DR services.

1.4 Outline of the Thesis

The rest of this thesis is structured as follows; Chapter 2 presents a background of the concepts and the methodologies used in this thesis. A brief overview of smart grids is presented first, followed by an overview on the DSM and DR programs. After that, an outline of a previously proposed HEMS mathematical model is presented. Next, the MPC approach and its advantages are illustrated. Chapter 3 presents the comprehensive mathematical model considering the interrelationships between LDC, ESD, and PV panel with its associated battery. In addition, it presents an MPC algorithm to reduce the impact of uncertainty associated with HEMSs' external parameters. The case studies, results, and analysis of the proposed approach is described. Chapter 4 proposes a bi-level optimization framework to coordinate a large number of HEMS and LDC to examine the impact of residential DR on a distribution network operated by a LDC. Chapter 5 summarizes the main contributions of the research presented in the thesis and suggests some possible directions for future research on the subject.

Chapter 2

Background Review

This chapter provides an overview of the main concepts related to the work in the thesis. Section 2.1 presents an overview of smart grid. Section 2.2 presents some basic concepts related to DSM and DR. Section 2.3 discusses the HEMS and its mathematical model. Section 2.4 presents an overview of the concept of the MPC approach.

2.1 Smart Grid

The notion of a smart grid is a power grid that provides advanced communication technologies and data analysis capabilities in order to enhance the security, reliability, and sustainability of the grid. This provision can facilitate the transformation of the current, less interactive and centralized, grid to one that is more cooperative, responsive, and less centralized [8]. The operation of smart grids involve many complex topics such as the integration of DERs and energy management of different entities in the electricity system. Indeed, the main features of the smart grid are listed below [42]:

- Facilitate active participation of the customers in different DR programs.
- Integrate centralized and distributed generation and storage options.
- Provide resiliency to different disturbances, and natural or cyber attacks.
- Optimize asset and maintain high operational efficiency.
- Provide a range of power quality levels to meet different customer preferences.
- Enable a variety of new products, services and markets.

2.2 Demand Side Management and Demand Response

DSM is an energy management approach to influence the demand side consumption in order to achieve a desired modification to the utility's load profile. DSM came into existence during the late 1970s [1], following the two energy crisis of that decade.

DSM includes several measures such as energy efficiency, energy conservation, strategic load growth, and DR programs. Energy efficiency focuses on minimizing the energy consumption of a device without affecting its operational performance and service provision [43]. Energy conservation is the reduction of energy use, which can be a change in the consumption behavior, for example. Strategic load growth is a strategy to increase the load level by electrification in order to reshape the load profile. DR programs refer to "a tariff or a program established to motivate changes in electricity use by end-use customers in response to changes in the price of electricity over time, or to design incentives to induce lower electricity use at times of high prices or when grid reliability is jeopardized" [8].

The DR programs can be beneficial to all parties involved, the customers, the LDC, and the participants in the electricity market. Participants in DR are financially rewarded either from their bill savings or incentive payments by the LDC [8], [44]. Furthermore, the DR programs benefit the LDC by providing it with more flexibility in grid management. Lower market prices can result from the reduced need for the operation of high cost generators, which are usually operated during the peak load hours.

The DR programs can be categorized as follows: incentive based and price-based programs [44], [45]. Load management programs and market based programs, such as DLC and interruptible load control, are part of the incentive based programs. Dynamic pricing schemes, such as RTP and TOU, form the price-based programs.

In the traditional load management programs, DLC is a program that can interrupt a customer load, usually residential and small commercial customers, in order to address an issue in the electricity system such as reliability, and provide incentive payments to the customers for their contribution. Interruptible load refers to a load management program that provides a discount in the electricity bill of the customers (industrial customers) as an incentive for their readiness to reduce their consumption as and when required [44]. In the price-based programs, RTP is a pricing scheme, where the electricity price fluctuates hourly based on the electricity market prices, while the TOU pricing scheme is a pre-determined pricing scheme for a block of hours over the day.

These different approaches that fall under the DR programs, aims to modify the load profile of the electric power system.

There are three main techniques that work toward the modification of the system load profile in addition to DSM strategies: peak clipping, valley filling, and load shifting.

2.3 Home Energy Management Systems and Mathematical Model

The HEMS is a residential controller that seeks to determine the optimal ON/OFF decisions of the household appliances/devices based on the customer's objective function and preferences. In addition, the HEMS helps the household to better evaluate, visualize, and manage the energy consumption by providing it with updated information about the energy use and the current energy price. According to [12], a study by Hydro One shows that "providing real-time displays to customers on Regulated Price Plan (RPP) and Time-of-Use (TOU) rates increased the load shifting impacts on typical days from 3.7% to 5.5% and on hot days (over 30°C) to 8.5%. In addition, the real-time feedback of the HEMS can decrease the overall energy consumption up to 13%".

The HEMS require the customers to update their preferences such as the minimum and maximum allowable temperature setting inside the house, in order to autonomously control their appliances. Two-way communication infrastructure is required to facilitate the autonomous control of the appliances/devices operation by HEMS. HomePlug, ZigBee, and Wi-Fi are the three common open communication protocols [12]. Figure 2.1 represents an overview of the HEMS.

Several mathematical models have been proposed to optimize the household appliances' and devices' operations. However, the mathematical optimization model, formulated in [31], is chosen to be the HEMS mathematical model in this work because it is comprehensive, and takes into account most of the typical household appliances. A brief background to the HEMS model is presented [31]:

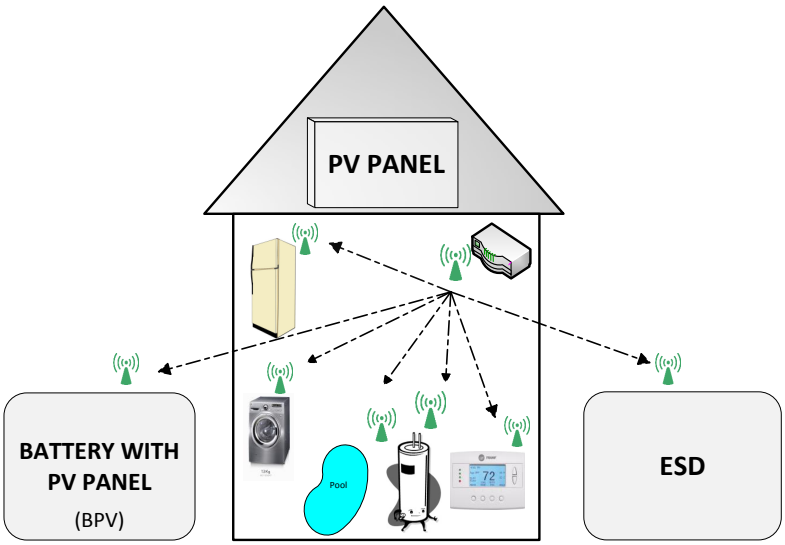


Figure 2.1: Overview of HEMS Structure.

2.3.1 Objective Function

The objective function seeks to minimize the customer's total energy cost, net of the revenue earned.

$$J = \sum_{t \in \mathcal{T}} \Bigg[\rho^{RTP}(t) \Big\{ \sum_{\substack{i \in \mathcal{A} \\ i \notin \{LI, ESD, PV\}}} P_i S_i(t) + \sum_{z \in LI} P_{LI_z} L_z(t) + \sum_{i \in \{ht, wh\}} \rho^{GAS} G_i(t) S_i(t) \Big\} - \rho^{SEL} \sum_{i \in \{ESD, PV\}} P_i^{LDC}(t) \Bigg] \quad (2.1)$$

In (2.1), $P_i S_i(t)$ and P_{LI_z} present the power drawn by the household appliances and the lighting system, respectively. The total gas consumption is presented by $G_i(t)$.

2.3.2 Operational Constraints of the Household Appliances [31]

In this section, the constraints of the mathematical optimization model of the HEMS are presented. The typical household appliances/devices comprises: HVAC, dishwasher, fridge, lighting system, pool pump, stove, washer and dryer, and water heater, in addition to an ESD and a PV panel.

Heating, Ventilation, and Air Conditioning System

The following mathematical model is used to represent the HVAC operation, considering the household preferences such as minimum and maximum temperature inside the house.

$$\theta_{in}^{min}(t) \leq \theta_{in} \leq \theta_{in}^{max}(t) \tag{2.2}$$

$$S_i(t) = \begin{cases} 0 \quad \text{or} \quad 1 & \text{if t}\in \mathcal{T}_i, i \in \{AC,HT\} \\ 0 & \text{if t}\notin \mathcal{T}_i, i \in \{AC,HT\} \end{cases} \tag{2.3}$$

$$S_i\big|_{t=1} = \begin{cases} 1 & \text{if } \theta_{in}\big|_{t=0} > \theta_{in}(t)^{max}, i = AC \\ 0 & \text{if } \theta_{in}\big|_{t=0} < \theta_{in}(t)^{min}, i = AC \end{cases} \tag{2.4}$$

$$S_i\big|_{t=1} = \begin{cases} 1 & \text{if } \theta_{in}\big|_{t=0} < \theta_{in}(t)^{min}, i = HT \\ 0 & \text{if } \theta_{in}\big|_{t=0} > \theta_{in}(t)^{max}, i = HT \end{cases} \tag{2.5}$$

$$S_{AC}(t) + S_{HT}(t) \leq 1 \qquad \forall t \in \mathcal{T}_i \tag{2.6}$$

In (2.2), the AC and HT operations are based on a pre-set minimum ($\theta_{in}^{min}(t)$) and maximum ($\theta_{in}^{max}(t)$) temperature by the household. Constraint (2.3) is used to allow the operation of the HVAC at certain set of time intervals only. As a result, the AC system operates when the inside temperature is above $\theta_{in}^{max}(t)$; while, the HT system operates when the inside temperature of the house is less than $\theta_{in}^{min}(t)$, as shown in (2.4) and (2.5), respectively. Constraint (2.6) prevents the operation of the AC and HT at the same time interval.

The change in the indoor temperature is related to many factors such as the activity level of the customer and the ambient temperature.

$$\begin{aligned} \theta_{in}(t) = \theta_{in}(t-1) + \tau\big[&\beta_{AC} AL(t) \\ &- \alpha_{AC} S_i(t) + \rho_{AC}(\theta_{out} - \theta_{in})\big] \qquad \forall t \in \mathcal{T}, i = AC \end{aligned} \tag{2.7}$$

$$\theta_{in}(t) = \theta_{in}(t-1) + \tau\big[\beta_{HT} AL(t) + \alpha_{HT} S_i(t) - \rho_{HT}(\theta_{out} - \theta_{in})\big] \qquad \forall t \in \mathcal{T}, i = HT \tag{2.8}$$

$$U_i(t) - D_i(t) = S_i(t) - S_i(t-1) \qquad \forall t \in \mathcal{T}_i, i \in \{AC,HT\} \tag{2.9}$$

$$U_i(t) + D_i(t) \leq 1 \qquad \forall t \in \mathcal{T}_i, i \in \{AC,HT\} \tag{2.10}$$

$$\sum_{k=t}^{t+MUT_i} S_i(k) \geq MUT_i - M(1 - U_i(t)) \qquad \forall t \in \mathcal{T}_i, i \in \{AC,HT\} \tag{2.11}$$

$$\sum_{k=t}^{t+MDT_i-1} S_i(k) \leq M(1 - D_i(t)) \qquad \forall t \in \mathcal{T}_i, i \in \{AC,HT\} \tag{2.12}$$

Equation (2.7) and (2.8) models the change in the indoor temperature as a result of the HVAC operation, the change in the activity level of the customer, or the change in the ambient temperature. Equation (2.9) and (2.10) are the coordinating constraints for the start-up and shut-down decisions of the AC and HT. In addition, minimum up-time (MUT_i) and minimum down-time (MDT_i) of the AC and HT are considered in (2.11) and (2.12).

Dishwasher

The dishwasher mathematical model is presented below:

$$S_i(t) = \begin{cases} 0 \quad \text{or} \quad 1 & \text{if t} \in \mathcal{T}_i, i \in \{DW\} \\ 0 & \text{if t} \notin \mathcal{T}_i, i \in \{DW\} \end{cases} \tag{2.13}$$

$$U_i(t) - D_i(t) = S_i(t) - S_i(t-1) \qquad \forall t \in \mathcal{T}_i \tag{2.14}$$

$$U_i(t) + D_i(t) \leq 1 \qquad \forall t \in \mathcal{T}_i \tag{2.15}$$

$$\sum_{t\in\mathcal{T}_i} S_i(t) = ROT_i \qquad \forall t \in \mathcal{T}_i \qquad (2.16)$$

$$\sum_{k=t}^{t+MST_i} S_i(k) \leq MST_i + M(1-U_i(t)) \qquad \forall t \in \mathcal{T}_i \qquad (2.17)$$

$$\sum_{k=t-MUT_i+1}^{t} U_i(k) \leq S_i(t) \qquad \forall t \in \{EOT_i + MUT_i + 1, LOT_i\} \qquad (2.18)$$

$$\sum_{k=t-MDT_i+1}^{t} D_i(k) \leq 1 - S_i(t) \qquad \forall t \in \{EOT_i + MDT_i + 1, LOT_i\} \qquad (2.19)$$

The dishwasher operates within the pre-determined time intervals preferred by the customer as modeled in (2.13). Minimum up-time, minimum down-time, and required operation time requirements in addition to maximum successive operation time are expressed mathematically in (2.16) to (2.19).

Fridge

The following mathematical model pertaining to fridge operation is formulated considering the technical aspects of the fridge as well as the customer preferences.

$$S_{FR}(t) = \begin{cases} 0 \quad \text{or} \quad 1 & \text{if t}\in \mathcal{T}_i \\ 0 & \text{if t}\notin \mathcal{T}_i \end{cases} \qquad (2.20)$$

$$S_{FR}\big|_{t=1} = \begin{cases} 1 & \text{if } \theta_{FR}\big|_{t=1}(t=0) > \theta_{FR}(t)^{max} \\ 0 & \text{if } \theta_{FR}\big|_{t=1}(t=0) < \theta_{FR}(t)^{min} \end{cases} \qquad (2.21)$$

$$\theta_{FR}^{min}(t) \leq \theta_{FR} \leq \theta_{FR}^{max}(t) \qquad \forall t \in \mathcal{T} \qquad (2.22)$$

$$\theta_{FR}(t) = \theta_{FR}(t-1) + \tau\left[\beta_{FR} A L_{FR}(t) - \alpha_{FR} S_{FR}(t) + \gamma_{FR}\right] \qquad \forall t \in \mathcal{T} \qquad (2.23)$$

The time intervals where the fridge can be in operation are modeled in (2.20). The constraint (2.21) ensures that if the initial temperature of the fridge is above the pre-determined maximum temperature, then it should be in operation; or else it should be in a standby mode. The customer preferred minimum ($\theta_{FR}(t)^{min}$) and maximum ($\theta_{FR}(t)^{max}$) temperature inside the fridge is specified in (2.22). The effect of the activity level, ON state, and OFF state on the fridge operation are represented by β_{FR}, α_{FR}, and γ_{FR} respectively and presented in (2.23).

Lighting System

The model of the lighting system is affected by two factors: daylighting ($L_z^{out}(t)$) and the minimum illumination required in zone z ($L_z^{min}(t)$).

$$L_z(t) + L_z^{out}(t) \geq (1 + K_t) L_z^{min}(t) \qquad \forall t \in \mathcal{T}_i \qquad (2.24)$$

The constraint (2.24) ensures that the illumination level in zone z is greater than the minimum required illumination. In addition, the lighting system load of the house is price elastic, which is modeled using K_t. K_t is equal to zero during the peak prices; whereas, K_t is equal one during the off-peak prices.

Pool Pump

The installation of pool pump along with the swimming pool is required to allow the householder to keep the water quality relatively high by treating the swimming pool water for a certain period of time during the day. The mathematical model of its operational constraints are as follows:

$$S_i(t) = \begin{cases} 0 \quad \text{or} \quad 1 & \text{if t}\in \mathcal{T}_i, i = PMP \\ 0 & \text{if t}\notin \mathcal{T}_i, i = PMP \end{cases} \qquad (2.25)$$

$$\sum_{t \in \mathcal{T}_i} S_i(t) = ROT_i \qquad \forall t \in \mathcal{T}_i, i = PMP \qquad (2.26)$$

$$U_i(t) \geq S_i(t) - S_i(t-1) \qquad \forall t \in \mathcal{T}_i, i = PMP \qquad (2.27)$$

$$\sum_{k=t-MUT_i+1}^{t} U_i(t) \leq S_i(t) \qquad \forall t \in \{EOT_i + MUT_i + 1, LOT_i\}, i = PMP \qquad (2.28)$$

$$\sum_{k=t-MDT_i+1}^{t} U_i(t) \leq 1 - S_i(t - MDT_i) \qquad \forall t \in \{EOT_i + MDT_i + 1, LOT_i\}, i = PMP \qquad (2.29)$$

$$\sum_{k=t}^{t+MST_i} S_i(k) \leq MST_i + M(1 - U_i(t)) \qquad \forall t \in \mathcal{T}_i, i = PMP \qquad (2.30)$$

The above set of constraints ensure that the operation of pool pump is within the customer's preferred pool operation time.

Stove

The mathematical model of the stove is presented to help determine the optimal operation time, based on the customer's objective, within his/her preferred operation time period. The mathematical optimization model of the stove is shown below.

$$S_i(t) = \begin{cases} 0 \quad \text{or} \quad 1 & \text{if t} \in \mathcal{T}_i, i = STV \\ 0 & \text{if t} \notin \mathcal{T}_i, i = STV \end{cases} \qquad (2.31)$$

$$U_i(t) \geq S_i(t) - S_i(t-1) \qquad \forall t \in \mathcal{T}_i, i = STV \qquad (2.32)$$

$$\sum_{t \in \mathcal{T}_i} S_i(t) = ROT_i \qquad \forall t \in \mathcal{T}_i, i = STV \qquad (2.33)$$

$$\sum_{k=t-MUT_i+1}^{t} U_i(t) \leq S_i(t) \qquad \forall t \in \{EOT_i + MUT_i + 1, LOT_i\}, i = STV \tag{2.34}$$

$$\sum_{k=t}^{t+MST_i} S_i(k) \leq MST_i + M(1 - U_i(t)) \qquad \forall t \in \mathcal{T}_i, i = STV \tag{2.35}$$

Washer and Dryer

The mathematical model of the washer and dryer is presented below:

$$S_i(t) = \begin{cases} 0 \quad \text{or} \quad 1 & \text{if t}\in \mathcal{T}_i, i = \{W, Dry\} \\ 0 & \text{if t}\notin \mathcal{T}_i, i = \{W, Dry\} \end{cases} \tag{2.36}$$

$$U_i(t) - D_i(t) = S_i(t) - S_i(t-1) \qquad \forall t \in \mathcal{T}_i, i = \{W, Dry\} \tag{2.37}$$

$$U_i(t) + D_i(t) \leq 1 \qquad \forall t \in \mathcal{T}_i, i = \{W, Dry\} \tag{2.38}$$

$$\sum_{t \in \mathcal{T}_i} S_i(t) = ROT_i \qquad \forall t \in \mathcal{T}_i, i = \{W, Dry\} \tag{2.39}$$

$$\sum_{k=t}^{t+MST_i} S_i(k) \leq MST_i + M(1 - U_i(t)) \qquad \forall t \in \mathcal{T}_i, i = \{W, Dry\} \tag{2.40}$$

$$\sum_{k=t-MUT_i+1}^{t} U_i(t) \leq S_i(t) \qquad \forall t \in \{EOT_i + MUT_i + 1, LOT_i\}, i = \{W, Dry\} \tag{2.41}$$

$$\sum_{k=t-MDT_i+1}^{t} D_i(k) \leq 1 - S_i(t)$$

$$\forall t \in \{EOT_i + MDT_i + 1, LOT_i\}, i = \{W, Dry\} \qquad (2.42)$$

The constraints (2.36) to (2.42) are modeled to provide the customer with the optimal operation schedule for both the washer and dryer based on the customer preferences. The washer and dryer are required to operate in a chronological sequence, where the operation of the dryer should follow the operation of the washer. The following constraints are included to coordinate the sequential operation of the washer and dryer.

$$U_{DRY}(t) \leq \sum_{k=t-\triangle_{W,DRY}}^{t-MUT_W} U_W(t-k)$$

$$\forall t \in \{EOT_i + \triangle_{W,DRY}, LOT_i - MUT_W\}, i = \{W, Dry\} \qquad (2.43)$$

$$S_{DRY}(t) + S_W(t) \leq 1 \qquad \forall t \in \mathcal{T} \qquad (2.44)$$

$$\sum_{t \in \mathcal{T}_{DRY}} U_{DRY}(t) = \sum_{t \in \mathcal{T}_W} U_W(t) \qquad (2.45)$$

Water Heater

Similar to the mathematical model of the fridge, the water heater model is presented below:

$$S_i(t) = \begin{cases} 0 \text{ or } 1 & \text{if t} \in \mathcal{T}_i, i = WH \\ 0 & \text{if t} \notin \mathcal{T}_i, i = WH \end{cases} \qquad (2.46)$$

$$S_i(t=1) = \begin{cases} 1 & \text{if } \theta_i(t=0) < \theta_i(t)^{min}, i = WH \\ 0 & \text{if } \theta_i(t=0) > \theta_i(t)^{max}, i = WH \end{cases} \qquad (2.47)$$

$$\theta_i^{min}(t) \leq \theta_i \leq \theta_i^{max}(t) \qquad \forall t \in \mathcal{T}_i, i = WH \qquad (2.48)$$

$$\theta_i(t) = \theta_i(t-1) + \tau\big[\alpha_i S_i(t) - \beta_i HWU(t) - \gamma_i\big] \qquad \forall t \in \mathcal{T}, i = WH \tag{2.49}$$

2.3.3 Operational Constraints of The Household Devices

Energy Storage Device

The ESD is assumed to be one of the typical household devices in the future. In [31], the amount of energy charged in the ESD is assumed to be known. The mathematical model of the ESD is shown below:

$$ESL_{PV}(t) = (1-\eta_1)ESL_{ESD}(t-1) + \tau[CHD_{ESD}(t) - S_i(t)DCH_{ESD}] \quad \forall t \in \mathcal{T} \tag{2.50}$$

$$ESL_{ESD}^{min} \leq ESL_{ESD}(t) \leq ESL_{ESD}^{max} \qquad \forall t \in \mathcal{T} \tag{2.51}$$

$$\sum_{k=t-MUT_i+1}^{t} U_i(t) \leq S_i(t) \qquad \forall t \in \{EOT_i + MUT_i + 1, LOT_i\}, i = ESD \tag{2.52}$$

$$\sum_{k=t-MDT_i+1}^{t} D_i(t) \leq 1 - S_i(t - MDT_i) \qquad \forall t \in \{EOT_i + MDT_i + 1, LOT_i\}, i = ESD \tag{2.53}$$

Photovoltaic Panel and Associated Battery

One of the main features of the houses in the future is the integration of distributed renewable energy resources such as the PV panels and the wind turbines. In [31], the installation of a rooftop PV panel with associated battery is considered. Consequently, the following mathematical model is considered.

$$S_i(t) = \begin{cases} 0 \text{ or } 1 & \text{if t}\in \mathcal{T}_i, i = PV \\ 0 & \text{if t}\notin \mathcal{T}_i, i = PV \end{cases} \tag{2.54}$$

$$CHD_{PV}(t) = \begin{cases} P_{CHD} & \text{if} \quad P_{PV}(t) \geq P_{CHD} \\ P_{PV} & \text{if} \quad P_{PV} \leq P_{CHD} \end{cases} \tag{2.55}$$

$$\begin{aligned} ESL_{PV}(t) = (1-\eta_1) ESL_{PV}(t-1) \\ + \tau[S_{PV,CHD}(t) CHD_{PV}(t) - S_{PV,DCH}(t) DCH_{PV}] \quad \forall t \in \mathcal{T} \end{aligned} \tag{2.56}$$

$$ESL_{PV}^{min} \leq ESL_{PV}(t) \leq ESL_{PV}^{max} \quad \forall t \in \mathcal{T} \tag{2.57}$$

$$S_{PV,DCH}(t) + S_{PV,CHD}(t) \leq 1 \quad \forall t \in \mathcal{T}_i \tag{2.58}$$

2.4 Model Predictive Control

MPC is an advanced control algorithm that employs a process model for computing a chronological succession of adjustments of variables over a future time horizon, repeatedly, based on a fundamental optimization model and prediction of uncertain variables [1]. The optimization model outputs provides the control decisions over the time horizon based on a given objective function; however, the control decisions of the first time interval is implemented. The optimization model keeps updating and generating the decision actions as well as proceeding over the time horizon, repeatedly.

The MPC has been used in several applications that requires dealing with large number of multi-variable constrained control problems in the process industries [47]. In addition, there are some applications of MPC in power system such as unit commitment problems with the presence of distributed energy resources, and the voltage regulation and var controlling in the microgrids [48].

There are many advantages of MPC approach that makes it very attractive for researchers in the power sector [48]:

- The ability to optimize the current time period decisions while taking into account the predicted events within the rest of the time horizon.
- The capability of updating the forecasted inputs, which makes it a powerful tool to handle uncertainties.
- The ability of providing a feedback on the system behavior.

- The capability of integrating constraints as well as adding new ones over the time horizon.
- The capability of handling operations with several controlled variables and constraints in a systematic way.

2.5 Summary

In this chapter, the characteristics of smart grids was discussed vis-a-vis the traditional power grid. Different basic concepts related to DSM and DR schemes was discussed thereafter. A previously proposed comprehensive mathematical model of the HEMS was discussed, and this will form the background to the work considered in the next chapter with an improved HEMS based on MPC. This is followed by a brief discussion of the definition, applications, and advantages of MPC approach.

Chapter 3

Model Predictive Control Based Home Energy Management System

3.1 Introduction

The mathematical model of the HEMS, proposed in [31] and discussed in the previous chapter, is modified in this chapter to model the interrelationships between the household, the ESD, and the PV panel (including battery) in a precise manner. Thereafter, the MPC approach is applied to mitigate the impact of uncertainty associated with forecasted parameters, which are the inputs to the HEMS model. Simulation studies are carried out to examine the various interrelationships and energy interchange between the entities within the HEMS.

3.2 Modified Home Energy Management System: Mathematical Model

In this work, the objective of the HEMS is to minimize the customer's total cost by operating different household appliances at low price hours or to minimize the total energy consumption, with/without a specified fixed/variable peak load cap. In this study, the typical house demand comprises the following appliances: fridge, water heater, lighting system, air-conditioning, dishwasher, washer, dryer, stove, and pool. The house is also equipped with a rooftop solar PV panel (with a battery) and an ESD. It is to be noted that

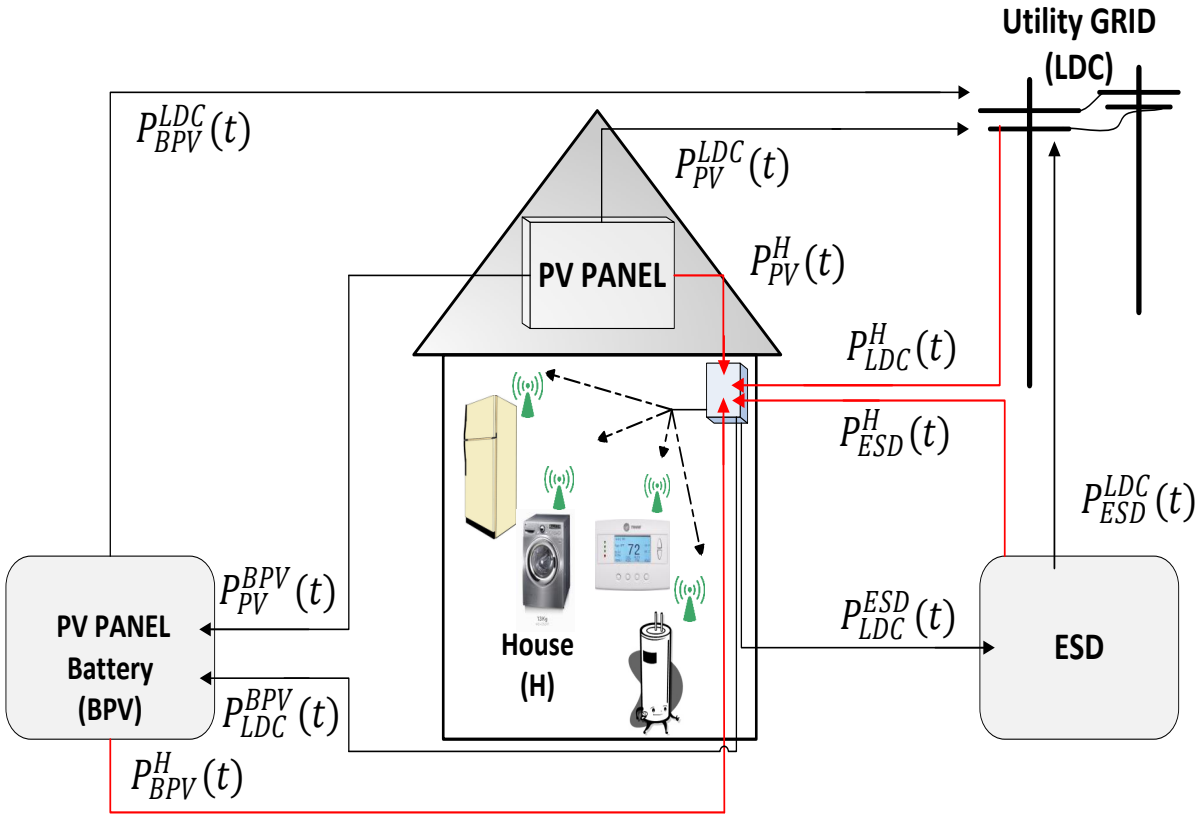


Figure 3.1: Comprehensive Representation of HEMS

this configuration of the house considers a battery with the PV panel and a separate ESD. The justification of this being that the ESD can provide emergency power (by charging from the grid) even when solar irradiation is low, and hence provides enhanced flexibility to the HEMS. The ESD may also be representative of a Plug-in electric vehicles (PEVs) being owned by the household, and which may serve as an ESD. A comprehensive representation of a house and the interrelationships between different entities are shown in Figure 3.1, and it should be noted that the power transfers between two entities are denoted by P_{From}^{To}. The operation of each entity is discussed below, with reference to Figure 3.1.

- The charging and discharging process of the ESD are controlled by the HEMS. The ESD is charged by the power drawn by the house from the LDC. At peak demand hours, the HEMS can discharge power from the ESD to the LDC and earn revenue.
- The PV panel battery (BPV) can be charged from the power drawn by the house

from the LDC or from the PV panel directly. The stored energy in the BPV can be used to supply the household appliances or sold to the grid. The HEMS can control the PV panel operation, *i.e.*, allocation of power between the household, the BPV, and the grid.

Indeed, the ESD and the PV panel battery create additional power demand by the household when RTP is low, for charging, and discharges when economically beneficial. The PV generation depends on the weather conditions and PV panel features.

3.2.1 Objective Functions

Minimize Energy Cost

The objective function of the HEMS is to minimize the customer's total cost of energy net of the revenue earned.

$$J = \sum_{t\in\mathcal{T}} \Bigg[\rho^{RTP}(t) \Big\{ \sum_{\substack{i\in\mathcal{A} \\ i\notin\{LI,ESD,BPV\}}} P_i S_i(t) + \sum_{z\in LI} P_{LI_z} L_z(t) + \sum_{i\in\{BPV,ESD\}} P^i_{LDC}(t) + P_{D0} \Big\} + \sum_{i\in\{HT,WH\}} \rho^{GAS} G_i S_i(t) - \rho^{SEL} \Big\{ \sum_{i\in\{BPV,ESD\}} P^{LDC}_i(t) + P^{LDC}_{PV}(t) \Big\} \Bigg] \quad (3.1)$$

In (3.1), the consumption by the household appliances and the charging power for the ESD and BPV represent the total power drawn from the grid. The term associated with ρ^{GAS} presents the total cost of gas consumption. The discharged power from storage devices and BPV accounts for the power sold to the grid; $\rho^{RTP}(t)$ and ρ^{SEL} represents the price of buying and selling from and to the LDC, respectively. It should be noted that (3.1) is a significantly revised objective of the HEMS from that of [31], and takes into account detailed bi-directional energy transfers between the LDC and the BPV, and between the LDC and the ESD.

3.2.2 The Modified Operational Constraints

Peak Load Constraint

This constraint ensures that the total load of the house is within a specified peak load cap,

$$\sum_{i\in\mathcal{A}} P_i S_i(t) + \sum_{z\in LI} P_{LI_z} L_z(t) + \sum_{i\in\{BPV,ESD\}} P_i^{LDC}(t) - \sum_{i\in\{BPV,ESD,PV\}} P_i^H(t) \leq P^{max}(t) \qquad \forall t \in \mathcal{T}_r \quad (3.2)$$

In constraint (3.2), the household load includes the appliances' consumption, charging power of the ESD and the BPV; net of the power discharged from the ESD, the BPV, and that generated by the PV panel. This is a new constraint included in the HEMS vis-a-vis [31] where minimizing of peak load was considered as an objective function. The inclusion of peak load as a constraint helps in the LDC control aspects, as will be demonstrated later.

Home Power Balance

This constraint ensures that the total power drawn by the household appliances at a given interval is met from the total power drawn from the grid, discharged to the house from the ESD and BPV, and generated by the PV system, as given below:

$$\sum_{i\in\mathcal{A}} P_i S_i(t) + \sum_{z\in LI} P_{LI_z} L_z(t) = P_{LDC}^H(t) + \sum_{i\in\{BPV,ESD,PV\}} P_i^H(t) \qquad \forall t \in \mathcal{T}_r \quad (3.3)$$

Energy Storage Device

In [31], the charging level of the ESD was assumed known at each time interval, which is not realistic. It is essential to model the ESD considering its realistic operational constraints, as presented below:

$$E_{ESD}(t) = E_{ESD}(t-1) + \tau[P_{LDC}^{ESD}(t)\eta_1 - (P_{ESD}^{LDC}(t) + P_{ESD}^H(t))/\eta_2] \qquad \forall t \in \mathcal{T}_r \quad (3.4)$$

$$E_{ESD}^{min} \leq E_{ESD}(t) \leq E_{ESD}^{max} \qquad \forall t \in \mathcal{T}_r \qquad (3.5)$$

$$P_{LDC}^{ESD}(t) \leq S_{C_{ESD}}(t) P_{C_{ESD}}^{max} \qquad \forall t \in \mathcal{T}_r \qquad (3.6)$$

$$P_{ESD}^{LDC}(t) + P_{ESD}^{H}(t) \leq S_{D_{ESD}}(t) P_{D_{ESD}}^{max} \qquad \forall t \in \mathcal{T}_r \qquad (3.7)$$

$$S_{C_{ESD}}(t) + S_{D_{ESD}}(t) \leq 1 \qquad \forall t \in \mathcal{T}_r \qquad (3.8)$$

In (3.4), the energy level of the ESD is affected by three variables: charging the ESD from the LDC, $P_{LDC}^{ESD}(t)$, discharging the ESD to the LDC $P_{ESD}^{LDC}(t)$, and discharging the ESD to the house $P_{ESD}^{H}(t)$. Constraint (3.5) ensures that the ESD energy level is within the pre-set minimum and maximum limits. The limits on charging and discharging power of the ESD are given by (3.6) and (3.7), respectively. Constraint (3.8) ensures that the charging and discharging process does not take place simultaneously.

Photovoltaic Panel with a Battery

The PV panel is one of the most popular renewable energy resources. The PV panel model in [31] is modified in this study with a more detailed and realistic architecture, as shown in Figure 3.1, and discussed below:

Solar Panel:

According to [49], the MicroFIT program of Ontario provides opportunity for residential customers to generate up to 10 kW of renewable energy and sell it with a guaranteed long term contract for an attractive fixed price incentive. Consequently, a PV panel with 3.6 kW generation capability has been chosen in this model. The PV panel will generate power, and the HEMS will optimize the usage of this power by distributing the PV generation to the battery, household, and utility as given below:

$$P_{PV}(t) = P_{PV}^{LDC}(t) + P_{PV}^{BPV}(t) + P_{PV}^{H}(t) \qquad \forall t \in \mathcal{T}_r \qquad (3.9)$$

Battery:

$$E_{BPV}(t) = E_{BPV}(t-1) + \tau\big[\big\{P_{LDC}^{BPV}(t) + P_{PV}^{BPV}(t)\big\}\eta_1 - \big\{P_{BPV}^{LDC}(t) + P_{BPV}^{H}(t)\big\}/\eta_2\big] \qquad \forall t \in \mathcal{T}_r \quad (3.10)$$

$$E_{BPV}^{min} \leq E_{BPV}(t) \leq E_{BPV}^{max} \qquad \forall t \in \mathcal{T}_r \quad (3.11)$$

Equation (3.10) presents the dynamic relationship of the energy level of the BPV between two consecutive time intervals, and (3.11) defines the limits on the energy level of the battery. As seen from (3.10), the PV panel battery can be charged by two ways: from the PV panel ($P_{PV}^{BPV}(t)$) or the LDC ($P_{LDC}^{BPV}(t)$). The charging procedure is formulated as follows:

$$P_{C_{BPV}}(t) = P_{LDC}^{BPV}(t) + P_{PV}^{BPV}(t) \qquad \forall t \in \mathcal{T}_r \quad (3.12)$$

The battery can discharge power to the house $P_{BPV}^{H}(t)$ or sell to the grid, $P_{BPV}^{LDC}(t)$, as follows.

$$P_{D_{BPV}}(t) = P_{BPV}^{LDC}(t) + P_{BPV}^{H}(t) \qquad \forall t \in \mathcal{T}_r \quad (3.13)$$

Furthermore, the following constraints are included:

$$P_{C_{BPV}}(t) \leq S_{C_{BPV}}(t) P_{C_{BPV}}^{max} \qquad \forall t \in \mathcal{T}_r \quad (3.14)$$

$$P_{D_{BPV}}(t) \leq S_{D_{BPV}}(t) P_{D_{BPV}}^{max} \qquad \forall t \in \mathcal{T}_r \quad (3.15)$$

Constraint (3.14) and (3.15) represents the maximum charging and discharging power for the BPV. The charging and discharging processes are also ensured to take place at different time intervals, as given below:

$$S_{C_{BPV}}(t) + S_{D_{BPV}}(t) \leq 1 \qquad \forall t \in \mathcal{T}_r \quad (3.16)$$

The overall HEMS model comprises the original constraints given by (2.2) to (2.49) and the modified set of equations discussed in this chapter, given by (3.1) to (3.16).

Table 3.1: Parameters of the HEMS Model [50]

Device	Parameter	Setting Value	Parameter	Setting Value	Parameter	Setting Value
Fridge	θ_{fr_0}	3	α_{fr}	2.75	P_{fr}	0.6 kW
	θ_{fr}^{min}	0	β_{fr}	0.605		
	θ_{fr}^{max}	10	γ_{fr}	0.14		
Water Heater	θ_{wh_0}	50	α_{wh}	4.4	P_{wh}	0.6 kW
	θ_{wh}^{min}	48	β_{wh}	0.068	HR_{wh}	0.297
	θ_{wh}^{max}	58	γ_{wh}	0.05	CG	0.029
Stove	EOT	65	ROT	12	P_{stv}	1.5 kW
	LOT	88	MUT	4	$MSOT$	12
Dishwasher	EOT	65	MUT	8	P_{DW}	0.7 kW
	LOT	92	MDT	4	$MSOT$	8
Washer	EOT	64	MUT	8	P_w	0.45 kW
	LOT	92	MDT	4	MSOT	8
Dryer	EOT	64	MUT	8	P_{dry}	1.1 kW
	LOT	92	MDT	4	$Gap_{W,Dry}$	8
Lighting	EOT	1	LOT	96	P_{li}	0.15 kW
Pool	EOT	29	MUT	1	P_{pmp}	0.75 kW
	LOT	96	MDT	1	ROT	40
Energy Storage Device	E_{min}	1 kWh	$P_{C_{ESD}}^{max}$	0.45	EOT	1
	E_{max}	3.6 kWh	P_{ESD}^{max}	0.45	LOT	96
PV Panel Battery	E_{min}	1 kWh	$P_{C_B}^{max}$	0.45	EOT	1
	E_{max}	3.6 kWh	$P_{D_B}^{max}$	0.45	LOT	96

3.2.3 Initial Settings of the HEMS Model

The initial parameters of the HEMS model are taken from [50]. Table 3.1 shows the considered devices in the model with their initial parameters and customer preferences.

3.2.4 Model Predictive Control

MPC is an advanced control algorithm that employs a process model for computing a chronological succession of adjustments of variables over a future time horizon, repeatedly, based on a fundamental optimization model and prediction of uncertain inputs [1]. Because of the highly uncertain nature of the weather, RTP, and other predictable parameters in an HEMS model, the MPC approach, as mentioned in [31], is integrated to optimize its decision making process.

In this work, a future horizon of K time intervals is chosen *i.e.*, every hour is divided

into 4 intervals of 15 minutes each (*i.e.*, 96 intervals over the day). Figure 3.2 shows the interaction between the HEMS hub and the controlled appliances. At time t (*i.e.*, the first run starts at 12 AM), the model runs for 96 intervals which is equivalent to a day-ahead scheduling; however, only the first interval decisions (output decision period as shown in Figure 3.2) are applied to the household appliances, while the rest of the output decisions are rejected. Thereafter, the time horizon is shifted one interval forward at every iteration. The optimal solution at each iteration is based on the current and forecasted information on weather, household's preferences and activity level, and RTP. The HEMS model, in the present case, is solved 96 times with updated data in order to minimize the customer energy cost over the day. Figure 3.3 is a flowchart representation of the MPC based HEMS operation.

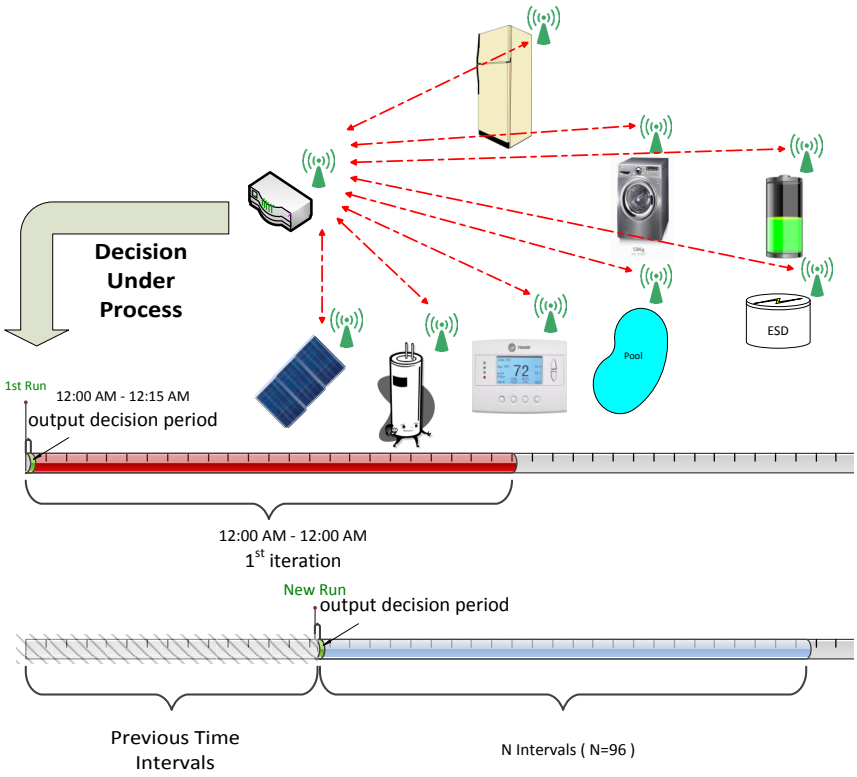


Figure 3.2: Schematic for Model Predictive Control of HEMS

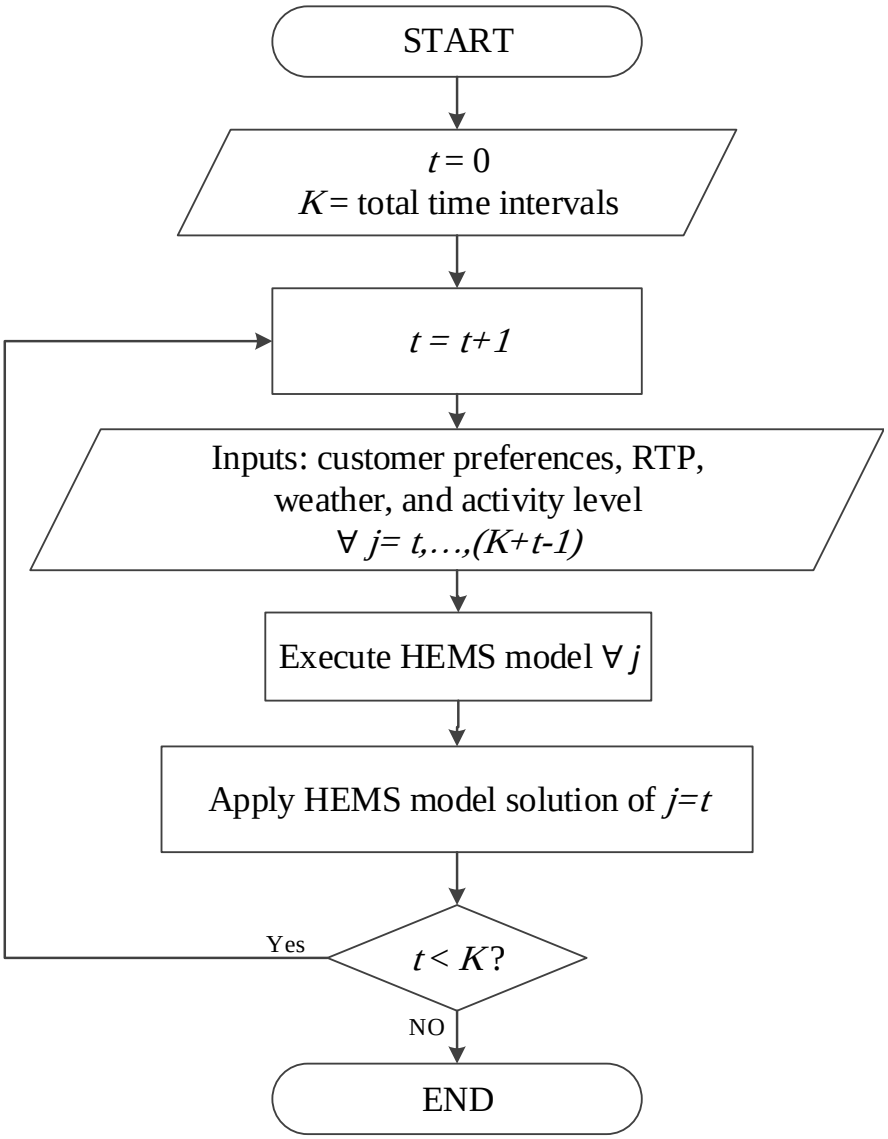


Figure 3.3: Flow Process of MPC Based HEMS.

3.3 Case Studies and Results

3.3.1 Case Studies

Three case studies are considered in order to examine the impact of MPC on the optimal operation of HEMS, as presented in Table 3.2 and explained below:

- Case 1: presents the optimal solution of the HEMS model for a fixed set of input parameters.
- Case 2: considers the optimal operational decisions obtained from Case 1 as fixed, and examines the performance of the HEMS when the inputs such as RTP, weather, and activity level vary. This case examines how robust the optimal decisions of the HEMS are, when the inputs change. It is to be noted that TOU prices as applied in Ontario, are only spread over three time blocks (peak, mid-peak, and off-peak) and hence not offer much variability to test the performance of the HEMS. Therefore, RTP has been used in this work, which varies every hour (in Ontario), and can be quite volatile at times. It is also envisaged that in the near future, retail customers will eventually be subjected to RTPs.
- Case 3: considers the same varying inputs of Case 2, but now the proposed MPC based approach is applied to the HEMS to continuously evolve new optimal operational decisions of the household appliances.

Table 3.2: Summary of Case Studies

Case	Description	Inputs
1	Base case optimal	Fixed over the day
2	Optimal HEMS decisions from Case 1, fixed	Updated continuously
3	MPC based approach	Updated continuously

The input data of the HEMS relies on customer preferences and forecasted parameters. The fridge, water heater, and the heating and cooling system require the customer to pre-determine the preferred minimum and maximum temperature, while the dishwasher, the washer, the dryer, and the stove require different settings such as the minimum up-time, minimum down-time, required operation time, and preferred operation hours. The forecasted RTP and weather conditions are retrieved from [51] and [52], respectively. The HEMS model requires an accurate forecasting. Updating the weather condition, activity level, and RTP on a continuous basis can reduce their prediction error percentage, thus leading to increased computational and operational efficiencies. Figures 3.4, 3.5, and 3.6 presents the plots of the forecasted values of the weather, activity level, and RTP respectively, over a period of 24 hours. These forecasted inputs are randomly generated by considering a $\pm 5\%$ error in forecast.

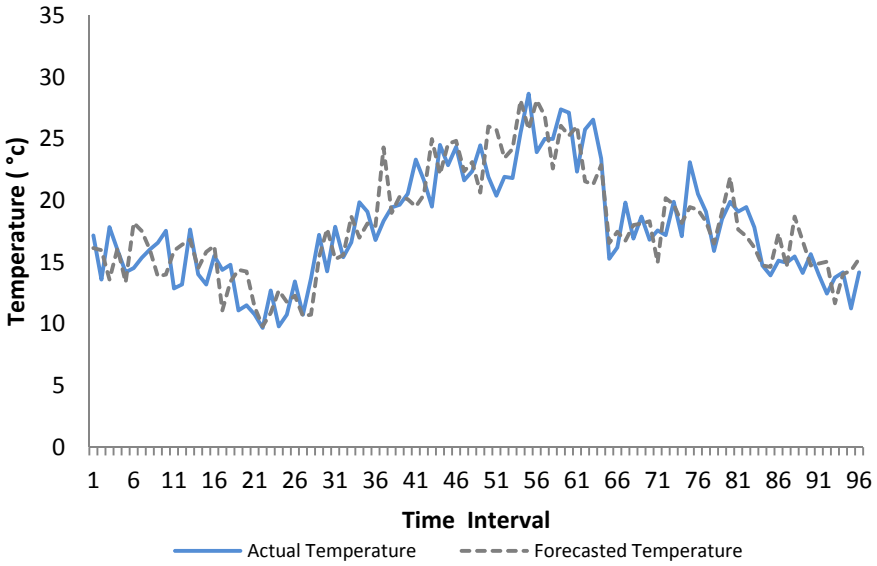


Figure 3.4: Actual and Forecasted Outdoor Temperature

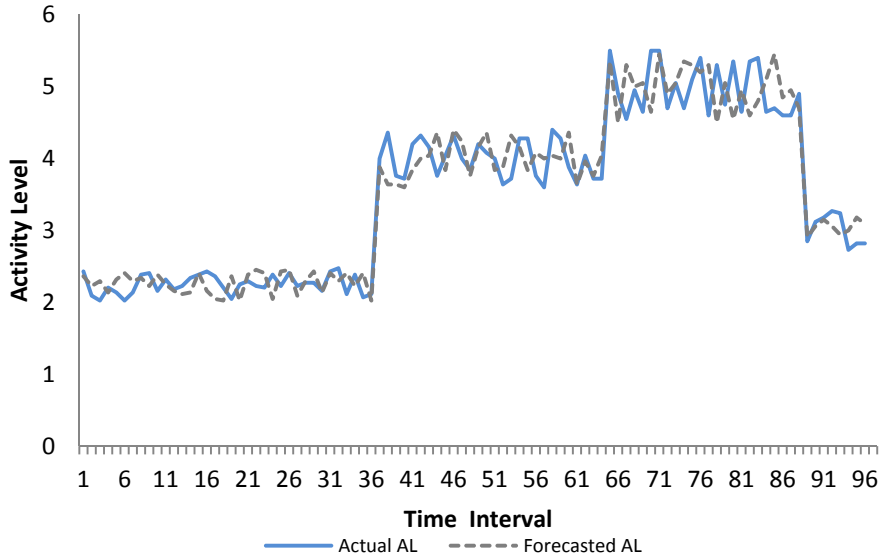


Figure 3.5: Actual and Forecasted Activity Level

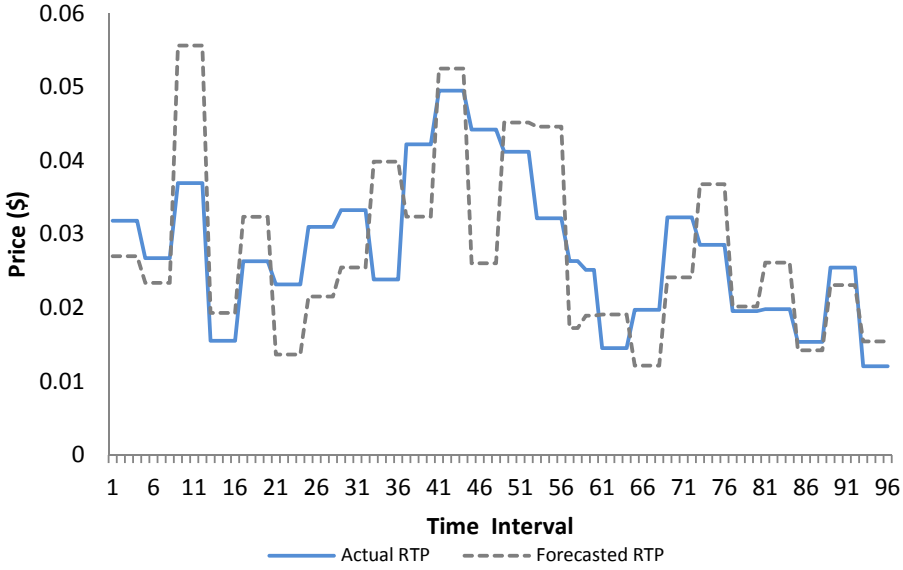


Figure 3.6: Actual and Forecasted RTP

3.3.2 Results

It is important to examine whether the optimal decisions obtained from the HEMS operations model pertaining to optimal scheduling of the appliances (Case 1), provide satisfactory performance when the input parameters such as the activity level or the RTP changes. Is it necessary to re-optimize the decisions over a horizon to arrive at a better solution?

Table 3.3 presents the household appliance-wise consumption on a summer day for the three cases described earlier. It can be noted from the HEMS model that the fridge, cooling system and the water heater operations are affected by variations in the activity level and RTP while the other appliances operations are only affected by variations in the RTP. The energy cost for the day increases slightly in Case 2 over Case 1 because the base case optimal decisions are persisted with, although input variations take place. However, if the MPC approach is used and the operational decisions are re-optimized on a continuous basis over a moving horizon (Case 3), a 12% reduction in the total daily energy cost over Case 2 was noted.

Figures 3.7 and 3.8 presents a comparison of the energy flow and the interrelationships between various entities in the house during OFF-Peak and ON-Peak load conditions. It is noted that in Case 3 the house draws more power than in Case 2 to charge the BPV and

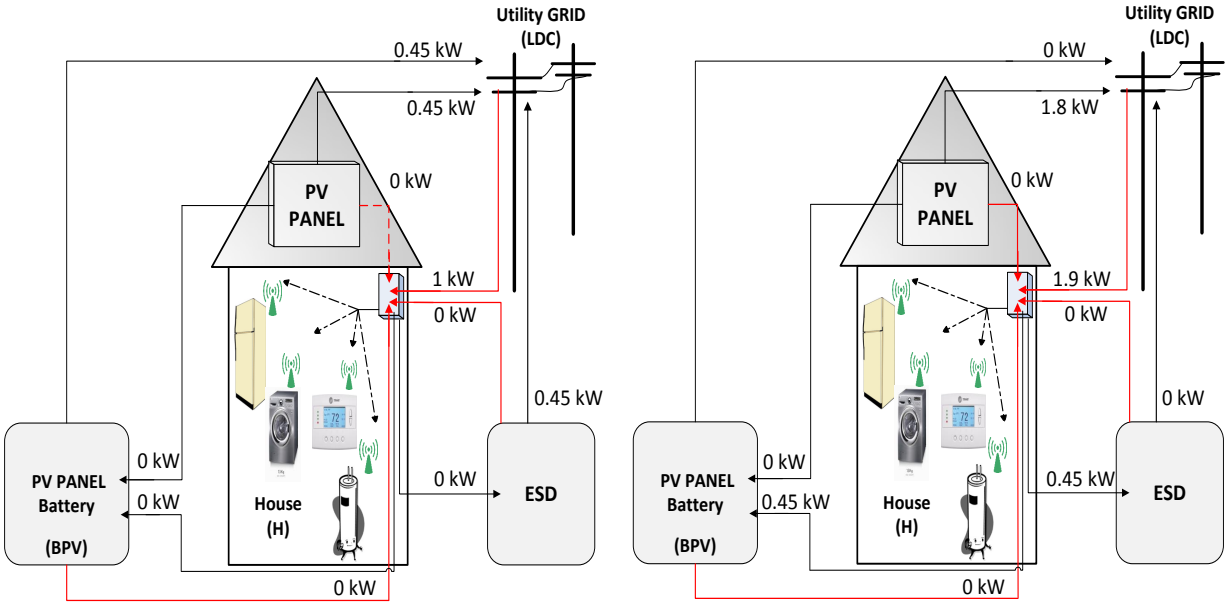


Figure 3.7: OFF-Peak Comparison between Case 2 and Case 3 at Time Interval 64

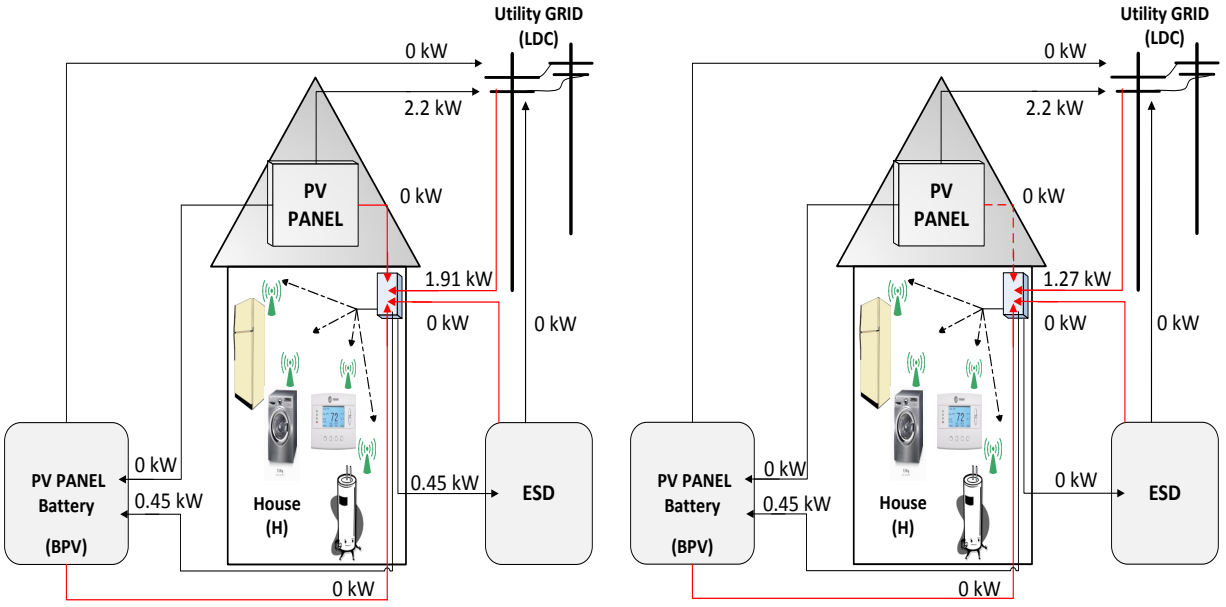


Figure 3.8: ON-Peak Comparison between Case 2 and Case 3 at Time Interval 58

ESD during the OFF-Peak period, as shown in Figure 3.7. However, in Case 3 the house draws less power than Case 2 during the ON-Peak period to avoid high RTP, as shown in

Figure 3.8.

It is also noted from Figure 3.7 that in Case 3 the house is able to sell more power to the LDC than in Case 2 by virtue of the MPC-based operation. Furthermore, comparing Figure 3.7 with 3.8 it is noted that the house sells more power to the LDC during ON-Peak conditions than during OFF-Peak.

Table 3.3: Energy Consumption of Household Appliances

Device		CASE 1		CASE 2		CASE 3	
		(kWh)	($)	(kWh)	($)	(kWh)	($)
Fridge		5.40	0.49	5.55	0.56	5.55	0.43
Water Heater	Elec.	0.90	0.08	0.90	0.09	1.05	0.07
	Gas	0.45	0.05	0.45	0.05	0.52	0.06
Lighting		8.39	0.86	8.25	0.83	8.24	0.80
AC		17.60	1.46	17.60	1.47	16.50	1.24
Dishwasher		1.40	0.10	1.400	0.10	1.40	0.07
Washer		0.90	0.07	0.90	0.07	0.90	0.07
Dryer		2.22	0.16	2.22	0.16	2.22	0.13
Stove		4.50	0.29	4.50	0.30	4.50	0.26
Pool		7.50	0.66	7.50	0.67	7.50	0.60
Total		49.26	4.21	49.27	4.29	48.38	3.76

Table 3.4: Energy Interchanges between Two Entities

From-To	CASE 1			CASE 2			CASE 3		
	DCH (kWh)	CHD (kWh)	REV ($)	DCH (kWh)	CHD (kWh)	REV ($)	DCH (kWh)	CHD (kWh)	REV ($)
ESD-LDC	20.24	22.50	5.85	20.12	22.37	5.79	19.53	21.68	5.70
BPV-LDC	20.24	22.50	5.83	20.15	22.40	5.81	20.15	22.85	5.86
PV-LDC	79.60	—	25.15	79.60	—	25.15	79.60	—	25.15
ESD-House	0.00	—	—	0.00	—	—	0.00	—	0.00
BPV-House	0.00	—	—	0.00	—	—	0.00	—	0.00
PV-House	0.00	—	—	0.00	—	—	0.00	—	0.00
Total	120.08	45.00	36.83	119.88	44.77	36.75	119.29	44.53	36.71

DCH: Discharge CHD: Charge REV: Revenue

Table 3.4 presents the amount of energy charged and discharged between two sets of entities of the HEMS, and the associated revenue for the three case studies. It can be roughly estimated that there will be a $15 increase in monthly profit in Case 3 over Case

2, just by implementing MPC. The results show very little difference between the three case studies because the variations in RTP are small. However, the difference in the revenue between Case 2 and Case 3 can be higher when the difference between the actual and forecasted RTP is significantly large. It is noted that there is no energy delivered to the household from the ESD and BPV because of the low RTP compared to the selling price to the utility.

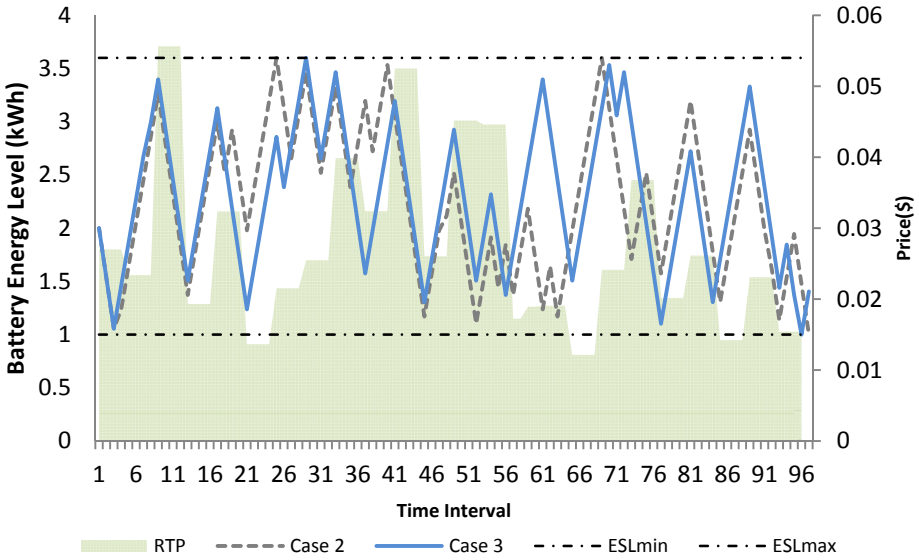


Figure 3.9: Energy Level of PV Battery vis-a-vis RTP

The HEMS model optimizes the BPV and ESD operation over the operating horizon. Figures 3.9 and 3.10 presents the battery energy level for the PV panel battery and the ESD, respectively, and from these the charging and discharging processes corresponding to the RTP variations are noted; at low RTPs the BPV and ESD operate in the charging mode in order to discharge during high demand or high RTP periods.

The activity level and the RTP have an influence on the fridge operation as illustrated in Figure 3.11, which, for example, starts cooling at time interval 43 to avoid operation during interval 48 when increased RTP is forecasted. At time interval 48, the HEMS manages this situation perfectly in Case 2 and 3 by turning OFF the fridge. However, the fridge is turned ON again in Case 2 at interval 53 because the operating decisions are not optimal for the fluctuating RTPs; on the other hand, Case 3 stipulates the fridge turn ON at interval 58, which is optimally determined by the MPC. Figure 3.12 shows that water heater operation is optimized in Case 3 as a result of implementing the MPC. On the

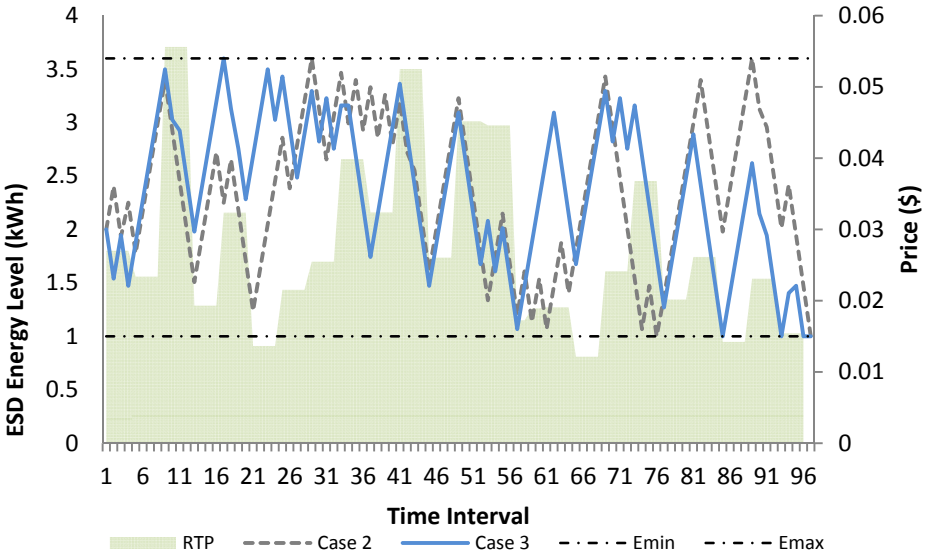


Figure 3.10: Energy Level of ESD vis-a-vis RTP

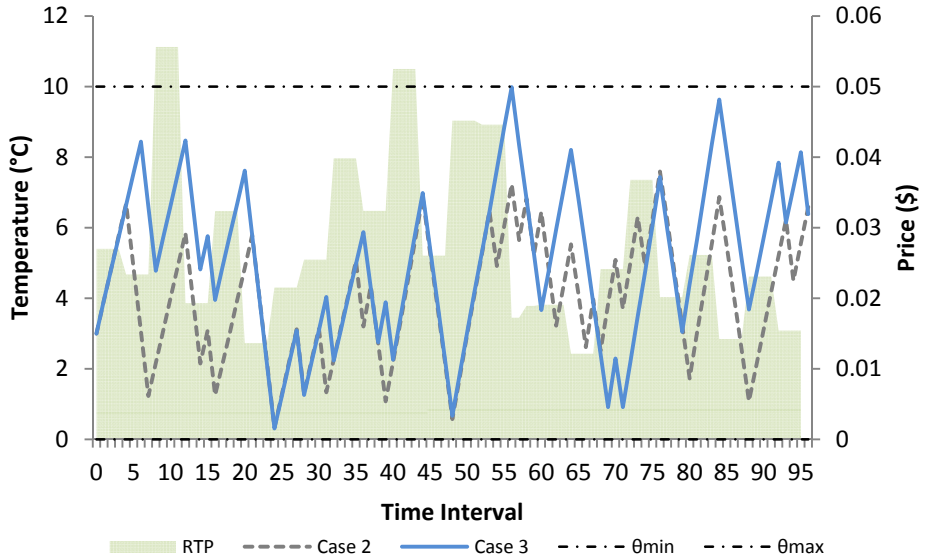


Figure 3.11: Refrigerator Operation vis-a-vis RTP

other hand, there are some unpredictable high prices in Case 2 causing the HEMS Case 1 optimal decisions to be rendered sub-optimal. Figure 3.13 illustrates the operation of

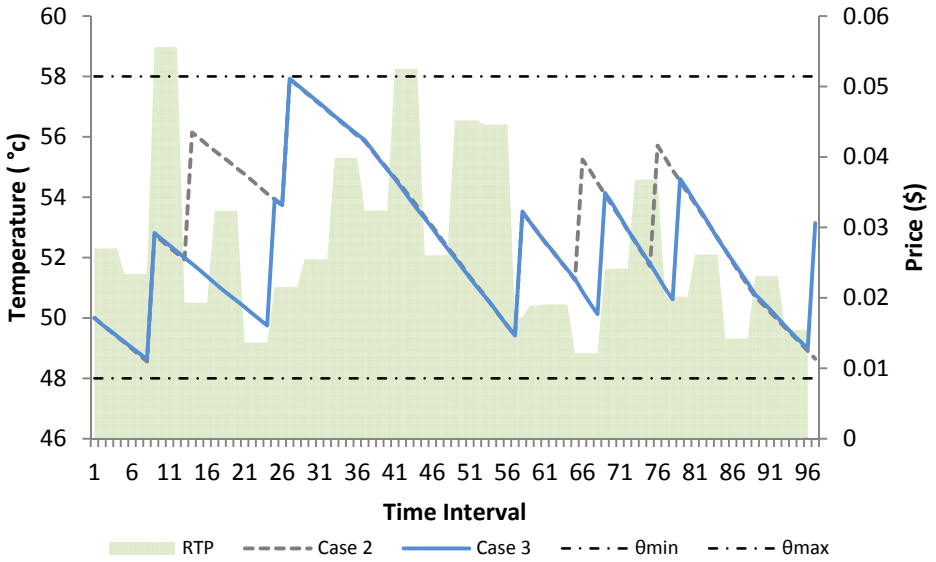


Figure 3.12: Water Heater Operation vis-a-vis RTP

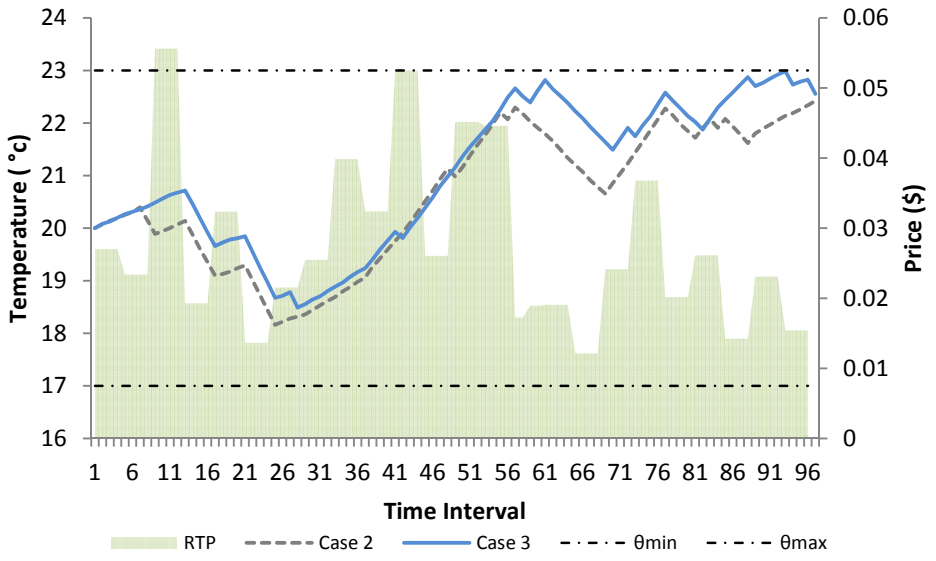


Figure 3.13: AC Operation vis-a-vis RTP

the AC system over the time horizon. The figure shows an increase in RTP between time intervals 8 and 13. The MPC based HEMS (Case 3) keeps the AC system OFF during

this period. Nevertheless, the HEMS in Case 2 turns the AC system ON during the same period which proves the lack of accurate prediction in Case 1 and the need for the MPC approach.

The General Algebraic Modeling System (GAMS) environment is used to solve the Mixed Integer Linear Programming Problem using the CPLEX solver. The MPC based HEMS model takes less than one minute to compute all the objective functions with less than 1% relative gap.

3.4 Summary

This chapter presented an MPC based HEMS model to take into consideration the impact of uncertainty in different predictable inputs associated with the model. The activity level, the weather condition, and the RTP are the main updated inputs of the MPC based HEMS model. The model of the ESD and the PV panel (including the battery) are modified from the previous work to be more realistic. The studies reveal that 12% energy cost savings can be attained using the proposed model without compromising on the customers' comfort level. The MPC based HEMS model is computationally efficient and requires less than one minute for a 24-hour MPC run, which is acceptable for the practical applications.

Chapter 4

Optimal Coordination of Home Energy Management System for Demand Response Provisions

4.1 Introduction

This chapter discusses the formulation of a bi-level optimization framework to coordinate a large number of HEMS with the LDC in order to evaluate the contribution of the customers to provide DR services. The mathematical model of the HEMS is same as that presented in Chapter 3.

4.2 Proposed Framework and Mathematical Models

4.2.1 Coordination of Multiple HEMS and LDC

In this work, a novel coordination framework between the multiple residential customers and the LDC is proposed. It is assumed that all houses are equipped with HEMS and receive updates to their inputs, such as forecasted price $\rho^{RTP}(t)$, forecasted weather, and the maximum power that can be drawn from the distribution grid. The respective HEMS hence optimizes the operation of the household appliances, taking into account the customer's comfort level and appliance constraints. The resulting optimal load profile of the residential

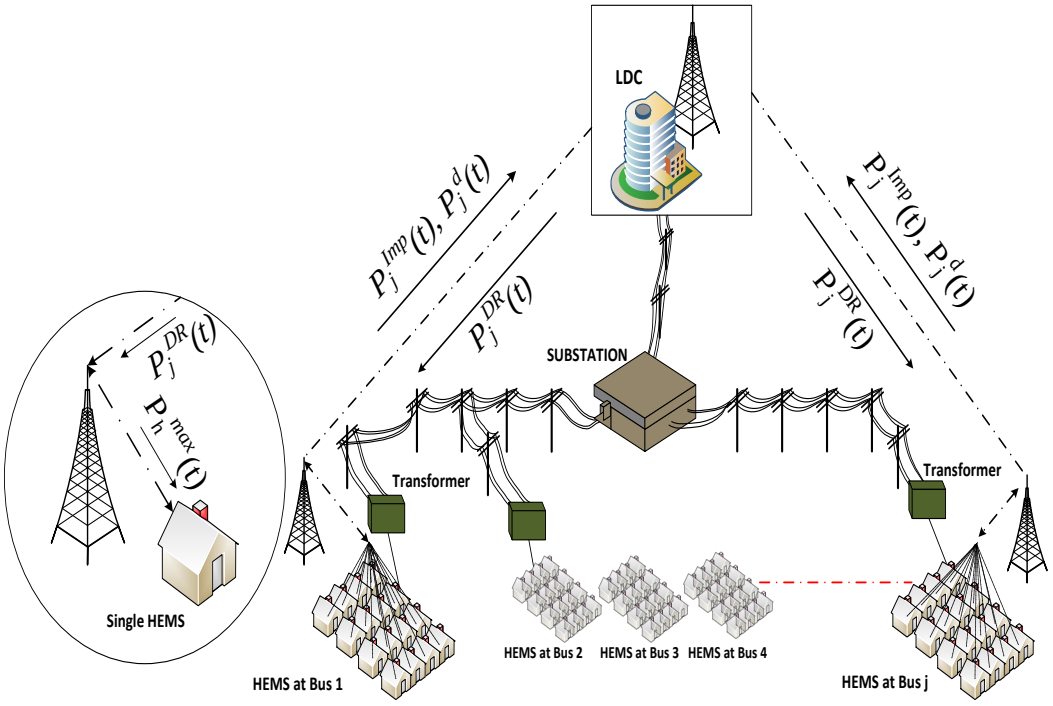


Figure 4.1: Schematic of Coordination between HEMS and LDC.

customer and other optimal decisions such as, how much power the house can sell to the LDC, is communicated to the LDC one day ahead (see Figure 4.1). For example, referring to Figure 3.1, the HEMS communicates to the LDC the optimal values of $P_{BPV}^{LDC}(t)$, $P_{PV}^{LDC}(t)$, and $P_{ESD}^{LDC}(t)$ denoting what it can sell to the LDC, as well as, $P_{LDC}^{H}(t)$ denoting what it would buy from the LDC.

The LDC gathers such information from all residential customers and aggregates them to construct the system load profile for next day. Using these bus-wise aggregated load profiles, the LDC carries out its operation analysis for the next day considering its objective (assumed, minimization of losses) and constraints. From this analysis, the hour-wise optimal DR amount required by the distribution system is determined. This bus-wise, hourly, optimal DR required, is proportionally allocated to each house and communicated back to the individual HEMS. The respective HEMS in turn incorporates these signals as a 'peak demand cap', and re-optimizes their respective appliance schedules. The proposed scheme converges when there is no further selection of DR requirement from the LDC's operations model (Figure 4.2).

The proposed coordination scheme is computationally very efficient and converges in

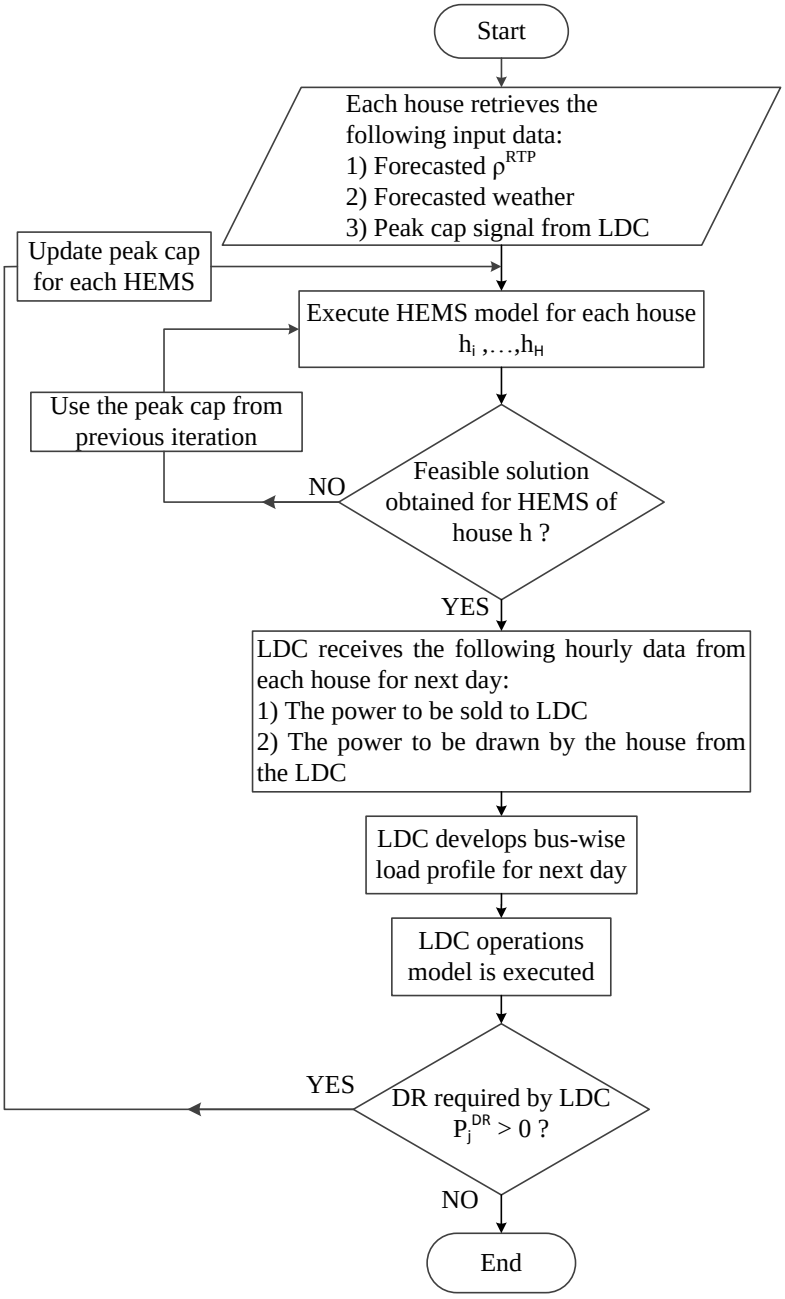


Figure 4.2: Coordination of Multiple HEMS and the LDC.

9 iterations, each iteration taking about one minute. The individual HEMS optimization programs will be executed in parallel by individual customers, and these require less than a minute to solve. Therefore, the proposed coordination scheme can be implemented in real-time or day ahead, easily.

4.2.2 Home Energy Management Systems

The HEMS model presented in Chapter 3 is considered. In order to represent each customer individually, unique activity levels and customer preferences (*i.e,* the required operation time and minimum up/down time of washer, dryer, stove, etc.) need to be considered. The optimal set of outputs from an HEMS includes: the decisions on appliance operation, the controlled load profile of the house, the energy sold/purchased to/from the LDC and the charging/discharging decisions of the ESD and battery.

The mathematical model of the HEMS is presented below:

Objective Function

The objective of the HEMS of a particular customer h is to minimize its total cost of energy, net of the revenue earned.

$$J_{h,j} = \sum_{t\in\mathcal{T}} \Bigg[\rho^{RTP}(t) \Big\{ \sum_{i\in\mathcal{A}\atop i\notin\{LI,ESD,BPV\}} P_{i,h,j} S_{i,h,j}(t) + \sum_{z\in LI} P_{LI_{z,h,j}} L_{z,h,j}(t) + \sum_{i\in\{BPV,ESD\}} P^{i}_{LDC,h,j}(t) + P_{D0,h,j} \Big\} + \sum_{i\in\{HT,WH\}} \rho^{GAS} G_{i,h,j} S_{i,h,j}(t) - \rho^{SEL} \Big\{ \sum_{i\in\{BPV,ESD\}} P^{LDC}_{i,h,j}(t) + P^{LDC}_{PV,h,j}(t) \Big\} \Bigg] \;\; \forall\; h \in \mathcal{H};\; j \in \mathcal{N} \quad (4.1)$$

Peak Load Constraint

This constraint ensures that the total load of the house h is within a limit specified by the LDC, $\widehat{P}^{max}_{h,j}(t)$.

$$\sum_{i\in\mathcal{A}} P_{i,h,j}S_{i,h,j}(t) + \sum_{z\in LI} P_{LI_{z,h,j}}L_{z,h,j}(t) + \sum_{i\in\{BPV,ESD\}} P^{LDC}_{i,h,j}(t) - \sum_{i\in\{BPV,ESD,PV\}} P^{H}_{i,h,j}(t) \leq \widehat{P}^{max}_{h,j}(t) \quad \forall h \in \mathcal{H};\ \forall j \in \mathcal{N} \quad (4.2)$$

$$\widehat{P}^{max}_{h,j}(t) = P^{max}_{h,j}(t) - P^{DR}_{j}(t)\big(\frac{P^{H}_{LDC,h,j}(t)}{P^{d}_{j}(t)}\big) \qquad \forall t \in \mathcal{T};\ \forall h \in \mathcal{H};\ \forall j \in \mathcal{N} \quad (4.3)$$

In constraint (4.2), the household load includes the appliances' consumption, charging power of the ESD and the PV panel battery; net of the power discharged from the ESD, the PV panel battery, and that generated by the PV panel. Constraint (4.3) presents the two-way communication between the LDC and the HEMS. The updated maximum specified demand of house h $\widehat{P}^{max}_{h,j}(t)$ is based on the previous maximum allowable demand $P^{max}_{h,j}(t)$ and a portion of the DR requested by the LDC at bus j.

The other constraints of the HEMS for house h remain the same, as given in (2.2) to (2.49) and (3.4) to (3.16).

4.2.3 LDC Operations Model

The main responsibility of the LDC is to deliver the power received from the transmission grid to the customers at the distribution level, such as small businesses and residential loads while maintaining the reliability and quality of service. The LDC operations model is presented below:

Objective Function

The objective of the LDC is to minimize the losses from the feeder power flows and power export to other entities; and to maintain DR requirements to minimum.

$$J = \sum_{t\in\mathcal{T}} \big[\frac{1}{2}\sum_{j=1}^{N}\sum_{k=1}^{N} G_{j,k}\big(V_j^2(t) + V_k^2(t) - 2V_j(t)V_k(t)\cos(\delta_j(t) - \delta_k(t))\big) + C_{LOSS}^{EXP} P_{LOSS}^{EXP}(t) + \sum_{j=1}^{N} C^{DR} P_j^{DR}(t)\big] \quad (4.4)$$

It should be noted that C^{DR} presents a large penalty factor associated with DR while C_{LOSS}^{EXP} represents the penalty factor associated with power loss from export to external grid. The objective function is subjected to the following power flow equations,

$$P_j^g(t) + P_j^{Imp}(t) + P_j^{DR}(t) - P_j^d(t) - P^{EXP}(t) = \sum_{k=1}^{N} V_j(t)V_k(t)Y_{j,k} \cos\big(\theta_{j,k}(t) + \delta_k(t) - \delta_j(t)\big) \qquad \forall t \in \mathcal{T};\ \forall (j,k) \in \mathcal{N} \quad (4.5)$$

$$Q_j^g(t) - Q_j^d(t) = -\sum_{k=1}^{N} V_j(t)V_k(t)Y_{j,k}\sin\big(\theta_{j,k}(t) + \delta_k(t) - \delta_j(t)\big) \qquad \forall t \in \mathcal{T};\ \forall (j,k) \in \mathcal{N} \quad (4.6)$$

Where,

$$P_j^{Imp}(t) = \sum_{h}^{H}\big(\sum_{i\in\{BPV,ESD\}} P_{i,h,j}^{LDC}(t) + P_{PV,h,j}^{LDC}(t)\big) \qquad \forall t \in \mathcal{T};\ \forall j \in \mathcal{N} \quad (4.7)$$

and

$$P_{LOSS}^{EXP}(t) = \alpha P^{EXP}(t) \quad (4.8)$$

$P_j^{Imp}(t)$ is the aggregate of the power sold to the grid by all the houses located at bus j, as given in (4.7). $P_{LOSS}^{EXP}(t)$ is the power loss incurred during actual power delivered to the external grid $P^{EXP}(t)$ while α is the associated loss factor, as shown in (4.8).

$$P_j^d(t) = \sum_{h}^{H} \Big(\sum_{\substack{i \in \mathcal{A} \\ i \notin \{LI, ESD, BPV\}}} P_{i,h,j} S_{i,h,j}(t) + \sum_{z \in LI} P_{LI_{z,h,j}} L_{z,h,j}(t) + \sum_{i \in \{BPV, ESD\}} P^i_{LDC,h,j}(t) + P_{D0,h,j} \Big) \quad \forall t \in \mathcal{T};\ \forall j \in \mathcal{N} \tag{4.9}$$

In (4.9), $P_j^d(t)$ represents the load at bus j and time t, as accumulated from multiple residential customers. In addition, the LDC operations model includes constraints on bus voltage and power drawn from the substation at each bus as given below:

$$V_j^{min} \leq V_j(t) \leq V_j^{max} \qquad \forall t \in \mathcal{T};\ \forall j \in \mathcal{N} \tag{4.10}$$

$$P_{g_j}^{min} \leq P_j^g(t) \leq P_{g_j}^{max} \qquad \forall t \in \mathcal{T};\ \forall j \in \mathcal{N} \tag{4.11}$$

4.3 Results and Discussions

The 33-bus distribution feeder system shows in Figure 4.3 [53] has been considered for the present studies. The LDC is responsible for managing the 33-bus system and meeting the demand of 1,295 houses connected at the feeder nodes. The number of houses at each bus is presented in Figure 4.4, which is obtained from the total load at the bus, and assuming that the connected load at a house is 7 kW and that all houses have the same amount of connected load.

It is crucial to evaluate the impact of DR on both customers and distribution system operation. The coordination scheme proposed and presented in Section 4.2 is applied to the test system and the convergence is obtained in 9 iterations after which $P_j^{DR}(t)$ becomes zero, as shown in Figure 4.5. It is also noted that the total cost to customers will increase over the iterations, as the LDC imposes grid constraints. The net effect of the imposition of the proposed coordination scheme is an increase of 1.8% in aggregated daily cost to customers.

Table 4.1 presents one typical household's appliance-wise consumption on a summer day. It can be noted that there is an increase in the consumption and energy cost between the initial appliance operation schedule and the final schedule after the 9^{th} iteration as a result of the peak cap imposed by the LDC, thus limiting the power that can be drawn from the grid at low price hours. It is important to mention that many households do not

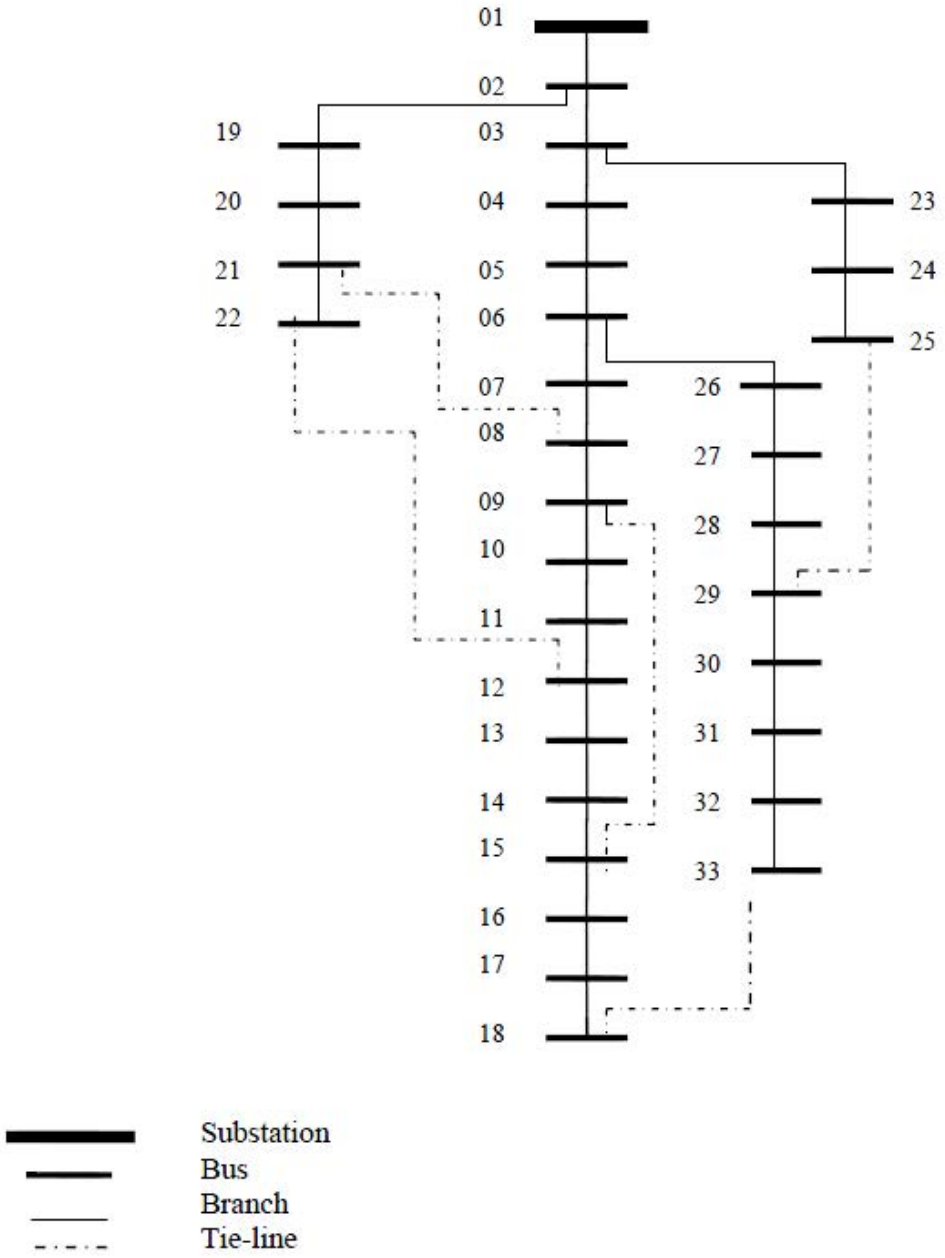


Figure 4.3: Layout of 33-Bus Feeder System [53].

change their initial consumption level either because the customers cannot reduce their

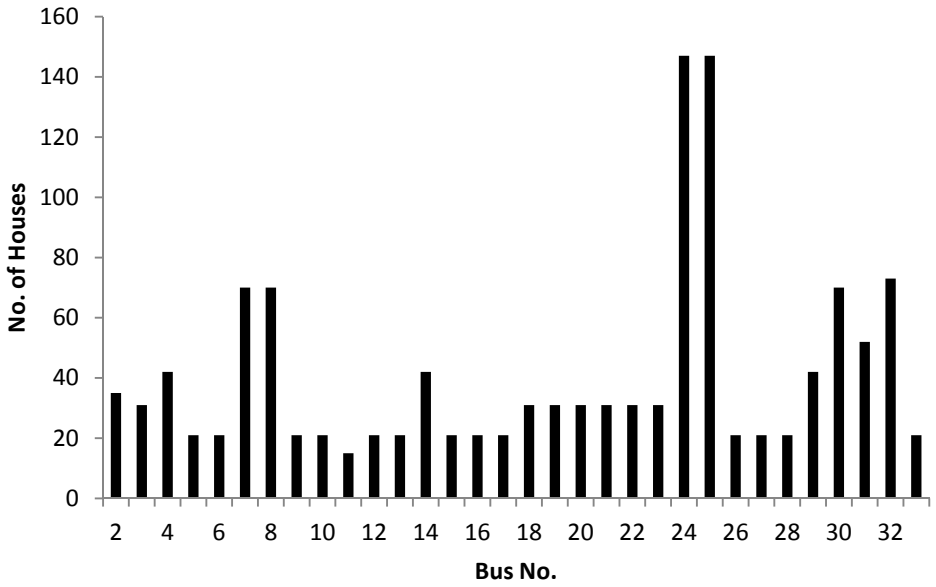


Figure 4.4: Number of Houses at Each Bus.

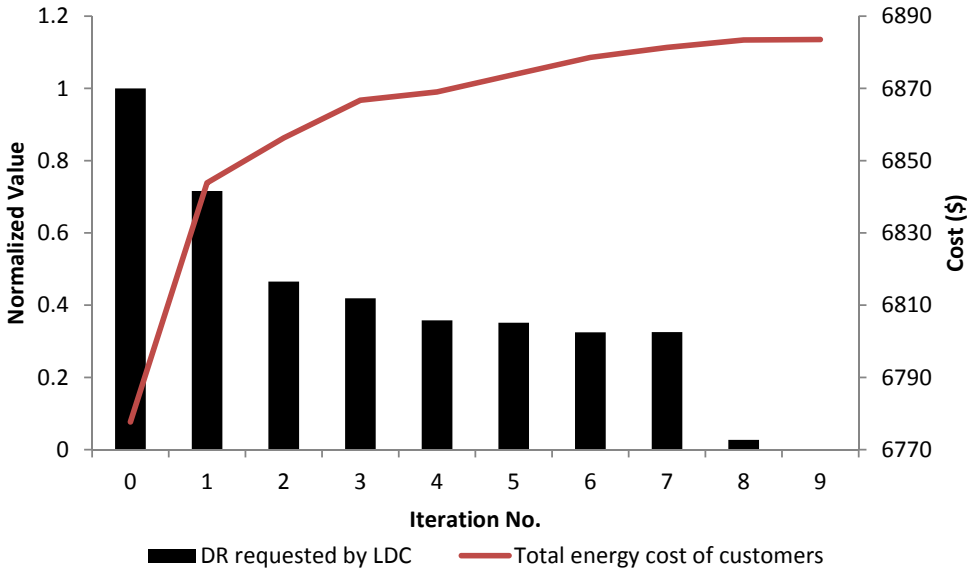


Figure 4.5: DR Required at Each Iteration.

power consumption any more or the LDC operations model does not opt for any DR at

Table 4.1: Energy Consumption of House #1,080

Device		Iteration 0		Iteration 9	
		Energy (kWh)	Cost ($)	Energy (kWh)	Cost ($)
Fridge		5.40	0.58	5.40	0.60
Water Heater	Elec.	0.90	0.09	0.90	0.10
	Gas	0.45	0.01	0.45	0.01
Lighting		4.98	0.56	4.98	0.56
AC		19.25	1.65	21.45	1.93
Dishwasher		1.40	0.11	1.40	0.23
Washer		0.90	0.07	0.90	0.13
Dryer		2.22	0.18	2.22	0.34
Stove		4.50	0.36	4.50	0.72
Pool		7.50	0.70	7.50	0.93
Total		47.50	4.31	49.70	5.56

Table 4.2: Energy Interchanges between Entities in House #1,080

From-To	Iteration 0			Iteration 9		
	DCH (kWh)	CHD (kWh)	REV ($)	DCH (kWh)	CHD (kWh)	REV ($)
ESD-LDC	17.68	21.11	3.40	18.72	22.06	3.52
BPV-LDC	18.76	21.78	3.64	18.00	20.59	3.40
PV-LDC	79.60	—	25.15	77.96	—	24.63
ESD-House	0.90	—	0.07	0.66	—	0.05
BPV-House	0.87	—	0.07	0.60	—	0.05
PV-House	0.00	—	0.00	1.64	—	0.18
Total	117.80	42.90	32.33	117.59	42.65	31.84

DCH: Discharged Power CHD: Charging Power REV: Revenue of House

that bus.

Table 4.2 presents a comparison of the energy transfers between various devices or entities, and the revenue or savings accrued by a particular house, house #1080. It is to

be noted that in iteration-0 the PV panel was supplying energy to the grid but as the LDC started imposing demand caps, some energy from the PV panel was diverted to supply the household's appliances in order to limit the power drawn from the distribution grid.

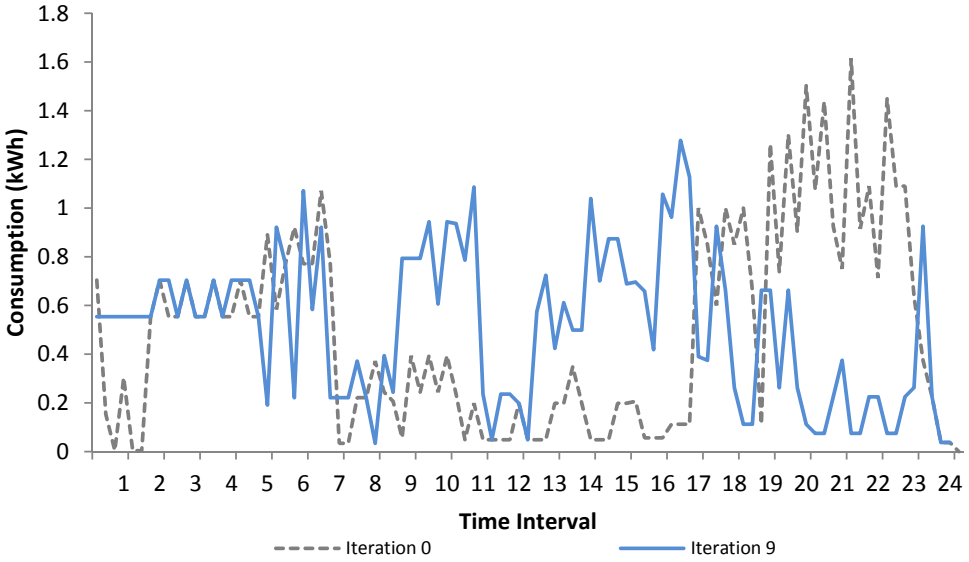


Figure 4.6: Optimal Load Profile for House #1,080.

Figure 4.6 illustrates the variation in the total household consumption for house #1080, between initial and final operational schedules. It is noted that the peak hours of power usage of the house is shifted as a result of peak signals sent by the LDC.

Figures 4.7 and 4.8 shows the temperature profile inside the refrigerator and the operation of the AC in the initial and final scheduling process, respectively. Furthermore, the large range between the minimum and maximum temperature limits indicates the customer consumption flexibility.

The energy level of the PV battery and the ESD are shown in Figures 4.9 and 4.10, respectively. The charging and discharging processes of the house devices are controlled by the HEMS only, which ensures the customers' right to use their energy on their household appliances or to sell it to the LDC.

The total power discharged to the LDC by the residential customers is shown in Figure 4.11. It is noted that a large amount of power is simultaneously discharged from the distributed energy resources within the houses; at the LDC level, this may result in surplus energy that needs to be consumed or sold to the upstream external grid.

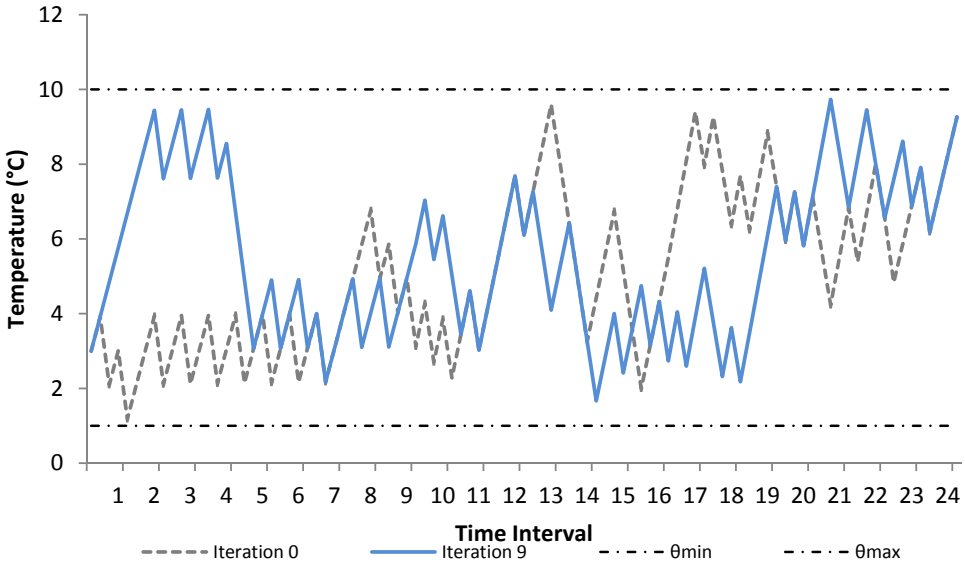


Figure 4.7: Optimal Temperature Profile inside Refrigerator in House #1,080.

Table 4.3: LDC Load Profile Characteristics

Iteration No.	Minimum Load	Peak Load	Average Load
	(kW)	(kW)	(kW)
Itr 0	369.075	8046.800	3314.141
Itr 9	388.500	6100.220	3358.070

It should be noted that the power imported from the external grid (Figure 4.12) is scheduled by the LDC based on the expected load and the power scheduled for purchase from residential customers.

Table 4.3 illustrates the improvements in the total load profile of the LDC. It is important to note that the proposed coordination scheme does not only shift the peak load, but it also reduces it and increases both the minimum and average load of the LDC, thus flattening the load profile.

Figure 4.13 shows the improvements in the average voltage profile at each bus over the day, which proves the usefulness of the proposed coordination scheme toward improvement in grid operations.

In this work, the problem converges in 9 iterations, as shown in Figure 4.5. It is important to mention that the number of iterations can vary based on the limits of the

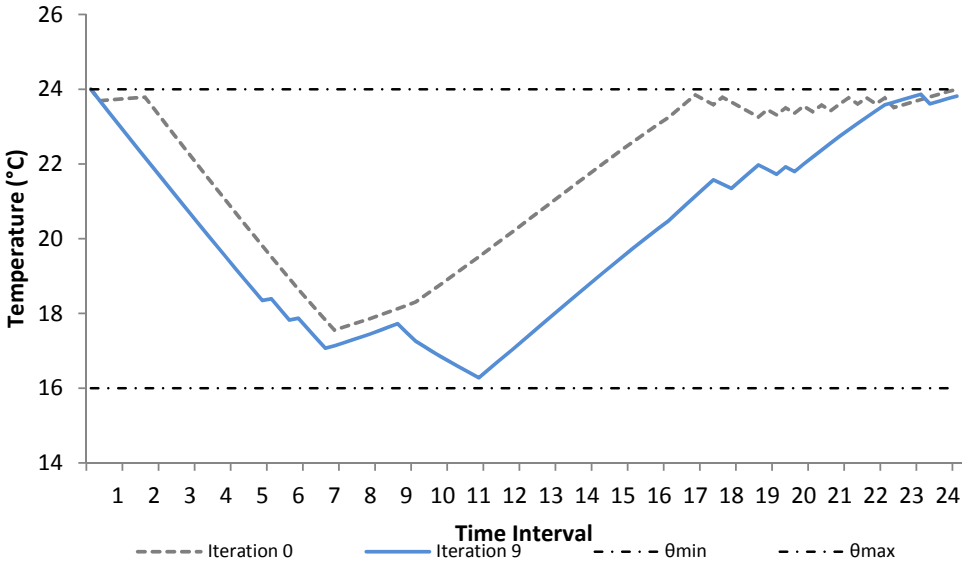


Figure 4.8: Optimal Indoor Temperature Profile in House #1,080.

power imported from the external grid and the customers' willingness to change their consumption behavior. In addition, the figure shows the impact of DR on the energy cost of the customers. The increase in the energy cost of the customers is due to the LDC peak signals which limits the customer energy consumption during low price hours. In fact, some customers do not influence the grid operation, so the LDC does not impose such a peak cap to limit the flexibility of their energy consumption.

4.4 Summary

This chapter proposed a novel coordination scheme between multiple HEMS and the LDC in order to enhance the grid operation and minimize the power losses. Basically, the proposed coordination scheme aims to evaluate the potential benefits of DR, in presence of HEMS, in helping the LDC to manage the grid operation.

A bi-level optimization framework was proposed to model the coordination problem. Consequently, the results of the proposed framework demonstrated considerable improvement in both the total load profile of the grid and the voltage level at each bus in the system, while maintaining the desired comfort level of each customer in the system.

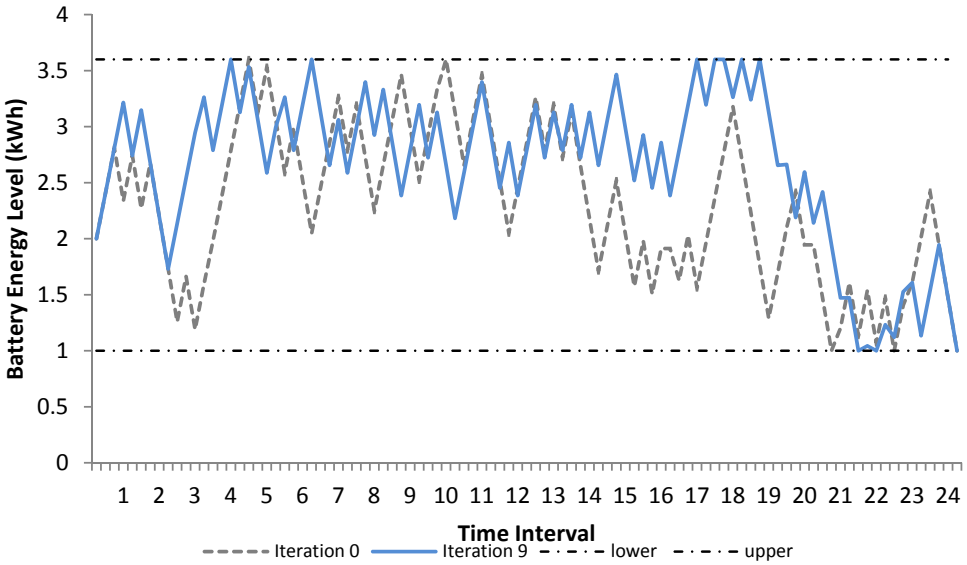


Figure 4.9: Optimal Energy Level of PV Battery in House #1,080.

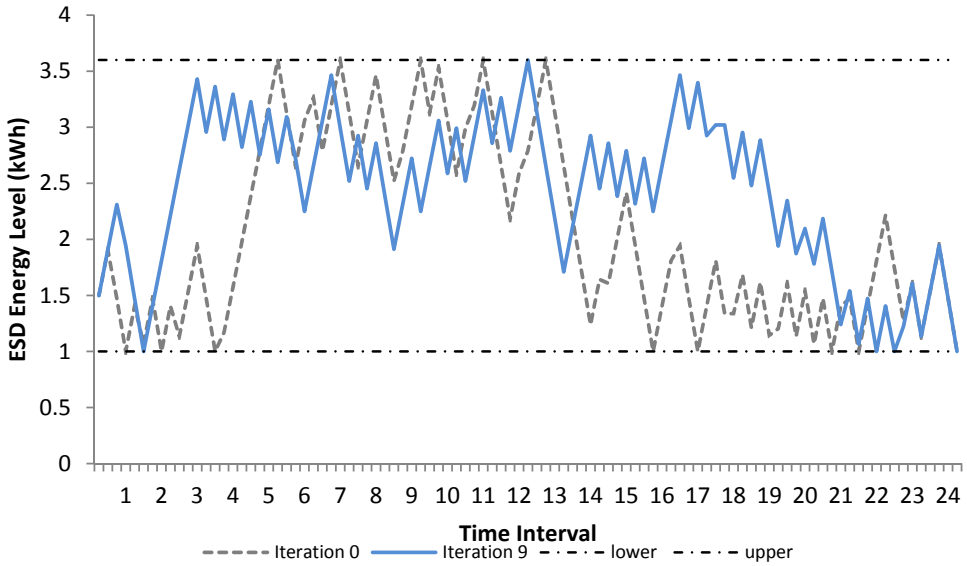


Figure 4.10: Optimal ESD Energy Level in House #1,080.

Improvement in the load profile of the LDC is achieved: Increasing in minimum (valley) load, increasing in the average load, and decreasing the peak load.

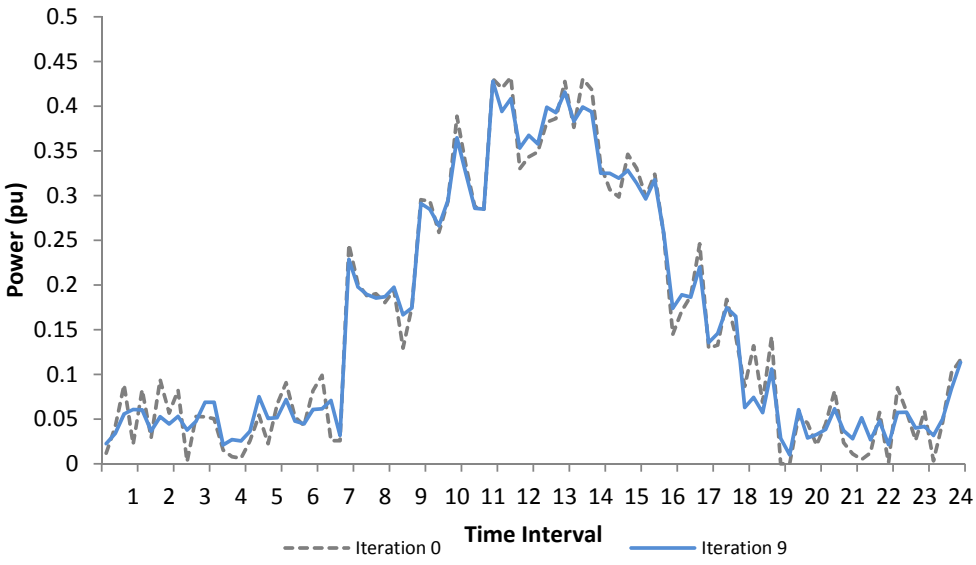


Figure 4.11: Total Power Received by LDC from Residential Customers.

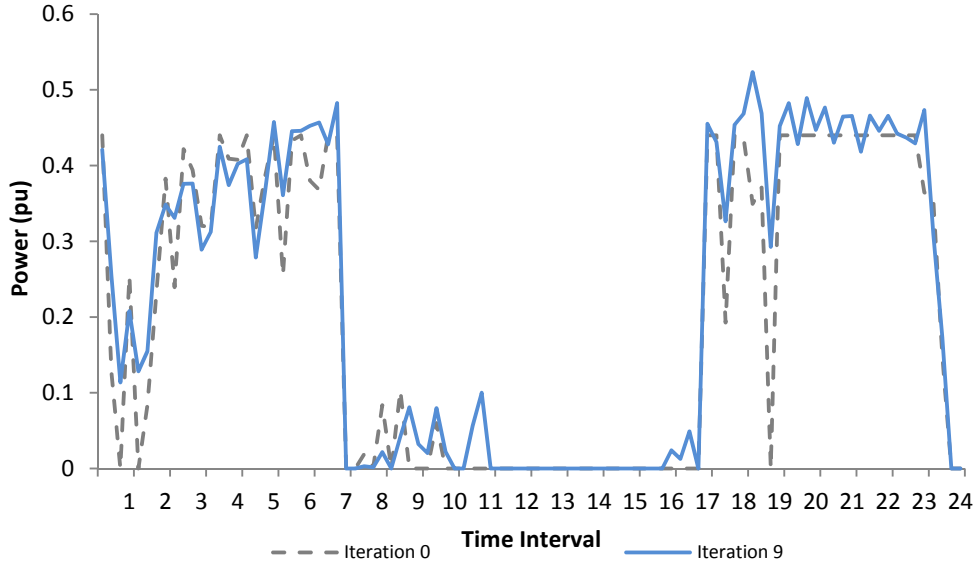


Figure 4.12: Power Imported from External Grid over Substation.

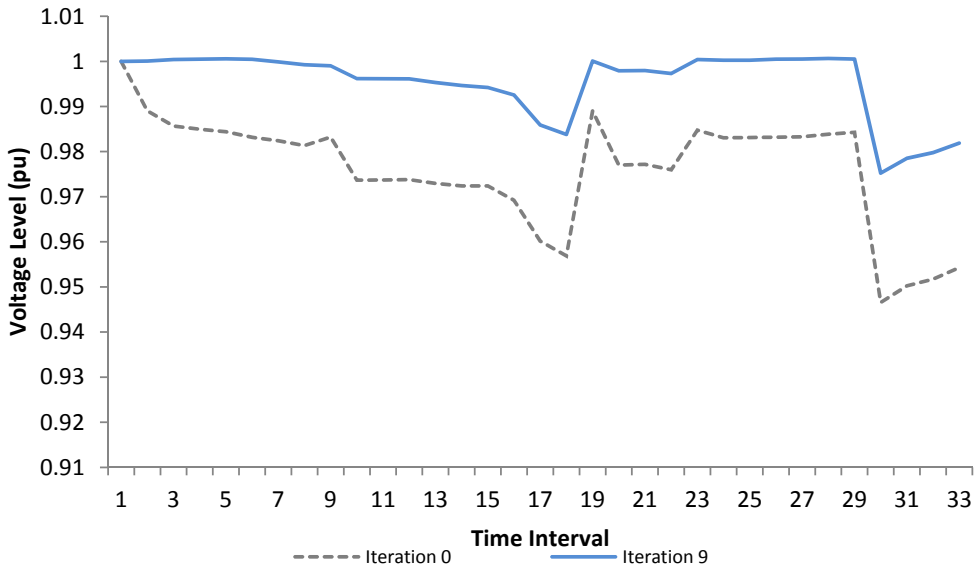


Figure 4.13: Average Voltage at Each Bus before and after Convergence.

Chapter 5

Conclusions

5.1 Summary

The research presented in this thesis concentrates mainly on the optimal operation of HEMS and the optimal coordination between multiple HEMS and the LDC. The residential sector accounts for a large portion of the electricity consumption and hence it is important to examine the energy management and efficient utilization of residential customer loads. This thesis presents some new models and coordination schemes for residential customers and the LDC to achieve improved operational performance. The motivations of this research, a brief review of the literature, and the research objectives were presented in Chapter 1.

The main contents of this thesis are presented briefly, as follows:

- Chapter 2 presents the background topics relevant to smart grids and the main concepts of DSM and DR. In addition, the fundamental mathematical model representation of the HEMS is described, which is the basis of this research. A brief discussion related to the concepts and applications of the MPC approach is also presented.
- Chapter 3 presents some new features and modifications to the mathematical model of the HEMS presented in Chapter 2, whereby the interrelationships between the LDC, ESD, and PV panel and its associated battery are represented in detail. It also proposes the application of the MPC approach to the HEMS in order to mitigate the impact of uncertainty associated with the external parameters. Some case studies and the relevant results of the proposed approach are discussed.

- Chapter 4 presents a novel coordination scheme between multiple HEMS and the LDC in order to enhance the grid operational performance, minimize the power losses, and create a provision for DR service from the residential customers. A bi-level optimization framework is presented. The effect of the proposed approach on the operation of the household appliances and the energy cost of a customer is examined.

5.2 Contributions of the Thesis

The main contributions of the research presented in this thesis are as follows:

- A comprehensive mathematical optimization model is formulated to model the power interchange between the house, the LDC, the ESD, and the PV with its associated battery. The HEMS mathematical model is an improvement over that reported in [31] with comprehensive representation of ESD and PV panel battery constraints. A detailed MPC approach is applied to mitigate the impact of uncertainty in the external parameters of the HEMS, such as activity level, weather, and RTP. The results of the proposed approach show an improvement in the decision process of the HEMS and a possibility of increasing the customer savings.

- A large dataset comprising multiple HEMS is developed with unique parameters and preferences for each HEMS such as activity level, and minimum up-time of the appliances, respectively, to represent the complete profile of a distribution feeder system with residential loads.

- A novel coordination scheme between multiple HEMS and the LDC is proposed that seeks to enhance the grid operational and create a provision of DR. A bi-level optimization framework is formulated to coordinate a large number of HEMS with the LDC in order to evaluate the contribution of the customers to provide DR services. A 33-bus system is developed as a model of the LDC. The proposed approach shows an improvement in the load profile of the LDC as well as the voltage profile at each bus in the system but with an increase of 1.8% in daily energy cost of the customers.

5.3 Future Work

Based on the research presented in this thesis, some suggestions for future work is presented below:

- In Chapter 3, the MPC-based HEMS is presented for a specific set of customer preferences. A stochastic HEMS model need be developed to generate more than one scenario of customer choices and behaviour patterns, and hence provide a better representation of the customer loads and more precise analysis of the inputs.
- In Chapter 4, the HEMS model does not consider the MPC approach within the proposed coordination scheme with the LDC. In a future work, multiple MPC-based HEMSs can be modeled to tackle the uncertainty in the system parameters, which can provide better insight into the residential DR contributions.
- PEVs are expected to penetrate the residential customers significantly in the coming years and these need to be considered within the HEMS models and consequently in the coordination scheme with the LDC, to examine their viability in DR service provisions.

References

[1] "International energy outlook 2013," U.S. Energy Information Administration, Tech. Rep. [Online]. Available: http://www.eia.gov/forecasts/archive/ieo13/pdf/0484(2013).pdf

[2] "Sources of greenhouse gas emissions," U.S. Environmental Protection Agency, Tech. Rep. [Online]. Available: http://www3.epa.gov/climatechange/ghgemissions/sources.html

[3] M. Jaccard, C. E. Association, C. G. Association *et al.*, "Demand side management potential in canada: energy efficiency study," 2006.

[4] "Smart meters," Hydro One, Tech. Rep. [Online]. Available: http://www.hydroone.com/myhome/myaccount/mymeter/pages/smartmeters.aspx

[5] "The smart grid: an introduction." [Online]. Available: http://energy.gov/sites/prod/files/oeprod/DocumentsandMedia/DOE_SG_Book_Single_Pages(1).pdf

[6] M. Erol-Kantarci and H. Mouftah, "Energy-efficient information and communication infrastructures in the smart grid: A survey on interactions and open issues," *Commun. Surveys Tuts.*, vol. 17, no. 1, pp. 179–197, Firstquarter 2015.

[7] S. Depuru, L. Wang, V. Devabhaktuni, and N. Gudi, "Smart meters for power grid; challenges, issues, advantages and status," in *Power Systems Conference and Exposition (PSCE), 2011 IEEE/PES*, March 2011, pp. 1–7.

[8] "Benefits of demand response in electricity markets and recommendations for achieving them," U.S. Dept. Energy, Tech. Rep., 2006.

[9] J. Kondoh, N. Lu, and D. Hammerstrom, "An evaluation of the water heater load potential for providing regulation service," *IEEE Trans. Power Syst.*, vol. 26, no. 3, pp. 1309–1316, Aug 2011.

[10] N. Lu, "An evaluation of the hvac load potential for providing load balancing service," *IEEE Trans. Smart Grid*, vol. 3, no. 3, pp. 1263–1270, Sept 2012.

[11] C.-M. Chu and T.-L. Jong, "A novel direct air-conditioning load control method," *IEEE Trans. Power Syst.*, vol. 23, no. 3, pp. 1356–1363, Aug 2008.

[12] N. Ruiz, I. Cobelo, and J. Oyarzabal, "A direct load control model for virtual power plant management," *IEEE Trans. Power Syst.*, vol. 24, no. 2, pp. 959–966, May 2009.

[13] C. Babu and S. Ashok, "Peak load management in electrolytic process industries," *IEEE Trans. Power Syst.*, vol. 23, no. 2, pp. 399–405, May 2008.

[14] S. Majumdar, D. Chattopadhyay, and J. Parikh, "Interruptible load management using optimal power flow analysis," *IEEE Trans. Power Syst*, vol. 11, no. 2, pp. 715–720, May 1996.

[15] K. Bhattacharya, M. Bollen, and J. Daalder, "Real time optimal interruptible tariff mechanism incorporating utility-customer interactions," *IEEE Trans. Power Syst*, vol. 15, no. 2, pp. 700–706, May 2000.

[16] K.-Y. Huang, H.-C. Chin, and Y.-C. Huang, "A model reference adaptive control strategy for interruptible load management," *IEEE Trans. Power Syst.*, vol. 19, no. 1, pp. 683–689, Feb 2004.

[17] F. Aminifar, M. Fotuhi-Firuzabad, and M. Shahidehpour, "Unit commitment with probabilistic spinning reserve and interruptible load considerations," *IEEE Trans. Power Syst.*, vol. 24, no. 1, pp. 388–397, Feb 2009.

[18] A. Moholkar, P. Klinkhachorn, and A. Feliachi, "Effects of dynamic pricing on residential electricity bill," in *Power Systems Conference and Exposition, 2004. IEEE PES*, Oct 2004, pp. 1030–1035 vol.2.

[19] S. Althaher, P. Mancarella, and J. Mutale, "Automated demand response from home energy management system under dynamic pricing and power and comfort constraints," *IEEE Trans. Smart Grid*, vol. 6, no. 4, pp. 1874–1883, July 2015.

[20] T. E. Andreas V. Stokke, Gerard L. Doorman, "An analysis of a demand charge electricity grid tariff in the residential sectors," *Energy Efficiency*, vol. 3, no. 3, pp. 267–282, Sept 2010.

[21] D.-C. Wei and N. Chen, "Air conditioner direct load control by multi-pass dynamic programming," *Power Systems, IEEE Transactions on*, vol. 10, no. 1, pp. 307–313, Feb 1995.

[22] A. Molina, A. Gabaldon, J. Fuentes, and C. Alvarez, "Implementation and assessment of physically based electrical load models: Application to direct load control residential programmes," *IEE Proc. Gener. Transmiss. Distrib.*, vol. 150, no. 1, pp. 61–66, Jan 2003.

[23] M. Sullivan, J. Bode, B. Kellow, S. Woehleke, and J. Eto, "Using residential ac load control in grid operations: Pg&e's ancillary service pilot," *IEEE Trans. Smart Grid*, vol. 4, no. 2, pp. 1162–1170, June 2013.

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

[25] M. Pedrasa, E. Spooner, and I. MacGill, "Robust scheduling of residential distributed energy resources using a novel energy service decision-support tool," in *Innovative Smart Grid Technologies (ISGT), 2011 IEEE PES*, Jan 2011, pp. 1–8.

[26] M. Pedrasa, T. Spooner, and I. MacGill, "Coordinated scheduling of residential distributed energy resources to optimize smart home energy services," *Smart Grid, IEEE Transactions on*, vol. 1, no. 2, pp. 134–143, Sept 2010.

[27] J. H. Yoon, R. Baldick, and A. Novoselac, "Dynamic demand response controller based on real-time retail price for residential buildings," *IEEE Trans. Smart Grid*, vol. 5, no. 1, pp. 121–129, Jan 2014.

[28] Y. Wang, X. Lin, and M. Pedram, "Adaptive control for energy storage systems in households with photovoltaic modules," *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 992–1001, March 2014.

[29] Y. Ozturk, D. Senthilkumar, S. Kumar, and G. Lee, "An intelligent home energy management system to improve demand response," *IEEE Trans. Smart Grid*, vol. 4, no. 2, pp. 694–701, June 2013.

[30] ——, "An intelligent home energy management system to improve demand response," *IEEE Trans. Smart Grid*, vol. 4, no. 2, pp. 694–701, June 2013.

[31] M. Bozchalui, S. Hashmi, H. Hassen, C. Canizares, and K. Bhattacharya, "Optimal operation of residential energy hubs in smart grids," *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 1755–1766, Dec. 2012.

[32] Z. Wu, S. Zhou, J. Li, and X.-P. Zhang, "Real-time scheduling of residential appliances via conditional risk-at-value," *IEEE Trans. Smart Grid*, vol. 5, no. 3, pp. 1282–1291, May 2014.

[33] X. Chen, T. Wei, and S. Hu, "Uncertainty-aware household appliance scheduling considering dynamic electricity pricing in smart home," *IEEE Trans. Smart Grid*, vol. 4, no. 2, pp. 932–941, June 2013.

[34] H. Nguyen, D. Nguyen, and L. Le, "Energy management for households with solar assisted thermal load considering renewable energy and price uncertainty," *IEEE Trans. Smart Grid*, vol. 6, no. 1, pp. 301–314, Jan 2015.

[35] P. Du and N. Lu, "Appliance commitment for household load scheduling," *IEEE Trans. Smart Grid*, vol. 2, no. 2, pp. 411–419, June 2011.

[36] C. Chen, J. Wang, Y. Heo, and S. Kishore, "MPC-Based appliance scheduling for residential building energy management controller," *IEEE Trans. Smart Grid*, vol. 4, no. 3, pp. 1401–1410, Sept 2013.

[37] C. Vivekananthan, Y. Mishra, and F. Li, "Real-time price based home energy management scheduler," *Power Systems, IEEE Transactions on*, vol. 30, no. 4, pp. 2149–2159, July 2015.

[38] T. Kim and H. Poor, "Scheduling power consumption with price uncertainty," *IEEE Trans. Smart Grid*, vol. 2, no. 3, pp. 519–527, Sept 2011.

[39] W. Shi, N. Li, X. Xie, C.-C. Chu, and R. Gadh, "Optimal residential demand response in distribution networks," *IEEE J. Sel. Areas Commun.*, vol. 32, no. 7, pp. 1441–1450, July 2014.

[40] Y. Li, B. L. Ng, M. Trayer, and L. Liu, "Automated residential demand response: Algorithmic implications of pricing models," *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 1712–1721, Dec 2012.

[41] A. Safdarian, M. Fotuhi-Firuzabad, and M. Lehtonen, "A distributed algorithm for managing residential demand response in smart grids," *IEEE Trans. Ind. Informat*, vol. 10, no. 4, pp. 2385–2393, Nov 2014.

[42] "Smart grids roadmap," International Energy Agency, Tech. Rep. [Online]. Available: https://www.iea.org/publications/freepublications/publication/smartgrids_roadmap.pdf

[43] A. Chuang and C. Gellings, "Demand-side integration in a restructured electric power industry," *CIGRE, number Paper C6-105, Session*, 2008.

[44] F. Staff, "Assessment of demand response and advanced metering," *Federal Energy Regulatory Commission, Docket AD-06-2-000*, 2006. [Online]. Available: http://www.ferc.gov/legal/staff-reports/12-20-12-demand-response.pdf

[45] M. Albadi and E. El-Saadany, "Demand response in electricity markets: An overview," in *Proc. IEEE Power Eng. Soc. Gen. Meeting*, June 2007, pp. 1–5.

[46] C. Gellings, "The concept of demand-side management for electric utilities," *Proc. IEEE*, vol. 73, no. 10, pp. 1468–1470, Oct 1985.

[47] A. B. Anderson, ABMS Bradley and M. Salciccioli., "Model predictive control," 2006. [Online]. Available: https://controls.engin.umich.edu/wiki/index.php/MPC

[48] A. Parisio, E. Rikos, and L. Glielmo, "A model predictive control approach to microgrid operation optimization," *IEEE Trans. Control Syst. Technol*, vol. 22, no. 5, pp. 1813–1827, Sept 2014.

[49] Independent Electrcity System Operator, "MicroFIT program." [Online]. Available: http://microfit.powerauthority.on.ca

[50] S. A. Hashmi, "Evaluation and improvement of the residential energy hub management system," Master's thesis, University of Waterloo, Sept. 2010.

[51] Independent Electrcity System Operator, "Hourly ontario energy price (HOEP) report." [Online]. Available: http://www.ieso.ca/pages/power-data/default.aspx#download

[52] Government of Canada, "Historical climate data." [Online]. Available: http://climate.weather.gc.ca

[53] A. Algarni, "Operational and planning aspects of distribution systems in deregulated electricity markets," PhD Thesis, University of Waterloo, Department of Electrical and Computer Engineering, 2009.