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Domestic Space Heating Load Management in Smart Grid

Potential Benefits and Realization

Mubbashir Ali

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Abstract

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Abstract

In future power systems, intermittent renewable generation sources are expected to have a considerable segment in the total generation assortment. Given the inconsistency and unpredictability of intermittent renewable energy sources, the fast growing integration of intermittent renewable generation could negatively affect the operations of power system. Since demand response (DR) is a flexible load shaping tool, it is viewed as a practicle solution to enhance the overall system efficiency in future smart grids.

The overall objective of this dissertation is to evaluate the possible advantages of responsive domestic heating, ventilation, and air conditioning (HVAC) loads for DR applications and the development of practical frameworks to realize them. Due to its considerable share in energy consumption profile and operational flexibility, the DR treatment is restricted to the HVAC load. The DR applications include the minimization of customer energy cost and increased utilization of intermittent generation while taking into account customers' thermal comfort. The goal of this dissertation is divided into three major tasks so as to describe the DR benefits for various applications. A comprehensive assessment of HVAC DR potential for up/down ramping is suggested in the first task. The second task proposes generic frameworks for HVAC load management that are directed towards minimizing customer energy payments while taking customer's preferences into consideration. Finally, the last task establishes tools for increased utilization of wind generation by optimally managing the cyclic operation of responsive HVAC loads.

To accomplish this dissertation objective, simulations are conducted using the proposed frameworks for Finnish systems. The following significant deductions are indicated in the results. The flexibility to unleash DR for up/down ramping is affected by the heat demand requirements, while upward DR is strongly limited by HVAC power ramping capability and allowed thermal comfort limits. Furthermore, utilization of DR will greatly shrink customer energy payments which mainly depends on the permissible indoor temperature deviation. The monetary savings are value added when DR is jointly activated in both energy and balancing market using the proposed model. Additionally, it is revealed that joint optimization of DR and RTTR will attain greater utilization of wind generation in distribution networks as weighed against DR activation alone.

The developed models can be utilized by power system operators and stake holders to enhance the system operation. Consequently, the developed tools will help to achieve a better understanding of HVAC DR potential and advantages and will act as support to maximize the DR enrollment at the end user level.

Keywords Demand response, HVAC, intermittent generation balancing, smart grids.

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Espoo, 28 April 2016

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List of Publications

This thesis consists of an overview of the following seven publications, hereafter, referred to as Roman numerals in the text:

I. **M. Ali**, A. Safdarian, and M. Lehtonen, “Demand response potential of residential HVAC loads considering users preferences,” in *IEEE PES Innovative Smart Grid Technologies Conference Europe*, 12-15 Oct. 2014, Istanbul, Turkey.

II. **M. Ali**, J. Jokisalo, K. Siren, and M. Lehtonen, “Combining the demand response of direct electric space heating and partial thermal storage using LP optimization,” *Electric Power Systems Research*, vol. 106, pp. 160-167, Jan. 2014.

III. **M. Ali**, J. Jokisalo, K. Siren, A. Safdarian, and M. Lehtonen, “A user-centric demand response framework for residential heating, ventilation, and air-conditioning load management,” *Electric Power Components and Systems*, vol. 44, no. 1, pp. 99-109, Jan. 2016.

IV. **M. Ali**, A. Alahäivälä, F. Malik, M. Humayun, A. Safdarian, and M. Lehtonen, “A market-oriented hierarchical framework for residential demand response,” *International Journal of Electrical Power and Energy Systems*, vol. 69, pp. 257-263, Jan. 2015.

V. **M. Ali**, M. Humayun, A. Safdarian, M. Degefa, and M. Lehtonen, “A Framework for activating residential HVAC demand response for wind generation balancing,” in *IEEE PES Innovative Smart Grid Technologies Conference Asia*, 4-6 Nov. 2015, Bangkok, Thailand.

VI. **M. Ali**, M. Degefa, M. Humayun, A. Safdarian, and M. Lehtonen, “Increased utilization of wind generation by coordinating the demand response and real-time thermal rating,” *IEEE Transactions on Power Systems*, in press (accepted for publication), 2015.

VII. **M. Ali**, M. Humayun, M. Degefa, A. Safdarian, and M. Lehtonen, “Optimal DR services from HVAC load aggregator in distribution systems hosting wind generation,” in *IEEE PES Innovative Smart Grid Technologies Conference Asia*, 4-6 Nov. 2015, Bangkok, Thailand.

Author's Contribution

In all of the publications [I]–[VII], the author of the thesis has the highest contribution. The author was accountable for developing the ideas and concepts, conducting the simulations, analyzing the observations and results, and finally writing the research papers. The contributions from the co-authors are indicated in the following.

I. A. Safdarian has contributed through feedback on results. M. Lehtonen supervised the work.

II. J. Jokisalo provided the building thermal model and K. Siren contributed through the discussion on the subtleties of building thermal model and also by commenting on the initial draft. M. Lehtonen supervised the work.

III. J. Jokisalo and K. Siren contributed in this publication by providing a detailed building model and parameters and also providing feedback on the draft version of paper. A. Safdarian helped though his detail comments and feedback on results. M. Lehtonen supervised the work.

IV. The co-authors of this article contributed in the manuscript through discussions and comments. M. Lehtonen supervised the work.

V. M. Humayun has strongly contributed through discussions and comments during the work. A. Safdarian suggested some sensitivity analyses and also commented on the initial and revised draft. M. Degefa played his part by commenting on the initial draft. M. Lehtonen directed the work.

VI. M. Degefa has contributed with the integration of the RTTR model in the optimization model and helped in setting up the optimization. M. Humayun contributed by suggesting some key sensitivity analyses and commenting on the entire draft. A. Safdarian helped through his constructive comments and thorough feedback on results. M. Lehtonen supervised the work.

VII. The co-authors contributed in the manuscript through discussions and comments. M. Lehtonen directed the work.

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List of Abbreviations

Abbreviation	**Description**
AMR	Automatic meter reading
ARIMA	Autoregressive integrated moving average
CoV	Coefficient of variance
DG	Distributed generation
DR	Demand response
EWH	Electric water heater
GAMS	General algebraic modelling system
HVAC	Heating, ventilation, and air conditioning
RTTR	Real-time thermal rating
SHEM	Smart home energy management system
STR	Static thermal rating
ToU	Time of Use
TSO	Transmission system operator

List of Symbols

Symbol	**Description**
b_t^e	Bonus price during time t (€/kWh)
f	Index of feeder
i, j	Indices of bus
lh	Length of optimization horizon
m^w	Variable that provides a level of freedom to curtail wind generation through regulating blades
n	Index of customers
$prob(\varepsilon)$	Probability of scenario ε
q_t	Heat demand at time t (kW)
r_t	Auxiliary variable in robust optimization model
t	Index of time
t_{end}	Event driven DR ending time
t_{start}	Event driven DR starting time
w_c	Wind speed corresponding to cut in speed (m/s)
w_r	Wind speed corresponding to rated power (m/s)
w_w	Wind speed (m/s)
C_a	Heat capacity of the indoor air (MJ/ ºC)
C_{am}	Combined heat capacity of air and building fabric (kJ/ ºC)
C_m	Heat capacity of the building fabric (MJ/ ºC)

C_t^e	Electricity wholesale price at time t (€/kWh)
$C_t^{e,\max}$	Upper bound of power price at time t (€/kWh)
$C_t^{e,\min}$	Lower bound of power price at time t (€/kWh)
E^{cap} (E_n^{cap})	Maximum thermal storage capacity (of customer n) (kWh)
E^{lh} (E_n^{lh})	Energy demand during optimization horzion (of customer n) (kWh)
H_{ame}	Joint thermal conductance of roof and wall (W/ºC)
H_e	Virtual conductance between external and internal temperature node points (W/ºC)
H_g	Ground thermal conductance (W/ºC)
H_m ,H_y	Thermal conductances which allows the C_m to grouped in the mass node point (W/ºC)
H_x	Ventilation air heat conductance (W/ºC)
K	Constant
L	Set of scenario
LoC	Loss of thermal comfort
N	Set of customers
P_r	Rated power of a wind turbine (kW)
P_w	Active power output of a wind turbine (kW)
$P^{ch,dhw,\max}$	Power rating of domestic hot water unit (kW)
$P^{DEH,\max}$	Rated power of direct electric heating system (kW)
$P^{hvac,\max}$ ($P_n^{hvac,\max}$)	Power rating of HVAC (of customer n) (kW)
$P^{TS,\max}$	Rated power of thermal storage (kW)
P_f^{ij} / Q_f^{ij} / S_f^{ij}	Active/Reactive/Apparent power flowing through feeder f from bus i to bus j
P_l^i / Q_l^i	Active/Reactive load served by the secondary substation at bus i
P_{lvg}^i / Q_{lvg}^i	Active/Reactive power of renewable generation installed in the low voltage network served by the substation at bus i

$P_{lvgc}^{i} / Q_{lvgc}^{i}$	Active/Reactive generation curtailment at the low voltage side
$P_{mvg}^{i} / Q_{mvg}^{i}$	Active/Reactive generation at the medium voltage side of the secondary substation at bus i
$P_{mvgc}^{i} / Q_{mvgc}^{i}$	Active/Reactive generation curtailment at the medium voltage side of the secondary substation at bus i
$P_{n,t}^{critical}$	Power of all critical appliances at time t of customer n (kW)
$P_{s}^{i} / Q_{s}^{i} / S_{s}^{i}$	Active/Reactive/Apparent power flowing through the transformers in the secondary substations connected to bus i
$P_{t}^{ch,dhw}$	Charging power of domestic hot water unit at time t (kW)
P_{t}^{DEH}	Power of direct electric heating system at time t (kW)
P_{t}^{hvac} ($P_{n,t}^{hvac}$)	Electrical power supplied to HVAC unit at time t (of customer n) (kW)
P_{t}^{TS}	Charging power of thermal storage at time t (kW)
$Q^{hvac,\max}$ ($Q_{n}^{hvac,\max}$)	Rated thermal output power of HVAC (of customer n) (kW)
Q_{t}^{hvac} ($Q_{n,t}^{hvac}$)	HVAC thermal output power at time t (of customer n) (kW)
Q_{t}^{m}	Heat released from the thermal masses of building structures at time t (kW)
$Q_{t}^{m,\max}$	Maximum amount of heat that can be released from the thermal masses of building structures at time t (kW)
$Q_{t}^{m,\min}$	Minimum amount of heat that can be released from the thermal masses of building structures at time t (kW)
$S_{s\_RTTR\_LIM}^{i}$	RTTR capacity limit for the substation transformer
$S_{f\_RTTR\_LIM}^{ij}$	RTTR capacity of feeder f from bus i to bus j
SoC_{t} ($SoC_{n,t}$)	State of charge of thermal storage at time t (of customer n)
$SoC_{t_{end}}$ ($SoC_{n,t_{end}}$)	Final level of state of charge of thermal storage (of customer n)
$SoC_{t_{o}}$ ($SoC_{n,t_{o}}$)	Initial level of state of charge of thermal storage (of customer n)
$SoC^{\max}$ ($SoC_{n}^{\max}$)	Maximum allowable state of charge of thermal storage (of customer n)

$SoC^{\min}$ ($SoC_n^{\min}$)	Minimum allowable state of charge of thermal storage (of customer *n*)
$S_{n,t}^{total}$	Total apparent load at time *t* of customer *n* (kWh)
T	Set of time
T_t^a ($T_{n,t}^a$)	Indoor ambient temperature of dwelling at time *t* (of customer *n*) (°C)
T_t^g	Ground temperature at time *t* (°C)
T_t^m	Thermal mass temperature at time *t* (°C)
T_t^{set} ($T_{n,t}^{set}$)	Set point temperature of dwelling at time *t* (of customer *n*) (°C)
T_t^x	Ventilation supply air temperature (°C)
V_{LOW}^i / V_{UP}^i	Lower/Upper acceptable voltage magnitude level at secondary substation at bus *i*
V^i	Voltage magnitude at bus *i*
V^j	Voltage magnitude at bus *j*
W^n	Weighting coefficient for setting comfort priority over demand response control of customer *n*
W_t	Coefficient representing load adjustment priority at time *t*
$X_t{}^p$	Penalty price for altering the set point temperature of dwelling at time *t* (€/kWh)
X^λ	Wind energy curtailment cost (€/MWh)
Y_f^{ij}	Admittance magnitude associated with feeder f
Z^{expected}	Customer's expected energy cost (€)
α	Weighting coefficient between expected electricity cost and discomfort cost
β	Weighting coefficient between expected cost and risk
γ	Binary variable (1 for load increment, 0 for load reduction)
δ_i / δ_j	Phase angle at bus *i*/ bus *j*
ξ_t ($\xi_{n,t}$)	Storage thermal losses at time *t* (of customer *n*) (kWh)

η (η^n)	Storage loss coefficient (of customer *n*)
θ_f^{ij}	Phase associated with feeder f
λ_t	Wind generation at time *t* (kW)
ε	Index of scenario
μ	Parameter for setting HVAC power operating limits
ν_t^{bin}	Binary variable, 1 if total wind generation is greater than modified load profile, 0 otherwise
π	Weighting coefficient between expected demand and stored heat energy
σ	Parameter for setting *SoC* opearting limits
τ_t, ψ	Dual variables of robust optimization model
υ_t	Demand limit at time *t* (kW)
ϕ (ϕ_n)	Internal temperature dead-band (of customer *n*) (ºC)
χ	Binary variable for (1) up and (-1) down regulation
Γ_t	Conventional generation at time *t* (kW)
Δt	Duration of time slot (hours)
ΔP_t^{hvac}	Deviation from original HVAC schedule at time *t* (kW)
Π	Parameter for controlling the robustness
Ψ^f	Financial risk (€)
Ω	Weighting coefficient between demand response and comfort

1. Introduction

1.1 Background

Globally, power grids are facing a list of acute challenges such as aging infrastructure, limiting energy resources, growing expectation of customers comfort level [1], and substantial load growth with the emergence of electric vehicles. This creates urgent requirements for the optimal utilization of power grids [2], [3]. As a result, a key tool to counter the above mentioned challenges is demand response (DR) [4]. DR is believed to be one of the integral components in enabling more efficient power systems operation of the future smart grid. The sheer progression of reliable communication and automatic meter reading (AMR) systems has paved the way for residential DR actions [5]. Amongst the residential load, thermostatically controlled appliances especially the heating, ventilation, and air conditioning load (HVAC) load, have gained a great deal of attention in smart grids for DR applications due to their flexible operation. According to a report from statistics Finland, the HVAC load has the highest share in household demand in Nordic countries annually [6]. Due to the slow thermal dynamics of well-insulated buildings in Nordic countries, the thermal masses of building structures act as a small storage buffer and can provide considerable load shifting capability. However, there is still an essential need to develop practical frameworks so as to motivate customers into shifting their energy consumption of the HVAC load to off-peak hours [4], [7].

In today's power systems, there is also a great concern regarding eco-friendly issues which has already paved the way for a large scale deployment of renewable generation in power systems [8]. In future smart grids, wind power generation sources are expected to have a considerable share in the total generation assortment. However, because of the variability and unpredictability of wind power, the large scale integration of wind generation will pose a major challenge in the form of enhanced operational flexibility requirements [9]. Their limited capacity value may lead to the grave problem of supply-load imbalance, thus jeopardizing the power system reliability. Power ramping and regulation requirements are also likely to increase, which will create technical difficulties for the system operators [10]. The classical approach of employing (a) backup generators that enable fast up/down ramping and (b) energy storage facilities, is expensive and complex but the environmental impact of these solutions are considerable [11]. An alternate solution would be to unleash DR as a load shaping tool to minimize the imbalance between demand and supply [12], [13]. This dissertation puts an emphasis on the design of the frameworks for HVAC load management in smart grids which thoroughly takes into account the customers' comfort and convenience. The proposed frameworks aims at achieving different objectives, more specifically, a customer's energy cost minimization and maximizing the utilization of wind generation.

1.2 Objective and Scope

The objective of the dissertation is the comprehensive quantification of potential benefits of responsive residential HVAC loads for DR applications as well as the development of practical frameworks to achieve them. The DR applications considered in the analysis include customers energy cost minimization and supply-demand imbalance minimization in the presence of intermittent generation. The proposed frameworks will allow the utility to assess the benefits of domestic HVAC DR and will provide an insight into the employment of DR at an end-user level. The dissertation objective is divided into following tasks.

Task 1: Develop a framework for a thorough quantification of upward DR (load increment) and downward DR (load reduction) capability of residential HVAC load considering customer's temperature preferences. Then perform the simulations to obtain the DR potential.

Task 2: Develop a user-centric framework for HVAC load management for customer's energy cost minimization. This task consists of following subtasks:

a) Develop an optimization approach for scheduling the operation of HVAC load integrated with partial thermal storage to minimize the customer's energy expenses in energy market. (Considering a snapshot of energy prices). Subsequently, assess the DR benefits using the developed model.

b) Develop a generic decision tool for scheduling the HVAC load for customer's energy payment minimization amid price and demand uncertainty while considering the customer's thermal comfort and risk preferences. Afterwards, showcase the effectiveness of the model with the simulations of appropriate case studies.

c) Develop a 2-stage decision framework for optimally scheduling the HVAC loads for customer's energy cost minimization in both energy market and balancing market.

Task 3: Develop a framework for HVAC load management for wind generation balancing. This task consists of following subtasks.

a) Develop a tool for activating the domestic HVAC DR for wind generation balancing (without considering network constraints) accounting customers' comfort and convenience. Subsequently, evaluate the DR benefits using the proposed framework.

b) Develop a framework for optimal collaboration of DR and network RTTR for increased utilization of wind generation. Later, justify the efficacy of the proposed approach by conducting simulations considering appropriate case studies.

c) Develop a tool for optimal collaboration of aggregator DR services in tandem, namely, customers' energy cost minimization in energy market and minimizing the wind energy curtailment cost.

To achieve the dissertation objective, at first thermal modeling of house close to the real world is performed and then the derived mathematical model of the building is used in the proposed frameworks of above mentioned tasks. The HVAC systems under study are (a) direct electric space heating/cooling system, hereafter, referred to as HVAC (b) electric space heating system integrated with thermal storage, hereafter, referred to as HVAC with storage. These installations have thermal storage capacities such as a hot water tank hence they enable shifting of energy demand without sacrificing the customers' comfort. Suitable case studies are performed on typical Finnish systems. Lastly, obtained results are analyzed to report the findings.

1.3 Contribution

This dissertation consists of seven publications [I]-[VII] which covers several frameworks for DR applications. The results are divided into three chapters. A brief synopsis of the contribution in each chapter is given in the following.

1.3.1 Domestic HVAC DR Potential for Up/Down Ramping

Chapter 3 covers the first publication [I] which investigates the prospective of DR through HVAC loads for up/down ramping potential without violating customer's thermal preferences. A mathematical tool is developed to thoroughly investigate the upward DR (load increment) and downward DR (load reduction) capability of the domestic HVAC load. This chapter provides an overview of availability of the DR through HVAC load which can be tapped to tackle power system stress conditions without violating preset consumer temperature preferences. The application of the mathematical model is showcased by presenting interesting case studies in order to probe the impact of customers' temperature preferences on the DR potential in Finnish system. Moreover, the additional benefits of having a thermal storage capacity integrated with HVAC system are also assessed through a set of simulations. The reported DR potential is significant from smart grids perspective as the HVAC load can be used as a tool for mitigating the power imbalance caused by intermittent renewable generation.

1.3.2 Domestic HVAC Load Management for Customer's Energy Cost Minimization

Chapter 4 discusses about different frameworks in publications [II]-[IV] to enable HVAC load management to minimize the customer's energy expenses. A tool for optimal scheduling of HVAC load in energy market is introduced in [II]. Next, price and demand uncertainty features are added in the modified tool in [III] which enables real-time HVAC load management. Finally, to address the problem of activating DR in balancing market, a two stage framework is presented in [IV] which enables co-optimization of energy attainment in energy market and also enables unleashing of flexibility in balancing market.

Publication [II] develops a unique framework for optimal scheduling of HVAC load which are integrated with partial thermal storage. The proposed DR control optimally coordinates the direct electric heating and partial thermal storage and results in minimum energy payment. The model takes into account the day-ahead announced energy prices and optimally schedules the HVAC load to reduce the customer's energy payment. The simulation results demonstrated that that the duo of partial thermal storage together with thermal inertia of the house can offer much flexibility in DR control. The proposed model can easily be integrated at the household level for better utilization of distributed energy resources under the *Smart Grid* scenario.

Publication [III] proposed a generic framework for real-time HVAC load management amid price and demand uncertainty. The proposed tool aims at minimizing a weighted sum of the expected energy payment, loss of user thermal comfort, and financial risk of a customer while strictly considering the end user preferences. The design works on a rolling horizon criteria. As the price and demand information is gradually revealed over time, the scheduling of HVAC system is updated accordingly. The model achieves a fair tradeoff between expected energy cost, thermal comfort, and financial risk while the user preferences are respected at all times. The proposed decision mechanism is formulated with flexibility, and can be easily be integrated into home load management system.

Publication [IV] address the problem of tapping DR through HVAC load in balancing market for the customers who are already enrolled in DR programs in energy market. The publication [IV] presents a hierarchical framework to enable customer's participation in both energy market and balancing market. The framework featuring 2-stages allows the customers to co-optimize the energy attainment and possible reserving some ramping flexibility in balancing market. The numerical analyses established that the instigation of DR in balancing market will lessen the customers' total energy payment.

1.3.3 Domestic HVAC Load Management for Wind Generation Balancing

In Chapter 5, the focus is on the problems of HVAC load scheduling in systems with high penetration of intermittent renewable generation. The last three publications [V]-[VII] discuss about the possible benefits and realization of DR through HVAC loads in the presence of large scale wind generation.

The publication [V] presents a unique centralized framework for realizing the HVAC DR potential for wind generation balancing. The proposed model manages the consumption of population of HVAC loads to tackle the variability of wind generation. The thermal comfort penalty is explicitly integrated in the objective function in order to oblige different customers' thermal preferences. Performance of the model is demonstrated though several case studies and sensitivity analyses representing typical Finnish system. The simulations results suggested that cyclic operation of HVAC load can be scheduled to facilitate the time-varying wind power balancing without foregoing the customers' thermal preferences.

In [VI], a new tool is developed to activate DR through HVAC loads in collaboration with network real-time thermal rating (RTTR) for increased utilization of distributed generation (DG). The tool contains an optimization model that manages the population of heating, ventilation and air conditioning (HVAC) loads for wind power balancing considering the RTTR of a distribution network. The performance of the design is demonstrated by performing a set of simulations on a typical Finnish distribution network plan. The results indicate that significant benefits can be realized by optimally harmonizing the DR and RTTR in a distribution network for wind generation balancing.

The last publication [VII] presents a framework for optimizing the DR applications in tandem; namely, energy cost reduction and wind generation balancing. The tool contains a formulation to manage the population of HVAC loads for optimizing the benefits of domestic DR in energy market and for wind integration services. The analysis which is conducted on a typical Finnish system indicates that joint optimization of DR services is beneficial as it facilitates energy cost savings along with better wind integration.

1.4 Dissertation Outline

The rest of the dissertation is organized as follows.

In Chapter 2, preliminary basics are discussed.

Chapter 3 investigates the influence of customer's temperature preferences on HVAC DR potential for up/down ramping [I]. A mathematical framework is presented and then case study is performed for different seasons and the associated DR potential is evaluated.

Chapter 4 presents the design and application of a tool for HVAC load management for customer's energy cost minimization [II]-[IV]. The HVAC system under study is a electric space heating load integrated with partial thermal storage. At first, an optimization problem is formulated to minimize the customer's electricity payment in a situation where energy prices are announced on a day-ahead basis. Next, the uncertainty issues are tackled by proposing a generic decision mechanism which allows user to tradeoff between expected electricity payment and financial risk due to the uncertain price and demand. The activation of DR in balancing market to bring maximum energy cost saving is also considered by proposing a two-stage framework for HVAC load management.

Chapter 5 discusses the potential benefits of HVAC load management in presence of large scale intermittent generation [V]-[VII]. At first, framework for activating DR for wind generation balancing is introduced. Then RTTR features of network are added in the modified framework. The efficacy of both the optimization tools is also exemplified by suitable case studies. Lastly, a tool for optimizing the DR services, namely, customer energy cost reduction and wind integration from the perspective of electrical aggregator is developed.

Finally, the dissertation is concluded and some potential future work is introduced in Chapter 6.

The publications [1]-[VII] are attached in the Appendix.

2. Preliminaries

2.1 Introduction

This section provides the backgorund information relevant to the dissertation regarding the demand response (DR), building thermal models, real-time thermal rating (RTTR) and wind output model.

2.2 Demand Response

Demand response (DR) is an adapted demand which comes either as a result of price responsiveness or to prevent any power system jeopardy, according to the U.S. department of Energy [4].

DR can be viewed as a versatile tool that provides opportunity to electrical customers to alter their business as usual consumption profile. The monetary gains offered for active participation is all the stimulus needed to respond [14]. DR presents quite a few advantages surrounding load profile flattening [15], [16], capital investment deferral [17], assets management [18], and system failure preemption [19]. To put it simply, DR enhances system efficiency and reliability by leading to changes in the consumption profile [20]. The umbrella of DR generally includes peak snipping, load shifting, valley filling, and flexible load shaping [21]. For example, load shifting refers to transferring energy consumption from peak periods to off peak periods. To achieve a high level of reliability and sturdiness in the system, peak snipping and valley filling can be done. A power system supplied with DR capabilities can decrease system costs, CO_2 emissions, and price volatility through shifting power consumption to periods characterized by low prices and high intermittent renewable power production.

2.2.1 Demand Response Programs

DR shows potential in its techno-economical solutions to make electricity demand more flexible which allows private customers to alter their demand profiles to fit the needs of the energy supply [22]. In the DR programs, electric utilities provide some reward to their residential customers since they are increasingly flexible in timing their energy consumption. Additionally, utilities provide a signal to their customers (typically electricity price) that are intended to steer the power consumption so as to get an aggregate demand that better matches the needs of the power generation. In particular, DR can be sorted into two categories, Price based DR and Incentive based DR [4].

Price based DR

Price based DR alludes to customer intentionally managing energy consumption due to varying prices [23]. Depending on the power system operator's objective, the price signal can either be the actual power price or a replica power price. Furthermore, depending on the DR program, the price signal can be deterministic or stochastic. Price based DR can be grouped further into a real-time DR program, critical peak pricing DR program, and Time of Use (ToU) DR program. The most straightforward out of all of them is ToU, where customers are usually presented with two different price periods by utilities, specifically peak price and off peak price periods [24]. The goal is to transfer the maximum amount of consumption from peak to off peak periods to achieve system efficiency, all the while giving customers financial benefits such as a reduced energy payment. However, in critical peak pricing, extra tariff is also applied during certain periods of the day. For instance, such tariffs are useful in extreme weather conditions when available generation may not be sufficient enough to meet the expected demand for a short duration. With the materialization of smart meter and advancements in ICT infrastructure, bidirectional communication between customer and system operator is now achievable which allows customers to participate in the real time DR program. As the name suggests, the real time DR program includes power prices that reveal the actual situation of the electricity market and power system and are sent to the customer to respond. Electricity consumers are charged prices that typically rise and fall on an hourly basis and are broadcasted either day-ahead or hours ahead before the actual delivery time [25].

Incentive based DR

Incentive based DR programs provide an opportunity for customers to gain financial rewards through modifying (load increment/decrement) consumption profiles. The goal of these programs is to control the energy consumption profile at times of peak periods or critical events [23]. These programs can also be advantageous since the DR magnitude from the customer can be anticipated in beforehand and thus give more flexibility to the operators in controlling the loads. However, customer preferences are violated in doing so and once in a while; even privacy is not taken into consideration. Key incentive-based DR programs include direct load control, emergency DR, interruptible rates, and demand bidding or buyback.

2.3 Residential Demand Response and HVAC loads

For a long time, loads from large-scale industries have operated as reserves used for maintaining the power balance. For instance, in Finland, the primary focus was towards industries like forestry, metal and chemical industries for some DR applications [26]. However, with the advent of smart grid and ubiquitous strong ICT infrastructure, the demand-side management is a natural opportunity at the residential sector to enhance power system operational efficiency [27].

Substantial researches have advocated on the potential and activation of domestic DR [28]- [38]. Domestic appliances can be classified into (a) Critical appliances (b) Flexible appliances. Dishwasher, HVAC, electric water heater (EWH), electric vehicles, and washing machine are some major flexible appliances while lightning loads and television are treated as a critical appliances due to their operational characteristic.

In terms of the DR treatment, the primary focus of this study will be on the domestic heating, ventilation and air conditioning (HVAC) load. The foremost reason for choosing the HVAC loads for DR application is due to their prevailing share of yearly energy consumption as well as the large impact they have on the domestic daily load profile. For instance, in Finland alone, the share of HVAC in residential energy consumption sector is more than 70% annually [6]. Most importantly, customer comfort, which is regarded as the pillar of any successful DR program can be easily gauged as compared to other appliances. For example, for the case of HVAC load, the customer's thermal comfort is a function of a temperature dead-band; while in the case of other appliances, it is hard to characterize the adequate limits of the customer's comfort. Additionally, other than a smart thermostat, no extra hardware is needed for making use of the power postponement features of HVAC loads.

The HVAC system under scrutiny is direct electric space heating/cooling (or simply HVAC) and HVAC integrated with thermal storage (commonly known as HVAC with storage). These installations have great thermal storage capacities like the hot water tank, and so they enable the shifting of energy demand without changing the customer's comfort level.

2.4 Building Thermal Model

2.4.1 1-Capacity Building Model

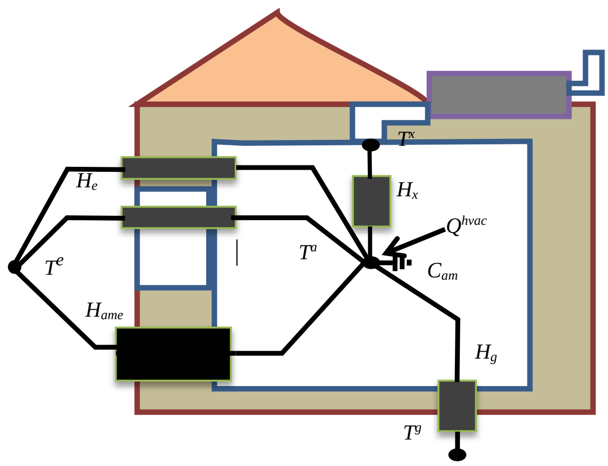

Figure 2.1. 1-Capacity building model.

1- Capacity model is a simple model to assess the indoor temperature in a dynamic situation. In this model as schematized in Figure 2.1, the building fabric heat capacity and air heat capacity is grouped as one capacity C_{am}. The indoor air node point is linked to the ventilation supply air temperature T^x through the ventilation air heat conductance H_x, to the ground temperature T^g through the conductance H_g and to the external temperature T^e through the joint conductance H_{ame} of the external walls and the roof. Between the external temperature T^e and indoor air temperature T^a, the infiltration air flow is connected. Through this, an assumption can be made that the infiltration air has not been warmed in the structures and the penetrating air flow has the temperature of the external air. The infiltration is in parallel with the windows, which have an insignificant thermal mass compared to the rest of the house envelope. To make the model more straightforward, a virtual conductance H_e between external and internal temperature node points is produced for infiltration heat capacity flow and windows heat conductance. In addition, the heating power Q^{hvac} is believed to be of convective nature and hence is distributed to the indoor air node point. Furthermore, the heat demand profile would include the effect of internal heat gains from lighting household appliances and occupancy. The energy balance for the indoor air node point is given by (1).

$$Q^{hvac} = C_{am}\frac{dT^a}{dt} + H_e\left(T^a - T^e\right) + H_{ame}\left(T^a - T^e\right) + H_g\left(T^a - T^g\right) + H_x\left(T^a - T^x\right) \quad (1)$$

The thermodynamic parameter values for a 1-Capacity model of a 180 m^2 two-floor single family house insulated according to the minimum requirements of the Finnish 2010 building code C3 [39] are given in Table 2.I. The structures of the house are medium massive.

TABLE 2.I

1-CAPACITY BUILDING THERMAL PARAMETERS

Parameter	Value
T^x	18 ^{0}C
C_{am}	11918 kJ/^{0}C
H_e	52.33 W/^{0}C
H_{ame}	41.26 W/^{0}C
H_x	87.43 W/^{0}C
H_g	15.54 W/^{0}C

2.4.2 2-Capacity Building Model

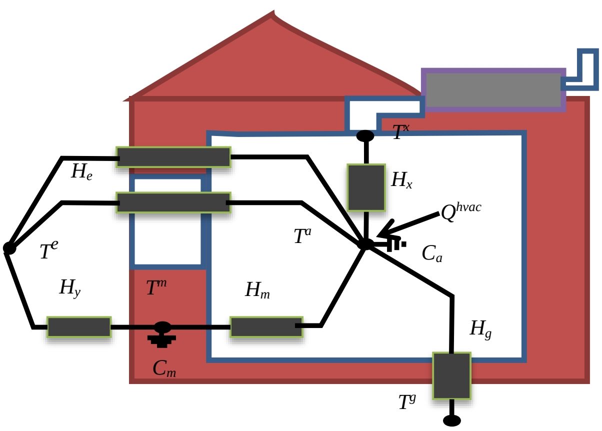

Figure 2.2. 2-Capacity building model.

The 2-Capacity model is a sophisticated model and has a reasonable accuracy in estimating the indoor air changes in a dynamic situation as compared to 1-Capacity model. One of the capacities is distributed to the building fabric while the other is distributed to the indoor air. Figure 2.2 illustrates the structure of the model.

There are two unknown temperatures by the name of T^a which is the indoor temperature, and T^m which is the building fabric or mass temperature. Additionally, T^e is the external outdoor air temperature, T^x is the ventilation supply air temperature and T^g is the ground temperature. The temperature node points are attached through heat conductances or when there is an air flow they are connected by a heat capacity flow. The infiltration (or exfiltration) air flow is linked between the external temperature and indoor temperature. From this an assumption can be made that there is no warming of the infiltration air in the structure and the penetrating air flow has same temperature as the external air. The windows are in parallel with the infiltration which have an insignificant thermal mass in comparison with rest of the building envelope. To break the model down further, a virtual conductance H_e between external and internal temperature node points is produced by adding up the infiltration heat capacity flow and windows heat conductance. The greatest thermal inertia of the building structures C_m is grouped in the mass node point which is from the external side joined to the outdoor air through the conductance H_y and from the internal side to the indoor air through the conductance H_m. Heat conduction in the solid wall material and convection on the surface is included in both conductances. The mass node point is situated in the undefined depth inside the building structure and embodies a type of mean temperature of the building mass. It has no physical equivalent and thus has a more supplementary role in the model. Even though the thermal capacity of the indoor air C_a is much smaller than the building mass C_m it still has a vital part in an application where the dynamics of the indoor air temperature is of chief concern. The indoor air node point is connected to T^x through the ventilation air heat capacity flow H_x and to the T^g through the conductance H_g. Since the heat capacity is included in the mass capacity, there is no separate counterpart. Moreover, Figure 2.2 portrays the idea that the heating (or cooling) power generated by the building HVAC system is presumed to be of convective nature and is therefore allocated to the indoor air node point. The energy balance for the indoor air node point can be represented by the following state space equation.

$$
\begin{aligned}
&\dot{X} = AX + B\rho \\
&Y = cX + d\rho \\
&\dot{X} = \begin{pmatrix} \dot{T}^a \\ \dot{T}^m \end{pmatrix}, X = \begin{pmatrix} T^a \\ T^m \end{pmatrix} \\
&A = \begin{pmatrix} -\dfrac{H_e + H_m + H_g + H_x}{C_a} & \dfrac{H_m}{C_a} \\ \dfrac{H_m}{C_m} & \dfrac{-(H_m + H_y)}{C_m} \end{pmatrix}, B = \begin{pmatrix} \dfrac{H_e T^e + H_g T^g + H_x T^x + Q^{hvac}}{C_a} \\ \dfrac{H_m}{C_m} \end{pmatrix} \\
&c = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}, d = \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \rho = 1
\end{aligned}
\tag{2}
$$

The above state space model can be transformed into approximately equivalent discrete time model and is given by the following set of equations.

$$T_t^a = \frac{T_{t-1}^a + \frac{\Delta t}{C_a}\left[H_m T_{t-1}^m + H_e T_t^e + H_g T_t^g + H_x T_t^x + Q_t^{hvac}\right]}{1 + \frac{\Delta t}{C_a}(H_m + H_e + H_g + H_x)} \tag{3}$$

$$T_t^m = \frac{T_{t-1}^m + \frac{\Delta t}{C_m}(H_m T_{t-1}^a + H_y T_t^e)}{1 + \frac{\Delta t}{C_m}(H_m + H_y)} \tag{4}$$

The thermodynamic parameter values for a 2-Capacity model of a 180 m^2 two-floor single family house insulated according to the minimum requirements of the Finnish 2010 building code C3 [39] are given in Table 2.II. The structures of the house are medium massive.

TABLE 2.II

2-CAPACITY BUILDING THERMAL PARAMETERS

Parameter	Value
H_e	52.2 W/°C
H_y	59.4 W/°C
H_m	928.8 W/°C
H_x	9 W/°C
H_g	86.4 W/°C
C_a	2.3 MJ/ °C
C_m	20.2 MJ/ °C
T^x	18 °C

2.5 Wind Model

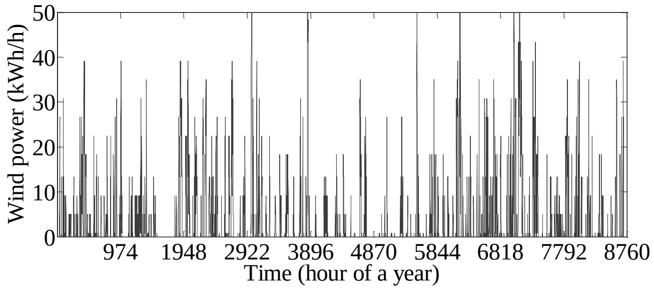

Figure 2.3. Wind power output profile of a 50 kW wind turbine.

A simple model (5)-(7) can be used to attain the active power generated by a wind turbine [40]. The hourly wind generation profile for a year from 50 kW turbine, depicting the large fluctuations in the wind output can be shown by Figure 2.3. The Finnish Meteorological Institute [41] provides a wind generation profile that is based on the hourly wind speed for a year.

$$P_w = \begin{cases} m^w \cdot w_w + K, & w_c < w_w \text{ and } w_r > w_w \\ P_r, & w_w \geq w_r \\ 0, & w_w \leq w_c \end{cases} \tag{5}$$

$$m^w = \frac{P_r}{w_r - w_c} \tag{6}$$

$$K = -m^w \cdot w_c \tag{7}$$

where,

P_w is the active power output of a wind turbine (kW)

w_w is the wind speed (m/s)

w_c is the wind speed corresponding to cut in speed (m/s)

w_r is the wind speed corresponding to rated power (m/s)

P_r is the rated power of a wind turbine (kW)

K is a constant

m^w is the variable that provides a level of freedom to curtail wind generation through regulating blades

2.6 Real-Time Thermal Rating

In the rising active distribution network, where the loading is highly stochastic, there is a concern among utilities to exercise their assets to the fullest. The real-time thermal rating (RTTR) system allows an active distribution network to run closer to an overload state without harm but more significantly, it enables the utilization of favorable conditions appropriated by environmental factors [40]. The basic principle in RTTR systems is that the total maximum loading capacities of underground cables, overhead lines, and transformers rely on the thermal limits of their insulation. The thermal states of their insulation are also reliant on the changing environmental conditions like wind speed, outside temperature and solar irradiation, nonetheless, one needs appropriate dynamic thermal models to convert the loading and environmental effects into thermal states of the components.

3. HVAC DR Potential for Up/Down Ramping

This chapter focuses on the task 1 of the dissertation (Tasks are defined in Chapter 1). This chapter provides an overview of availability of the demand response (DR) through heating, ventilation and air conditioning (HVAC) load which can be tapped to tackle power system stress conditions without violating preset customer temperature preferences.

3.1 Introduction and Literature Review

Because of the greater access to fluctuating renewable energy sources, the need for balancing power would profusely increase in future grids [42], [43]. As a result, DR with its various economic and environmentally-friendly advantages, is an effective tool in dealing with this enormous issue [44], [45]. The HVAC load is a part of the highest form of electricity usage and accounts for 70% of total energy consumption of the buildings in Finland. Consequently, its operation can be altered without causing inconvenience to the consumers as long as the control scheme is rational. This is due to the fact that the thermal masses of building structures operate as a source of storage buffer because of the slow thermal dynamics of the building fabrics.

In literature, HVAC load scheduling in a smart home, along with other potential thermostatic controlled appliances, have gained a lot of attention [46]-[58]. For example, a control algorithm for water heater load management with a consideration to user preferences to minimize energy expense has been presented in reference [46]. The authors of [47] established the idea of optimizing the HVAC load and electric vehicles operation to obtain a balance between user comfort and energy expenditure. The work [48] studied a feasible but suboptimal control strategy for HVAC load management to bring favorable DR. The work presented in [49] included different price-based DR algorithms for controlling the HVAC load using hardware-in-the loop simulations. In [50], a hardware implementation that includes domestic smart air-conditioning unit systems was studied and presented in detail. Overall, even with all these referenced works, there is still immense need to gain a deeper understanding of the availibility and flexibility of HVAC load. However, there are a few articles that give insight on this area. For instance, the authors in [51] established the DR potential of EWH to handle a minimum generation situation, whereas, authors in [52], [53] measured the load reduction potential of electric space heating systems. The work in [54] presented a methodology to enumerate the DR flexibility of domestic thermostatically controlled appliances. However, thermal models employed are too simple for real-world applications. The study [55] presented the DR potential of domestic ventilation system in Nordic countries. The work [58] reported the ramping rate flexibility of domestic air-conditioning and refrigeration for provision of reserve services

Prior to [I], neither of the works offer a wide-range estimation of upward/downward DR potential of residential HVAC load.

3.2 Proposed Formulation

This section presents a mathematical formulation for evaluating the DR potential. The method aims at managing the HVAC load such that maximum availability occurs during the DR event period without compromising on user temperature preferences. The objective function (8) can be mathematically stated as:

$$\min \sum_{t=t_{start}}^{t_{end}} (-1^{\gamma})(W_t)\left(P_t^{hvac} + P_t^{ch,dhw}\right), \qquad \forall t, t_{start}, t_{end} \in T \tag{8}$$

s.t.

$$0 \le P_t^{hvac} \le P^{hvac,\max}, \quad \forall t \in T \tag{9}$$

$$0 \le P_t^{ch,dhw} \le P^{ch,dhw,\max}, \quad \forall t \in T \tag{10}$$

$$0 \le Q_t^{hvac} \le Q^{hvac,\max}, \quad \forall t \in T \tag{11}$$

$$\left(P_t^{hvac} + P_t^{ch,dhw}\right) \le \upsilon_t, \quad \forall t \in T \tag{12}$$

$$\sum_t (P_t^{hvac} + P_t^{ch,dhw})\Delta t \ge E^{lh} \tag{13}$$

$$(T_t^{set} - \frac{\phi}{2}) \le T_t^a \le (T_t^{set} + \frac{\phi}{2}), \quad \forall t \in T \tag{14}$$

$$(SoC_{t+1} - SoC_t)E^{cap} = (P_t^{hvac} - Q_t^{hvac})\Delta t - \xi_t, \forall t \in T \tag{15}$$

$$SoC^{\min} \le SoC_t \le SoC^{\max}, \forall t \in T \tag{16}$$

$$\xi_t = \eta SoC_{t-1}, \quad \forall t \in T \tag{17}$$

where,

t_{start} is the event driven DR starting time

t is the index of time

T is the set of time

t_{end} is the event driven DR ending time

γ denotes the binary variable (1 for upward DR, 0 for downward DR)

W_t is the coefficient representing load adjustment priority at time *t*

P_t^{hvac} is the electrical power of HVAC unit at time *t* (kW)

$P^{hvac,\max}$ is the power rating of HVAC unit (kW)

$P_t^{ch,dhw}$ is the charging power of domestic hot water unit at time *t* (kW)

$P^{ch,dhw,\max}$ is the power rating of domestic hot water unit (kW)

υ_t represents the demand limit at time *t* (kW)

Δt is the time interval (hours)

E^{lh} is the energy demand during optimization horzion (kWh)

T_t^{set} denotes the set point temperature of dwelling at time *t* (ºC)

ϕ is the internal temperature dead-band (ºC)

T_t^{a} is the indoor ambient temperature of dwelling at time *t* (ºC)

SoC_t represents the state of charge of thermal storage at time *t*

$SoC^{\min}$ is the minimum allowable state of charge of thermal storage

$SoC^{\max}$ is the maximum allowable state of charge of thermal storage

E^{cap} is the maximum thermal storage capacity (kWh)

Q_t^{hvac} is the HVAC thermal output power at time *t* (kW)

$Q^{hvac,\max}$ is the rated thermal output power of HVAC (kW)

ξ_t denotes the storage thermal losses at time *t* (kWh)

η is the storage loss coefficient

The maximum rating of HVAC load and domestic hot water system are bounded by (9) and (10) respectively. The rated output power of HVAC is bounded by (11). The constraint (12) bounds the maximum hourly demand while (13) ascertains the total energy requirement is fulfilled. The upper and lower indoor ambient temperature is respected by (14). The evolution of the stored energy in thermal tank is given by (15) while *SoC* of thermal storage is bounded in (16). The thermal losses are determined by (17).

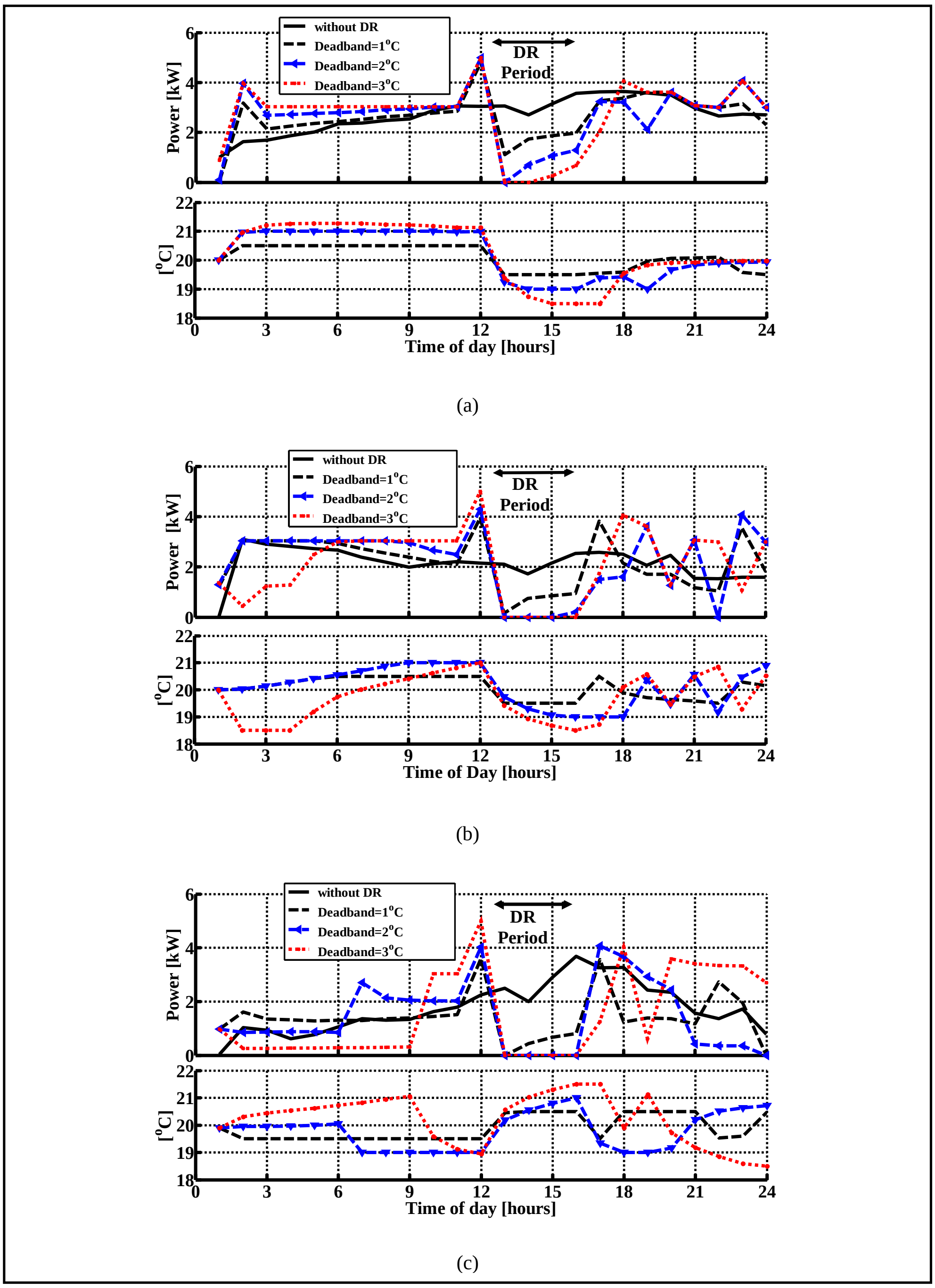

Figure 3.1. Downward DR capability of HVAC load (without Storage) versus temperature dead-band. (a) Winter (b) Spring (c) Summer

3.3 Case Study and Results

A typical medium massive structure house as schematized in Figure 2.2 is considered for the case study. The analyses are conducted for three distinct weather profiles [I] representing spring, winter and summer conditions. The optimization problem formulated in Section 3.2 is solved via the general algebraic modelling system (GAMS) [59] environment first for two case studies designated as Case 1(downward DR capability) and Case 2 (upward DR capability) for HVAC. After this, in the latter part of this section, the effect of integrating thermal storage with HVAC on DR is investigated. For the basic case study we presume that the DR event period is between 13:00-16:00 during the day and the priority of each hour of that period is same. The indoor temperature set point is presumed to be 20ºC.

The downward DR capability is illustrated in Figure 3.1 with 3 distinct weather profiles of a year, specifically winter, spring, and summer respectively, where each result is then compared with the base case i.e., no DR. An observation can be made on the fact that the heat from thermal masses of building structures is radiated as the demand is either postponed or preponed such that the highest load reduction occurs during the DR event period without risking user temperature dead-band partialities. As user preferences of indoor temperature dead-band gets flexible, the downward DR potential is increased. The subplots of Figure 3.1 illustrate the indoor temperature in various scenarios of temperature dead-band preferences. Notably, the quality of service and temperature preferences for users is not debased and is given the utmost consideration.

Table 3.I shows the downward DR potential as fraction of the heating demand during different seasons of the year. The results describe that the maximum percent share of load reduction is obtained during mildly cold weather or summer time. In contrast, if the dead-band range in not that flexible, partial load reduction can be attained in severe weather conditions. As expected, the load adjustment potential increases with the greater flexibility in indoor temperature deviation.

TABLE 3.I

HVAC DOWNWARD DR POTENTIAL (%)

Temperature Dead-band (ºC)	Winter	Spring/Autumn	Summer
1	32.62	68.48	82.67
2	69.22	97.67	100.00
3	90.00	100.00	100.00

Given that the heating load is dominating during winter periods, it is crucial to gain an understanding of downward DR versus different deferment periods, particularly during the cold winter weather. Figure 3.2 portrays the load deferment potential of HVAC loads functioning with 3 different temperature dead-band settings assuming an avg. outside temperature of -7 ^{0}C. The results confirm that maximum load reduction can be achieved for a couple of hours even in unfavorable cold climates with a flexible temperature operating range. It is clear that the longer the interruption duration, the lesser the shifting potential.

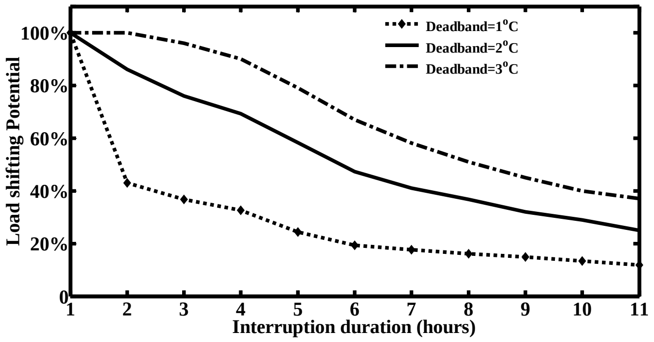

Figure 3.2. HVAC load deferment potential during winter weather.

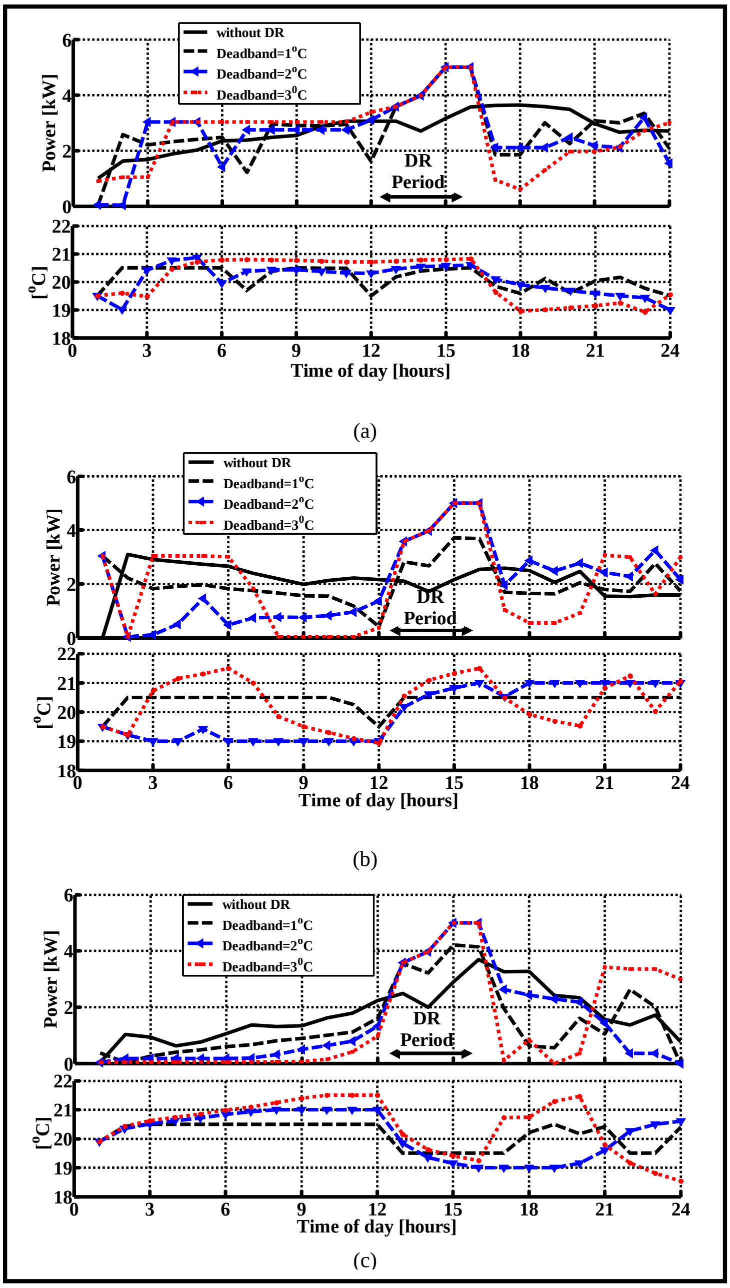

Figure 3.3. Upward DR capability of HVAC load (without storage) versus temperature dead-band. (a) Winter (b) Spring (c) Summer

Next, a case (Case 2) investigated the role of HVAC as a power sink during different times of the year. Given the user indoor temperature preferences, the question of how to determine the maximum load that can be stored in building masses during the DR event is also discussed. The impact of temperature dead-band on the upward DR flexibility of HVAC loads w.r.t different outside weather profiles is exemplified in Figure 3.3. The operation profiles of HVAC loads show that during 13:00-16:00 hours, the HVAC endeavors to store energy in building structures by increasing its power, particularly in order to absorb the maximum power. As expected, user temperature settings are the most sensitive boundaries and they control the degree of energy that can be stored in building thermal masses.

The maximum amount of load that can be increased during the DR event for different dead-band settings is listed in Table 3.II. These results reveal that because of the high thermal inertia of the building, the capability for the upward DR through HVAC load is enormous, regardless of the outside weather profile. However, the restrictive factor for storing heat in the building is the rated power of the HVAC.

TABLE 3.II

HVAC UPWARD DR POTENTIAL (%)

Temperature dead-band (ºC)	Winter	Spring/Autumn	Summer
1	40.7	51.3	36.7
2	40.7	106.3	58.6
3	40.7	106.3	58.6

HVAC integrated with thermal storage

Finally, an analysis is conducted to determine the load adjustment potential when thermal storages are incorporated with the HVAC system. Hot water stored in the thermal storage tank is used for domestic use and space heating purposes. The thermal storage losses are ignored since the storage losses of a commercially available thermal storages are minimal [60]. The thermal storage capacities are represented as a fraction of total demand of a typical winter day. So for the sake of safety, the minimum storage levels are restricted to be 10% of the total capacity. Additionally, the initial level of storage is considered to be 25% of the storage level. Given that the thermal storage can contain heat energy that can be used for later operation, a larger DR duration period is selected. Unlike earlier base cases where each hour of DR event has equal priority, here the various hours were assigned distinct priority weights.

The influence of various storage capacities on the load adjustment potential for winter and spring, are represented in Figure 3.4. Figure 3.4a portrays the downward DR potential of the HVAC system, equipped with a thermal storage. It is obvious that storage scheduling is done in a manner that allows for maximum discharging during hours that are assigned the highest priority for downward DR. The result shows that the larger the storage capacity, the greater the potential for offsetting the energy demand. During spring time, the potential is comparatively higher because of the smaller heat demand. The charging profile of the thermal storage when the purpose is to maximize the upward DR during priority hours is depicted in Figure 3.4b. In this instance of power sinking, the full storage surpasses the partial ones due to the greater capacity and higher charging rate. However, the partial and full storage follow relatively the same scheduling profile during mild weather. Naturally, the fixed potential of 100% thermal storage is larger than a 25% storage capacity tank.

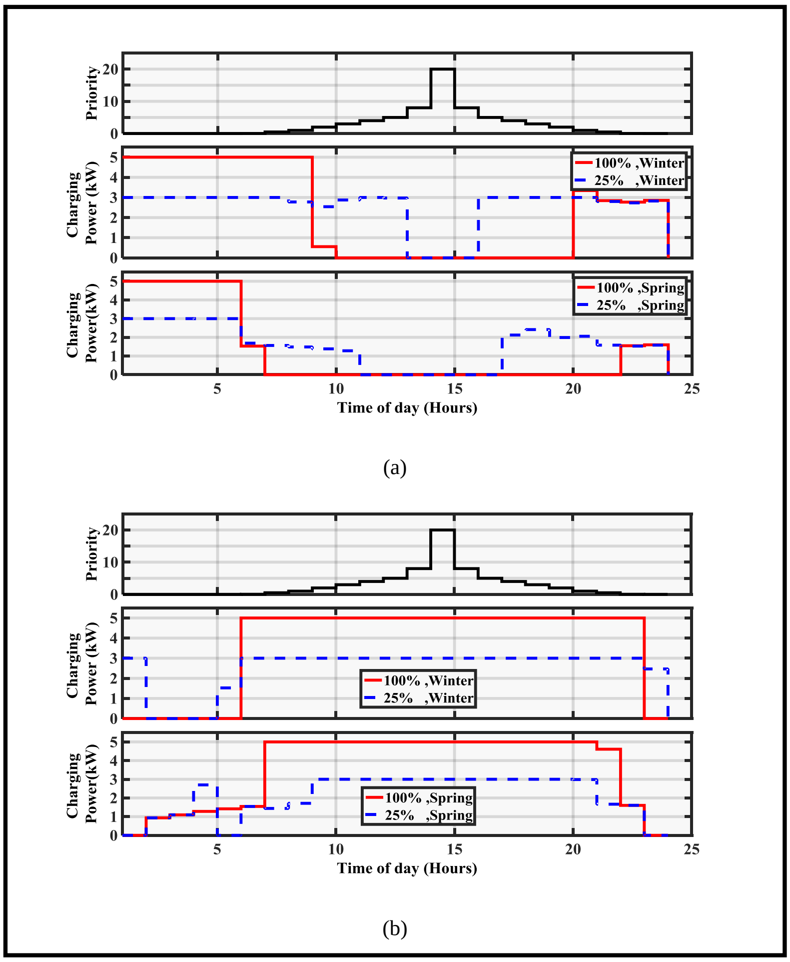

Figure 3.4. DR potential of HVAC load integrated with thermal storage (a) downward DR (b) upward DR.

Figure 3.5 displays the load adjustment potential of HVAC load with storage. The partial storage (25%) has the least DR potential during winter times, while a full storage can offset the load for 12-14 hours even during cold weather.

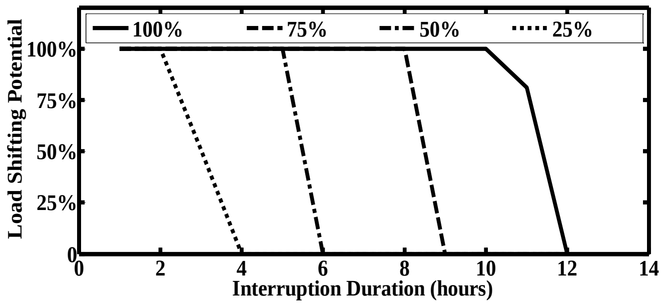

Figure 3.5. Load adjustment potential of HVAC integrated with thermal storages during winter.

3.4 Concluding Remarks

In this chapter, the flexibility of domestic HVAC loads to provide up/down DR is quantifed while considering the customers temperature preferences. A mathematical model is setup to investigate the DR potential considering user temperature preferences. The obtained results suggested that the flexibility to provide DR is affected by the heat demand requirements and customer's temperature preferences. DR flexibility has a strong correlation with temperature dead-band and potential subdued during extreme weather. The upward DR is strongly limited by power ramping capability and thermal comfort limits. HVAC systems with storage provide more flexible operation for up/down DR. The proposed framework wil help the aggregator to prepare upward/downward DR flexibility bids in order to activate them in balancing markets for economic gains.

4. HVAC Load Management for Customer’s Energy Cost Minimization

Chapter 4 focused on the frameworks for heating, ventilation and air conditioning (HVAC) load management for customer’s energy cost minimization under different scenarios. This chapter addresses the application of decision frameworks for customers to minimize their energy payment (Task 2). After the introduction and relevant literature review, an optimization tool is designed for HVAC load management for customer’s cost minimization assuming price and demand to be certain during optimization horizon. Next, uncertainty and risk features are added to modify the decision model and make it more generic. Lastly, problem of activating demand response (DR) in balancing market is addressed by presenting a hierarchial framework which allows the customers to maximize economic gains.

4.1 Introduction and Literature Review

All around the world, power systems are facing the challenge of the integration of intermittent renewable generation with numerous forms of distributed energy sources. This generates urgent requirements for optimization of power system operations. DR [3], [61] is one major piece of technology which may respond to this challenge.

Due to the increase of interest in residential DR, many researchers have looked towards domestic thermostatic load management. Authors in [62] researched a linear programming approach for storage control under dynamic power pricing to lower the customers’ energy payment. Optimization of the energy storage scheduling to accomplish the same cost minimization objective is described in [63]. The authors of [64] also utilized the building thermal dynamics to maximize the profit of a micro grid including intermittent renewable generation. In the context of home load management, sources [65], [66] optimize the HVAC and domestic hot water consumption under a real-time pricing environment, nonetheless thermal dynamic models employed are too simplistic for real-world applications. An investigation was conducted in [67] of the economic advantages of HVAC integrated with solar storage facility in a home load management context. The research in [68] describes a dynamic programming approach that was used for the optimization of an ice storage air-conditioning system. The work in [46] established a model for optimally scheduling the electric water heaters (EWH) derived from price and consumption forecasts without violating the consumers’ thermal comfort. The authors of [34] explored the real-time DR control for smart home load management. To bring customer's economic savings, the authors of [47] facilitated the load management of HVAC and electric vehicles. The proposed DR model assesses the cost of discomfort and temperature preferences; nevertheless, the framework does not take the uncertainty and risk issues under consideration. Generally, these existing research works consider the HVAC and thermal energy storage in separation, whereas the possible benefits of collaboration of HVAC and thermal energy storage for DR applications has not been investigated. Moreover, in view of the above literature survey, it can be concluded that the research reported in the literature lacks a generic framework for the HVAC load management accounting customers thermal comfort, uncertainty and risk issues together while employing accurate thermal models.

In addition, despite its importance, the realization of HVAC DR in the balancing market has not been assessed well in the literature. However, the focus has been on evaluating the DR potential of domestic thermostatic loads in the balancing power market. For example, the work in [69] considers customers temperature preferences when investigating the system-wide power balancing potential through the EWH load. The results given are important, nevertheless the control scheme for managing the load is non-optimal thus, to execute the same regulation services, a large number of EWH are needed. To address this inadequacy, the authors of [70] measured the HVAC load potential for providing intra-hour power balancing services in the regulating power market. The research documented the considerable capability of the HVAC load for the power balancing reserve. Sources [45], [71] also described the potential of overseeing the thermostatic load for different ancillary services in balancing power market. The articles showcased that the thermostatic load aggregation in the balancing power market can be advantageous from the customer's and system's perspective. The authors of [72] developed a novel temperature set point control algorithm for EWH control for mitigating the power system disturbances. The research revealed that registering the load in the balancing market for power regulation can be a major enabler to increase the operation of intermittent generation in energy mix. The viability of releasing up/down regulation services from commercial HVAC loads is described in [73]. A centralized control module that offers continuous up/down regulation services in the balancing market is devised by the authors of [74]. The majority of the aforementioned articles measured the potential benefits of HVAC and EWH loads in the balancing market but did not comprehensively discuss the rational realization and establishment of this DR potential in the regulating market. Furthermore, the idea that a residential consumer can mutually participate in the energy and balancing power market by co-optimizing the energy attainment and storing some up/down flexibility in the balancing market with regards to preferences and thermal comfort was also not included in most of the works. Therefore, a comprehensive model is necessary to realize the total potential of DR considering customer preferences and the problem itself is tackled in [75], [76].

The above reviewed literature survey indicates that a systematic joint model of both dwelling and thermal energy storage which is appropriate for unleashing the maximum benefits is needed. Morover, appropriate tools for HVAC load management is needed which can thoroughly account for customer's thermal comfort and financial risk preferences. Furthermore, the idea that a residential consumer can mutually participate in the energy and balancing power market by co-optimizing the energy attainment and storing some up/down flexibility in the balancing market requisites attention too.

4.2 Optimal DR through HVAC Load Integrated with Partial Thermal Storage

This section presents a decision framework for optimizing the DR control of HVAC load integrated with partial thermal storage. The objective of the proposed framework is the optimal collaboration of direct electric space heating (HVAC) and partial thermal storage in order to lessen the customer's energy payment without sacrificing customer's temperature preferences. In the proposed model, 1-Capacity building model as schematized in Figure 2.1 is employed to estimate the space heating requirement. The proposed optimal strategy is scrutinized by performing simulations. The analysis results exhibit that the duo of partial heat storage together with thermal inertia of the house can offer much flexibility in load scheduling.

4.2.1 System Model

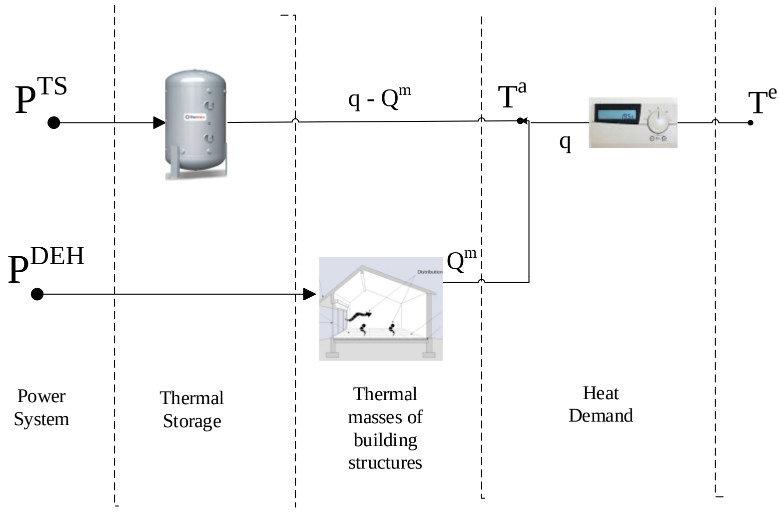

Figure 4.1. System model.

The house's thermal model and thermal storage are coupled for the application of DR as shown in Figure 4.1. The thermal energy storage can be charged via P^{TS} during valley price period to reserve the heat energy for later use during peak price hours. In case of an inadequate state of charge, *SoC*, of thermal storage to meet the heat demand *q*, the power may also be directly delivered to the house for heating via P^{DEH}. The thermal masses of the building structures can act as a buffer and would be exploited if the *SoC* of thermal storage is insufficient during peak price periods. This heat released from the thermal masses of building structures is termed as Q^m. The disproportionate utilization of thermal masses of the building structures is limited by the allowable indoor temperature T^a. The formulation of the optimal DR tool is discussed in the following section.

4.2.2 Proposed Optimal DR Control

The objective of the proposed tool is to optimize the HVAC load integrated with partial thermal storage to minimize the customer's total energy cost without violating the customer's temperature preferences.

$$\min \sum_t \left[C_t^e \left(P_t^{TS} + P_t^{DEH} \right) \Delta t + X_t{}^p \left(Q_t{}^m \right) \Delta t \right] \tag{18}$$

s.t.

$$0 \le P_t^{TS} \le P^{TS,\max}, \forall t \in T \tag{19}$$

$$0 \le P_t^{DEH} \le P^{DEH,\max}, \forall t \in T \tag{20}$$

$$Q_t{}^{m,\min} \le Q_t{}^m \le Q_t{}^{m,\max},\ \forall t \in T \tag{21}$$

$$(SoC_{t+1} - SoC_t)E^{cap} = \left[P_t^{TS} + (Q_t{}^m - q_t) \right] \Delta t, \forall t \in T \tag{22}$$

$$SoC^{\min} \le SoC_t \le SoC^{\max},\ \forall t \in T \tag{23}$$

$$\sum_t \left(P_t^{TS} + P_t^{DEH} \right) \ge E^{lh} \tag{24}$$

$$\sum_t (Q_t{}^m - P_t^{DEH}) = 0 \tag{25}$$

where,

C_t^e is the electricity wholesale price at time *t* (€/kWh)

P_t^{TS} denotes the charging power of thermal storage at time *t* (kW)

$P^{TS,\max}$ is the rated power of thermal storage (kW)

P_t^{DEH} represents the electrical power of direct electric heating system at time *t* (kW)

$P^{DEH,\max}$ denotes the rated power of direct electric heating system (kW)

$X_t{}^p$ is the penalty price for altering the set point temperature of dwelling at time *t* (€/kWh)

$Q_t{}^m$ is the heat released from the thermal masses of building structures at time *t* (kW)

t is the index of time

T is the set of time

q_t is the expected heat demand at hour t (kWh)

Δt is the time interval (hours)

E^{lh} is the energy demand during optimization horzion (kWh)

SoC_t represents the state of charge of thermal storage at time t

$SoC^{\min}$ is the minimum allowable state of charge of thermal storage

$SoC^{\max}$ is the maximum allowable state of charge of thermal storage

To make sure that stored energy in the thermal storage is used first, the penalty price (the latter term) is affixed in (18). The direct control, for instance releasing heat out of the house masses, is to be expected when the *SoC* of thermal storage is insufficient during critical periods. Any value provided can be taken by the penalty factor if it is smaller than the price difference of shifted hours. Furthermore, the aggregator companies may set and adjust the penalty price derived from contracts with consumers and it could be viewed as compensation to consumers. Nonetheless, the study does not focus on how detailed subject of setting the penalty price is connected to electricity markets.

Constraints (19) and (20) bound the rated power of direct electric heating and charging power of thermal storage respectively. The constraint (21) bounds the heat relased from the thermal masses. Constraint (22) describes the *SoC* evolution and (23) ascertains the bounds on *SoC*. Constraint (24) ascertains that the total energy demand requirements are fulfilled. Whereas, the constraints in (25) establish that the total heat taken from the thermal masses of the building structures to be restored within finite duration.

4.2.3 Model Implementation

The execution of this proposed optimal DR control does not call for any expensive hardware. A form of two-way communication is necessary between the load control center and homes and is required to be incorporated with the existing thermostats to control the room temperatures as well as the charging of the thermal storage. A survey can be performed by the aggregator company to record a customer's occupancy and the thermodynamic parameters of house and storage. The customer sets the indoor air temperature and allowable thermostat dead-band they require which is then sent to the load control center through a communication channel. This load control center optimizes the heat load management derived from the spot price/penalty price and user preferences; and sends the signal to the smart thermostats to manage the indoor air temperature and thermal storage charging accordingly. It is a rolling process and the aggregator companies provide compensation to customers who participate in the DR program.

4.2.4 Case Study and Results

A case study is performed in order to investigate the proposed DR tool for a single house scenario in Finland. The hourly spot prices are taken from Nordpool [77]. The indoor temperature set point is presumed to be 20°C. The optimization problem is solved using linear programming solver in MATLAB. The resultant HVAC scheduling given different storage sizes are illustrated in Figure 4.2, Figure 4.3 and Figure 4.4.

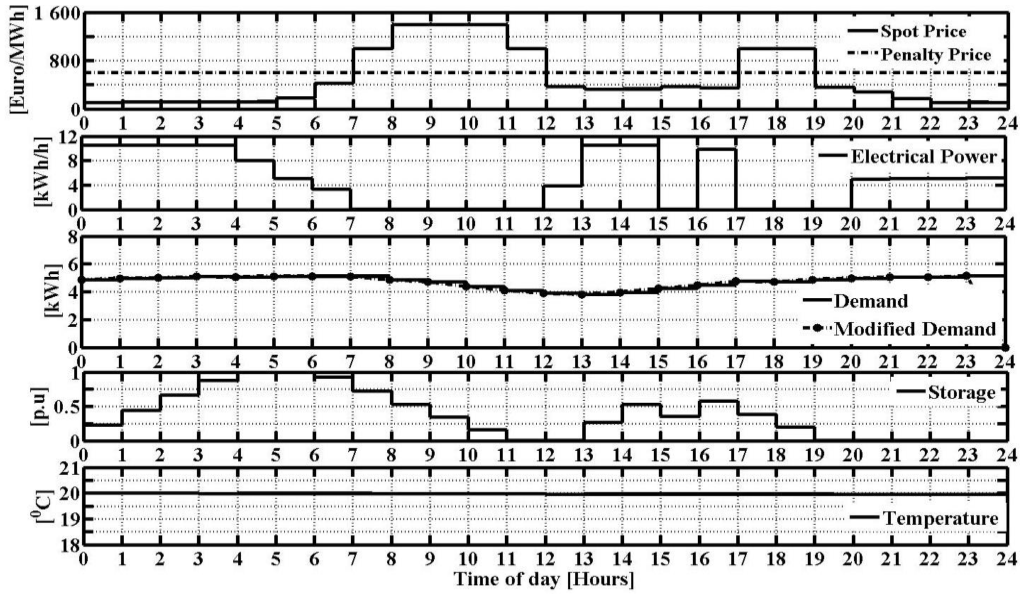

Figure 4.2. Optimal DR control of HVAC with 40% Thermal Storage.

Figure 4.2 depicts the idea that the larger the thermal storage integrated with HVAC systems, the greater the flexibility in heat load management. With larger-sized thermal storages, the heat is not taken from the thermal masses of building structures. As an alternative, the scheduling of thermal storage is such that the stored heat in the storage tank coast the peak price periods effortlessly and therefore the heat transfer between the building structures and indoor air is prevented. There will be no loss of comfort since the hourly indoor ambient temperature will be held constant.

In contrast, as illustrated by Figure 4.3, the DR optimization model exploited the flexibility of HVAC, in the case of smaller storages (≤ 20%), by employing the heat stored in the storage and in the building structures. Evidently, the thermal masses of building structures is only used during peak periods and they work together with the thermal storage only when the *SoC* of thermal energy storage is not sufficient enough to coast the peak price period. The thermostat set point governs the heat stored and released in the thermal masses of building structures. While, utilizing the thermal masses of building structures results in the change in indoor temperature, there is a small loss of comfort however the internal tempearture dead-band stayed within the permissible limit (± 2 °C).

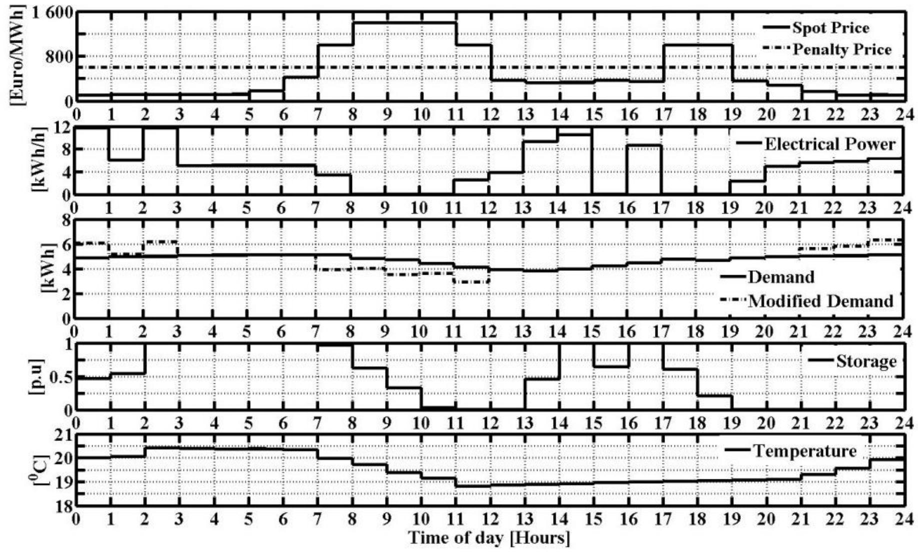

Figure 4.3. Optimal DR control of HVAC with 20% Thermal Storage.

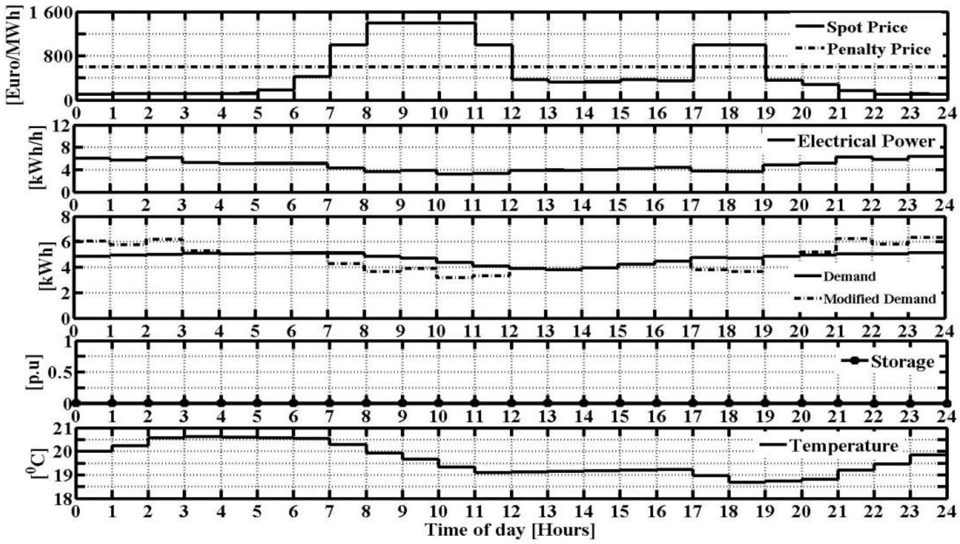

Figure 4.4. Optimal DR control of HVAC without Thermal Storage

Figure 4.4 describes that when there is no storage, the DR control oversees the direct electric space heating load by changing the set point within the permissible temperature dead-band. The pre-heating of the house envelope is done optimally, before peak periods take place.

In all cases, as the internal temperature dead-band changed within tolerable limits, the thermal comfort has not been impinged upon. The optimal control efficiently links the DR potential of direct electric space heating and thermal storage. Evidently, the effect of thermal storage on the flexibility of DR control is proven in the simulation results. The DR potential of sufficient storage level is enormous; however minimum storage capacity is more practical too than having no storage at all. Ultimately, larger storages have more flexibility in responding to price variations while low capacity stages are prone to operating close to and between their extreme limits.

Table 4.I appraised the economic benefits of DR controls and compares them with the business as usual (without DR). The ‘Limited DR strategy’ refers to the strategy where thermostat set point control is not utilized. In other words, the thermal masses of the building structures were unutilized in that strategy. Notably, partial storage space heating load can bring considerable DR potential regardless of having low size storage.

TABLE 4.I

COMPARISON OF CUSTOMER ENERGY COST SAVINGS UNDER DIFFERENT DR STRATEGIES

DR Strategies	HVAC load without Storage	HVAC with 20% Storage	HVAC with 40% Storage
Proposed strategy	5.51 %	38.2 %	46 %
Limited DR strategy	0	32.8 %	46 %

4.3 HVAC Load Management Considering Uncertainties and Risk

In the previous section, a tool for managing HVAC systems in energy market was proposed. However, with the materialization of smarter control technologies and intermittent generations, the expectation that real time prices will be the most common tariff in the future seems even more likely. The price and load uncertainty could create a major problem in scheduling ahead of time and can be an influential factor for customers to register in real time based DR programs [25]. Usually, customer participation in DR programs is influenced by the monetary risk imposed by the price and demand uncertainty. This section proposes a decision framework for real-time DR through HVAC load amid price and demand uncertainty. The optimization model selects the best combination of expected cost, risk and thermal comfort given the predefined user preferences. To showcase the performance of the proposed tool, simulations are performed considering a typical medium massive structure as schematized in Figure 2.2.

4.3.1 Proposed Optimization Model

The proposed generic framework offers a tool for customers to manage HVAC load all the while taking into account a customer's comfort level and risk priorities. It is expected that a residential customer would have different priorities when it comes to energy cost, financial risk hedging and thermal comfort. A multi-objective function is modeled to prove an opportunity for residential customers to choose the arrangement that best fits their needs. Risk aversion, uncertainty and customer dissatisfaction is considered by the developed scheduling tool in the decision making. A scenario based stochastic programming approach is used to deal with the price and load uncertainty [78]. The greater the number of scenarios, the better the accuracy of solution, nonetheless this occurs at the cost of model complexity, and thus it is too cumbersome for practical applications. Nevertheless, techniques such as scenario reduction [79], [80] may come handy when it comes to the reduction of the number of preliminary scenarios without disparagingly compromising the solution accuracy. In this section, however, normal probability density function which is then casted into 7 probable discrete scenarios has been used to model the uncertainties. Consequently, the possible scenarios are generated and then the optimization problem is worked out through all the scenarios. The flow diagram of the proposed framework is exhibited in Figure 4.5. The framework includes following 5 modules:

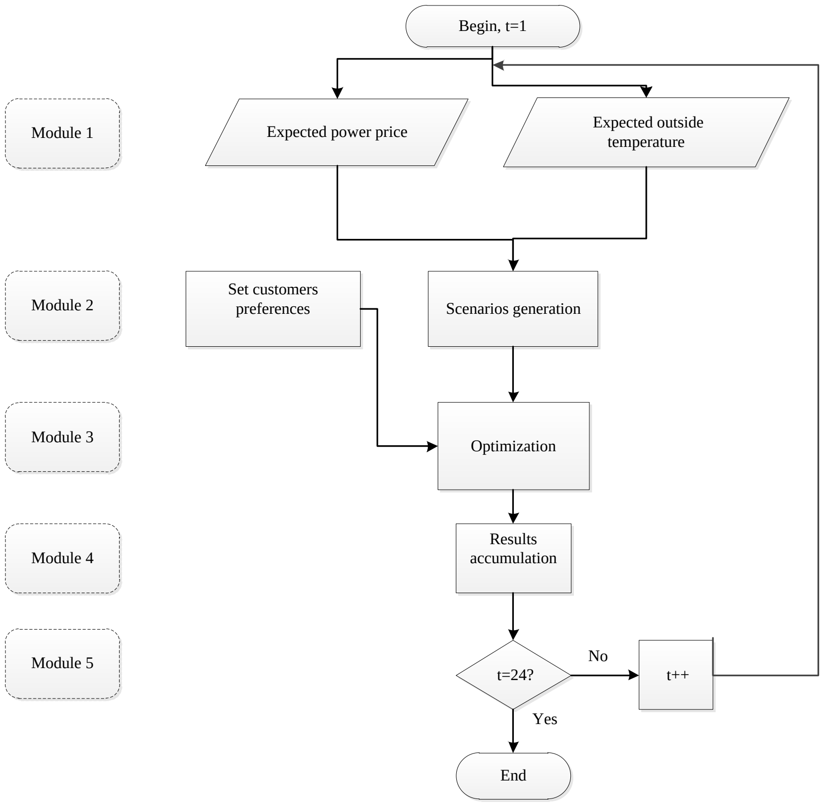

Figure 4.5. Flow diagram of the proposed decision framework.

•**Module 1**: In this basic module, input data associated with the framework such as power prices and outside temperature are loaded.

•**Module 2**: For modeling the uncertainty, probable scenarios are generated in this module based on the well-known 7 piece approximation of normal probability density function. Furthermore, customers’ thermal comfort and risk priorities as well as ambient temperature preferences are gathered which serve as input constraints of the DR model.

•**Module 3**: This module deals with the following optimization model to achieve the trade-off between customer’s energy payment, thermal comfort and risk.

The objective function (26) can be mathematically stated as:

$$\min\{Z^{\text{expected}} + \alpha\left(LoC\right) + \beta\left(\Psi^{f}\right)\} \tag{26}$$

$$Z^{\text{expected}} = \sum_{\varepsilon} prob(\varepsilon) \sum_{t} \left(C^{e}_{t,\varepsilon} (P^{hvac}_{t}) \right) \Delta t, \forall t \in T, \forall \varepsilon \in L \tag{27}$$

$$LoC = \sqrt{\frac{\sum_{t=1}^{lh} (T^{set}_{t} - T^{a}_{t})^{2}}{lh}} \tag{28}$$

$$\Psi^{f} = \sqrt{\sum_{\varepsilon} prob(\varepsilon) \left\{ \sum_{t} \left(C^{e}_{t,\varepsilon} (P^{hvac}_{t}) \right) \Delta t - Z^{\text{expected}} \right\}^{2}}, \forall t \in T, \forall \varepsilon \in L \tag{29}$$

s.t.

$$0 \le P^{hvac}_{t} \le P^{hvac,\max}, \quad \forall t \in T \tag{30}$$

$$\left(P^{hvac}_{t} \right) \le \upsilon_{t}, \forall t \in T \tag{31}$$

$$\sum_{t} (P^{hvac}) \ge E^{lh} \tag{32}$$

$$(T^{set}_{t} - \frac{\phi}{2}) \le T^{a}_{t} \le (T^{set}_{t} + \frac{\phi}{2}), \forall t \in T \tag{33}$$

$$(SoC_{t+1} - SoC_{t}) E^{cap} = (P^{hvac}_{t} - Q^{hvac}_{t}) \Delta t - \xi_{t}, \forall t \in T \tag{34}$$

$$SoC^{\min} \le SoC_{t} \le SoC^{\max}, \ \forall t \in T \tag{35}$$

$$0 \le Q^{hvac}_{t} \le Q^{hvac,\max}, \forall t \in T \tag{36}$$

$$\xi_{t} = \eta SoC_{t-1}, \quad \forall t \in T \tag{37}$$

where,

Z^{expected} is the customer's expected energy cost (€)

α represents the weighting coefficient between expected electricity cost and discomfort cost

β is the weighting coefficient between expected electricity cost and financial risk

LoC is the loss of thermal comfort

Ψ^{f} is the financial risk (€)

$prob(\varepsilon)$ is the probability of scenario ε

C_t^e is the electricity wholesale price at hour t (€/kWh)

P_t^{hvac} is the electrical power of HVAC unit at time t (kW)

$P^{hvac,\max}$ is the power rating of HVAC unit (kW)

t is the index of time

T is the set of time

Δt is the time interval

ε is the index of scenario

L is the set of scenario

lh is the length of optimization horizon

υ_t represents the demand limit at time t (kW)

E^{lh} is the energy demand during optimization horizon (kWh)

T_t^{set} denotes the set point temperature of dwelling at time t (ºC)

ϕ is the internal temperature dead-band (ºC)

T_t^a is the indoor ambient temperature of dwelling at time t (ºC)

SoC_t represents the state of charge of thermal storage at time t

$SoC^{\min}$ is the minimum allowable state of charge of thermal storage

$SoC^{\max}$ is the maximum allowable state of charge of thermal storage

E^{cap} is the maximum thermal storage capacity (kWh)

Q_t^{hvac} is the HVAC thermal output power at time t (kW)

$Q^{hvac,\max}$ is the rated thermal output power of HVAC (kW)

ξ_t denotes the storage thermal losses at time t (kWh)

η is the storage loss coefficient

The objective function (26) includes three conflicting terms. The first term models the energy payment of the customer using the expected over all of the considered scenarios. Customer thermal dissatisfaction costs are represented by the *LoC* in the objective function along with α as the comfort coefficient. The greater value of α is symbolic of a comfort-prioritizing customer and one who is not keen on forfeiting their thermal comfort. On the other hand, lower values of α characterize a comfort-sacrificing/energy-conscious customer, one who will have no trouble forfeiting their thermal comfort for the sake of financial gains. Financial risk due to price uncertainty marks the last term in the objective function which is taken into account using the mean-variance approach

[81]. The risk-coefficient β primarily represents a customer's risk-taking behavior. The larger the β value, the greater the customer's concern for risk. In contrast, a risk-affine customer is represented by a lower β value.

By modifying the weighting coefficient α and β, the customers can select among them according to their preferences and priorities. In this study, classical weighted sum approach is used to solve the multi-objective problem and has the feature of always finding a pareto-optimal solution.

The rated power of the HVAC is enforced by (30). The fact that the total heating load remains under a pre-defined demand limit is established by constraint (31). The following constraint copes with the required heat energy to be supplied to the house during the optimization horizon (32). By allowing the indoor temperature to sway within the pre-defined upper and lower temperature limits, constraint (33) guarantee that user temperature preferences remain intact. In the case of HVAC integrated with thermal storage, modeling is required for storage characteristics, such as stored thermal energy and thermal losses. The equation (34) expresses the dynamics of thermal storage. Constraints (35), (36) present bounds on the maximum thermal energy stored in the tank and discharging power respectively, while (37) describes the thermal losses accumulated every hour.

•**Module 4**: The trajectory of decision variables are collected in this module and only the first step decisions are implemented.

•**Module 5**: This module verifies whether or not the optimization horizon is concluded. If not, then the above series of steps are repeated until the end of optimization horizon is attained.

4.3.2 Case Study and Results

The performance due to our proposed optimal scheme is analysed considering a single house scenario. It is assumed the house is composed of a typical medium massive structure as schematized in Figure 2.2. Without the loss of generality, it is further supposed that the outdoor temperature can be forecasted with high accuracies. This assumption is backed by the fact that sliding window approach introduces a feedback which naturally provides a safeguard against uncertainty especially if the optimization horizon is short. The nonlinear optimization problem framed in Section 4.3.1 is solved via the general algebraic modelling system (GAMS) environment [59]. Simulations are conducted for the following cases.

- Case 1. Impact of comfort parameter on expected cost
- Case 2. Impact of Risk parameter on expected cost.

Table 4.II tabulates the impacts of comfort parameters α on the expected electricity cost in a winter day. The penalty factor α is wide-ranging in a certain interval while weighting parameter β is set to zero. Customers would choose a higher value for α in order to enforce the strict customer thermal comfort requirement. The results show that the expected payment increases when the α value increases. When presented with a

comfort-prioritizing customer, the expected cost is higher than that of a customer who is willing to compromise on their thermal comfort. The customer willing to agree to a wider temperature deviation has to pay about 24% less than the customer who would insist on a strict thermal comfort requirement. The hourly temperature deviation is the highest and the cost payment is at its minimum in the case where α is zero. Notably, the upper and lower indoor temperatures are within acceptable limits by the customer, hence the user quality of service is not compromised. In contrast, when α has the maximum value (α=0.66), the indoor temperature deviation is the smallest (80% less than the case when α =0).

TABLE 4.II

SUMMARY RESULTS OF CASE I

α	Expected Cost (€)	Indoor Temperature Deviation (ºC)	Min. Temperature (ºC)	Max. Temperature (ºC)
0.00	2.33	1.62	18.0	22.7
0.30	2.37	1.27	18.7	22.9
0.40	2.45	1.08	18.8	22.6
0.50	2.51	0.92	19.1	22.2
0.60	2.56	0.80	19.1	21.9
0.65	2.65	0.67	19.3	21.7
0.66	2.87	0.34	20.2	21.4

Next, the impact of risk parameter β on expected energy payment is investigated. The problem is illustrated for a comfort-sacrificing customers (α = 0) by altering the risk coefficient β in certain intervals to acquire numerical results. To implement risk-hedging, a customer would select a higher value of β. Figure 4.6 shows the expected payments associated with different risk-levels. The plot illustrates an inverse relationship between risk (cost standard deviation) and expected payment. The higher the risk, the smaller the expected payment. The energy cost of a risk-affine customer is about 10% lower than a risk-averse customer. Evidently, risk cannot be diminishing completely and there is a lower bound of risk-hedging.

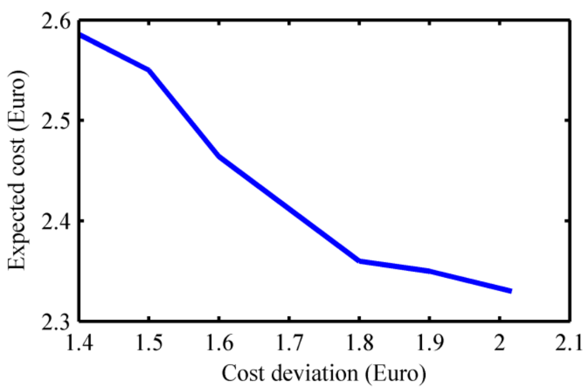

Figure 4.6. Risk versus Expected payment evolution.

4.4 HVAC Load Management in Balancing Market: A Two Stage Framework

This section offers a framework to enable customers' participation in balancing market along with energy market. The framework features 2-stages which allows the domestic customers to co-optimize the energy attainment in energy market and possible reserving some flexibility in balancing market. In the Nordic power market system, the aggregator is compelled to declare their day-ahead power proposal to the respective subsequent transmission system operator (TSO) before the actual power delivery phase. Nevertheless, it is possible for the aggregator to experience negative repercussions due to forecasting errors and face power mismatch issues during the actual delivery phase which could result in large penalties for infringing upon the hourly power nominations. Luckily, the aggregator can manage the group of HVAC loads integrated with thermal storage in the balancing market to lessen the power balancing penalty rather than buying the balancing power from TSO, to handle the power mismatch penalty. Under this background, a hierarchical framework that engages the residential customers to participate in balancing power market is setup. Two stages are included in the decision support tool. In the first stage of DR management, which is called the energy market stage, customers are provided day-ahead hourly prices to optimize their load usage in order to obtain the least energy payment that is possible. Additionally, this stage allows for a customer to determine their energy management decision. The second stage is set up in order to register customers in the balancing power market and offers hourly monetary incentive to customers to encourage the load shaping through up/down regulation of the load. To showcase the performance of the proposed hierarchical framework, simulations are performed considering a typical Finnish residential household.

4.4.1 Decision Framework

Figure 4.7 depicts the developed decision framework. In the first stage, the aggregator gives consumers the day-ahead power prices. Using the hourly prices, expected heat demand forecast, thermal storage model and user operating flexibility, in order to achieve the minimum energy payment, the energy scheduling controller optimizes the storage charging operation. The scheduling is done in a way that does not affect the customer's quality of service. The output power decision matrix is communicated to smart home energy management (SHEM) unit followed by the energy schedule submitting a load decision matrix to the aggregator. In the second stage, energy management is executed on a rolling window basis for the next 24 hours with 1 hour resolution. During this stage, the customers are offered bonus prices for adjusting their prior made decisions which encourages customers to participate in the regulating market at the next hour. The bonus price for regulating up/down power is communicated to the energy scheduler 10 minutes before the hour in operation. Only if the newer energy payment is less than the Stage 1 energy cost, the energy scheduler update the decision matrix. If the DR is not activated, then the aggregator may gradually increase the bonus price up to a certain maximum limit. Then, the altered output charging decision matrix is relayed to aggregator and also communicated back to the SHEM for managing the HVAC load accordingly.

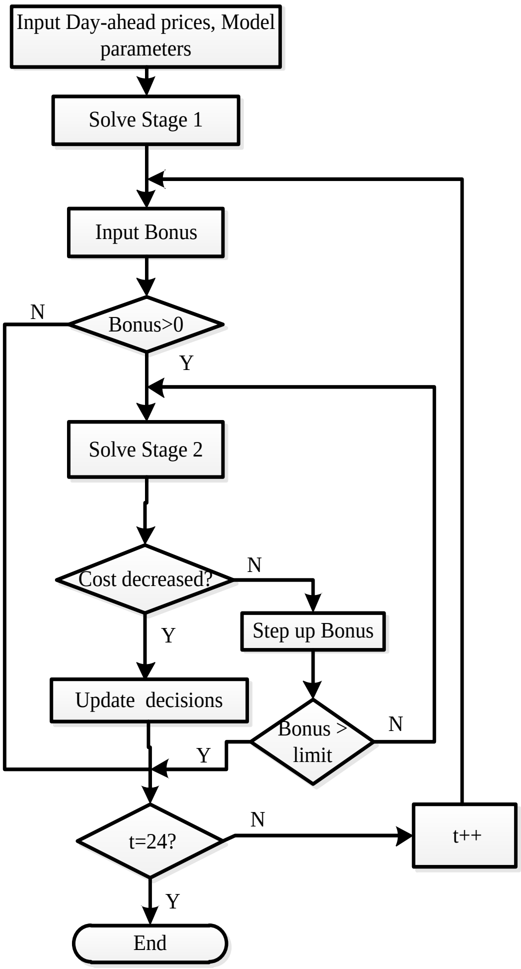

Figure 4.7. Flow chart representing the hierarchical model.

Stage 1: Energy Market Stage

In the first stage, the objective is to minimize the energy payment of the customer. It can be mathematically stated as:

$$\min \sum_t C_t^e P_t^{hvac} \Delta t \tag{38}$$

It is to be noted that the uncertainties are not taken into consideration in the objective function (38). However, in order to make any DR program attainable, the uncertainties related to the price and load must be carefully dealt with. This section includes the employment of the robust optimization approach [82] for dealing with the price and load uncertainties. The price and load uncertainties sets for the robust optimization framework are based on the information on the stochastic nature of data. To achieve this, one must first create scenarios using a stochastic programming approach [78] and then using them as guidelines for representing the price and load uncertainty intervals set. An assumption can be made that the power price and load uncertainty distribution follows a normal distribution pattern while the standard deviation is known ahead. Even though this approach is more conventional, it is strong against possible uncertainty scenarios.

The above equation represents the cost minimization objective function that can be translated into robust counterpart (39) using duality properties and linear equivalence, in order to account the uncertainties.

$$\min \sum_t C_t^{e,\min} P_t^{hvac} \Delta t + \sum_t \tau_t + \psi\ \Pi \tag{39}$$

The dual variables in the model are ψ and τ_t. The robustness of the proposed mathematical model is controlled by parameter Π. A higher value for Π is chosen to impose the harsher concerns on price uncertainty. On the other hand, Π = 0 specify an optimistic solution since, in this case, the influence of price uncertainty is disregarded. The objective function (39) is subjected to a number of operational constraints that are described below.

$$(1-\mu)P^{hvac,\max} \leq P_t^{hvac} \leq \mu P^{hvac,\max}, \quad \forall t \tag{40}$$

$$(1-\sigma)SoC^{\max} \leq SoC_t \leq \sigma SoC^{\max}, \quad \forall t \tag{41}$$

$$(SoC_{t+1} - SoC_t)E^{cap} = (P_t^{hvac} - Q_t^{hvac})\Delta t - \xi_t, \forall t \in T \tag{42}$$

$$\xi_t = \eta SoC_{t-1}, \quad \forall t \in T \tag{43}$$

$$0 \leq P_t^{hvac} \leq P^{hvac,\max}, \quad \forall t \in T \tag{44}$$

$$0 \leq Q_t^{hvac} \leq Q^{hvac,\max}, \forall t \in T \tag{45}$$

$$Q_t^{hvac} \geq \pi q_t, \forall t \in T \tag{46}$$

$$SoC_{t_{end}} \geq SoC_{t_o} \tag{47}$$

$$\psi + \tau_t \geq r_t \left(C_t^{e,\max} - C_t^{e,\min}\right), \quad \forall t \tag{48}$$

$$\tau_t \geq 0, \forall t \tag{49}$$

$$\psi \geq 0 \tag{50}$$

$$r_t \geq P_t^{hvac}, \forall t \tag{51}$$

where,

C_t^e represents the power price at time *t* (€/kWh)

$C_t^{e,\min}$ represents the lower bound of power price at time *t* (€/kWh)

$C_t^{e,\max}$ represents the upper bound of power price at time *t* (€/kWh)

P_t^{hvac} is the electrical power of HVAC unit at time t (kW)

$P^{hvac,\max}$ is the power rating of HVAC unit (kW)

Δt is the time interval (hours)

SoC_t is the state of charge of thermal storage at time t

$SoC^{\min}$ is the minimum allowable state of charge of thermal storage

$SoC^{\max}$ is the maximum allowable state of charge of thermal storage

E^{cap} is the maximum thermal storage capacity (kWh)

Q_t^{hvac} is the HVAC thermal output power at time t (kW)

$Q^{hvac,\max}$ is the rated thermal output power of HVAC (kW)

ξ_t denotes the storage thermal losses at time t (kWh)

η is the storage loss coefficient

q_t is the expected heat demand at time t

t is the index of time

T is the set of time

τ_t / ψ are dual variables of robust optimization model

Π is a parameter for controlling the robustness

μ denotes the weighting coefficient for setting HVAC power operating limits

σ represents the weighting coefficient for setting SoC opearting limits

π is the weighting coefficient between expected demand and stored heat energy

r_t is an auxiliary variable in robust optimization model

The upper and lower ramping power limit of storage heating unit are bounded by constraint (40). Depending on user preferences, the weighting coefficient $0.5<\mu\leq 1$ will set an operating limit. For example, in the situation where the customers want to actively involve themselves in the balancing market, the user could perhaps reserve some power flexibility for ramping up and down at all times by allocating a value of $0.5<\mu\leq 1$. The maximum thermal energy that can be accumulated in the storage is set in constraint (41). In order to coordinate the power balancing and energy attainment goal, the storage capacity is virtually divided. The thermal storage SoC can be restricted in the first stage so that during Stage 2, there is always a load shifting potential in hand. The tradeoff is set by the coefficient 0.5<σ≤1. For example, during the second stage, σ=0.9 will allocate a reserve margin of 10% of the total storage capacity for regulation purpose whereas in Stage 1, the thermal storage should neither exceed the 90% *SoC* nor fall below than 10% *SoC* limit. Equation (42) describes the storage evolution. The equation (43) represents the thermal storage losses. Constraints (44), (45) bound the limits on the electrical input and thermal outpower power of the HVAC respectively. Constraint (46) takes into account customer’s thermal comfort. It establishes that the total energy discharge from the thermal storage must be equal to the hourly expected heat demand. The actual hourly heat demand can change from the expected demand, depending on the forecast accuracy. One way to deal with the demand uncertainty issue is to manage the thermal storage scheduling for the worst case by storing more thermal energy than the expected heat energy prerequisite. The demand uncertainty level that is considered and set by the customer is enforced by the coefficient π≥1. This approach will enable the customers for the possible realization of demand uncertainty and thus ensure that the customer's quality of service is not compromised. The final stage of charge should at least be equal to the original level of stored energy prior to the optimization as set by (47). To acquire the robust counterpart of an uncertain linear programming problem, equations (48)-(51) are employed.

Stage 2: Balancing Power Market Stage

Bonus price incentives are given out in the second stage to encourage customers to participate in the balancing market. The goal of this stage is to maximize the customers' bonus which eventually lessens their total energy payment as described by objective function (52). Using a moving window approach, the following set of optimization is executed on an hourly basis.

$$\max\ (\chi) b_t^e \Delta P_t^{hvac} \tag{52}$$

s.t.

$$0 \le \left(P_t^{hvac} + \Delta P_t^{hvac}\right) \le P^{hvac,\max}, \quad \forall t \in T \tag{53}$$

$$(SoC_{t+1} - SoC_t)E^{cap} = (P_t^{hvac} + \Delta P_t^{hvac} - Q_t^{hvac})\Delta t - \xi_t, \forall t \in T \tag{54}$$

$$SoC^{\min} \le SoC_t \le SoC^{\max}, \ \forall t \in T \tag{55}$$

$$0 \le Q_t^{hvac} \le Q^{hvac,\max}, \forall t \in T \tag{56}$$

$$Q_t^{hvac} + \xi_t = q_t, \forall t \in T \tag{57}$$

$$\xi_t = \eta SoC_{t-1}, \quad \forall t \in T \tag{58}$$

where,

χ represents the binary variable for (1) up and (-1) down regulation

b_t^e is the bonus price during time slot *t* (€/kWh)

ΔP_t^{hvac} represents the deviation from original HVAC schedule during time slot *t* (kW)

The fact that the new charging power shall not surpass the maximum power restriction and bound the net change in power deviation is certain in constraint (53). Notably, the coefficients σ, μ as set by the customer in the Stage 1 will affect the ΔP_t^{hvac} flexibility. The key storage elements and comfort constraints are described in constraints (54)-(58) which is similar to Stage 1. In order to encourage the customer to alter his/her schedule, the new cost after Stage 2 should be lower than the Stage 1 promised cost. Any commercially available solver can easily solve the framework which is casted as a linear programming problem.

4.4.2 Case Studies and Results

In this section, numerical analyses are carried out to present the effectiveness of the proposed framework. The developed framework is applied to the standard Finnish single house scenario. The medium massive structure house is considered which is equipped with HVAC integrated with thermal storage unit. The hourly heat load profiles are created using IDA software [83]. Based on the expected heating demand and time-varying standard deviations, 7 probable scenarios are produced using a 7 step well-known approximation of normal distribution. It was assumed that in the worst case and if one takes the generated scenarios as a guideline, the heating load can drift in a 5% margin and load certainty coefficient π thus takes value of 1.05. For the simulation, the typical hourly day-ahead time varying prices are chosen for Stage 1 scheduling and are taken from Nordpool [77]. The proposed formulation is solved using GAMS [59] environment. Simulations are conducted for the following two distinct cases.

•**Case A**: This case represents the base case, where flexibility of HVAC load is maximally utilized during Stage 1. For this case, parameters are set as μ=100%, and σ=100%.

•**Case B**: In this case, activation of DR in Stage 1 is done in manner that by reserving some availability for Stage 2. Here, the parameter setting is as follows μ=80%, and σ=80%.

Table 4.III includes a presentation of the total energy cost after Stage 2. Evidently, the benefits of proposed formulation scheme can be seen as the customer's energy payment decreases if the DR is also triggered in the balancing power market instead of Stage 1 alone. The final energy costs are less for Case B compared to Case A for partial storages, as revealed by the simulation results. However, the total energy costs in Case B are faintly higher compared to Case A for bigger thermal storages. There are two reasons for the contrasting results for full size storages. (a) It is essential to note that the coefficients μ, and σ for reserving flexibility during Stage 2 were not optimized in any way; thus the full storage, which has greater load regulation potential, cannot fully release the total benefits of the suggested framework. The selection of μ, and σ relies on many factors, for instance accurate forecasting of regulating prices, customer risk preferences, and thermal comfort priority which makes the task troublesome. However, the optimal choice of coefficients σ and μ, which in itself is a difficult job, will be able to garner more DR advantages in the balancing power market (b) In the Finnish market, the variance of energy market prices and regulating power prices is relatively low. The proposed framework, however, is still successful since it demonstrates how a domestic

HVAC load can be efficiently employed in the balancing power market to facilitate the customer to achieve maximum economic gains.

TABLE 4.III

OVERVIEW OF RESULTS

Storage size (% of typical daily energy requirement)	Case A		Case B	
	Stage 1	Stage 2	Stage 1	Stage 2
25 %	0.964 €	0.911 €	1.08 €	0.90 €
50 %	0.89 €	0.762 €	1.031 €	0.76 €
75 %	0.87 €	0.725 €	1.032 €	0.917 €
100 %	0.86 €	0.687 €	1.041 €	0.9 €

4.5 Conclusion

This chapter presented comprehensive frameworks for HVAC load management in smart grid. The proposed price based DR mechanisms aim to minimize the customer energy cost while respecting customer preferences under different scenarios. At first, optimization model is proposed to investigate the envisioned benefits withour considering uncertainty. Next, uncertainty and risk features are incorporated in the decision framework. Then simulations are perfomed considering a typical Finnish single house scenario. The results of the study revealed that significant monetary benefits are achieved by employing DR through HVAC loads. Moreover, it is showcased that the optimal utilization of thermal masses of building structures together with thermal storage will reap significant benefits without sacrificing customer thermal comfort. The decision model also provides an opportunity for customer to tradeoff between financial risk and expected cost depending on customer preferences. The proposed DR frameworks are formulated with customer's partialities and cost-economic in mind and thus can be easily incorporated into the SHEM unit.

5. HVAC Load Management for Wind Generation Balancing

Intermittent renewable generation such as solar and wind are non-dispatchable owing to their variability and stochasticity. This chapter deals with development of tools to activate demand response (DR) through heating, ventilation and air conditioning (HVAC) loads for balancing intermittent generation so that customers consume the renewable generation rather than spilling the excess generation (Task 3). To begin with, a tool for activating DR for wind generation balancing is developed. Next, the framework is reformed to add the real-time thermal rating (RTTR) features of network in the optimization. The usefulness of both the developed tools is illustrated by selective case studies. Finally, a tool for optimizing the DR services namely customer energy cost reduction and wind integration from the perspective of electrical aggregator is developed.

5.1 Introduction and Literature Review

In upcoming power systems around the world, wind energy generation sources may have a considerable share in the total generation mix. However, enhanced operational flexibility requirements will be a big problem in the wide-spread integration of wind generation because of the inconsistency and unpredictability of wind power [9]. There's a chance of supply load imbalance due to the wind power limited capacity value that jeopardizes the power system reliability [10], [84]. Power ramping and regulation requirements may also be put into effect, creating technical difficulties for the system operators [85].

To deal with the mentioned problem, additional flexibility resources are necessary in smart grids. A practical solution is to use the flexibility from demand side resources [13] which will lead to better operation of intermittent renewable generation. Lately, the advantages of load management of thermostatically controlled appliances for the increased operation of intermittent renewable generation have been explored [69]-[72], [74], [86]. For example, [69] investigated the electric water heater (EWH) load potential for load shifting and supply-load balancing. The work studied in [72] presented a centralized domestic DR framework for providing short term balancing reserves to cope with the variability of wind generation. The results recounted the significant potential of EWH loads to regulate the system frequency at all times. Although several researchers have addressed the issue yet, a comprehensive optimization solution is missing which takes into account the customers' thermal comfort.

Another concern is that, If DR potential is to be deployed for distributed generation (DG) balancing; the network capacity has to be capable of supporting the load associated with high DG output. The author in [87] presented a hiearchial residential DR model considering static network rating. However, due to the traditionally used static rating (STR) of thermally susceptible components [88], [89], DR potential can be hindered by limited network capacity during period of high DG output. This will result in limiting the DG output, consequently obstructing also the DR benefits. Lately, many studies [90], [91] have advocated that conventionally used networks STR should be substituted with real-time (dynamic) thermal rating to utilize the network capacities for maximal utilization of renewable generation, particularly considering the forthcoming scenario of large scale diffusion of intermittent renewable generation. RTTR can be used as a tool to efficiently utilize the intermittent renewable generation as suggested by studies in [40], [92]. Weather dependent rating of the distribution network will facilitate DR actions, i.e., shifting load from low DG output (low wind speed) times to high DG output (high wind speed) times. Synergy in coordinating DR and RTTR is implied by the idea that both DG output and RTTR based capacity depend on outside weather variables such as wind speed and ambient temperature. Therefore, RTTR can make use of the weather dependent capacity to avoid capacity-constraint-based DG curtailment thus completely facilitating DG actions.

A number of aggregator-pro DR models are proposed in the prevailing literature. The work [93], proposed a DR strategy, whereby the electrical aggregator can participate in the energy market for bulk DR transaction. The research reported in [94], [95] proposed an approach to utilize DR for maximizing the aggregator economic gains while concurrently alleviating network peak load issues. The market potential of residential load acting as frequency reserve control is studied by [96]- [98]. The work in [99] proposed an aggregator-based DR framework to optimize the micro combined heat and power units scheduling for reducing the network over laod problem. The study [100] developed aggregator based HVAC DR framework to cope with problem of intra-hour balancing. The study [101] focused from the perspective of an aggregator who can optimally achieve the enery management in the energy market. The authors of [102] suggested an incentive based DR approach with the objective of achieving the desired load profile in order to minimize the penalty costs faced by aggregator. The work in [103] proposed an aggregator-focused DR methodology to cope with the variability of intermittent generation whereby, the aggregator act as an arbitrator between end user and utility to fulfil the grid limitations.

Prior to [V], none of the work thoroughly discussed the activation of HVAC load for wind generation balancing considering customers' temperature preferences. Neither any research investigated the potential benefits of coordinating RTTR and DR for wind balancing until [VI]. In addition, a framework to optimize aggregator focused DR services in the system of large scale intermittent DGs were missing before [VII].

5.2 Activation of HVAC DR for Wind Generation Balancing

This section develops an optimization tool for wind generation balancing through HVAC DR considering customers thermal comfort. The tool determines the optimal energy consumption of HVAC loads to tackle the variability of wind generation. In the proposed optimization model, thermal comfort penalty is explicitly incorporated in the objective function to account for customer convenience. The developed tool performance is justified thorough simulations considering typical Finnish system. A broad sensitivity analyses is conducted to investigate the impact of different parameters such as customers' enrollment, and wind penetration on results. The subtleties of optimization model and case studies are given in the subsequent section.

5.2.1 Proposed Model

Let there be interaction between wind power producers and residential consumers under the smart grid environment. It is presumed that the common understanding between production portfolios and consumers group allows the wind power entity to manage the operation of the HVAC load for improved deployment of variable renewable generation. In response, based on the flexibility and willingness of their participation level, each customer gets some financial reward. The management of the load must be done in such a way that customer comfort is a priority and thermal preferences remain unscathed. For this to occur, a user eccentric decision tool must be developed to effectively control the load without lessening customers' thermal comfort and respecting their priorities. Provided in this section is a mathematical model which will act as a tool for smart scheduling of the HVAC loads with a priority being consumer comfort. The goal of the framework is the minimization of time-varying supply minus net demand while decreasing the thermal comfort loss. The objective function can be given as follows.

$$\min \sum_{t} \left(\left| (\Gamma_t + \lambda_t) - \sum_{n} W^n (P_{n,t}^{critical} + P_{n,t}^{hvac}) \right| + \Omega \sum_{n} (1 - W^n) \left| T_{n,t}^{a} - T_{n,t}^{set} \right| \right) \tag{59}$$

The first part of the objective function is the minimization of deviation between wind generation and net demand. The following part is the optimization of customers' thermal comfort which entails that users' hourly desired set point temperature is to be deviated to the smallest extent as possible. It is worth mentioning that customers have the full authority to alter the weighting coefficient W^n = [0, 1], and can choose thermal comfort over load control by setting a lower W^n value.

The objective function is subjected to the following constraints.

$$(T_{n,t}^{set} - \frac{\phi_n}{2}) \le T_{n,t}^{a} \le (T_{n,t}^{set} + \frac{\phi_n}{2}), \forall t \in T, \forall n \in N \tag{60}$$

$$0 \le P_{n,t}^{hvac} \le P_{n}^{hvac,\max}, \quad \forall t \in T, \forall n \in N \tag{61}$$

$$0 \le Q_{n,t}^{hvac} \le Q_{n}^{hvac,\max}, \quad \forall t \in T, \forall n \in N \tag{62}$$

$$P_{n,t}^{critical} + P_{n,t}^{hvac} \le \upsilon_t, \quad \forall t \in T, \forall n \in N \tag{63}$$

$$(SoC_{n,t+1} - SoC_{n,t}) E_{n}^{cap} = (P_{n,t}^{hvac} - Q_{n,t}^{hvac}) \Delta t - \xi_{n,t}, \forall t \in T, \forall n \in N \tag{64}$$

$$SoC_n^{\min} \le SoC_{n,t} \le SoC_n^{\max}, \forall t \in T, \forall n \in N \tag{65}$$

$$\xi_{n,t} = \eta^n SoC_{n,t-1}, \quad \forall t \in T, \forall n \in N \tag{66}$$

$$\sum_t (P_{n,t}^{critical} + P_{n,t}^{hvac}) \le E_n^{lh}, \forall n \in N \tag{67}$$

$$SoC_{n,t_{end}} = SoC_{n,t_o} \ , \forall n \in N \tag{68}$$

where,

Γ_t is the conventional generation at time t (kW)

λ_t is the wind generation at time t (kW)

W^n denotes the weighting coefficient for setting comfort priority

$P_{n,t}^{critical}$ represents the power of all critical appliances at time t of customer n (kW)

Ω denotes the weighting coefficient between DR and comfort

t is the index of time

T is the set of time

n is the index of customer

N is the set of customer

$P_{n,t}^{hvac}$ is the electrical power of HVAC unit at time t of customer n (kW)

$P_n^{hvac,\max}$ is the power rating of HVAC unit of customer n (kW)

υ_t represents the demand limit at time t (kW)

Δt is the time interval (hours)

E_n^{lh} is the energy demand of customer n during optimization horizon (kWh)

$T_{n,t}^{set}$ denotes the set point temperature of dwelling at time t of customer n (^{o}C)

ϕ_n is the internal temperature dead-band of customer n (^{o}C)

$T_{n,t}^{a}$ is the indoor ambient temperature of dwelling at time t of customer n (^{o}C)

$SoC_{n,t}$ represents the state of charge of thermal storage of customer n

E_n^{cap} is the maximum thermal storage capacity of customer n (kWh)

$SoC_n^{\min}$ is the minimum allowable state of charge of thermal storage of customer n

$SoC_n^{\max}$ is the maximum allowable state of charge of thermal storage of customer n

$Q_{n,t}^{hvac}$ is the HVAC thermal output power at time t of customer n (kW)

$Q_n^{hvac,\max}$ is the rated thermal output power of HVAC of customer n (kW)

$\xi_{n,t}$ denotes the storage thermal losses at time t of customer n (kWh)

η^n is the storage loss coefficient of customer n

Constraint (60) ascertains that the indoor ambient temperature is bound to stay within the set internal temperature deadband. HVAC system can work at continuos power level while bounded by maximum rated powers as described by (61) and (62). Maximum hourly demand limit is bounded by (63). The expression (64) determines the amount of stored energy in the tank. Constraint (65) bounds the *SoC* of thermal storage, while storgae losses are determined by (66). The costraints (67) ascertains that total energy consumtion should be less than the business as usual daily energy requirement. Constraint (68) ascertains that the final and intial level of storage must be equal.

5.2.2 Case Studies and Results

The proposed model is applied to a Finnish system comprising of 50 households. The hourly consumption data is acquired from automatic meter reading (AMR) data and then disaggregation of the critical load from the total load is done by executing multiple regression analysis on a big set of hourly consumption data [104]. 2-capacity building model is employed to generate the heating load, by considering the outside temperature of a typical mild winter day. The house areas are distributed within 180-220 sq. meters via normal distribution. An assumption can be made that the power production portfolio mainly consists of wind generation.

To demonstrate the application of the developed tool for wind generation balancing, results for the following case studies are described.

Case I: Without DR control.

Case II: With DR through HVAC load. In this study, users have the liberty to set temperature preferences and weight coefficient W^n. An assumption can be made that W^n and $P_n^{hvac,\max}$ are normally distributed in [0, 1] and [3 kW, 4 kW] intervals respectively among users, to capture diversity, while indoor temperature can drift in the range [19.5, 22.5] °C with the average indoor temperature of 21 °C.

Case III: With DR through HVAC load integrated with thermal storage. The maximum storage capacity is considered to be around 50% of total daily heating demand of a household with maximum charging capability of 6 kW. The storage losses are deemed to be insignificant, W^n values and indoor temperature preferences are kept similar to Case I.

Additionally, sensitivity analyses are conducted to investigate the influence of customer DR enrollment and wind penetration on results.

The load profile situation for the consumer group in Case I is illustrated in Figure 5.1. During mid-night and morning time the load profile is quite flat. However, in terms of hourly matching, the system load profile is far from the volatile generation profile. Consequently, the total deviation of load profile from volatile generation is about 416 kW.

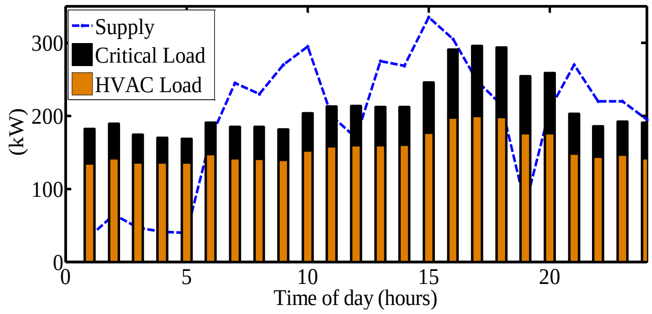

Figure 5.1. Load balancing situation in Case I.

The total demand profile of the studied user group in Case II, where operation of HVAC loads is optimized to minimize the deviation between supply and total demand is portrayed by Figure 5.2. The results indicate that the load tries to shift the operation in a timely manner in order to align itself with volatile generation. The DR potential is released by accumulating the amount of heat in building masses when down regulation is necessary. To carry minimum deviation between the load-supply profiles, the stored heat can be released from the thermal masses of building structures. Nevertheless, there is a limit to the DR potential in coping with the intermittent supply due to indoor temperature limits and customers' comfort concerns.

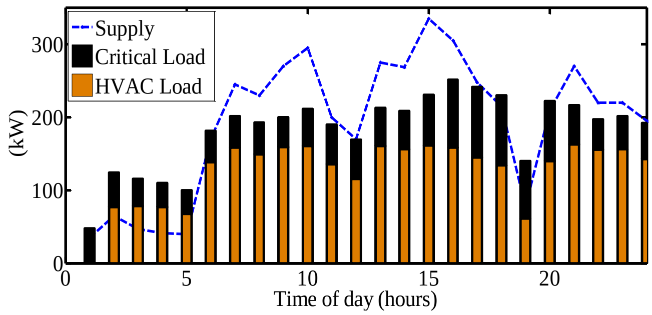

Figure 5.2. Load balancing situation in Case II.

The situation in Case III is illustrated in Figure 5.3, where the total load profile is acquired by coordinating the operation of thermal storage combined with the HVAC load. The illustration clearly defines the inclination of the load profile of the consumer group to accurately follow the volatile generation profile, thus resulting in least deviation between the supply-demand curves. The total deviations during the horizon decrease only to 55.41 kW, which is 4 times better than in Case II. Because of the presence of thermal energy storage, this timely shifting of load is done flawlessly in this case.

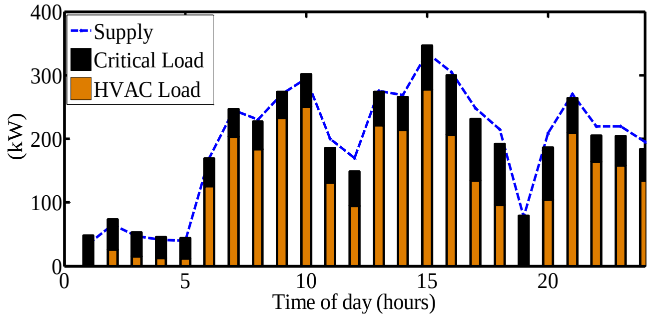

Figure 5.3. Load balancing situation in Case III.

Results Sensitivity Scrutiny

Impact of reducing thermal comfort priority

Representative studies are infused with different values on comfort objectives in order to explore the impact of users' thermal comfort on the success of the DR control. Cases II and III are simulated by altering the W^n value. For Cases II and III, the total deviation between supply and demand profiles for a different W^n value is listed in Table 5.I. According to acquired results, in Case II the DR performance increases (deviation decreases) almost by 5.1%, 9.7% and 15.4% when W^n is increased by 1/4th, half, and 3/4th, respectively. Case III portrays a significant improvement that can be observed as the W^n value is increased. If customers are willing to slightly relinquish their thermal comfort, the deviation is reduced by half. Furthermore, an analysis was conducted on the most positive case to examine the maximum potential for the representative study by setting weight coefficient (W^n =1) on customer comfort objectives. The results indicated the absolute improvement in Case I (29.2 %) and Case II (96.4 %).

TABLE 5.I

INFLUENCE OF USERS' THERMAL COMFORT ON COMULATIVE DEVIATION BETWEEN VOLATILE GENERATION AND DEMAND

Change in W^n	Case II	Case III
------	247 kW	55.41 kW
W^n increased by 1/4th	234.8 kW	45.0 kW
W^n increased by half	223.1 kW	36.5 kW
W^n increased by 3/4th	208.9 kW	28.4 kW
W^n = 1	175.2 kW	1.6 kW

How much wind integration can be handled?

The findings for Case II and Case III with $W^n = 1$ are highlighted in Figure 5.4. The reported result gives a picture of the level of wind penetration that can be attained. These results can be construed as that around 30% of wind generation can be almost undertaken by coordinating the HVAC loads. With the thermal storage integration with HVAC system, the wind integration potential is much greater. Visibly, a great deal of wind power (around 90%) can easily be facilitated by managing the population of HVAC loads equipped with thermal storage.

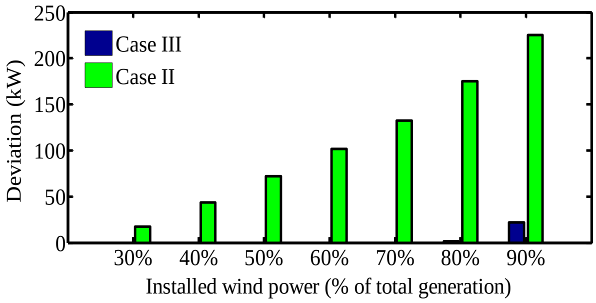

Figure 5.4. Wind power deviation capturing ability in different cases.

5.3 Activation of HVAC DR for Wind Generation Balancing Considering Network RTTR

This section presents a tool for optimal collaboration of residential HVAC DR and RTTR to match the distributed wind power output. Utilizing network real time thermal models, this section presents a tool to deploy the network capacity released as a result of robust dependence between wind power and the real-time network thermal state for tapping the HVAC DR potential. The benefits of applying RTTR in overhead networks, as a new tool to release network capacity, as well as DR, as a load shaping tool, when network capacity is limited is thoroughly investigated. Additionally, the study examines the influence of the DR penetration level and HVAC key parameters on the total benefits achieved by the joint optimization of DR and RTTR. The study utilizes a typical Finnish distribution network plan and relevant case studies are presented.

5.3.1 Proposed Model

This section includes a presentation of a chronological system to assess the joint benefits of coordinating DR and RTTR for wind generation utilization. Let there be an aggregator with a share of wind generation and a large population of HVAC loads. It is advantageous for the aggregator to execute real-time management of the load such that the utilization of wind generation is maximized. In response, depending on their participation level, customers are awarded with a financial bonus. Consequently, it assembles information from the residential load and the wind forecaster to make sufficient control decisions. However, the aggregator must take into consideration each customer's temperature preferences. Furthermore, since the ramping capability of responsive loads can be influenced by the network capacity, the power flow study has to be conducted at every time-step to determine that load commitment does not infringe upon any network capacity limits.

The optimization routine is executed in real-time for the following 24 hours with 1-hour resolution in a moving window style. Figure 5.5 illustrates the simulation procedure and is discussed in the following.

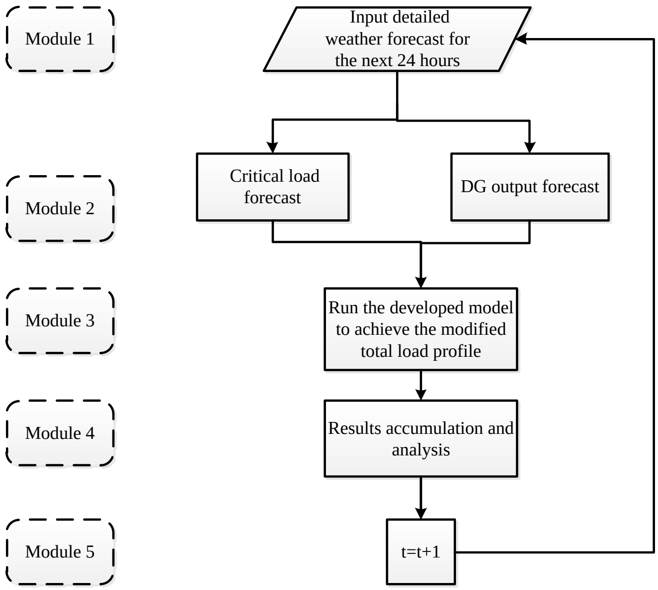

Figure 5.5. Flowchart of the proposed methodology.

The RTTR method is reorganized each hour using revised forecasts of weather variables for the next 24 hours. Dynamic thermal models of underground cables, overhead lines and transformers are used by the RTTR method to give the next hour capacity using previous hour initial thermal states and next hour forecasts of the weather variables, DG output and load. Numerical representation of every available heat transfer mechanism such as convection, conduction and radiation is incorporated in thermal modeling. This work studies the dynamic thermal model of underground cables in unfilled conduit installations which is employed from [40]. Standards IEEE Std. C57.91-2011 and IEEE Std. 738-2006 are used respectively in [105], [106] for distribution transformers and overhead lines.

Module 1: At first, weather related data is obtained. The data is composed of information for the next 24 hours. A simple Autoregressive Integrated Moving Average (ARIMA) model is used to forecast weather variables such as wind speed [107].

Module 2: In this block, wind output and non-HVAC load is forecasted.

Module 3: In this module, the domestic load profiles of consumer groups are optimized such that total load matches the wind profile to the utmost. Following optimization model determines the optimal load profile of consumer group with respect to wind profile. The objective function is to minimize the deviation between the wind output and total load and is given by:

$$\min \sum_t \left(\left| (\lambda_t) - \sum_n (P_{n,t}^{critical} + P_{n,t}^{hvac}) \right| \right) \tag{69}$$

s.t.

$$(T_{n,t}^{set} - \frac{\phi_n}{2}) \le T_{n,t}^{a} \le (T_{n,t}^{set} + \frac{\phi_n}{2}) \text{ },\forall t \in T, \forall n \in N \tag{70}$$

$$0 \le P_{n,t}^{hvac} \le P_{n}^{hvac,\max}, \quad \forall t \in T, \forall n \in N \tag{71}$$

$$0 \le Q_{n,t}^{hvac} \le Q_{n}^{hvac,\max}, \quad \forall t \in T, \forall n \in N \tag{72}$$

$$P_{n,t}^{critical} + P_{n,t}^{hvac} \le \upsilon_t, \quad \forall t \in T, \forall n \in N \tag{73}$$

$$(SoC_{n,t+1} - SoC_{n,t})E_n^{cap} = (P_{n,t}^{hvac} - Q_{n,t}^{hvac})\Delta t - \xi_{n,t}, \forall t \in T, \forall n \in N \tag{74}$$

$$SoC_n^{\min} \le SoC_{n,t} \le SoC_n^{\max}, \forall t \in T, \forall n \in N \tag{75}$$

$$\xi_{n,t} = \eta^n SoC_{n,t-1}, \quad \forall t \in T, \forall n \in N \tag{76}$$

$$\sum_t (P_{n,t}^{critical} + P_{n,t}^{hvac}) \le E_n^{lh}, \forall n \in N \tag{77}$$

$$SoC_{n,t_{end}} = SoC_{n,t_o} \text{ }, \forall n \in N \tag{78}$$

$$P_f^{ij} = -Y_f^{ij} V_i V_j \cos(\delta_i - \delta_j + \theta_f^{ij}) + Y_f^{ij} V_i^2 \cos(\theta_f^{ij}) \tag{79}$$

$$Q_f^{ij} = -Y_f^{ij} V_i V_j \sin(\delta_i - \delta_j + \theta_f^{ij}) + Y_f^{ij} V_i^2 \sin(\theta_f^{ij}) \tag{80}$$

$$S_f^{ij} = \sqrt{P_f^{ij2} + Q_f^{ij2}} \tag{81}$$

$$-S_{f\_RTTR\_LIM}^{ij} \le S_f^{ij} \le S_{f\_RTTR\_LIM}^{ij} \tag{82}$$

$$P_s^i = P_l^i - P_{lvg}^i + P_{lvgc}^i \tag{83}$$

$$Q_s^i = Q_l^i - Q_{lv\mathrm{g}}^i + Q_{lv\mathrm{g}c}^i \tag{84}$$

$$S_s^i = \sqrt{P_s^{i2} + Q_s^{i2}} \tag{85}$$

$$-S_{s\_RTTR\_LIM}^{i} \le S_s^{i} \le S_{s\_RTTR\_LIM}^{i} \tag{86}$$

$$P_{mvg}^i - P_{mvgc}^i - P_s^i - \sum_j P_f^{ij} = 0 \tag{87}$$

$$Q^{i}_{mvg} - Q^{i}_{mvgc} - Q^{i}_{s} - \sum_{j} Q^{ij}_{f} = 0 \tag{88}$$

$$V_{LOW} \leq V_{i} \leq V_{UP} \tag{89}$$

$$0 \leq P^{i}_{lvgc} \leq P^{i}_{lvg} \tag{90}$$

$$0 \leq P^{i}_{mvgc} \leq P^{i}_{mvg} \tag{91}$$

$$(S^{total}_{n,t}) \leq \upsilon_{n,t}, \quad \forall t \in T, \forall n \in N \tag{92}$$

where,

λ_t is the wind generation at time t (kW)

$P^{critical}_{n,t}$ represents the power of all critical appliances at time t of customer n (kW)

t is the index of time

T is the set of time

n is the index of customer

N is the set of customer

$P^{hvac}_{n,t}$ is the electrical power of HVAC unit at time t of customer n (kW)

$P^{hvac,\max}_{n}$ is the power rating of HVAC unit of customer n (kW)

υ_t represents the demand limit at time t (kW)

Δt is the time interval (hours)

E^{lh}_{n} is the energy demand of customer n during optimization horizon (kWh)

$T^{set}_{n,t}$ denotes the set point temperature of dwelling at time t of customer n (°C)

ϕ_n is the internal temperature dead-band of customer n (°C)

$T^{a}_{n,t}$ is the indoor ambient temperature of dwelling at time t of customer n (°C)

$SoC_{n,t}$ represents the state of charge of thermal storage of customer n

E^{cap}_{n} is the maximum thermal storage capacity of customer n (kWh)

$SoC^{\min}_{n}$ is the minimum allowable state of charge of thermal storage of customer n

$SoC^{\max}_{n}$ is the maximum allowable state of charge of thermal storage of customer n

$Q^{hvac}_{n,t}$ is the HVAC thermal output power at time t of customer n (kW)

$Q_n^{hvac,\max}$ is the rated thermal output power of HVAC of customer *n* (kW)

$\xi_{n,t}$ denotes the storage thermal losses at time *t* of customer *n* (kWh)

η^n is the storage loss coefficient of customer *n*

i, *j* are the indices of bus

f is the index of feeder

$P_f^{ij} / Q_f^{ij} / S_f^{ij}$ denotes active/reactive/apparent power flowing through feeder f from bus i to bus j

Y_f^{ij} denotes the admittance magnitude associated with feeder f .

V^i is the voltage magnitude at bus *i*

V^j is the voltage magnitude at bus *j*

δ_i is the phase angle at bus *i*

δ_j is the phase angle at bus *j*

θ_f^{ij} represents the phase associated with feeder f

$S_{f\_RTTR\_LIM}^{ij}$ is the RTTR capacity of feeder *f*

$P_s^i / Q_s^i / S_s^i$ is the active/reactive/apparent power flowing through the transformers in the secondary substations connected to bus i

P_l^i / Q_l^i is the active/reactive load served by the secondary substation at bus i

P_{lvg}^i / Q_{lvg}^i is the active/reactive power of renewable generation installed in the low voltage network served by the substation at bus i

P_{lvgc}^i / Q_{lvgc}^i is the active/reactive generation curtailment at the low voltage side

$S_{s\_RTTR\_LIM}^i$ is the RTTR capacity limit for the substation transformer

P_{mvg}^i / Q_{mvg}^i denotes the active/reactive power of renewable generation installed in the medium voltage side of the secondary substation at bus i

P_{mvgc}^i / Q_{mvgc}^i denotes the active/reactive generation curtailment at the medium voltage side of the secondary substation at bus i

V_{LOW}^i / V_{UP}^i is the lower/upper acceptable voltage magnitude level at secondary substation at bus *i*

$S_{n,t}^{total}$ is the total apparent household load at time *t* of customer *n* (kWh)

The equation (70) establishes that the indoor temperature stays in range of the set-point temperature and does not breach the set temperature dead-band. HVAC system can work at continuos power level while bounded by maximum rated powers as described by (71) and (72). Maximum hourly demand limit is bounded by (73). The expression (74) determines the amount of stored energy in the tank. (75) bounds the *SoC* of thermal storage, while storage losses are determined by (76). The constraint (77) ascertains that total energy consumtion should be less than the business as usual daily energy requirement. (78) ascertains that the final and intial level of storage must be equal. This constraint confirms that the claimed advantages are not at the expense of the initial level of stored thermal energy in the storage tank.

The network constraints are produced using a basic power flow study. Equations (79)-(92) guarantee that voltage, feeder and substation capacity limits are not breached. Furthermore, a contingency plan to curtail the DG and/or exploit DG potential is formed. In (82) and (86), the RTTR capacity limits are renewed for each time step.

Module 4: In this step, trajectory of all the decision variables is gathered. However, the following time steps decisions are executed

Module 5: Steps of Modules 1-4 are revised after updating the input variables.

5.3.2 Case Studies and Results

A typical Finnish distribution network of a 40 MVA primary substation feeding sixteen secondary substations in a 20 kV system as Figure 5.6 schematized is used as a test network while network paremeter are given in [VI]. It is assumed that 40 wind turbines of 1 MW capacity are connected directly to the primary substation only serving 600 houses equipped with HVAC with storage. 2-Capacity building model (Figure 2.2) is employed to capture the dynamics of indoor ambient temperature. The input data relating to the building thermal parameters and HVAC system can be found in [VI]. The diversity is captured using Monte Carlo simulation and it is supposed that the parameters follow a uniform distribution.

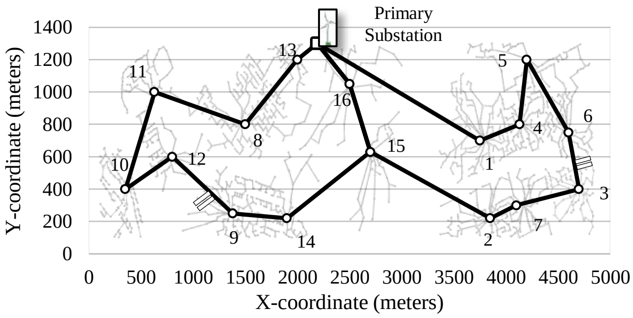

Figure 5.6. Test network used in the simulation.

To showcase the benefits offered from the proposed methodology, three distinct case studies were conducted as follows.

Case I: Without DR

Case II: Activating DR for wind balancing considering network STR

Case III: Activating DR for wind balancing considering network RTTR

Figure 5.7 depicts the load profile after DR is applied in the presence of customarily used STR (Case 2). The result confirms that the load endeavors to match the wind generation with little success. The HVAC load is cleverly scheduled such that there is some minimization of the total deviation between wind and load. From Case I, the total deviation is reduced by approximately 48%. The DR potential is unleashed thanks to the domestic thermal storages that enable load shifting in order to absorb wind power. Notably, customer preferences are respected during all times. However, as stated previously, distribution networks containing a high wind generation may be likely to face generation curtailment due to the network STR. This incident is examined between 06:00-08:00 hours and during 17:00-19:00 hours, with a total generation curtailment of 67.7 MWh. The load supply matching is disturbed due to the high generation periods. As a result, due to the limited static network capabilities, the DR potential for wind generation balancing is not fully sustained. The operation of DGs could be improved if the network would have more permitted capacity. It is important to reveal that the mismatching and DG curtailment is a result of the thermally susceptible components which are limited by STR.

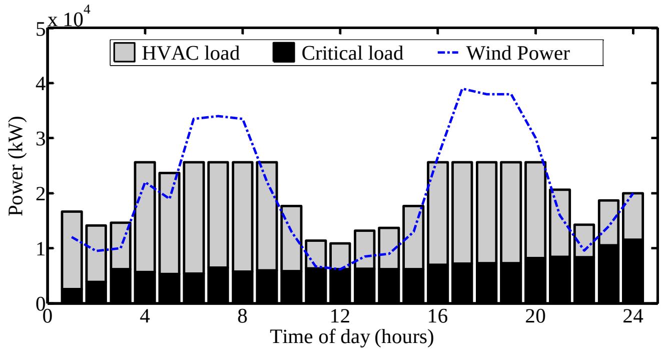

Figure 5.7.   Load profile situation in Case II.

Figure 5.8 portrays the load situation in Case III, where the total load profile is managed by applying RTTR alongside DR as a pair to curb the variability of the wind generation. Visibly, the load profile almost precisely matches the wind generation with the exception of a couple of evening hours. The DR potential is better utilized in this case due to the RTTR, which releases hidden network capacity to support the increased DG penetration. From Case II, the expected generation curtailment is reduced by 83%. The results show RTTR has established itself as a useful tool in mitigating the congestion effects due to stochastic wind generation. When compared to Case I, the total mismatch decreases by 89%. Since there is about a 41% improvement if RTTR is used instead of STR, the results are promising. This slight mismatch during 17:00-19:00 proves that there is still a need for better capacity usage to fully accommodate intermittent generation during the peak hours. Nevertheless, the curtailment of renewable generation confirms that the advantages of RTTR can reach upper limit. Although RTTR ratings are more elevated than STR, they are also bound.

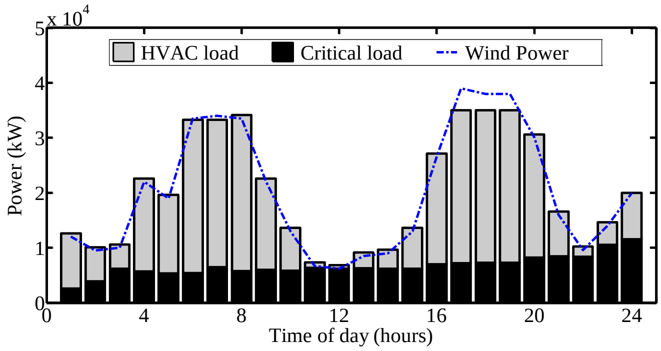

Figure 5.8. Load profile situation in Case III.

A summary of the basic results achieved are registered in Table 5.II. It is worth mentioning here that the aggregate energy consumption in Cases II and III are lower than in Case I. This endorses that the proposed tool is effective in coping with wind fluctuations without bargaining energy efficiency.

TABLE 5.II

OVERVIEW OF BENEFITS IN CASES I-III

Characteristic	Case I	Case II	Case III
Energy consumption	324.4 MWh	323.2 MWh	323.3 MWh
Total deviation	60.7 MW	31.8 MW	6.4 MW
Wind curtailment	133 MWh	67 MWh	10.9 MWh

Sensitivity Analyses

The situation where RTTR and DR are jointly operated in network circuits composed of only overhead lines is illustrated in Figure 5.9. This case is simulated as RTTR benefits greatly depend on network configuration and because the thermal state of overhead lines is highly dependent on weather variables like wind speed, which also favourably coincides with wind generation. The deviation decreases to 1.02 MW, which is roughly 30 times less than that in Case II and 6 times lower than in Case III. Additionally, the amount of wind speed curtailment is considerably diminished to just 1.5 MWh. The results conclude that networks with overhead lines can engage in more wind generation when DR and RTTR are in use. The RTTR system leads to greater efficiency in the overhead network due to the inherent lower thermal time constraints of overhead lines. The system performance has considerably improved because the RTTR of overhead lines greatly link with wind speed, which is not the case if the network has only underground cables.

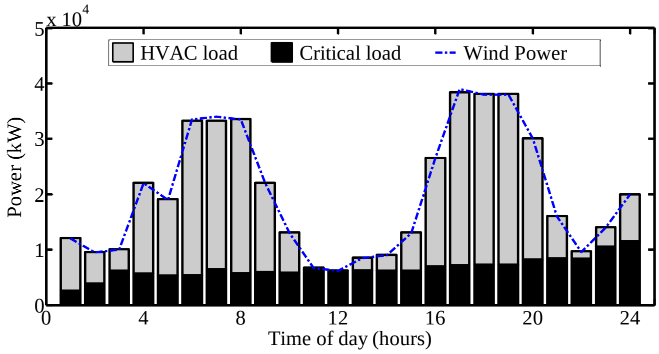

Figure 5.9. Load profile situation when DR and RTTR employed in overhead networks.

The evolution of the total standard deviation between wind-load versus HVAC rated power is exemplified in Figure 5.10. The result shows that a greater level of utilization of wind generation is attained as the HVAC rated power increases. As can be examined from the results, the total deviations between load and wind are visibly lessened when the HVAC rated power is increased from 3 kW to 4.5 kW. Higher HVAC power offers more flexibility in the ramping capability, as confirmed from the results; however, the advantages are restricted by the net storage capacity after a certain rated power level. Additionally, the effect of storage capacity on the performance of the strategy is prominent. Here, full storage refers to storage capacity 80-100% of the energy utilization of a mild winter day, while partial storage lives up to its name of covering only a fraction of the total daily energy utilization (i.e., 15-20% of total energy demand). The larger the storage size, the more improved the performance of the proposed model for wind generation balancing. It is apparent that full storage is about twice as suitable as partial storage for wind generation balancing with greater HVAC rated power. However, the most sensitive parameter is the rated power due to the ramping capabilities which are strongly linked to the charging power.

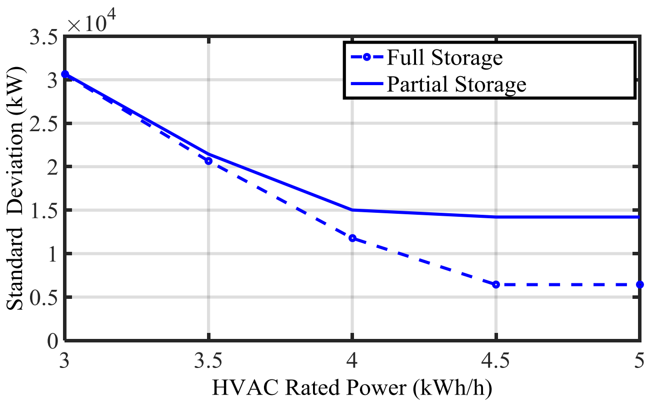

Figure 5.10. Impact of HVAC rated power on total wind-load deviation.

In the standard simulation, it was presumed that all the customers are active participants in the DR programs; however, this may not be true in practice. Thus, it is essential to evaluate the impact of consumers' enrollment level on the benefits proposed by coordinating DR and RTTR. Simulations are performed by altering the customers' enrollment for Cases II and III only. Some information about the influence of the customers' penetration level on the results are provided in Table 5.III.

TABLE 5.III

IMPACT OF CONSUMER'S PENETRATION LEVEL ON RESULTS

Enrollment level	Total Deviation (Wind-load)		Wind Curtailment	
	Case II	Case III	Case II	Case III
100 %	31.8 MW	6.4 MW	67.7 MWh	10.9 MWh
95 %	33.0 MW	8.4 MW	68.03 MWh	11.2 MWh
90 %	34.2 MW	10.5 MW	68.3 MWh	13.5 MWh
80 %	36.7 MW	14.8 MW	69.2 MWh	19.9 MWh
70 %	39.2 MW	19.4 MW	70.3 MWh	25.9 MWh
60 %	41.8 MW	24.5 MW	71.3 MWh	31.3 MWh
50 %	44.5 MW	30.0 MW	78.3 MWh	37.9 MWh

As estimated, the advantages are greatly sensitive to the customer penetration level, particularly when RTTR is used (Case III) instead of STR (Case II). The benefits decrease as the number of enrolled customers decrease. It was observed that even if only 50% of the customers are enrolled in DR programs, the employment of RTTR offers more advantages than the 100% customer enrollment in Case II. This result will act as a strong motivator for the aggregator to give incentives to distribution companies if they utilize RTTR instead of STR.

5.4 A Framework to Optimize Aggregator Focused DR Services

The preceding section determines the methods for activating DR for wind generation balancing. Given the swift deployment of intermittent renewable generation in distribution network level, the opportunity of DR aggregator services will enlarge proportionally. However, the restricted DR potential will render the electrical aggregator to optimize its commercial portfolio considering technical issues and monetary remunerations of each service [108]. This section proposes a model for optimizing the aggregator focused DR services in distribution networks hosting large amount of wind generation. The model selects for the optimal activation of DR in energy market and wind generation balancing. Simulations performed on a typical Finnish distribution system indicate the worth of the proposed model.

5.4.1 Proposed Model

The commencement of DR takes place on a day-ahead basis between an aggregator and it's customers. It is presumed that the responsibility of aggregator is to decrease the energy costs to customers as well as bear the cost of any wind curtailment at the same time. Therefore, the aggregator has two points to focus on; (a) The aggregator will attempt to optimize the load management so they can bring minimum energy cost to the energy market, (b) By allowing the load to follow the wind profile so as to minimize the wind spill, the aggregator wishes to reduce the wind energy curtailment cost.

$$\min \sum_t \{C_t^e \sum_n (P_{n,t}^{hvac} + P_{n,t}^{critical})\Delta t\} + X^{\lambda}\{v_t^{bin}(\lambda_t - \sum_n (P_{n,t}^{hvac} + P_{n,t}^{critical}))\} \tag{93}$$

s.t.

$$[\lambda_t - \sum_n (P_{n,t}^{hvac} + P_{n,t}^{critical})]v_t^{bin} \geq \lambda_t - \sum_n (P_{n,t}^{hvac} + P_{n,t}^{critical}) \forall t \in T \tag{94}$$

$$(T_{n,t}^{set} - \frac{\phi_n}{2}) \leq T_{n,t}^{a} \leq (T_{n,t}^{set} + \frac{\phi_n}{2}),\ \forall t \in T, \forall n \in N \tag{95}$$

$$0 \leq P_{n,t}^{hvac} \leq P_n^{hvac,\max}, \quad \forall t \in T, \forall n \in N \tag{96}$$

$$0 \leq Q_{n,t}^{hvac} \leq Q_n^{hvac,\max}, \quad \forall t \in T, \forall n \in N \tag{97}$$

$$P_{n,t}^{critical} + P_{n,t}^{hvac} \leq \upsilon_t, \quad \forall t \in T, \forall n \in N \tag{98}$$

$$(SoC_{n,t+1} - SoC_{n,t})E_n^{cap} = (P_{n,t}^{hvac} - Q_{n,t}^{hvac})\Delta t - \xi_{n,t}, \forall t \in T, \forall n \in N \tag{99}$$

$$SoC_n^{\min} \leq SoC_{n,t} \leq SoC_n^{\max}, \forall t \in T, \forall n \in N \tag{100}$$

$$\xi_{n,t} = \eta^n SoC_{n,t-1}, \quad \forall t \in T, \forall n \in N \tag{101}$$

$$\sum_t (P_{n,t}^{critical} + P_{n,t}^{hvac}) \leq E_n^{lh}, \forall n \in N \tag{102}$$

$$SoC_{n,t_{end}} = SoC_{n,t_o}\ , \forall n \in N \tag{103}$$

$$P_f^{ij} = -Y_f^{ij} V_i V_j \cos(\delta_i - \delta_j + \theta_f^{ij}) + Y_f^{ij} V_i^2 \cos(\theta_f^{ij}) \tag{104}$$

$$Q_f^{ij} = -Y_f^{ij} V_i V_j \sin(\delta_i - \delta_j + \theta_f^{ij}) + Y_f^{ij} V_i^2 \sin(\theta_f^{ij}) \tag{105}$$

$$S_f^{ij} = \sqrt{P_f^{ij2} + Q_f^{ij2}} \tag{106}$$

$$-S_{f\_LIM}^{ij} \leq S_f^{ij} \leq S_{f\_LIM}^{ij} \tag{107}$$

$$P_s^i = P_l^i - P_{lvg}^i + P_{lvgc}^i \tag{108}$$

$$Q_s^i = Q_l^i - Q_{lvg}^i + Q_{lvgc}^i \tag{109}$$

$$S_s^i = \sqrt{P_s^{i2} + Q_s^{i2}} \tag{110}$$

$$P_{mvg}^i - P_{mvgc}^i - P_s^i - \sum_j P_f^{ij} = 0 \tag{111}$$

$$Q_{mvg}^i - Q_{mvgc}^i - Q_s^i - \sum_j Q_f^{ij} = 0 \tag{112}$$

$$V_{LOW} \leq V_i \leq V_{UP} \tag{113}$$

$$(S_{n,t}^{total}) \leq \upsilon_{n,t}, \quad \forall t \in T, \forall n \in N \tag{114}$$

Where,

λ_t is the wind generation at time t (kW)

ν_t^{bin} is binary variable, 1 if total wind generation is greater than modified load profile, 0 otherwise

$P_{n,t}^{critical}$ represents the power of all critical appliances at time t of customer n (kW)

t is the index of time

T is the set of time

n is the index of customer

N is the set of customer

$P_{n,t}^{hvac}$ is the electrical power of HVAC unit at time t of customer n (kW)

$P_n^{hvac,\max}$ is the power rating of HVAC unit of customer n (kW)

υ_t represents the demand limit at time t (kW)

Δt is the time interval (hours)

E_n^{lh} is the energy demand of customer n during optimization horizon (kWh)

$T_{n,t}^{set}$ denotes the set point temperature of dwelling at time t of customer n (^oC)

ϕ_n is the internal temperature dead-band of customer n (^oC)

$T_{n,t}^{a}$ is the indoor ambient temperature of dwelling at time t of customer n (^oC)

$SoC_{n,t}$ represents the state of charge of thermal storage of customer n

E_n^{cap} is the maximum thermal storage capacity of customer n (kWh)

$SoC_n^{\min}$ is the minimum allowable state of charge of thermal storage of customer n

$SoC_n^{\max}$ is the maximum allowable state of charge of thermal storage of customer n

$Q_{n,t}^{hvac}$ is the HVAC thermal output power at time t of customer n (kW)

$Q_n^{hvac,\max}$ is the rated thermal output power of HVAC of customer n (kW)

$\xi_{n,t}$ denotes the storage thermal losses at time t of customer n (kWh)

η^n is the storage loss coefficient of customer n

i, j are the indices of bus

f is the index of feeder

$P_f^{ij} / Q_f^{ij} / S_f^{ij}$ denotes active/reactive/apparent power flowing through feeder f from bus i to bus j

Y_f^{ij} denotes the admittance magnitude associated with feeder f.

V^i is the voltage magnitude at bus i

V^j is the voltage magnitude at bus j

δ_i is the phase angle at bus i

δ_j is the phase angle at bus j

θ_f^{ij} represents the phase associated with feeder f

$P_s^i / Q_s^i / S_s^i$ is the active/reactive/apparent power flowing through the transformers in the secondary substations connected to bus i

P_l^i / Q_l^i is the active/reactive load served by the secondary substation at bus i

P_{lvg}^i / Q_{lvg}^i is the active/reactive power of renewable generation installed in the low voltage network served by the substation at bus i

P_{lvgc}^i / Q_{lvgc}^i is the active/reactive generation curtailment at the low voltage side

P_{mvg}^i / Q_{mvg}^i denotes the active/reactive power of renewable generation installed in the medium voltage side of the secondary substation at bus i

P_{mvgc}^i / Q_{mvgc}^i denotes the active/reactive generation curtailment at the medium voltage side of the secondary substation at bus i

V_{LOW}^i / V_{UP}^i is the lower/upper acceptable voltage magnitude level at secondary substation at bus i

$S_{n,t}^{total}$ is the total apparent household load at time t of customer n (kWh)

The equation (95) establishes that the indoor temperature stays in range of the set-point temperature and does not breach the set temperature dead-band. HVAC system can work at continuos power level while bounded by maximum rated powers as described by (96) and (97). Maximum hourly demand limit is bounded by (98). The expression (99) determines the amount of stored energy in the tank. (100) bounds the *SoC* of thermal storage, while storage losses are determined by (101). The costraints (102) ascertains that total energy consumtion should be less than the business as usual daily energy requirement. Consstraint (103) ascertains that the final and intial level of storage must be equal.This constraint confirms that the claimed advantages are not at the expense of the initial level of stored thermal energy in the storage tank.

The network constraints are produced using a basic power flow study (104)-(114).

5.4.2 Case Studies and Results

3200 households are considered to be equipped with HVAC systems that are integrated with medium to large thermal storage (70-100% of daily energy demand storage capacity). The critical load of the household is attained by executing the multiple regression analysis on a big set of hourly load data acquired from AMR data, while the HVAC load is attained from the 2-Capacity building model (Figure 2.2) simulation. To create variety in the load population, the critical load is randomized by evenly distributing around the mean value. The HVAC system and building data is borrowed from [VI] and is based on the Finnish scenario. The storage losses are assumed to be insignificant. Nordpool [77] is the source used to present the wholesale electricity prices while the outside temperature profile is taken from the Finnish Meteorological Institute [41]. The current in-feed tariff of wind power in Finland is the basis for the wind energy curtailment cost, X^{λ}, set at 0.083 €/kWh.

The following case studies are offered to highlight the performance of the proposed framework.

•**Case 1**: In this case, the aggregator deals with the HVAC load to lessen the total cost in the energy market only.

•**Case 2**: This case comprises of the aggregator focusing on minimizing the wind energy curtailment cost only.

•**Case 3**: This case includes a situation where the aggregator tries to optimize both DR services and therefore manages the total load profile to decrease the weighted sum of energy costs in the day-ahead market and cost of green energy curtailment as portrayed in (93).

The overview of the costs and amount of wind spill in different cases is listed in Table 5.IV. It can be seen that the total financial cost is the least when the DR service is optimized jointly instead of a single focus optimization. The total cost is the largest if the aggregator greedily optimizes from the energy market perspective and disregards the wind spilling cost.

TABLE 5.IV

OVERVIEW OF BASIC RESULTS

Case	Energy cost	Wind spill Cost	Total Cost	Wind spill
Case 1	9 k€	16.89 k€	25.89 k€	203.5 MWh
Case 2	11.11 k €	6.65 k€	17.76 k€	80.1 MWh
Case 3	10.25 k€	6.71 k€	16.96 k€	80.9 MWh

Sensitivity Analyses

<u>*Impact of wind and market prices correlation on cost of different cases:*</u>
Let us next study the influence of wind production and market price correlation. A graph is illustrated in Figure 5.11 and it portrays the evolution of total cost with correlation between wind power and market price.

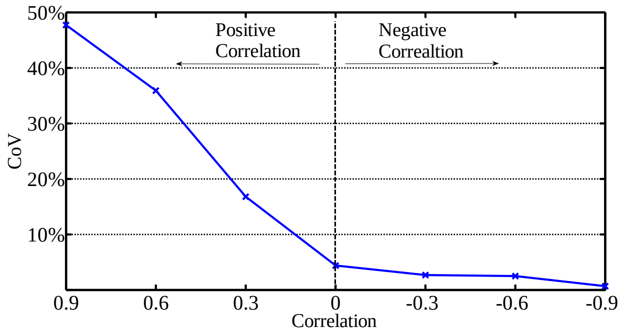

Figure 5.11. Influence of wind power and energy price correlation on total cost volatility among different cases.

The coefficient of variance (CoV) is used as a parameter for the comparison between costs in different scenarios and shows the extent of variability in relation to the average costs in Cases 1-3. It can be seen that the greater the positive correlation, the larger the CoV thus the volatility of costs in different cases is higher. In contrast, when the correlation is highly negative, the CoV is lower and subsequently the volatility of costs is lower as well. A higher CoV value indicates that the advantages of employing joint optimization of DR services are considerable compared to the benefits attained from a CoV that is lower. The aggregator will obtain the most benefits of optimizing the aggregator DR services when wind and market prices have a highly positive correlation and vice versa.

<u>*Effect of wind curtailment cost on different cases:*</u>
To portray the impact of the cost inflicted by wind energy curtailment, a sensitivity analysis is conducted on Case 3 and the results are specified in Figure 5.12. The results indicate that the total cost of aggregator decreases in an almost linear fashion with the reduction in wind curtailment cost. In contrast, with the decrease in wind curtailment cost, the total wind curtailment increases almost exponentially. Interestingly enough, even if wind curtailment cost is reduced to about half i.e. 0.04 €/kWh there is no effect on the amount of wind spilling. This can be due to the large value of cost caused by wind curtailment.

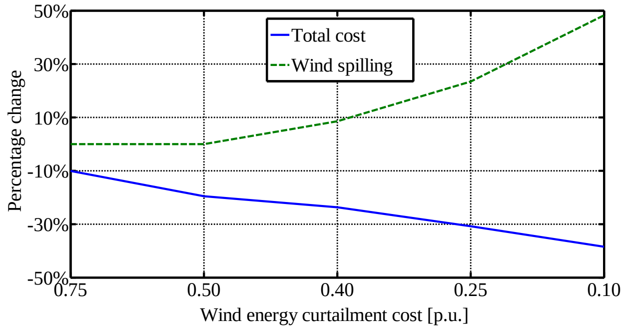

Figure 5.12. Influence of wind energy curtailment cost on total cost and wind curtailment in Case 3.

5.5 Conclusion

The integration of a large scale intermittent renewable generation in smart grids will necessitate additional operational flexibility. This chapter presented tools for optimal utilization of intermittent generation by activating DR through HVAC load. At first, an optimization model is formulated for managing the population of domestic HVAC loads for balancing wind generation while respecting customer temperature preferences. Then, joint optimization of RTTR and DR through HVAC load was proposed for coping the variability of wind generation. Using both the tools, wind utilization problem was solved for various scenarios encountered by utilities in a typical Finnish distribution system. A broad set of sensitivity analyses were also investigated to exhibit the influence of key parameters on the obtained results. Simulation results confirmed that optimally managing the cyclic operation of population of HVAC loads will curb the variability of wind geneartion. It is showcased that the tandem of RTTR and DR will reap significant benefits in utilization of wind generation owing to the possible synergy between wind and weather depending network rating. These results will serve as a strong stimulus for the utlities to manage domestic HVAC loads for intermittent genartion balancing.

6. Conclusions and Future Works

6.1 Conclusions

Demand response (DR) is believed to be one of the most important tools to improve the effectiveness and dependability of the future smart grid. Rather than altering electricity generation to equal variations in demand, the demand itself could be made more flexible to ease the integration of intermittent renewable generation resources and reduce requirements on the electric power generation infrastructure. The chief purpose of the dissertation was to evaluate the potential advantages of domestic DR under the smart grid paradigm. The treatment of DR in this study is limited to heating, ventilation and air conditioning (HVAC) load for potential DR applications. The HVAC load was considered due to its significant share in daily load profile and operational characteristic.

The dissertation goals were segmented into three main tasks that were classified as standalone chapters. The first task includes an investigation of HVAC upward/downward DR potential in various seasons with regards to customer temperature choices. To begin, an optimization model is suggested to measure the DR potential while taking into account temperature preferences. Simulations were performed regarding a typical Finnish single household situation. According to the simulation results, the load presents remarkable flexibility for up/down ramping and DR potential increases as the customers permit wider temperature dead band. DR potential is value-added when the HVAC system is incorporated with thermal storage, as illustrated by the results. To gain understanding about the availability and flexibility of the HVAC, the suggested optimization model can be put in place by electrical aggregators which can be then used for designing DR flexibility bids in markets.

Chapter 4 illustrates the second task, which concentrates on the development of a customer-oriented framework for optimal management of the HVAC load aimed at minimizing customer energy payments. The task was further divided into three subtasks. The first subtask describes the mathematical model for optimal coordination of HVAC load and partial thermal storage for minimizing energy costs using an overview of the power prices. The second task deals with the uncertainty and risk features that are included in the proposed model to make it more generic. The third subtask suggested a way to activate DR in both the energy and balancing market through a two stage framework for HVAC load management. Additionally, using typical Finnish systems' case studies, simulations were conducted while taking into account a single medium massive structure house scenario. The results indicated the considerable financial savings that can be attained through the activation of HVAC DR without hindering a customer's thermal comfort and preferences. The proposed decision frameworks address the comfort, risk and cost economic concerns and hence will encourage the customers to actively participate in DR program managed by electrical aggregator who aims at maximizing the economic gains and system efficiency.

Lastly, tools for activating DR through HVAC loads in the midst of large scale wind generation are suggested in Chapter 5. This task was also further divided into three subtasks. The development of an optimization model for managing the population of HVAC loads directed towards the maximal utilization of wind generation is dealt with within the first subtask. The second subtask is the improvement of subtask 1 where real-time thermal rating (RTTR) and DR are combined to create one flexible tool for wind generation balancing. A tool for optimizing the aggregator based DR services in the presence of extensive wind generation is introduced in the third subtask. Taking into account a typical Finnish distribution network plan, simulations are conducted in order illustrate the application of the proposed tools. The results indicated that by optimally managing the cyclic operation of the HVAC loads, the proposed framework facilitated the integration of intermittent generation. Furthermore, the results prove that the RTTR and DR partnership will bring considerable advantages in terms of wind generation balancing especially in congested networks where the DR potential could be hindered by the static network ratings. Lastly, it is demonstrated from the aggregator's monetary gains perspective, that the joint optimization of DR applications (energy cost minimization and wind generation balancing) is advantageous. The suggested tool will be especially useful to network operators and stakeholders in providing a clear picture of the available enabling technologies given the large access to intermittent renewable generation in distribution networks.

6.2 Future Works

The proposed frameworks will facilitate additional DR research and practical work. The following section discusses fascinating extensions of the current work.

- The building thermodynamic modeling can be more refined by thoroughly considering the impact of internal heat gains on the ambient temperature dynamics. Internal heat gain plays a key role particularly in the nearly zero energy buildings and is defined as the percentage of energy consumed by domestic appliances that counteracts energy that would otherwise be provided by the HVAC system. By taking internal heat gains and the complexity of human activities in the residential sector into consideration the building model can potentially be improved thus it will be useful in capturing a more precise picture of thermal comfort which is viewed as the foundation for any DR application.

- In Chapter 4, a decision framework for HVAC load management amid uncertainty environment is presented. The problem is solved using non-linear optimization method. Nevertheless, simple heuristic algorithms like the genetic algorithm or particle swarm optimization may be especially useful when computational complexity takes precedence over solution accuracy. However, convergence and efficiency loss of these algorithms must be examined.

- DR is a tool to improve the overall system efficiency. However it is imperative, given the restructuring of power markets, to investigate the potential benefits of DR with respect to different market stake holders. For example, if DR is to be setup for network capacity management then ultimately the potential of DR for wind integration will lessen and vice versa. Ultimately, an interesting research venture would be the development of a framework for optimal DR allocation among different market players.

- To mitigate the variability of intermittent generation, the dissertation introduced the idea to use DR through the HVAC load as a tool. However, enabling strategies are needed for the large scale practical realization of the proposed framework since the centralized framework experiences issues such as computational complexity and lack of customer privacy. Therefore, a possible interesting extension can include a multi-agent based system wide decentralized management framework in order to protect customer privacy and ensure robust control.

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Appendix

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