The Hong Kong Polytechnic University

Department of Building Services Engineering

# Development of An Interactive Building Energy Demand Management Strategy for Smart Grid

**Xue Xue**

**A thesis submitted in partial fulfillment of the requirements for the Degree of Doctor of Philosophy**

August, 2014

# CERTIFICATE OF ORIGINALITY

I hereby declare that this thesis is my own work and that, to the best of my knowledge and belief, it reproduces no materials previously published or written, nor material that has been accepted for the award of any other degree or diploma, except where due acknowledgement has been made in the text.

I also declare that the intellectual content of this thesis is the product of my own work, except to the extent that assistance from others in the project's design and conception or in style, presentation and linguistic expression is acknowledged.

**Xue Xue**

Department of Building Services Engineering

The Hong Kong Polytechnic University

Hong Kong, China

August, 2014

# ABSTRACT

Abstract of thesis entitled: Development of An Interactive Building Energy Demand Management Strategy for Smart Grid

Submitted by : Xue Xue

For the degree of : Doctor of Philosophy

at The Hong Kong Polytechnic University in August, 2014

This thesis presents an interactive building energy demand management strategy for the interaction of commercial buildings with a smart grid and facilitating grid optimization. A simplified building thermal storage model is developed for predicting and characterizing power demand alteration potentials of individual buildings together with a model for predicting the normal power demand profiles of buildings. The implementation details of the interactive strategy for the complex building central chilling systems are also investigated for ensuring their controllability and energy efficiency.

To analyze and quantify the power demand and the demand alteration characteristics of commercial buildings in a smart grid, a dynamic simulation platform for the complex building central chilling systems was built by considering passive and active building thermal storages. To formulate the interactive building energy demand management strategy, simplified models of the simulation platform were employed (e.g., chillers, pumps, air handling units, etc.) or developed (e.g., the simplified building thermal storage, pricing mechanism, etc.). A genetic algorithm-based (GA) method is also developed to identify the parameters of the simplified building thermal

storage model.

The simulation test results show that commercial buildings can contribute significantly and effectively in power demand management or alterations with building power demand characteristics identified properly. The demand alterations from building demand side can help effectively in releasing the grid power imbalance under an interactive operation.

To design and develop a fast chiller power demand response control strategy for smart grid applications (e.g., make use of the power demand of HVAC systems as operating reserves for relieving grid power imbalance), the chiller sequence control and the control logic of the building central chilling systems need to be rearranged. Compared with conventional indoor temperature set-point reset strategy, the developed strategy can provide an accurate estimation of power demand reduction in advance, and enable a fast response fulfilling the operation requirements of the grid on the premise of indoor thermal comfort. Simulation tests are also conducted to estimate the potential of reserve and investigate the impact on the thermal comfort when adopting the developed strategy. The resulting imbalance distributions of the chilled water flow rate and the indoor and air temperature caused by the chiller demand limiting control strategy are also investigated and solved.

Based on the simplified building thermal storage model, online and offline applications of active thermal storages (e.g., PCM tank and chilled water tank, etc.) in buildings for smart grid are discussed and tested on the simulation platform.

Lastly, the software tools (i.e., TRNSYS and MATLAB) and implementation details for conducting online and offline application tests are presented.

# PUBLICATIONS ARISING FROM THIS THESIS

## Journal Papers

2015 Xue, X., S.W. Wang, C.C. Yan, and B.R. Cui. A fast chiller power demand response control strategy for buildings connected to smart grid. *Applied Energy*. 137: 77-87.

2014 Yan C.C., X. Xue, S.W. Wang, and B.R. Cui. A novel air-conditioning system for proactive power demand response to smart grid. *Energy Conversion and Management* DOI: 10.1016/j.enconman.2014.09.072.

2014 Wang, S.W., X. Xue, and C.C. Yan. Building power demand response towards smart grid: a review. *HVAC & R Research*. 20(6): 665-687.

2014 Xue, X., S.W. Wang, Y.J. Sun, and F. Xiao. An interactive building power demand management strategy for facilitating smart grid optimization. *Applied Energy*. 116: 297-310.

2014 Cui, B.R., S.W. Wang, C.C. Yan and X. Xue. Evaluation of a Fast Power Demand Response Strategy Using Active and Passive Building Cold Storages for Smart Grid Applications. Accepted by *Energy Conversion and Management*.

2014 Cui, B.R., S.W. Wang, D.C. Gao and X. Xue. Effectiveness and Life-cycle Cost-Benefit Analysis of Active Cold Storages for Building Demand Management for Smart Grid Applications. Accepted by *Applied Energy*.

2013 Xue, X., S.W. Wang, Y.J. Sun, and F. Xiao. A chiller demand limiting strategy for frequency controlled reserve in smart grid. Submitted to *International*

*Journal of Energy Research*.

## Journal Papers under Preparation

2014 Yan C.C., B.R. Cui, S.W. Wang and Xue, X. A systematic Performance Assessment and Comparison of HVAC-based Demand Response Measures, Prepared for submission.

## Conference Papers

2014 Xue, X., and S.W. Wang. Involving Smart Buildings in Smart Grid. Submitted to 2014 *IEEE International Conference on Automation Science and Engineering* (CASE2014), 18-22, August 2014, Taipei, Republic of China.

2014 Cui B.R., S.W. Wang, C.C. Yan, X. Xue. A compound fast chiller power demand response strategy for buildings. *The 13th International Conference on Sustainable Energy Technologies* (SET2014), 25-28th August, 2014. Geneva, Switzerland.

2014 Cui, B.R., S.W. Wang, and X. Xue. Effects and performance of a demand response strategy for active and passive building cold storage. Submitted to *6$^{th}$ International Conference on Applied Energy (ICAE2014)*, 30, May-2, June 2014, Taipei, Republic of China.

2014 Yan, C.C., X. Xue, and S.W. Wang. A novel air-conditioning system for proactive demand response to smart grid. Submitted to *6$^{th}$ International Conference on Applied Energy (ICAE2014)*, 30, May-2, June 2014, Taipei, Republic of China.

2013 Xue, X., S.W. Wang, Y.J. Sun, and F. Xiao. A chiller demand limiting strategy for frequency controlled reserve in smart grid. *12th International Conference on Sustainable Energy Technologies (SET2013)*, 26-29, August 2013, Hong Kong, China. [Best Paper Award]

2013 Wang, S.W., and X. Xue. Optimization of building electrical demand elasticity for smart grid. *11th REHVA World Congress and 8th International Conference on IAQVEC (CLIMA2013)*, 16-19, June 2013, Prague, Czech Republic.

2012 Xue, X., and S.W. Wang. Interactive building load management for smart grid. *IEEE - Power Engineering and Automation Conference (PEAM2012)*, 14-16, September 2012, Wuhan, China. DOI: 10.1109/PEAM.2012.6612459

# ACKNOWLEDGEMENTS

I would like to express my sincerest appreciation to Professor Shengwei Wang, my supervisor, for his readily available supervision, valuable suggestions, patient encouragement and continuous support during the course of this research. Also, I would like to thank Professor Fu Xiao, my co-supervisor, for her support and encouragement to me over entire process of my PhD study.

I would also like to thank all colleagues in the research team, especially Dr. Yongjun Sun, Dr. Diance Gao, Dr. Chengchu Yan, Dr. Kui Shan and Dr. Yang Zhao. Their talents and diligence always inspire and encourage me to be better.

Finally, I would like to express my deepest appreciation to my best friends, Grace Luo, Emily Cheung and Daisy Yang, for their understanding, support and encouragement in the past years. I would also like to dedicate this thesis to my family members: my grandparents, Dingyuan Xue, Huilian Luo, Shuxiang Peng and Youwen Chen, my parents, Yueming Xue and Yun Peng, my sister, Han Xue, for their unconditional trust and support in my life.

# TABLE OF CONTENTS

# LIST OF FIGURES

# LIST OF TABLES

# NOMENCLATURE

| | |
|---|---|
| $A$ | effective area [$m^2$] |
| $B$ | operation energy cost |
| $C$ | thermal capacitance [$J/m^2K$] |
| $COP$ | coefficient of performance |
| $E$ | effective storage capacity [kWh] |
| $E$ | Euler's number |
| $J$ | objective function |
| $N$ | number of frequency points |
| $P$ | power demand or power capacity [kW or MW] |
| $Q$ | cooling/heating load or heat [kW] |
| $R$ | thermal resistance [$m^2K/W$] |
| $R$ | electricity price or price rate |
| $T$ | temperature [°C] |
| $T$ | time [minute or hour] |
| $\Sigma$ | summation |

**Greek symbols**

| | |
|---|---|
| $T$ | time constant [hour] |
| $H$ | storage efficiency [%] |
| $\Delta$ | variation |

**Superscripts**

| | |
|---|---|
| $'$ | associated with interaction process |

| | |
|---|---|
| *K* | number of iteration |

**Subscripts**

| | |
|---|---|
| *act* | actual |
| *bui* | building |
| *C* | charging |
| *cont* | controllable |
| *conv* | convective heat |
| *D* | discharging |
| *ew* | associated with external wall |
| *est* | estimated |
| *fr* | fresh air |
| *im* | associated with building internal mass |
| *i, in* | inside, indoor air |
| *K* | the $k^{th}$ data |
| *la* | latent heat |
| *o, out* | outside |
| *rf* | roof |
| *rad* | radiation |
| *set* | associated with temperature set-point reset strategy |
| *sys* | associated with HVAC system |
| *shed* | sheddable |
| *tot* | total |

# CHAPTER 1 INTRODUCTION

## 1.1 Motivation

Over the last decade, smart grid has become an attractive and new concept for power grid industry and the other related disciplines. With increasing concern on energy shortage and environment protection, as well as the integration of renewable energy, traditional power grid cannot serve the energy users in an efficient, green and safe manner any more. In order to address these issues, smart grid, with new characteristics (e.g. energy efficiency, low emission, flexibility, reliability, high quality, security, cost-effective, etc.), has been considered as a promising solution for future grid in plans of many countries (DOE 2003; European Commission 2006; Ha and Nakata 2006; Yuan and Hu 2011).

Recent efforts focused mainly on infrastructure upgrading (e.g. power electronic equipment (Rahim 2004; Hong et al. 2007; Gulez 2008; Suvire and Mercado 2010; Vachirasricirikul et al. 2010; Nayeripour et al. 2011), superconducting devices (Goto et al. 2001; Yagi et al. 2008; Mukoyama et al. 2009; Hu et al. 2010), distributed generation/storage (Khattam and Salama 2004; Rújula 2009; Heyd 2010; Järventausta et al. 2010; Márquez et al. 2010; Toledo et al. 2010; Nair and Garimella. 2010; Virulkar et al. 2011), micro-grid (Tanrioven 2005; Obara 2007; Li et al. 2008; Morais et al. 2010; Kamel et al. 2010; Notton et al. 2011; Kamel et al. 2011), smart meter (Hartway et al. 1999; Hor and Crossley 2006; Faruqui et al. 2010; Olmos et al. 2011; Depuru et al. 2011;

Sadinezhad and Agelidis 2011) and new technology application (e.g. information and communication technologies (ICT) (Wang et al. 2011; Gao et al. 2011; Wissner 2011), advanced metering infrastructure (AMI) (NYSEG 2007), development of control strategy/platform (e.g. distribution automation (Kokai et al. 1998; Thukaram et al. 1999; Su et al. 2000; Bouhouras et al. 2010; Oshiro et al. 2010; Popovic et al. 2011), supervisory control and data acquisition (Igure et al. 2006; Torriti et al. 2010; Kang et al. 2011; Korres 2011), demand response (Sezgen et al. 2007; Stadler 2008; Cappers et al. 2010; Wang et al. 2010; Faria and Vale 2011; Moghaddam et al. 2011; Wang et al. 2011; Orecchini and Santiangeli 2011), and grid energy management system (Al-Hamadi and Soliman 2005; DeGroff 2010; Zhang et al. 2010; Meliopoulos et al. 2011; Bazmi and Zahedi 2011; Berredo et al. 2011). However, studies and applications mostly concern on updating of devices and applying new technologies at power generation, transmission and distribution processes. Few studies were reported on power usage process at demand side, where electricity users' behavior and characteristics affect the operation and performance of the entire smart grid significantly.

In general, power grid plans its expansion schedule and generation arrangement according to electricity load forecasting (Padmakumari et al. 1999; Xie et al. 2000; Kandil et al. 2001; Kandil et al. 2001; Al-Hamadi and Soliman 2004; Ghiassi et al. 2006; Amjady and Keynia 2008; Niu et al. 2009; Xia et al. 2010; AlRashidi and EL-Naggara 2010; Pedregal and Trapero 2010; Nazih and Fawwaz 2011). Accuracy of short-term load forecasting is an important indicator for ensuring electricity service quality and energy saving. In order to improve electricity quality/efficiency, studies have been conducted on uncertainty of renewable energies (Hammons 2008; Deshmukh and Deshmukh 2008; Alsayegh et al. 2010; Silva 2010; Beaudin et al. 2010; Mitchell et al. 2010; George and Banerjee 2011; Arnulf et al. 2011; Glasnovic and Margeta 2011; Athanasios et al. 2011) and voltage/frequency variations elimination (Hingorani and Gyugyi 2000; Metke and Ekl 2010; Li et al. 2010; Sarwar and Asghar 2011; Aquino-Lugo et al. 2011; Seethalekshmi et al. 2011) when "plug-in" smart grid. Distributed generation is usually consisted by main power plants supplemented with renewable energy resources, which satisfies the electricity demand of the entire grid. Distributed storage also helps buffer energy surplus and shortage in smart grid. Micro-grid is developed with autonomic and self-healing functions by combining distributed generation and storage (Cleveland 2007; Thananunsophon et al. 2011; Pearson. 2011). With the integration of renewable energy sources and application of distributed generation technologies, the accuracy of load prediction, the electricity quality and security of smart grid have become more and more important for the operations of grids. Moreover, individual load predictions at demand side may play their roles in improving the accuracy of the load prediction of the entire grid which is usually conducted at supply side nowadays.

Smart gird cannot be "smart" without an intelligent and autonomic energy network (Goldman et al. 1997; Meliopoulos et al. 2007; Hart. 2008; Sood et al. 2009). Smart meter, which communicates with smart grid and controls electrical equipment automatically, plays an important role in AMI (Advanced Metering Infrastructure). Supported by ICT (Lallement et al. 2006; Tuite 2010; Røpke et al. 2010; Kume and

Rissanena 2011), smart grid can achieve transmission efficiently and correctly with a large amount of data. Studies have been conducted on time-based pricing optimization (Gungor and Lambert 2006; Herter 2007; Lijesen 2007) and a kind of comprehensive control platform for overall smart grid real time optimization (Baladi et al. 1998; Oliveira et al. 2010). These studies have resulted in that the smart power grid can set electricity price more reasonable, guide users' behavior more proper, eliminate grid peak demand and delay new power plants expansion. However, information flow (i.e. the communication between generators and users) is transferred only in "one-way" direction in the past. More and more attention (Brazier et al. 2002; Zhang and Meng 2010; Marijic et al. 2010) has been paid on the "two-way" direction information flow due to its more effective communication and interactions between users in the networks. The performance of power grids can be greatly improved by adopting ICT, smart meters and intelligent energy networks. However, some important information (e.g. dynamic pricing (Baladi et al. 1998), potentials and costs of demand responses) from both supply and demand sides, which could be very beneficial for enhancing the performance of the smart grid, has not been addressed yet.

Demand response (i.e. price-based or incentive-based) has been becoming a necessary measure for changing gird load profile and fulfilling the grid's expectation from the supply side because of electricity users' participation. The basic function of power supply is to meet the need of users and optimize energy usage in a grid (Omer 2008). The interaction between supply and demand sides is a crucial and attractive aspect in smart grid application. In fact, smart meters have been successfully used in many countries for residential buildings by adopting real time pricing (Depuru et al. 2011). However, very limited studies can be found on the grid optimizations and the interactions/ between commercial buildings and smart grids. Interfacing building automation systems to smart metering systems seems to be an obvious and attractive option for establishing the interaction between smart grids and commercial buildings and for implementing interactive control strategies.

Accurate short-term load predictions of whole districts/regions are important for optimizing the operation and production of a smart grid which improve both the grid efficiency and the electricity service quality. Most of the existing load prediction methods used by electricity grids are mainly based on the history data of the overall energy consumption (Chan et al. 2006; Soares et al. 2008; Wang et al. 2008; Mamlook et al. 2009; Amjady and Keynia 2009; Zio and Aven 2011; Li et al. 2011). The accuracy of existing methods may not satisfy the need of a smart grid. The main reason is that the history data cannot correctly reveal real demand in future due to the active interactions between smart grid and the demand side. In addition, most existing methods treat different types of users as a whole by which the different load characteristics of each type of users cannot be utilized effectively. On the contrast, the load prediction of individual buildings can handle these problems better and the prediction results can be sent to the control center of smart grid in real time. A more accurate overall load prediction then can be obtained by aggregating all these prediction results of a large number of individual buildings.

Many efforts have been made on individual building cooling load prediction. The prediction methods basically can be grouped into three categories: physical model (Henze et al. 1997; Braun and Chaturvedi 2002; Braun 2003), black box model (Henze et al. 2004; Zhou et al. 2005; Lee and Braun 2008) and grey box model (Wang 1998; Braun et al. 2001; Lee and Braun 2008). Due to the need for real time communication in smart grids, using physical models seems to be not practical because of their high computation loads and great complexities in model construction and parameters fitting. In addition to the requirement of large amount of training data, black box models cannot guarantee reliable outputs especially when the application situation is beyond the training data range. Compared with physical models and black box models, grey box models appear to be more promising for its acceptable reliability and lower requirements of computation load and training data. The existing grey box models, however, are still inadequate in terms of the integration of weather prediction and adaptive capability. Hence, efforts are still needed to develop methods with a better accuracy for predicting the load of large number of buildings that are connected to a smart grid. In fact, the load characterization of both residential buildings and commercial buildings is identified as one of the main subtasks for smart grid applications in Annex 58, a newly proposed IEA ECBCS research program (Roels 2011).

Demand response has been considered as an essential means for improving the performance of power grids. It generally refers to the actions or controls taken by the users for changing their load profiles under a specified pricing policy (Luis et al. 2008). With such controls (e.g. load shifting or peak demand limiting), cost saving can be achieved by participants. Basically, demand response methods are classified into two main categories, i.e. incentive-based programs and price-based programs (Albadi and El-Saadany 2008). Previous studies mainly addressed efforts on the impacts and benefits of different programs (e.g. load shifting or peak demand limiting) when a particular electricity policy is applied (Goldman and Kito 1995; Gungor and Lambert 2006; Herter 2007; Lijesen 2007). The main limitation of these studies is that the demand response was operated in a unidirectional pattern which cannot meet the requirements of active interaction between smart grid and users.

## 1.2 Aim and Objectives

The aim of this study is to develop an interactive building energy demand management strategy for facilitating smart grid applications. Active interactions between the supply side (i.e., suppliers of smart grid) and the demand side (i.e., customers of smart grid) are essential for realizing the overall benefit. Smart grid can optimize the electrical network performance (e.g., improving the power reliability/quality, energy efficiency and economics) by collecting and analyzing historic/real time data (e.g., generation capacities, operating reserves, load profiles, storage efficiencies, electricity prices, etc.) of all the participants (e.g., suppliers, delivers, customers, etc.).

In practice, there is a reciprocal relationship between the power supply and power demand: the supply capacity of power strongly depends on the costs of generation and delivery (e.g., fuel cost, capital and operation costs of power devices/systems, environmental cost, etc.) while the final retail price restrict the power demand of individual end-users. Power demand characteristics and control strategies of end-users are valuable for smart grids when setting power generation plans and arranging operation schedules. According to the needs of characterizing power demand potentials of end-users and developing the interactive strategy commercial buildings in this study, the detailed objectives and subtasks are listed as follows:

(1) Identify the key characteristic indices and functions of buildings and heating, ventilation and air-conditioning (HVAC) systems for representing their thermal storage capabilities and the realization costs associated with load profile alterations;

(2) Develop and validate an altered building load profile prediction algorithm for setting proper dynamic pricing;

(3) Develop and validate an optimal control strategy for achieving the maximum cost savings to buildings under a given dynamic pricing;

(4) Develop a test platform for real time communication and interactions between a smart metering system and a building automation system (BAS);

(5) Develop a fast chiller power demand response control strategy for grid operating reserve with building passive and active thermal storages.

## 1.3 Organization of This Thesis

This chapter outlines the motivation of the research by presenting the need of developing an interactive building energy demand management strategy for the smart grid. The recent studies on load prediction and demand response of end-users are also presented. The feasibility of developing an interactive energy demand management strategy between buildings (especially commercial buildings with large scale HVAC systems) and smart grid is discussed as well. It presents the aim and objectives of this thesis. The subsequent chapters are organized as follows.

Chapter 2 presents a comprehensive literature review on the state of the art of the developments and applications of power management in smart grid, as well as the impacts and benefits of demand response actions and activities of end-users in different building sectors. The critical issues (e.g., peak load and power imbalance) and electricity tariffs (e.g., time-based and incentive-based programs) of electrical grid are also discussed.

Chapter 3 presents a simplified building thermal storage model, which is developed for predicting and characterizing power demand alteration potentials of individual buildings. A genetic algorithm-based (GA-based) method is developed for identifying the parameters of the simplified thermal storage model. Together with a model for predicting the normal power demand profiles of buildings, the power demand characteristics and the demand alteration potentials of buildings are investigated and estimated.

Chapter 4 presents the validation of the developed simplified building thermal storage model for different weighted building envelopes (i.e., light, medium and heavy weight buildings) under different weather conditions (i.e., spring, summer and winter)with different control strategies (i.e., pre-cooling and temperature reset).

Chapter 5 presents the typical configuration and specification of HVAC systems and the building model in building systems and dynamic test platform. The use of the simplified building thermal storage model is also introduced. The test conditions and control strategies are introduced in this chapter. The test condition includes the weather data and characteristics of buildings. The control strategies include normal control, pre-cooling control, temperature reset control and demand limiting control.

Chapter 6 presents an interactive building power demand management strategy for facilitating smart grid optimization. Commercial buildings can contribute significantly and effectively in power demand management or alterations with building power demand characteristics identified properly. Benefits (e.g., energy and cost savings) can be achieved by obtaining the power demand alteration potentials of buildings and energy information of grids, and conducting their interactions and optimizations. A simple dynamic electricity pricing mechanism is also introduced.

Chapter 7 presents a fast chiller power demand response control strategy for operating reserves in smart grid. In order to maintain the balance between power supply and demand, a demand limiting strategy is developed to treat the power demands of chillers as cost-effective operating reserves instead of extra generation capacities of power plants. The possibility of providing operating reserves (e.g., frequency controlled reserve) at power demand side is discussed. The developed strategy can provide an accurate estimation of power demand reduction in advance, and enable a fast response fulfilling the operation requirements of the grid. The impact on the thermal comfort when implementing the demand limiting strategy is studied.

Imbalance issues of chilled water distribution and indoor air temperature are also investigated and solved.

Chapter 8 summarizes the main work and contributions of this study, and gives recommendations for future applications and further research in the subject area such as the online and offline smart grid applications of active thermal storages in commercial buildings.

# CHAPTER 2 BUILDING POWER DEMAND RESPONSE METHODS: A REVIEW

Smart grid has been drawing more and more attentions particularly when more renewable generations are integrated. In order to ensure the power reliability and energy efficiency in an electrical grid, many researches and applications have been conducted at power supply side to solve the critical issues of grids, e.g. peak load and power imbalance. Buildings, as the major end-users at the power demand side, can also play a significant and cost-effective role by making use of their power demand responses. Different demand response programs (e.g., time-based and incentive-based) have been developed and applied for encouraging end-users to change their energy usage behaviors expected by the grids. Generally, buildings are able to limit and/or shift the power demands under specific incentives. Although many researches and applications have been investigated and conducted on power demand aspects concerning the building system configuration and the control strategies of power demand optimization, a systematic review on building power demand response methods is still missing. This chapter therefore presents a comprehensive review on the strategies, impacts and benefits of building power demand response in a grid in order to systematically evaluate and make better use of their demand response potentials.

Section 2.1 presents an overview of the existing studies concerning on power management in smart grid. Section 2.2 presents the current researches and applications on grid power management especially focusing on two critical issues: peak load issue and power imbalance issue. Section 2.3 presents the state of the art of the actions and activities of building power demand response in residential, commercial and industrial sectors. Section 2.4 introduces different types of electricity tariff for building power demand responses. Section 2.5 discusses on the future trend of building power demand response. A summary of this chapter is given in Section 2.6.

## 2.1 An Overview

The power balance between supply and demand sides of an electrical grid is one of the most important issues in the grid operation. The forecasting of power generations and power demands is the essential premise for generation arrangement and power management. It is not difficult to obtain the regular power generations (e.g., fossil-fuel, hydraulic and nuclear generations, etc.) and the load of end-users with a very high accuracy for the conventional electrical grid (Alfares and Nazeeruddin 2002; Aung et al. 2011; Siwek et al. 2009). However, when the integration of renewable energies is considered as the important aspect in the development of the smart grid by many countries (DOE 2003; European Commission 2006; Yuan and Hu 2011), the accurate forecasting of the power generations becomes a big challenge involving with a large amount of uncertain and intermittent renewable generations (Hammer et al. 1999; Mellit et al. 2006; Wang et al. 2011).

The power imbalance and peak load have become two critical issues in an electrical grid operation, which can significantly affect the power reliability and quality, as well as the energy efficiency. The grid operation arrangement is usually planned based on the day-ahead predictions of power generations and demands while the actual power generations (e.g., wind generation) and demands (e.g., building demands) change dynamically and might be quite different with the predicted ones. Once a large amount of wind power is involved, the power imbalance could frequently happen particularly when the operating reserves of a grid are inadequate. The peak load is usually resulted by the power demand characteristics of the end-users (e.g., the power usage patterns and schedules of lightings, air conditioners, traffics and industrial productions, etc.). Although the duration of peak load may be relatively short (e.g., only 1% of load hours account for 11% peak load in a year (Earle et al. 2009)), the huge redundant capacities of power plants are still required as standby to ensure that the power demand can be met at any time.

In order to maintain the balance of power supply and demand cost-effectively, besides developing the efficient and low-cost operating reserves, many efforts have been paid on other two aspects: 1) Employ energy storage devices/systems (e.g., batteries, flywheels and pumped-storage power stations, etc.) to change/discharge the power for relieving the power imbalance and/or peak load. 2) Encourage end-users to change their power usage behaviors through incentive benefits (i.e., implement the power demand response programs). The application of the former aspect is usually subject to either the high initial/operation costs and the low storage capacities, or the geographic conditions. The application of the latter aspect strongly depends upon the capabilities and the voluntaries of end-users. Therefore, the power demand response programs (i.e., time-based and incentive-based) should be carefully designed in order to incent the abilities of the end-users at power demand side. In fact, the potentials of the end-users in the power management are very comparative with those of the power supply side. For instance, the end-users can be contributed as the major effort in peak load shaving instead of a huge capacity of grid energy storages (e.g., 7.5MW/100 minutes (Vazquez et al. 2010)).

The end-users at power demand side (e.g., buildings) can not only help the electrical grid to shift their peak loads from peak periods to off-peak periods, but also can treat their demands as "operating reserves" in a more cost-effective manner than using the extensively employed thermal storages. Buildings, as the major end-users, consume around 40% of total end-use energy all over the world (Kolokotsa et al. 2011) and over 90% of total electricity in high density urban areas, such as Hong Kong (Hong Kong EMSD, 2012). Buildings therefore can play an active and important role in power balance regulation and grid operation. Buildings actually have considerable flexibility/elasticity in power demands (e.g., cooling load shifting and peak power demand limiting) due to its huge thermal storage capacity using building thermal masses, water/ice storages and phase change materials, etc.

Most of the existing power demand control methods and strategies for buildings only consider the impacts and cost benefits of buildings rather than the actual needs of the grid (e.g., response time and response quantity). There is still no systematical review on the participation and interaction of the building power demand response when involved in the grid-scale power management. This chapter therefore presents a comprehensive review on the researches and applications on or related to building power demand response in building sectors including residential buildings, commercial buildings and industrial sector. The feasibility of developing proper building power demand response strategies for online and offline applications of smart grids is also discussed.

## 2.2 Power Management in Grid

The power management of an electrical grid is essential to the safety, the power reliability and quality, and the energy efficiency of the grid. Through power management, the power balance between the supply and demand side should be maintained in all different time scales such as long-term (e.g. yearly), medium-term (e.g. monthly) and short-term (e.g. daily, minutely) as shown in Figure 2.1 (Faria and Vale 2011). The power demand response programs are mainly developed for addressing the medium-term power management (e.g., the price-based demand response) and the short-term power management (e.g., the incentive-based demand response). Among them, the short-term (i.e. daily, hourly and minutely) power management is especially concerned by the grid due to its significant impacts on the next-day generation arrangement (e.g., peak load issue) and the real time operation (power imbalance issue). It is worth mentioning that, the price-based (or time-based) demand response can contribute to the daily peak load reduction while the incentive-based demand response can contribute to either the daily peak load reduction or the real time power balance (DOE 2006).

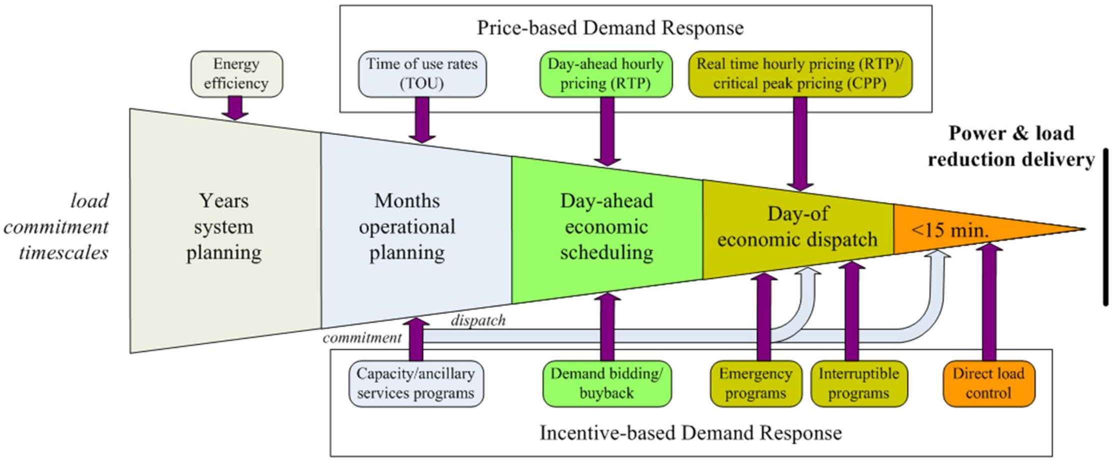



Figure 2.1 Power generation planning and operation scheduling in different time scales (Faria and Vale 2011).

### 2.2.1 Power Management for Peak Load Issue

In an electrical grid, load factor is usually employed to represent the level of peak loads (e.g., daily peak load), which is defined as the average load divided by the peak load in a specific time period, as shown in Equation (2.1).

$$f_{load} = \frac{P_{avg}}{P_{peak}} \tag{2.1}$$

Where, $f_{load}$ is the load factor. $P_{avg}$ is the average electrical load of a grid in the given time period. $P_{peak}$ is the peak electrical load of the grid in the same time period. A high load factor is preferred by the grid because it represents higher energy efficiency and less required generation and transmission capacities/costs. The load factor is determined by the power demand characteristics of electrical terminal devices/systems and the energy usage behaviors of the end-users. Different manners of demand side management can be conducted to improve the load factor, as summarized in Figure 2.2 (Gellings 1985).

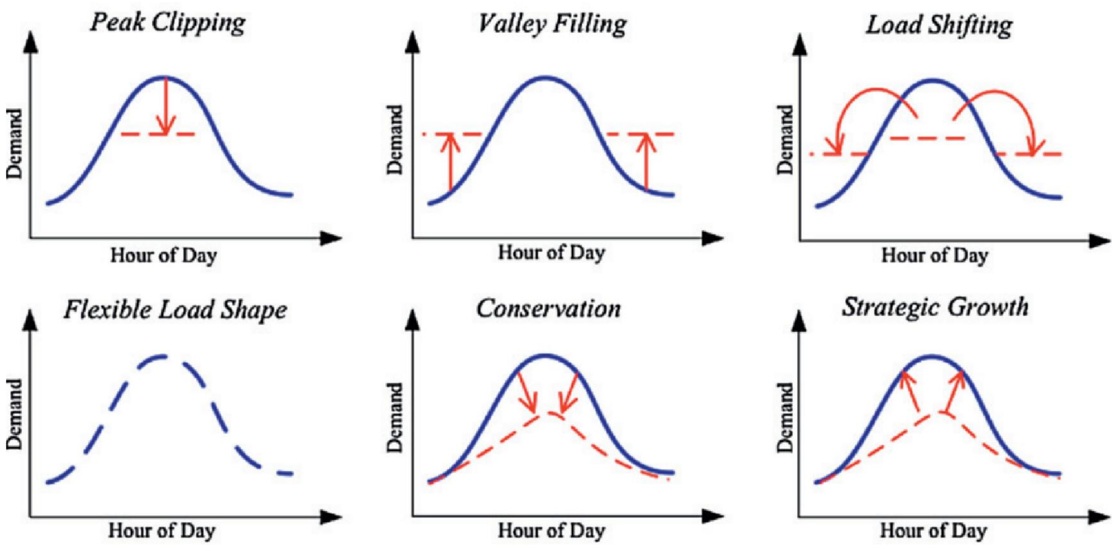



Figure 2.2 Demand side management categories in an electrical grid (Gellings 1985).

Generally, incentive electricity prices are needed to enable the demand response voluntaries of the end-users. Time-based and incentive-based demand response programs are two typical incentive programs, which have been developed and implemented to help the grid achieving the desired load profile. Direct and indirect control approaches of the demand responses in the load management are also introduced by Kostková et al. (2013). For the direct load management, the grid has the right to directly control the devices/systems of the end-users for reducing peak load and/or handling emergency situation. For the indirect load management, the grid does not directly control the end-uses but sends the price signals to end-users in order that the expectation on the load reduction/shifting can be achieved when end-users reduce their power demand subject to the incentive pricing.

### 2.2.2 Power Management for Power Imbalance Issue

To ensure the grid's safety and to prevent damage of power devices/systems, the power balance should be maintained in all different time scales. A sudden loss of power supply may result blackouts (e.g., U.S. blackout in 2003, India and Brazil blackouts in 2012) if no proper action is taken. In order to prevent such collapses in power systems, effective measures and technologies are required to provide fast and accurate load shedding (Laghari et al. 2013). The status of power balance can be well reflected by the power frequency of the grid. As a result, the power imbalance management is actually the process of maintaining a stable power frequency (e.g., 50Hz or 60Hz) (Kirby et al. 2008). Operating reserves are the essential backups for recovering the frequency drop when power imbalance is happened. The operating reserves can be generally grouped into three categories: 1) frequency response reserve, 2) spinning/non-spinning reserve, and 3) replacement reserve (Kirby 2003). The cost of operating reserves is usually very high and could result an extreme electricity price increases in a short time (Wang et al. 2011). Energy storage devices/systems (batteries, flywheels, electric vehicles and thermal storages, etc.) can be employed in the grid to relieve the power imbalance by charging/discharging the power/energy. For instance, the molten salt storage for solar thermal power generation has been considered as a promising technology by the smart grid for the power management in recent years (Yogev and Kribus 2013).

Smart grid is designed to consider the overall performance in power reliability, energy efficiency, economics and sustainability by optimizing the behaviors of all participants (e.g., suppliers, delivers and consumers, etc.). The coordination among all participants particularly between the power supply side and demand side is therefore very essential for achieving a cost-effective power management. With the development of mature technologies such as supervisory control and data acquisition, advanced metering infrastructure, smart meters, grid energy management system, and building automation systems (BAS), the bidirectional connections (i.e., “two-way” power flow and information flow (Rahimi and Ipakchi 2010)) between power supply and demand sides can be established effectively. Under such kind of bidirectional framework, the grid can achieve a better performance in maintaining the power reliability and quality, and the energy efficiency, by properly coordinating the distributed generations, storages and demands.

### 2.2.3 Demand Response Actions and Activities of End-users

The demand response voluntaries of end-users (e.g., buildings) are the key issue of the power demand response as one of the most important measures for the grid power managements. Schweppe et al. (1988) developed a classic pricing model named spot pricing (i.e., dynamic pricing) and pointed out the relationship between the electricity prices and the power demands. Figure 2.3 shows a compromising process of spot pricing through the power supply and demand curves. The supply curve indicates that the electricity price increases when the power supply increases. By contrast, the demand curve indicates that the power demand decreases when the electricity price increases. The basic principle of spot pricing is that the electricity price is eventually determined through the compromising between the cost of power supply and the status of power balance, which aims to maximize the overall economic benefits.

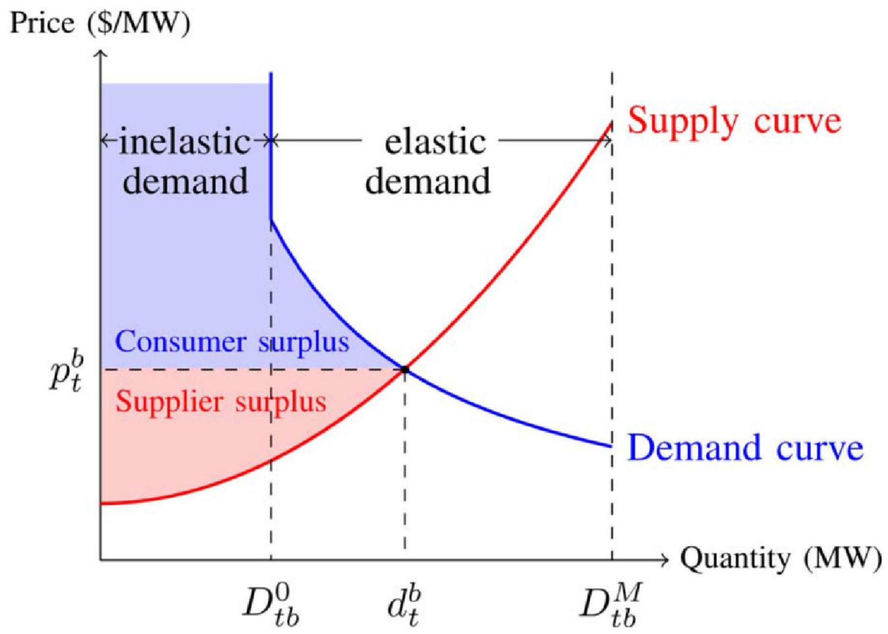



Figure 2.3 An example of price-elastic demand curve (Zhao et al. 2013).

The power demands of the end-users can be divided into two categories: elastic demand (i.e., controllable load) and inelastic demand (i.e., sheddable load). The power supply and demand eventually reach an equilibrium at the intersection point ($d_t^b$, $p_t^b$), which is corresponding to the maximum economic benefits (i.e., the total shadow area in the Figure 2.3). The responsiveness of power demand to electricity price is usually defined as demand-price elasticity representing by an elasticity coefficient, as defined by Equation (2.2) (Zhao et al. 2013):

$$\xi = \frac{\Delta d / d_0}{\Delta p / p_0} \tag{2.2}$$

where, $\Delta d$ and $\Delta p$ are the changes in power demand and electricity price respectively. $d_0$ and $p_0$ are the base power demand and the base electricity price respectively. Many power demand response models (e.g., potential, logarithmic, exponential and linear functions (Yousefi et al. 2011)) were developed to represent the demand response potentials of the end-users in the grid. However, the actual power demand behaviors of the end-users cannot be represented by simple functions and are also very difficult to be predicted. Therefore, the energy information (e.g., power demands and demand response potentials) from the end-users is becoming very essential for the grid spot pricing and power management.

The aggregate effect of the different power demand responses is also a critical issue in the grid power management, which should be investigated carefully in designing the incentive prices. For instance, the peak load of a grid may significantly differ with the sum of all the individual peak loads of the end-users since the peak hours of power demands for different end-users may not fall in the same peak period. In such cases, some demand response programs (e.g., direct load control or peak demand charge) cannot achieve their original objectives but affect the satisfactions of consumers (Schweppe et al. 1988). Medina et al. (2010) proposed a method on demand response scheduling and implementation for aggregating the behaviors of different end-users in the grid to solve this problem. Moreover, indices that can represent the demand response capabilities of the end-users are needed for obtaining the interactive process between power supply and demand sides corresponding to the load factor. A demand factor has been already defined to represent the power demand characteristics of the end-users, which can also be employed and further developed as an factor indicating the potentials of the power demand response. It is defined as the maximum power demand divided by the maximum possible power demand in a specific time period, as shown in Equation (2.3). Where, $P_{\max}$ is the maximum power demand of an end-user in the given time period. $P_{cap}$ is the maximum *possible* power demand of the end-user in the given time period.

$$f_{demand} = \frac{P_{\max}}{P_{cap}} \tag{2.3}$$

## 2.3 Building Power Demand Response

The electricity usage patterns of different building end-users are very different in practice. Classification of the power demand characteristics and estimation of the demand responses for different end-users, not only support the generation planning and operation scheduling of a grid, but also allow the end-users to understand their power demand potentials in benefiting to themselves (e.g., energy and cost savings) and the grid (e.g., valuable power demand responses) (Zhou et al. 2013). Buildings have great potentials in power demand response due to the considerable amount of elastic demands (e.g., the demands of heating/cooling). Buildings can be roughly divided into three sectors: residential, commercial and industrial. Table 2.1 lists the responsiveness of different building sectors in the load management of U.S. utility (Kueck et al. 2001). The residential and commercial sectors take relative small fractions while the industrial sector takes a big fraction of total demand response (nearly a half).

Table 2.1 U.S. utility load management by customer class (Kueck et al. 2001)

| Customer Class | Capability (MW) | Utilization, (MW) | Utilization or Capability (%) | Capability of Total (%) | Utilization of Total (%) |
|---|---|---|---|---|---|
| Residential | 7583 | 3888 | 51.3% | 27% | 29% |
| Commercial | 6067 | 3349 | 55.1% | 22% | 25% |
| Industrial | 13708 | 6123 | 44.7% | 49% | 45% |
| Other | 473 | 281 | 59.4% | 2% | 2% |
| Total | 27840 | 13641 | 49.0% | | |

Although many demand response programs have been successfully implemented in residential, commercial and industrial sectors, most of these end-users are respond to the electricity prices in a passive meaner which cannot maximize the demand response potentials. Meanwhile, the existing demand response programs may not fulfill the real time requirements of the electrical grid. The current status of power demand response in buildings is therefore investigated to help understanding the role and trend of the demand responses towards the future smart grid. In the residential and commercial sectors, estimation of power demands and demand response potentials are very complicated due to the dynamic outdoor conditions and the indoor human comfort requirements. By contrast, it is not difficult to obtain the power characteristics and demand response capabilities of the industrial sector, particularly the industrial processes. The researches and applications in building power demand response of residential and commercial sectors are therefore the main focus.

### 2.3.1 Demand Response in Residential Sector

The residential sector contributes a significant ratio of total peak load in the grid. For this reason, critical peak pricing and/or time of use pricing are usually implemented in residential buildings for achieving peak load reduction during the specific periods (Herter 2007; Herter et al. 2007; Hamidi et al. 2009). For instance, about 4.2% of the peak load, which is considerable to the grid, can be reduced by conducting the residential demand response in Norway (Saele and Grande 2011). Moreover, the residential sector consumes about 63% of total energy in the building sectors (Poel et al. 2007; Balaras et al. 2007).

With the development and application of smart meters in residential buildings, the price information of power supply side and the energy usage behaviors of power demand side can be effectively collected and communicated for further power and load managements. Smart meters can also be employed as the controllers in residential buildings when the renewable generations (e.g., wind turbines and photovoltaics) and the energy storages (e.g. electric vehicles and thermal storages) are integrated. Conventional energy meters are based on a unidirectional communication while smart meter system is based on a bidirectional communication (Depuru et al. 2011). Conventional meters collect the historical energy consumption data of end-users for the electricity bills with a non-negligible time delay. While the smart meter system can collect and store the real time/history data for dynamic control and optimization of both power supply and demand sides.

Smart meters, as the terminal elements in advanced metering infrastructure, can be considered as the micro electrical “automation systems” for the residential end-users. Smart meters can even be used for forecasting the next-day energy usage behaviors and electricity loads of the residential end-users by analyzing their historical data (e.g., the usage of the house appliances including lightings, refrigerator, air conditioner, television, water heater, wash machine and oven, etc.). In order to make use of the power demand response of the house appliances, sheddable and controllable loads during a certain period need to be clearly noted and scheduled. In other words, different house appliances have different priorities in power demand responses according to the demand characteristics and schedules. Generally, the demand response priorities of the house appliances can be scheduled from the thermal demands (e.g., air-conditioning) to mechanical/visual demands (e.g., washers and lights) (Broeer et al. 2014). The demand response potentials of appliances are usually affected by human behaviors and outdoor weather conditions.

An accurate estimation of the residential power demands is the premise of finding out the demand response potentials. Javed et al. (2012) considered that the forecasting accuracy of the existing short term load forecasting models can be further enhanced by considering occupancy behaviors. Therefore, a single multi-dimensional model concerning the anthropologic and structural variables has been developed. The enhanced model can forecast the power demands and demand responses more efficiently and accurately than using the traditional global measures. Modeling and aggregate effect of the residential demands are very important for the grid setting proper demand response programs (Gyamfi and Krumdieck 2012; Gilbraith and Powers 2013). Actually, the responsiveness of the residential demand is very dependent on the electricity tariffs and user behaviors. For instance, Darby and McKenna (2012) reviewed the residential demand responses in cold climates where price-based (e.g., time of use pricing, critical peak pricing and real time pricing, etc.) demand response programs are still considered as the effective means for peak load reduction and load shifting.

The responsiveness of power demand is usually defined as a demand-price elasticity representing the sensitivity of user demand to the electricity price. The demand-price elasticity can be used to establish the relationship between the demand response and the electricity price, the impact on the peak load reduction/shifting load, and the influence on the grid voltage and power losses (Fan and Hyndman. 2011; Venkatesan et al. 2012; Woo et al. 2013). In (Gyamfi et al. 2013) and (Gottwalt et al. 2011), the unresponsiveness of the residential end-users (e.g., constrained by demand behaviors and appliance utilization patterns) and the variation of demand elasticity (e.g., incented by electricity tariffs) are considered as the major barriers for grid power management. In (He et al. 2012), a Monte Carlo simulation was conducted aiming to quantify residential demand responsiveness under time of use prices. The results indicated that peak demand responsiveness are 8.41% and 21.26% when the peak-time price increases by 20% and 40%, respectively.

Dave et al. (2013) presented a system behavior modeling focusing on the participant population size, the household flexibility in terms of demand response, and the available size of load shifting/shedding. In this point of view, the aggregate effect of the individual loads and demand responses is also important for grid scale control and optimization. For instance, aggregate effect of thermostatically controlled loads (e.g., loads of air-conditioners and fridges) can affect the overall performance of the load management (Perfumo et al. 2012). By considering the characteristics of the individual loads and the aggregate effect of the power demand responses, the grid can then interact with the residential end-users more effectively. As shown in Figure 2.4, the interaction between power supply side (i.e., grid) and power demand side (i.e., residential houses), can not only help the grid in conducting power generation planning and operation scheduling, but also help the residential houses achieve their own economic benefits. Electricity prices (e.g., time of use pricing and real time pricing) are the key medium for facilitating the interaction to reach compromised results. It is worth mentioning that, the residential power demand response contributes to the grid mainly from two aspects: 1) by conducting optimal scheduling of the electrical appliances (i.e., smart metering and smart control), and 2) by optimal control and arrangement in power consumptions, storages and generations (i.e., integrated renewable generations and energy storages).

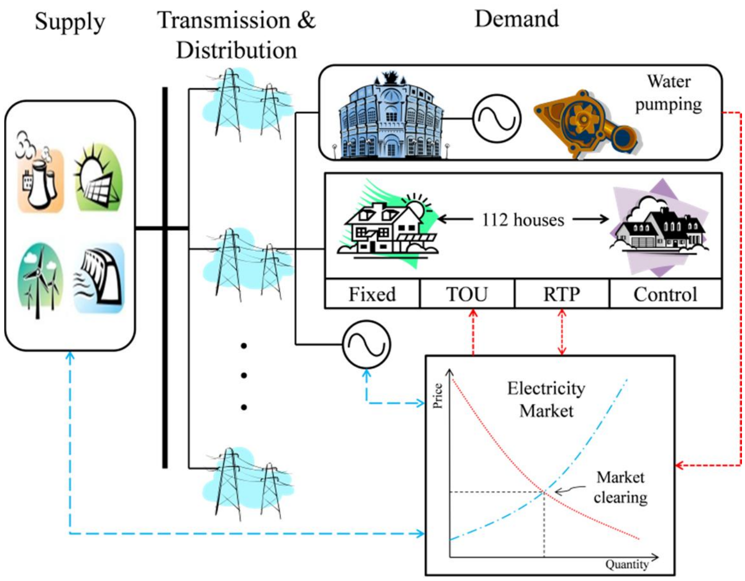



Figure 2.4 Overview of a smart grid demonstration project where both suppliers and consumers are the participants in the real time electricity market (Broeer et al. 2014).

*Smart Metering and Smart Control*

The available technologies such as home energy management system (HEMS), smart meters and smart sensors/controllers, etc. can enable effective communication and coordination between the electrical grid and the residential end-users to achieve an optimal load management. With the help of home area network such as wireless sensor network (Erol-Kantarci and Mouftah 2011), HEMS can play a more efficient role in load management optimization for the grid and energy/cost savings for the end-users (A.D. Giorgio and L.P. Pimpinella. 2012; Kailas et al. 2013; Ren et al. 2013; Zhang et al.2013). It is also convenient for the end-users and the grid to establish a two-way communication based on the advanced metering infrastructure and the mature communication protocols. Figure 2.5 shows a schematic of the load management for a residential house, with integrating wind turbine, photovoltaics (PV) and electric vehicle (EV) (Lujano-Rojas et al. 2012). Predicted and real time information of power consumptions, generations, and electricity prices are collected by the HEMS for its analysis and optimal controls. In the HEMS, smart meter is usually responsible for controlling the terminal devices.

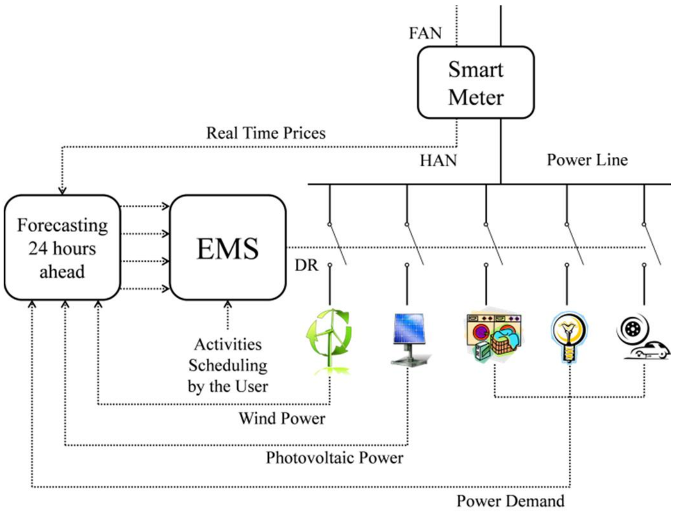



Figure 2.5 Smart houses for its load management (Lujano-Rojas et al. 2012).

Smart meters, as the key “connectors” between the residential end-users and the grid, are generally used to collect and provide day-ahead/real time information (e.g., the electricity usage and prices) for optimizing the daily power consumption and maximizing the benefits (Jin and Mechehoul 2010; Doostizadeh and Ghasemi 2012; Gans et al. 2013). It is worth mentioning that the information and data provided by smart meters are the premise of conducting the corresponding controls. When a residential end-user integrates both power generations and energy storages, it can be treated as a small "micro-grid" in the grid. Optimal scheduling and coordination of the devices/systems in different energy processes (i.e., consumption, storage and generation) in the "micro-grid" are very essential in contributing to the grid power balance (Pedrasa et al. 2010; Molderink et al. 2010; Kriett and Salani 2012).

In the optimal load scheduling, peak load reduction of the residential end-users is usually achieved by 1) coordinating the timing of frequent intermittent loads and 2) moving the time-flexible loads from peak hours to off-peak hours (Dlamini and Cromieres 2012). As the variables (e.g., water temperature and indoor air temperature) in some residential functions can float in a certain range, Nghiem et al. (2011) developed a green scheduling method to reduce the overall peak load demand of devices/systems by utilizing the thermal characteristics. In fact, water heaters and air conditioners are the major contributors of load management and power demand response in the residential sector. Direct load control is a popular means implemented for the electric water heaters shaving their power demands in the critical peak periods and then restoring the heat demands in the off-peak periods (Ericson 2009; Paull et al. 2010; Du and Lu 2011). In (Kondoh et al. 2011), simulation results showed that approximately 33,000 water heaters can provide a 2 MW regulation service 24 hours per day. Figure 2.6 illustrates a typical thermal characteristic curve of an electric water heater and dedicated power demand. As mentioned, power demands can be easily shifted to fulfill the needs of the electrical grid by properly scheduling thanks to the water temperature can float within a certain range.

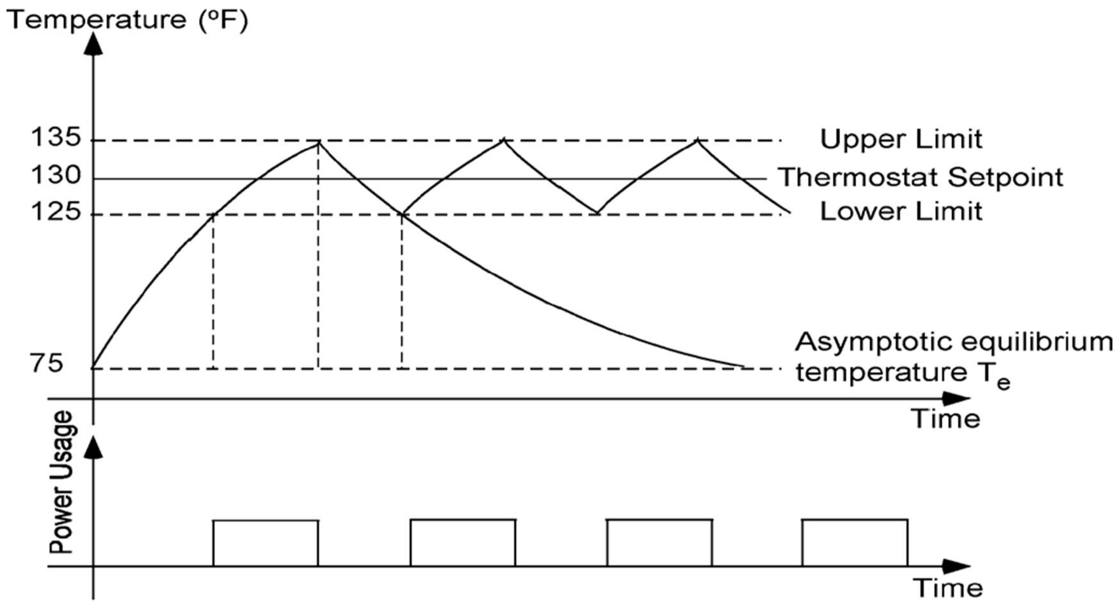



Figure 2.6 A typical thermal characteristic curve of an electric water heater power demand (Du and Lu 2011).

Heating, ventilation and air-conditioning (HVAC) systems account for 36% of the total building energy usage (Klein et al. 2012). Moreover, 30% of residential electricity is consumed by air-conditioning units in some urban areas such as Hong Kong (Lam 2000). HVAC systems are the most crucial systems affecting both indoor thermal comfort and energy/power consumption in buildings. In order to estimate the power demand characteristics of air-conditioning units, El-Ferik et al. (2006) developed a physical model. The effect of different outdoor conditions (e.g., outdoor humidity and solar radiation) can also be successfully captured by the model. The indoor thermal comfort, affected by many factors such as the indoor humidity and air temperature, etc., is also concerned during the power demand response periods. The comfort level is usually indicated by a predicted mean vote (PMV) value and a predicted percentage dissatisfied (PPD) value, and can also be influenced by the clothing and activity intensity of occupancy (Fanger 1970; EN ISO 7730 2005). Based on an artificial neural network (ANN), Moon and Kim (2010) developed thermal control model for air-conditioning system to ensure the thermal comfort.

In the residential houses, the power demand responses of HVAC systems are usually limited by the indoor thermal comfort. In order to minimize the impact on the thermal comfort and maximize the cost benefit of end-users, predictive control and optimal arrangement are necessary. Avci et al. (2013) adopted the model predictive control (MPC) method in HVAC systems, which can provide an efficient demand response to the grid. Tiptipakorn and Lee (2007) developed a residential consumer-centered load control strategy for the major appliances (e.g., air-conditioners/heaters) to response the grid subject to the different thermal comfort boundaries in summer and winter respectively. Significant energy saving (about 20%) and cost saving (about 30%) were achieved by conducting the strategy. A price-based thermostat set-point control strategy was adopted to reduce the peak demands and save the cost of end-users under the time of user prices (Surles and Henze 2012). It is worth noticing that the actual grid energy cost saving may be less than the overall cost saving of the end-users if the time of use prices are not properly set. Leow et al. (2013) presented an occupancy-moderated zonal space-conditioning by considering the number of air-conditioning zones and occupancy, the randomness of occupancy patterns and thermal mass of the residence. The estimated results showed that costing saving was from 20% to 30% under different conditions.

Niro et al. (2013) presented a practical strategy for large-scale control of residential refrigerators to achieve the peak load reduction in distribution systems. The refrigerators can be flexibly disconnected for short periods without impacting on the delivered services. Furthermore, average peak load reductions (0.2-0.9 kW per household or 10%-35%) were achieved in (Newsham et al. 2011). The authors argued that direct load control of air conditioners cannot contribute to the given events without proper incentives and arrangement.

The power demand-price elasticity of the residential end-users is mainly contributed by the thermal devices/systems and limited by the behaviors of the occupancy. Smart meters and energy management system are essential parts in enabling the power demand response of the residential end-users. Generally, they are responsible to collect/analyze the historical and real time data, coordinate the power supply and demand sides, and conduct the optimal control strategies. In addition, the integration of distributed generations (e.g., wind turbines and PV) and storages (e.g., batteries, EV and thermal storages) has become a new trend in residential development (e.g., zero energy buildings). There are still many challenges and opportunities in developing/implementing optimal control strategies especially when power consumption, distributed generation and storage are comprehensively integrated in the smart gird.

*Integrated Renewable Generations and Energy Storages*

The integrated renewable generations and energy storages are the necessary supplements for the residential end-users regulating and optimizing their load profiles. Combined heat and power (CHP) plant, located at the power demand side, is considered as one of the promising solutions to achieve peak load reductions. CHP plants can fulfill the requirements of the thermal and power demands of the end-users simultaneously (Lin and Yi 2000; Peacock and Newborough 2007; Jiang and Fei 2011; Chen et al. 2012; Bianchi et al. 2013). The peak load reductions of the end-users mainly depend on the capacities and outputs of CHP plants. Compared with the large power plants, CHP plants can be flexibly controlled for grid-scale power regulation and optimization due to its small generation capacity and wide distribution. The heat and power outputs of CHP plants are relatively predictable and controllable compared with the renewable generations.

Due to the intermittent and uncertain characteristics of renewable sources (e.g., wind speed and solar radiation), the renewable generations generally have to operate with energy storages such as batteries. In PV generation systems, batteries play an important role in self-power regulations such as improving individual load factors and reducing peak loads (can be up to 65% in some desert areas) (Castillo-Cagigal et al. 2011; Boehm 2012; Zeng et al. 2013; Zhao et al. 2013). Vokas et al. (2006) designed a 30 $m^2$ hybrid PV-thermal system which can cover a remarkable percentage of the domestic heating (47.79%) and cooling demands (25.03%) and achieve power demand reduction accordingly. For grid-connected PV systems, efficiency-enhanced design, scheduling/control of generation and storage processes and system monitoring can significantly affect the performance of both local and grid-scale power generations and load managements (Wong et al. 2008; Matallanas et al. 2012; Ayompe and Duffy 2013; Batista et al. 2013).

Wind energies, as the other important renewable sources, can usually support the solar power generation as the supplement especially in the nighttime. The interoperation of wind and solar power generations is very necessary due to their uncertainties and intermittences. The optimal configuration of the interoperating system (also called hybrid generation system) has attracted more and more attentions from both power supply and demand sides (Yang et al. 2007; Zhou et al. 2010). Moreover, the coordination between the renewable generations (e.g., wind generation) and residential consumptions (e.g., house appliances) is also very important in the power demand response (Fitzgerald et al. 2012; Finn et al. 2013). A considerable amount of the peak demand reduction (i.e., exceed 60%) was observed in (Finn et al. 2013) by properly coordinating the dishwasher usage and the wind power.

Considering the power balancing requirements and reliability of the grid, the penetration of intermittent energy resources are recommended to not exceed 20% or 25% (Stadler 2008). In order to enlarge the demand response capability of the residential end-users, energy storages, are the good choices for the load management due to their flexibility in charging and discharging energy/power. In residential applications, the electrical energy storages (e.g., batteries and electric vehicles) and thermal energy storages (e.g., water heater tank, building thermal masses) are commonly adopted. For instance, Leadbetter and Swan (Leadbetter and Swan 2012) considered that the battery storage system installed in different electricity intensity homes with a capacity ranging from 5 kWh/2.6 kW to kWh/5.2 kW are suitable for their peak demand shavings. EVs (electrical vehicles) can contribute great efforts in power balance as a kind of grid frequency controlled reserves. By coordinating the charging and discharging processes, the power demands of EVs can be shifted from the peak periods to the off-peak periods (Finn et al. 2012; Xu et al. 2013). Druitt and Früh (2012) simulated the demand response effect of 1,000 EVs under a scenario with 30% of UK power demands provided by wind generation. The results showed that significant improvements can be achieved in grid load following generation with the introduction of EV. Compared with the electrical storages, thermal storages are more considerable both in storage capacity and in the initial/operation cost. For instance, the structural thermal masses in dwellings can help reducing the electricity usage during peak periods by 48.4%-67.5% with different insulation levels (Reynders et al. 2013). The combination of the heat pumps and thermal storages is also very popular in residential demand response (Wang et al. 2012; Arteconi et al. 2013).

Actually, both the passive design/efficiency improvement (Synnefa et al. 2007; Borg and Kelly 2011) and the active system controls (Pietila et al. 2012; Newsham et al. 2013; Nghiem et al. 2013) in the residential sector can contribute significantly in the peak load reductions and/or load shifting. One of the major differences between the passive and active power demand responses is that, the passive means usually take effect with a static and long-term pattern while the active means usually take effect with a dynamic and short-term pattern. In (Synnefa et al. 2007), the test results showed that increasing the roof solar reflectance can reduce cooling loads by 18%-93% and peak cooling demand 11%-27%. In (Nghiem et al. 2013), 77.8% in peak demand and 31.2% in total energy consumption can be saved by applying green scheduling.

Using available technologies (e.g., information and communication technologies, smart meters and energy management system, etc.), the residential buildings integrating the generations, storages and consumptions can act as the distributed elements to interact with the grid. In other words, the residential buildings can play a more active role in power management especially in real time power balance. Residential buildings can either operate in off-grid modes to ensure the basic building functions under certain emergent events, or operate in on-grid modes to help grid achieving high power reliability/quality and energy efficiency by relieving the peak load/power imbalance. Figure 2.7 shows an overall picture of how the residential buildings can contribute to a future smart grid in different power/load management phases (Williams et al. 2013). The valuable details of both power and information flows in the grid, are becoming more and more important for the policy/decision-making and the day-ahead/real time controls.

Most of researches and applications in the residential power demand response are mainly focused on the amounts of peak load reduction, electricity usage reduction and the corresponding cost saving. Except the direct load control of the house appliances can respond to the grid immediately, the response speed of others load management approaches is less concerned due to the demand response voluntaries of the end-users are usually incented by electricity tariffs. However, for the future smart grid where the power demands is an important and cost-effective "operating reserve", the response speed should be highly concerned especially when a large amount of renewable generations are "plugged-in".

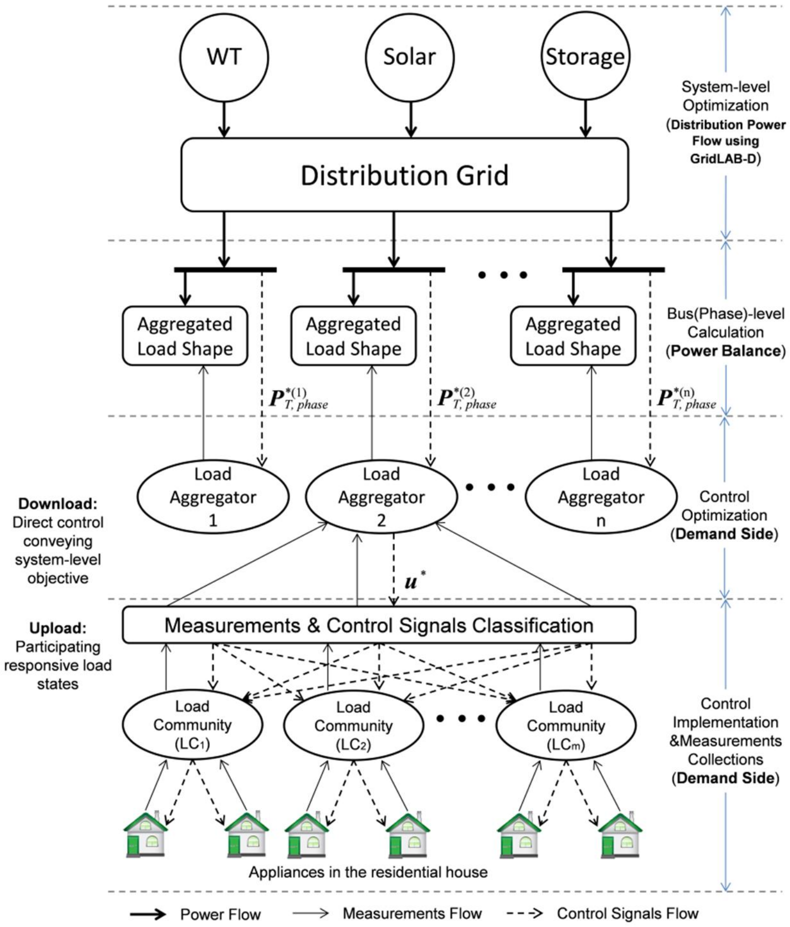



Figure 2.7 Smart self-regulating distribution systems for the residential houses (Williams et al. 2013).

### 2.3.2 Demand Response in Commercial Sector

Commercial buildings consume approximately 40% of the total energy end-use (Omer 2008). Moreover, about 50% of the whole energy consumption in building is used for cooling/heating purposes (Pérez-Lombard et al. 2008). The increase speed of energy usage in the commercial sector (i.e., 2.8% on annual average) is also faster than that of other sectors in last several decades (Andrews and Krogmann 2009). In some urban areas such as Hong Kong, commercial buildings consume about 60% of the total the electricity and in which about 50% of the accounted electricity is consumed by air-conditioning systems (Qi et al. 2012). Energy savings and demand responses of the commercial sector can mainly be achieved through the following manners: 1) improving the performance of building envelope, 2) improving the energy efficiency of the devices/systems in buildings, 3) optimizing the schedules and controls of the devices/systems in buildings.

Passive designs of the building (e.g., orientation, shape, shading, envelope, glazing, passive systems, etc.) and active controls of the devices/systems (e.g., local and supervisory controls) are two important measures in improving energy efficiency and achieving energy/cost savings without sacrificing occupancy comforts and system functions (Escrivá-Escrivá 2011; Pacheco et al. 2012; Wang and Ma 2008). Sadineni et al. (2011) presented a comprehensive review on the energy saving effect of the building envelope components including walls, roofs, windows, thermal insulations and thermal masses, etc. A significant ratio of the heating/cooling load is resulted by the external gains (e.g., heat transfers, radiations and infiltrations, etc.). Windows of commercial buildings can significantly affect not only the heating/cooling load but also the daylight performance. For instance, the heat loss ratio of the windows to the total heat losses of all various envelope parts can be as high as 60% in commercial buildings (Grynning et al. 2013). In order to reduce the heating and cooling loads, as well as the lighting consumption, new types of windows with up to 68% transmittance (e.g., electro-chromic windows) have been developed (Baetens et al. 2010). Smart window control and design (e.g., double shin envelope/facade) can reduce a considerable heating/cooling load (Dussault et al. 2012). 7.2%-18% of heating/cooling load reduction for double skin facade was reported respectively (Kim et al. 2011; Joe et al. 2013).

Different system configurations and improvements such as radiant cooling systems, thermally activated building systems, and compact fluorescent lamps, building-integrated photovoltaic (BIPV), etc. contribute another important fraction in energy and peak power savings of the commercial sector (Stetiu 1999; Trifunovic et al. 2009; Sun and Yang 2010; Rijksen et al. 2010; Trifunovic et al. 2011). Lund (2012) considered that renewable electricity (e.g., generated by PV) of the urban areas may annually satisfy over 30% of all energy and over 70% of all electricity demand by properly adopting the thermal storages. Although the renewable generations (e.g., wind turbines and PV) (Dalton et al. 2009; Zhang et al. 2012; Cao et al. 2014) and CHPs (Mago and Smith 2012; Chua et al. 2012; Smith et al. 2013; Lee et al. 2013) play important roles in peak load reduction as well as the heating/cooling load reduction of the commercial buildings, the controllability and quantity of the renewable demand responses are still limited compared with those of the controllable loads and stored thermal energies.

The total power demand (i.e., electricity load) of a commercial building can be further divided into two major parts: inelastic demands and elastic demands. Generally, the electricity load of a commercial building is contributed by various building service systems including HVAC systems, lightings and electrical equipment, lifts and elevators, etc. (Yan et al. 2012). Electricity loads of lightings, electrical equipment, transportation and other appliances can be normally categorized as the sheddable demands, which can be conveniently obtained by their operation schedules. By contrast, electricity loads of HVAC systems are the controllable loads which are possible to be altered by the power demand controls. However, the electricity loads in HVAC systems are relatively difficult to predict due to the dynamic characteristics of the working conditions (e.g., outdoor weather conditions and variable internal gains).

*Forecasting of building heating/cooling load*

There are many approaches and methods for building heating/cooling load forecasting including white box model (i.e., physical model), grey box model (e.g., RC-based model) and black box model (e.g., ANN-based model), etc. Yao et al. (2004) presented a brief introduction on the linear regression (LR) model, autoregressive integrated moving average (ARIMA) model, ANN model and grey model (GM). Foucquier et al. (2013) presented different building modeling approaches for estimating the energy performance including physical model (e.g., CFD approach, zonal approach and multi-zone/nodal approach), statistical methods (e.g., multiple LR/conditional demand analysis (CDA), genetic algorithm (GA), ANN and support vector machine (SVM) and hybrid models. Grey model especially RC-based model appears to be a promising approach for smart grid applications (e.g., for estimating and conducting day-ahead/real time power demand response) due to its acceptable reliability and lower requirements of computation load as well as the training data (Antonopoulos and Koronaki 1998; Braun and Chaturvedi 2002; Wang and Xu 2006; Lee and Braun 2008).

Building thermal masses can significantly affect the estimation of the building heating/cooling load due to their considerable capacitances and resistances that may result the reduction and delay of the external heat fluxes (Antonopoulos and Koronaki 1999; Antonopoulos and Koronaki 2000). When building thermal masses are the only thermal storages in buildings, the identification of the thermal characteristics and estimation of the thermal performance are the premises of forecasting the building heating/cooling load and the basis of estimating the power demand response potentials. For instance, thermal parameters of the internal thermal masses can be conveniently identified using GA-based method (Wang and Xu 2006).

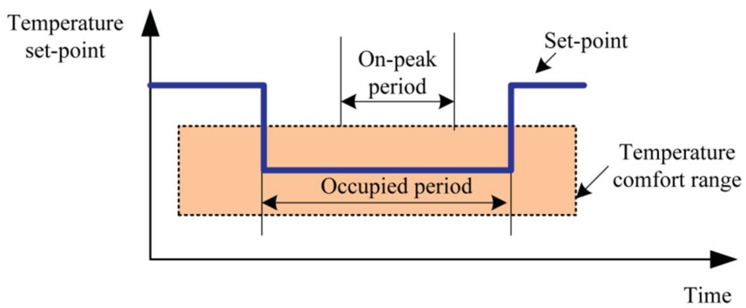
Actually, the electricity load forecasting particularly the heating/cooling load forecasting of the commercial buildings can provide the effective and supplementary energy consumption information (e.g., power demand and demand elasticity) for grid conducting efficient power management. In large scale commercial buildings, thermal storages including building thermal masses, phase change materials (PCM) and water/ice storages can effectively contribute to grid in shifting the peak load and relieving the power imbalance.

*Power demand response using thermal storages*

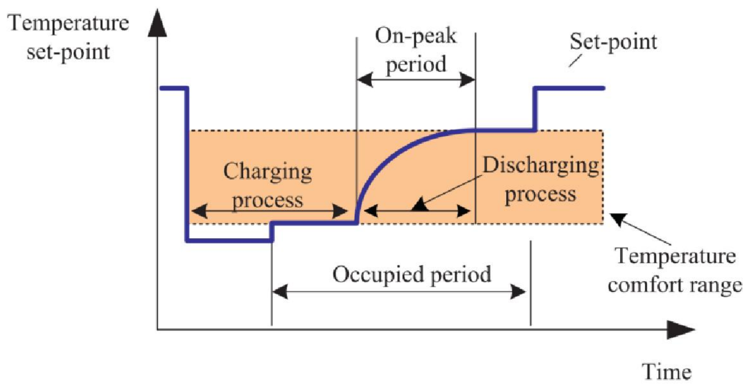
In recent years, thermal storages are considered as one promising technologies of commercial buildings for peak load shaving, and treated as the supplementary energy sources when integrating with renewable energies (Ban et al. 2012; Arteconi et al. 2012; Parameshwaran et al. 2012; Tatsidjodoung et al. 2013). The optimal control of thermal storages is very important when the building thermal demand is treated as one of the potential building power demand responses. Thermal storages in commercial buildings can generally be categorized into two categories: active thermal storages (e.g., ice storage, water storage, centralized PCM, etc.) and passive thermal storages (e.g., building thermal masses and decentralized PCM). The main difference between the active and passive storages is that, active thermal storages can be controlled flexibly by a stable control variable (e.g., a fixed temperature for energy charging/discharging) freeing from the limitations of the indoor/outdoor conditions. By contrast, passive thermal storages generally do not have a fixed phase changing temperature and has more constraints.

*Building thermal masses*

Previous researches and applications concerning building thermal masses mainly focused on the night precooling process and the daytime peak demand reduction, which are generally incented by the time of use prices and/or the peak demand charge (Sun et al. 2013). The charging control strategies of the building thermal masses during the precooling period (e.g., the off-peak period) (Keeney and Braun 1997; Xu et al. 2004; Yang and Li 2008; Yin et al. 2010; Sun et al. 2012), the discharging control strategies of the building thermal masses (e.g., resetting the indoor air temperature set-point) during the peak period (Xu et al. 2005; Xu and Zagreus 2006; Lee and Braun 2008; Sun et al. 2010), as well as the corresponding durations are significantly affecting the cooling load profile, the power demands of the HVAC systems and the corresponding energy operation cost. For instance, the peak load can be effectively reduced by 25% of the cooling capacity (i.e., 3165 kW) by adopting the precooling strategy, the capital and operation costs ($500,000 and $25,000 per month) of the chiller systems can be achieved accordingly (Keeney and Braun 1997). In (Xu et al. 2004), the indoor air temperature was maintained at the lower boundary of the comfort region during the office hours while allowed to float to the upper temperature boundary during the peak hours (i.e., 2p.m.-5p.m.). With this strategy, the chiller power was reduced by 80%-100% (1 W/ft$^2$-2.3 W/ft$^2$) without causing any thermal comfort complaints. In (Yin et al. 2010), precooling tests were conducted on eleven buildings, and 15%-30% reduction of the power demand during the peak period was reported. In (Sun et al. 2010), a power demand limiting strategy was developed based on the prediction of the building monthly peak demand (i.e., the average value in any 15 minutes), 8.51%-10.45% of the electricity cost saving can be achieved by minimizing the peak demand charge. Figure 2.8 shows a typical precooling and discharging control strategies of the building thermal masses during unoccupied and occupied periods respectively. The indoor air temperature set-point is set to a low value aiming to store cold energy in building thermal masses and is set to a high value to release the "stored" cold energy. It is worth mentioning that the indoor air temperature should be maintained in the specific boundaries to ensure the indoor thermal comfort.




(a)




(b)

Figure 2.8 Indoor air temperature set-points of (a) night setup control strategy (b) precooling and demand limiting strategy (Lee and Braun 2008; Sun et al. 2013).

As the precooling and/or demand limiting control strategies for the building thermal masses are developed mainly based on variations of the indoor air temperature, the performance of the power demand response is constrained by the following factors: the thermal capacitance of building thermal masses, the performance of HVAC systems, electricity price structure, weather conditions, occupancy thermal comfort, etc. The development of control strategies for the building thermal masses is relatively complicated compared with the active thermal storages (e.g., ice /water storage) due to the physical properties of the building thermal masses and indoor thermal constraints. Although the day-ahead and real time control strategies have been developed to achieve load shifting, peak load reduction in (Chen 2001) and (Braun 2003), the response speed (or response delay) of the power demands (e.g., after resetting the indoor air temperature set-point) has not been discussed.

In (Henze et al. 2004) and (Zhou et al. 2005), different combinations of the active and/or passive thermal storages systems for shifting peak loads were investigated. Results showed that active plus passive thermal storages systems can save energy cost up to 26% compared with the case without thermal storages. In order to enlarge the capability of the power demand response in commercial buildings, heavy-mass building and/or larger active thermal storage capacity are strongly recommended for thermal demand optimal control and building load management. Moreover, the predictive optimal control for active and passive thermal storages is also very important for the building load management when suffering the uncertainties from the models and weather conditions (Liu and Henze 2004; Henze et al. 2004; Henze et al. 2005; Morgan and Krarti 2010).

*Ice and water storages*

Both ice storage and water storage are usually employed as the centralized thermal storages at chilled water supply side of the HVAC systems to achieve peak load shaving and load shifting. For instance, the peak cost savings are 27%-31% by employing the ice storage in different climates of U.S. (Sehar et al. 2012). The chiller capacity and peak demand could be decreased by 50% and 31.2% respectively by employing chilled water storage (Boonnasa and Namprakai 2010). Figure 2.9 and Figure 2.10 illustrate the operation principle of a typical thermal storages system for cooling application (e.g., ice/water storage or centralized PCM). The thermal storages usually charges the cold energy during the off-peak periods (e.g., nighttime) and discharges the cold energy during the peak periods (e.g., daytime) to achieve cooling load shifting and/or peak load shaving (Sun et al. 2013). It is worth mentioning that, the power demand of the HVAC systems is usually determined by their provided cooling loads. In this point of view, the power demand response of the HVAC systems is dependent on the cooling demand response of the systems.

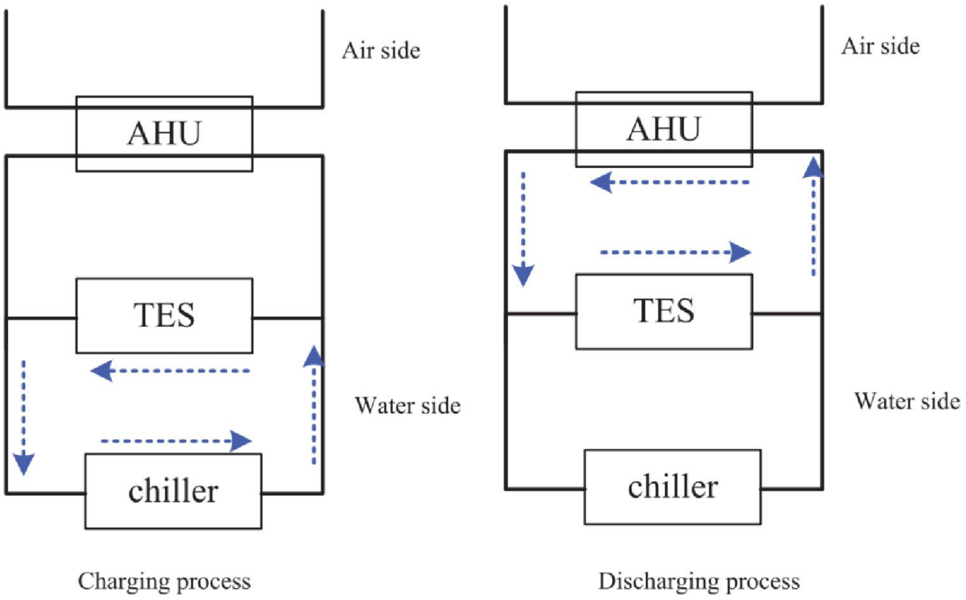



Figure 2.9 Schematics of charging and discharging processes using thermal storage system (Sun et al. 2013).

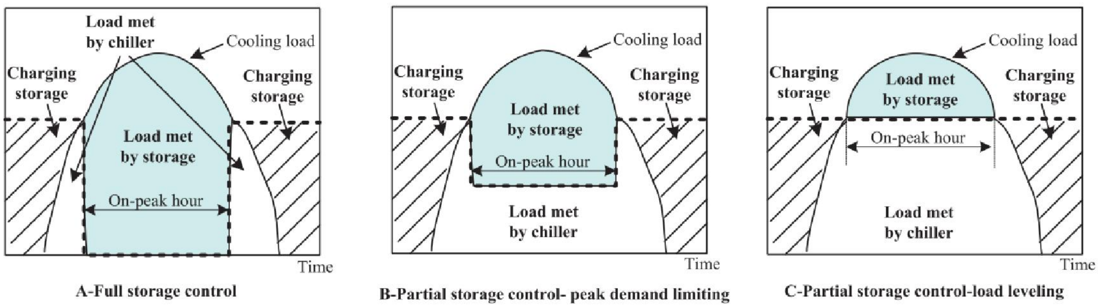



Figure 2.10 Storage capacity based control strategies of thermal storages system for peak load shaving (Sun et al. 2013).

Different optimal control strategies and algorithms were developed for improving the performance of the ice/water storage systems (Drees and Braun 1996; Massie et al. 2004; Lee et al. 2009; Hajiah and Krarti 2012; Hajiah and Krarti 2012). However, most of these optimal controls are mainly developed based on day-ahead electricity prices and operation arrangement. The actual power demand response of the systems may not fulfill the requirements of real time applications in the grid (e.g., minutes-ahead response) yet.

*Phase change materials*

Phase change materials (PCM), as one of the major latent heat thermal storages, has been considered as a promising energy storage in the following aspects: narrowing the gap between the peak and off-peak loads of energy/electricity demand, saving the energy operation cost of building under specific electricity tariffs such as time of use prices and critical peak prices, reducing diurnal temperature fluctuations concerning the indoor thermal comfort, and utilizing the free cooling at night for day peak cooling load shaving (Zhang et al. 2007; Zhu et al. 2009; Qureshi et al. 2011; Waqas and Din 2013). The modeling and optimal control of the building integrated PCM are very essential for accurately estimating the thermal performance. An idealized model for peak load shifting and a simplified RC-model have been respectively developed for investigating the indoor thermal performance (Halford and Boehm 2007; Zhu et al. 2010). The results showed that the developed models can represent the thermal characteristics of the PCM quite well. Diaconu (2011) pointed out that the energy performance of the PCM-enhanced envelope is also influenced by the occupancy and ventilation patterns. Walsh et al. (2013) reported that 67% reduction in chiller peak-time operation can be achieved by employing PCM tank with free-cooling. Figure 2.11 shows an application of PCM integrating into the air supply side of the HVAC systems. Three different operation modes (i.e., charging, ordinary and discharging operations) are respectively conducted according the requirement/arrangement (Yamaha and Misaki 2006). It is worth mentioning that, for the building integrated PCM, the indoor air temperature and the phase change temperatures of PCMs are the main constraint in their charging/discharging processes.

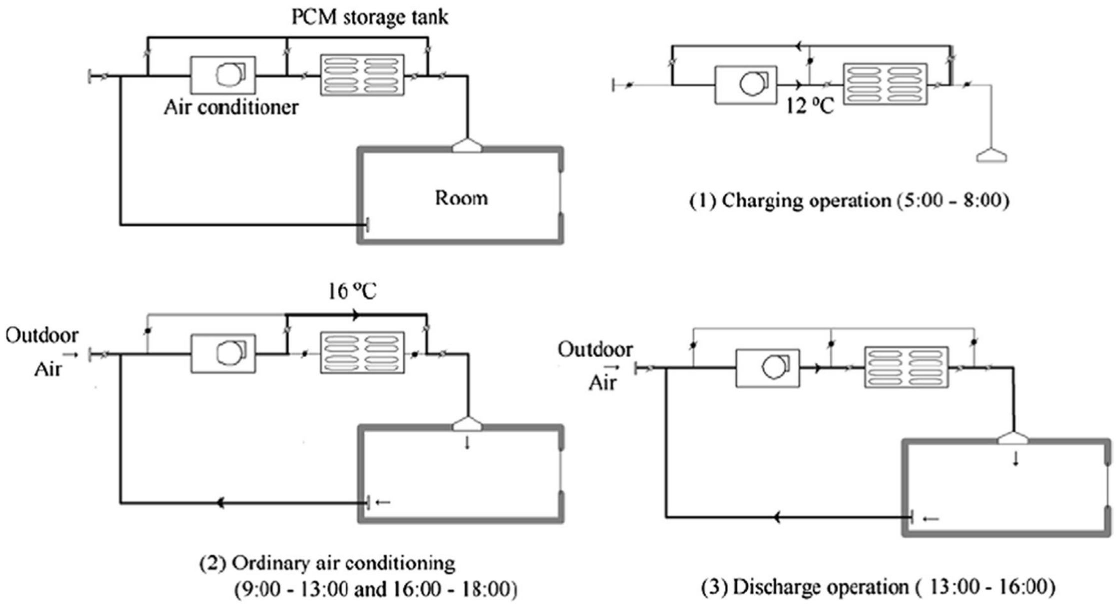



Figure 2.11 Schematics of PCM integrating with the air supply side of the HVAC systems (Yamaha and Misaki 2006).

<u>*Optimal control strategies of HVAC systems*</u>

Building automation and control provide a possible way for involving the commercial buildings into a smart grid. Besides the improvements on thermal performance of building envelope and energy efficiency of the devices/systems, the supervisory and optimal controls of the devices/systems are also the important means in conducting demand side load management for the grid. In commercial buildings, the controls of power demand response in lightings, electrical appliances, lifts and elevators are relatively simple. For instance, power demand reduction in lighting systems can be achieved by properly interact the artificial light and the daylight. Power demand in motors (e.g., pumps and elevators) can also be reduced by adopting variable-speed drive. However, the amount the power demand alteration contributed from these systems is relatively low compared with that of the HVAC systems.

The system configuration and optimal control of the HVAC systems in commercial buildings are more complicated than those of the other building systems. The energy savings of the HVAC systems can be achieved mainly by two approaches: HVAC systems fault detection and diagnosis (Cui and Wang 2005), and HVAC supervisory and local controls (Wang and Ma 2008). Chiller, as the major component in the HVAC systems, consumes a significant electricity ratio and is considered having a huge potential in power demand response. For instance, the power demand of chillers can dramatically increase during the morning/precooling start period. High peak demand charges and aggregated peak load for the electrical grid are usually resulted during that period. Therefore, the optimal start control and sequencing control of chillers for avoiding the peak demand is very essential for the daily operation of the HVAC systems in commercial buildings. Different combinations of the operating chiller numbers and precooling lead time can result different power demands (Sun et al. 2010). The optimal operating chiller numbers can be identified according to the cooling down requirements and the power demand limitations. Behl et al. (2012) adopted a green scheduling for chillers and thermal storages aiming to achieve higher COPs by improving the PLR of chillers. The maximum peak power demand reduction of a university can be as high as 0.9 MW which is quite considerable for grid in its power management. When treating the chiller power demand as one of the demand response sources, the accurate estimation of the power demand of chillers become an important issue. Sun et al. (2009) developed a strategy to improve the control reliability in chillers based on a fused cooling load measurement.

The optimal control and operation scheduling can also be implemented at heating/cooling demand side as the indoor air temperature is allowed to vary within a certain range. In fact, the power consumption of the HVAC systems in commercial buildings is significantly affected by the indoor air set-points (Wang et al. 2013). Figure 2.12 illustrates the control logic of the indoor air temperature set-point reset strategy for reducing the peak demand. The set-point is continuously updated according the actual power demands of the chiller plants/HVAC systems.

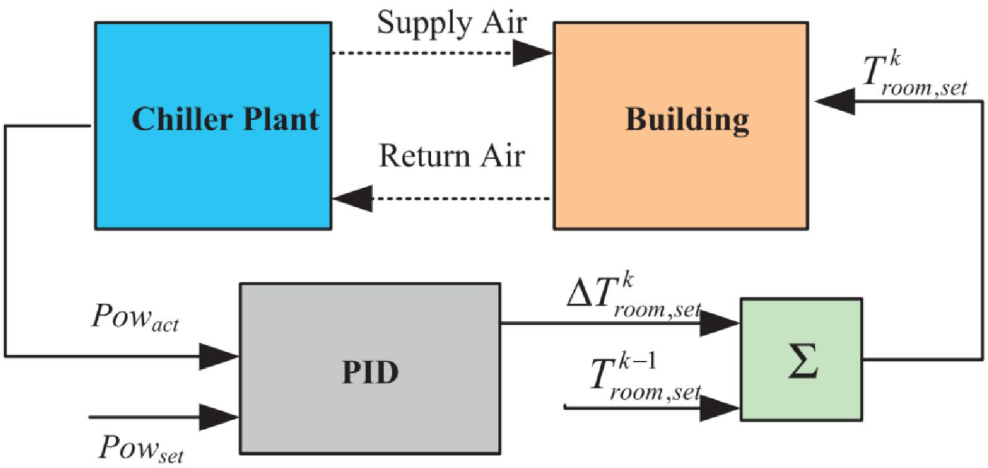



Figure 2.12 The schematics of PID demand limiting algorithm for indoor air temperature set-point reset (Sun et al. 2010).

In order to provide a fast power demand response to the grid from commercial buildings especially from HVAC systems, the possibility and the availability of treating building power demands (e.g., power demands of air-conditioning) as spinning/non-spinning “reserves” is also presented (Kueck et al. 2009; Kiliccote et al. 2011). For instance, Hao et al. (2013) considered that 15% of fan power capacity in the HVAC systems can be deployed for the regulation purposes while having little effect on the building indoor air temperature. The estimation results also showed that fans in existing commercial buildings in the U.S. can provide about 70% of the existing national regulation reserve in the frequency band [1/600, 1/8]. Figure 2.13 shows the control logic for regulating the fan power to follow the grid regulation signal.

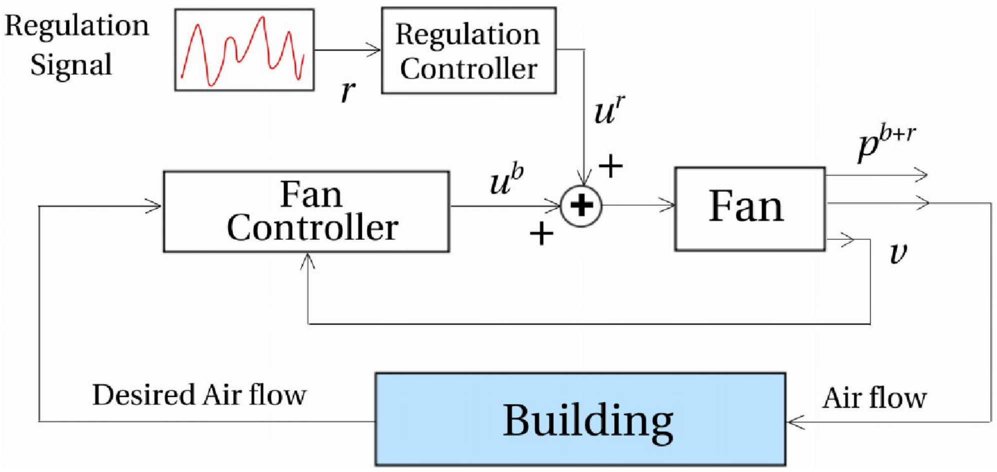



Figure 2.13 The control logic of regulating fan power responding to the regulation signal (Hao et al. 2013).

On-site cogeneration such as the combined cooling, heating, and power (CCHP) systems can contribute significantly in peak demand and energy consumption reductions (Mago and Hueffed 2010; Siler-Evans et al. 2012). Khan et al. (2004) reported that 13% ( 23%) reduction in peak demand, 16% (21%) reduction in energy consumption can be achieved by cogeneration (the data in parenthesis are the result with thermal storages).

Both local control and supervisory control in commercial building are usually implemented by building automation systems (BAS). BAS work not only to collect the detailed energy information such as heating/cooling load of building and the power demands of different building devices/systems for further analysis, but also to conduct the optimal controls of power demands in buildings, system and component levels. With the mature technologies including BAS and information and communication technologies, the communication and interaction between the power supply and demand sides can be conveniently established and conducted for the overall optimization by considering the power reliability/quality, energy efficiency and economic benefits. An agent-based building energy simulation process is demonstrated for the interaction between the aggregate load profile of individual buildings and the electricity prices of the grid (Zhao et al. 2010). The individual energy usage behaviors and power demand potentials of the end-users which are very sensitive to the electricity prices can affect the aggregate effect of the demand response.

The possible control strategies for power demand responses in commercial buildings are recommended to be developed in HVAC systems and lighting systems (Watson et al. 2006). HVAC-based demand response strategies contain fan speed regulation, fan quantity variation, supply air temperature reset and central chiller plant control, etc. Lighting-based demand response strategies contain zone lighting on/off control, fixture/lamp on/off control, step and continuous dimming controls, etc. Table 2.2 gives a summary of field test results responding to demand response events.

Table 2.2 Average and maximum power demand savings during automated DR tests (Watson et al. 2006)

| Results by Year | Number of sites | Duration of Shed (Hours) | Average Savings (%) | Maximum Savings (%) |
|---|---|---|---|---|
| 2003 | 5 | 3 | 8% | 28% |
| 2004 | 18 | 3 | 7% | 56% |
| 2005 | 12 | 6 | 9% | 38% |

### 2.3.3 Demand Response in Industrial Sector

The industrial sector consumes about 37% of the total end-use energy of world (Abdelaziz et al. 2011). Moreover, the electricity consumed by the industrial sector can be as high as 60% of the total generation in the developing countries such as India (Ashok and Banerjee 2000). As mentioned in the Table 2.1, the industrial sector contributes a significant ratio in grid power management due to its considerable power capacities of the devices/systems. The power demands in industrial sector are usually prescheduled, most of which are not constrained by outdoor weather conditions and the indoor human comforts. The power demand characteristics and the demand response potentials of this sector can then be easily obtained and estimated. Generally, the power demand response in the industrial sector can be roughly divided into two types based on the control manners: 1) direct load management and 2) indirect load management.

*Direct load management*

Direct load management, including direct load control and interruptible load control, is usually required to response immediately in reducing peak demands and/or dealing with the emergency situations. For the direct load control, the electrical grid can directly manage the operation of specific end-use appliances to achieve its desired load reduction usually based on the previous agreements. Industrial processes such as metal works, mine works, wood and chemical processing, etc. have participated the direct load control programs for many years (Bailey 1998; Nolde and Morari 2010; Zhao et al. 2011). For the interruptible load control, the main difference is that the grid notifies the participated end-users its load curtailment in advance while the end-users have the right to conduct the control or not. The amount of such type of power demand response is usually significant and sometimes ranges from 50 MW to 1000 MW.

The direct load control program is usually based on contracts while the interruptible load control program usually relying on the electricity tariffs. Actually, the industrial end-users prefer to conduct the responses relying on their back-up generations and storages rather than on the direct curtailments of energy use (Majumdar et al. 1996; CRA 2005; Albadi and El-Saadany 2008). Moreover, the optimal controls for CHP and priority of the production processes can also be considered as the effective responses in the load shedding (Mitra et al. 2013; Goh et al. 2013).

*Indirect load management*

The indirect load management is mainly developed based on the electricity prices. It is not mandatory program as based on contracts and also does not require the fast demand responses as the direct load control does. Generally, the grid sends the electricity prices to the end-users for the consideration of load management. Time-based demand response programs in the industrial sector have already been conducted for many years. For instance, significant peak load reductions (e.g., 50% of the steel plant) can be achieved under critical peak prices which are designed to reduce/shave the peak load during the critical peak periods (Ashok 2006; Pelzer et al. 2008; Rankin and Rousseau 2008). Considerable energy saving and peak load reduction (e.g., 49% cost saving and 8-25% energy reduction during peak hours) can be achieved under time of use pricing which is originally designed to improve the load factor of the grid (Lee and Chen 2007; Middelberg et al. 2009; Abdelaziz et al. 2011). The industrial end-users can also respond to the real time pricing, which is used to represent the real time power supply (Zarnikau et al. 2007). It is worth mentioning that various forms of storage (e.g., storage in sources, energies and productions, etc.) play important roles in the power demand response of the industrial sector.

## 2.4 Electricity Tariffs for Power Demand Responses

For decades, the electrical grid can buffer the power imbalance at demand side by setting different electricity tariffs. Time-based and incentive-based demand response programs have been already developed and applied for encouraging end-users to change the energy usage behaviors. With the incentives, buildings can limit and/or shift the power demands according to their own considerations. A brief introduction on different electricity pricing mechanisms is presented herein. A summary of the reviewed the paper under different electricity tariffs is also presented in Table 2.3.

- Time of use (TOU) pricing is that, the electricity prices are set for the specific time periods (e.g., peak period and off-peak periods). These price settings aim to incent end-users to shift their loads from peak period to off-peak period for cost benefits, and to help the grid achieving load factor improvement and generation capacity reduction.
- Critical peak pricing (CPP) is that, the TOU pricing in effect but with special

prices for the peak demand days/hours when the prices can be several times higher than usual prices. CPP is different from the peak demand charge. Peak demand charge accounts the kVA value consumed by the end-users during a certain period (e.g., maximum average value during any 15 minutes/30 minutes in a day/month).

- Real time pricing (RTP), also called dynamic pricing, is that the electricity prices may change as often as hourly or even shorter (e.g., 15minutes). The real time prices are usually announced a day ahead or a few hours ahead.
- Direct load control (DLC) program is that, the electricity utilities have the right to directly control (e.g., switch off) the specific devices/systems of end-users by offering a certain payment based on the previous signed agreements (e.g., contracts). Direct load control is usually conducted during high-demand periods or emergency situations of the grid.
- Demand side bidding (DSB) program is that, a competitive and negotiated program where end-users offer their availabilities in load reduction quantities and the expected cost benefits in advance (e.g., a day ahead or an hour ahead, etc.). Once the market accepts the offer, the end-users are expected to reduce the declared load and will receive the stated payments. Otherwise, the end-users will be penalized if they cannot accomplish the declared load reduction. The main difference between the demand side bidding and other demand side management measures is that demand side bidding involves the short-term discrete changes into individual load profiles of the end-users while other demand side managements involve sustainable and permanent changes into the load profiles.

Table 2.3 Summary of power demand response under different electricity tariffs

| End-user Sectors | Electricity Tariffs | References | Adopted Control Strategies | Main Results/Achievements |
|---|---|---|---|---|
| Residential | TOU | He et al. 2012; Giorgio and Pimpinella 2012 | Event driven binary linear Programming (Giorgio and Pimpinella 2012). | 21.07% cost saving can be obtained by when the smart home controller the planning is performed (Giorgio and Pimpinella 2012). |
| | CPP | Herter et al. 2007 | Event driven temperature set-point reset. | During 5-h critical peak periods, participants without control technology used up to 13% less energy than they did during normal peak periods. Participants equipped with programmable communicating thermostats used 25% and 41% less for 5 and 2 h critical events. |
| | RTP | Saele and Grande 2011;<br>Lujano-Rojas et al. 2012;<br>Kriett and Salani 2012;<br>Zhang et al. 2013;<br>Avci et al. 2013 | Direct load control (Saele and Grande 2011);<br>Integer linear programming (Kriett and Salani 2012; Zhang et al. 2013);<br>Model predictive control (Avci et al. 2013). | The observed demand response was 1 kWh/h for each end-user with standard electrical water heaters. The demand response potential from 50% of Norwegian households can be estimated at 1,000 MWh/h (4.2% of registered peak load demand in Norway) by aggregating this kind of response (Saele and Grande 2011). |
| Commercial | TOU | Chen 2001;<br>Henze et al. 2005 | Sequential optimization (Chen 2001);<br>Priority control (Henze et al. 2005) | Based on total utility cost, savings of about 26% for the passive and active thermal storages can be achieved (Chen 2001);<br>The chiller priority system achieves more energy savings with 15%, 26% 39% for different climate zones: Seattle, Helena and Duluth, respectively (Henze et al. 2005). |

| | | | | |
|---|---|---|---|---|
| | TOU plus PDC | Keeney and Braun 1997;<br>Liu and Henze 2004 | Precooling control and temperature set-point reset (Keeney and Braun 1997; Liu and Henze 2004). | The strategy reduced cooling energy use costs by 15% and the total cooling electricity demand was reduced by 18% (Keeney and Braun 1997). |
| | TOU, CPP or PDC | Xu et al. 2004;<br>Lee and Braun 2008;<br>Yin et al. 2010;<br>Sun et al. 2012 | Precooling control and temperature set-point reset (Xu et al. 2004; Lee and Braun 2008; Sun et al. 2012). | The chiller power was reduced by 80-100% (1-2.3 W/ft2) during normal peak hours from 2-5 pm without causing any thermal comfort complaints (Xu et al. 2004).<br>The demand-limiting strategy resulted in approximately 30% reductions in peak cooling loads compared to night setup control strategy for a 5-h on-peak period of 1 PM to 6 PM (Lee and Braun 2008); |
| Industrial | TOU | Ashok and Banerjee 2000;<br>Ashok. 2006;<br>Mitra et al. 2013 | Interlock control (Ashok and Banerjee 2000). | The individual load factor was improved by 4.5%. The reduction in peak demand was 0.85 MW. The electricity cost saving was about 2.8% (Ashok and Banerjee 2000). |

## 2.5 Discussions

With the available and mature technologies such as information and communication technologies, advanced metering infrastructure, smart meters, home energy management system and BAS, bidirectional connections and real time communication/interaction between the building end-users and the smart grid can be effectively built for the overall optimization of both power supply and demand sides (Aung et al. 2012; Khan and Khan 2013). In order to encourage the buildings to play a more active role in power demand response in the smart grid, mature electricity markets should be established to incent the voluntaries of the end-users, to optimize the costs of power supply and electricity use, and most importantly to ensure the reliable operation of the power systems. Actually, NIST has proposed a conceptual model for a future smart grid with involving the central operators, markets, service providers and different categories of end-users (NIST 2012). As shown in Figure 2.14, useful information is exchanged within the power and information flows, and optimal controls/arrangements can also be effectively conducted during different power processing stages: generation, transmission, distribution and consumption.

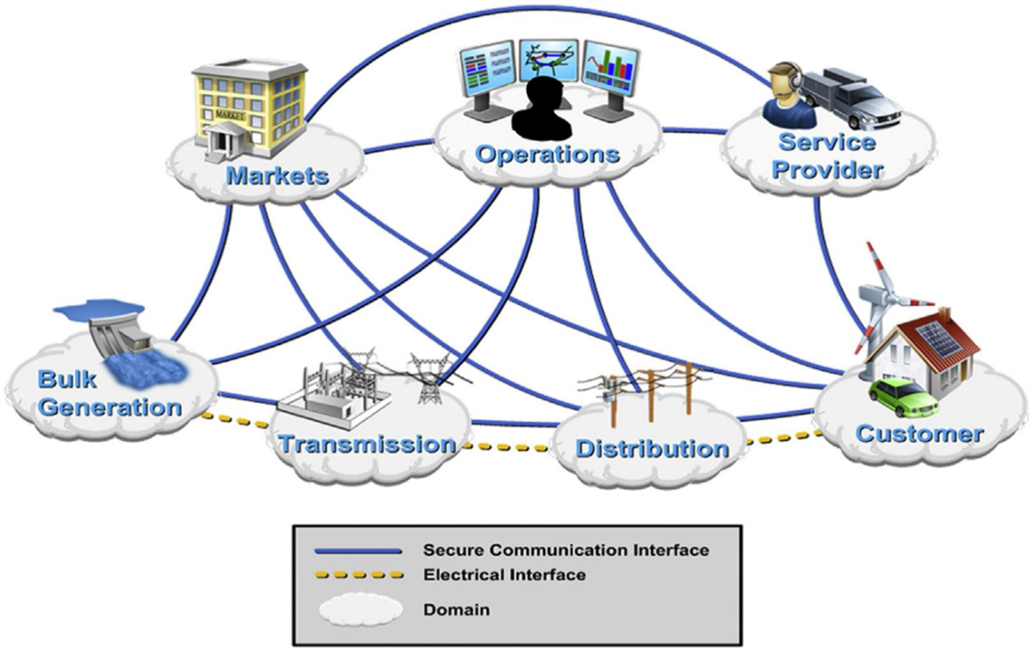



Figure 2.14 NIST conceptual model for Smart Grid (Khan and Khan 2013).

In order to meet the requirements (e.g., the quantity and speed of demand response) of relieving the peak load and power imbalance at demand side, power demand responses of the end-users are recommended to be developed based on different time scale: day-ahead (i.e., offline power demand response) and hour-ahead/15 minutes-ahead (i.e., online power demand response). The offline power demand response such as load shifting and peak load shaving (i.e., coarse power demand regulation in a relative longer period) is expected to contribute in improving the grid load factor. Due to the power/load forecasting errors or emergency events may happen at both the power supply and demand sides, the online power demand response is therefore expected to contribute in improving the grid reliability and quality by treating the power demands as the real time "operating reserves" (i.e., fine power balance tuning regulation in a relative longer period). The future smart grid is being developed aiming at achieving multiple objectives (e.g., power reliability/quality, energy efficiency and costs, etc.) and involving different participants (e.g., power suppliers/delivers, operators and end-users, etc.). The grid power management is also becoming more and more complicated.

## 2.6 Summary

This chapter provides a comprehensive review on the current studies on power demand responses in building sectors. Peak load and power imbalance, as two critical power management issues in electrical grid, are briefly introduced. Power demand responses from the end-users are able to help grid in conducting the power management such as load shifting, peak demand shaving and dynamic power regulation. Conclusive remarks and recommendations for developing more cost-effective power demand response in future smart grid are drawn as follows:

(1) Buildings can significantly contribute their power demand response potentials to relieve peak load and grid power imbalance problems. Incentive demand response programs (i.e., electricity tariffs) should be designed to motivate the voluntaries of the end-users since the demands responses from the end-users are much more cost-effective than operating reserves at power supply side.

(2) With the developments of the technologies such as information and communication technologies, advanced metering infrastructure, smart meters, home energy management system and BAS, the communications between the power supply and demand sides have been changing from the static "one-way" into the dynamic "two-way". Bidirectional connections and two-way flows (i.e., power and information flows) between the smart grid and the end-users bring new challenges and opportunities in various aspects such as the overall generation

planning, operation control and scheduling, energy and cost optimizations. Moreover, the energy information of the end-users (e.g., power demands and demand response capacities) can serve the grid as redundant data for its load forecasting and operating reserve arrangement.

(3) Although there are already many demand response programs (e.g., time-based and incentive-based) for encouraging the end-users to change their energy usage behaviors, more electricity pricing mechanisms (e.g., offline-based and online-based) are still needed to be developed/implemented for different types of end-users (e.g., industrial, residential and commercial) with different objectives (e.g., improving the load factor and maintaining the power frequency). The aggregate effect of changing individual load profiles of a large number of end-users should be also carefully considered.

(4) Thermal storages of buildings, including the active (e.g., ice and water storages, etc.) and passive (e.g., building thermal masses and phase change materials, etc.) storages, can actually play an important and active role in building power demand response. Thermal storages can not only enable more capabilities of the building power demand response by charging/discharging thermal energy, but can also self-regulate the individual load profiles of buildings when renewable generations are integrated.

# CHAPTER 3 DEVELOPMENT OF A SIMPLIFIED BUILDING THERMAL STORAGE MODEL

Distributed thermal storages at power demand side can contribute significantly for smart grid power balance in different power processes including generation, transmission and consumption, etc. Thermal storages of buildings, as the major storage sector at power demand side, usually consist of the active (e.g., ice and water storages, etc.) and passive (e.g., building thermal masses and phase change materials, etc.) storages. These thermal storages of buildings can play an important and active role in power demand response. This chapter investigates the characteristics of passive thermal storage (i.e., building thermal masses) in commercial buildings.

Different commercial buildings have different potentials in power demand alteration due to their own thermal storage capabilities and system configurations. The power demand management of commercial buildings is usually accomplished by load shifting and/or peak demand limiting controls, which need a certain realization cost (e.g., increase of the overall energy consumption). The power demand alteration potential and the associated realization cost are therefore the essential indices of the building characteristics for predicting the power demand response under the specific electricity prices of a smart grid, which provide valuable information for smart grid optimization. In order to enable the passive thermal storages of buildings to fulfill the application requirements of the smart grid, a simple and effective thermal storage model is needed to be developed for representing the thermal characteristics of the passive thermal storage (i.e., building thermal masses in this study).

Section 3.1 presents an introduction of the inspiration and original idea of developing a simplified building thermal storage model, which is based on thermodynamics analogized to the electric theory. Section 3.2 presents the development of the simplified building thermal storage model in detail. Section 3.3 presents the specifications of building structures and working conditions for the development of the simplified thermal storage model. Section 3.4 presents the parameters identification of the simplified thermal storage model in different types of buildings including light, medium and heavy weighted buildings. Section 3.5 presents and discusses the results of parameters identification. A summary of this chapter is given in Section 3.6.

## 3.1 Introduction

Compared with physic model and black model, grey box model (e.g., RC model) is suitable for predicting the building heating/cooling load due to its high accuracy and low requirements on the history data and computing load. For instance, a 3R2C model representing building envelope and a 2R2C model representing building internal masses are developed for predicting the cooling load of commercial buildings (Wang and Xu 2006). Figure 3.1 shows the configuration of the simplified building energy models for a typical building. In the model, a building consists of two parts: 1) building envelope including external walls, roof and windows, etc., 2) building internal masses including internal walls, floors, ceilings, partitions and furniture, etc. The indoor space of the building is assumed to be a single zone, and the indoor air is assumed to be well mixed.

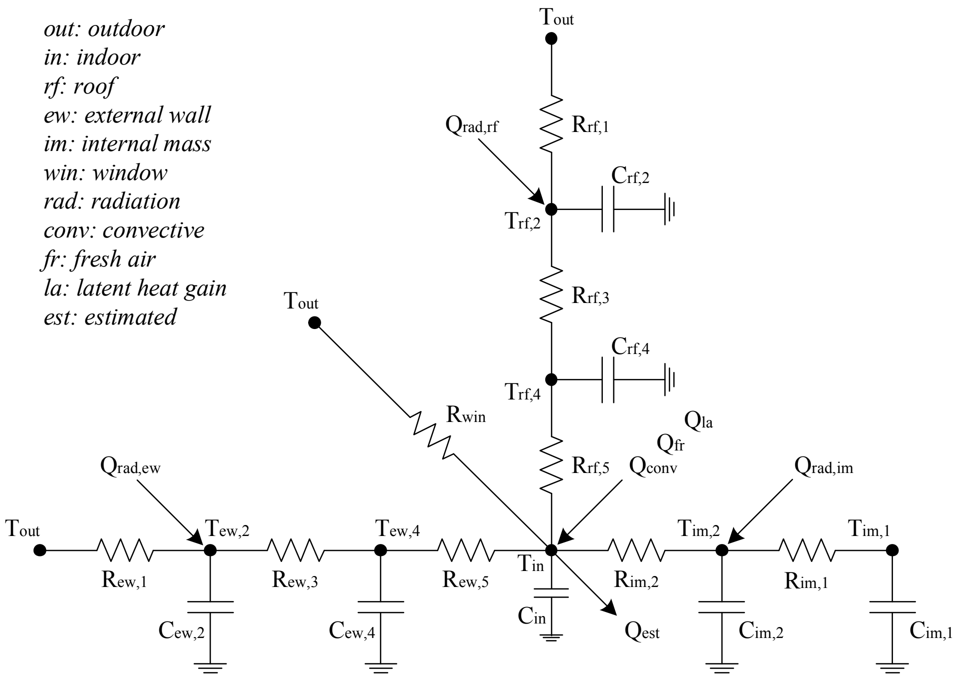



Figure 3.1 Configuration of the simplified building energy model of a typical building.

Based on thermal energy balance, the actual cooling load of a building can be estimated by the following differential Equations (3.1) to (3.7).

$$C_{rf,2}\frac{dT_{rf,2}(t)}{dt} = \left(\frac{T_{out}(t) - T_{rf,2}(t)}{R_{rf,1}} - \frac{T_{rf,2}(t) - T_{rf,4}(t)}{R_{rf,3}}\right)A_{rf} + Q_{rad,rf} \tag{3.1}$$

$$C_{rf,4}\frac{dT_{rf,4}(t)}{dt} = \left(\frac{T_{rf,2}(t) - T_{rf,4}(t)}{R_{rf,3}} - \frac{T_{rf,4}(t) - T_{in}(t)}{R_{rf,5}}\right)A_{rf} \tag{3.2}$$

$$C_{ew,2}\frac{dT_{ew,2}(t)}{dt} = \left(\frac{T_{out}(t) - T_{ew,2}(t)}{R_{ew,1}} - \frac{T_{ew,2}(t) - T_{ew,4}(t)}{R_{ew,3}}\right)A_{ew} + Q_{rad,ew} \tag{3.3}$$

$$C_{ew,4}\frac{dT_{ew,4}(t)}{dt} = \left(\frac{T_{ew,2}(t) - T_{ew,4}(t)}{R_{ew,3}} - \frac{T_{ew,4}(t) - T_{in}(t)}{R_{ew,5}}\right)A_{ew} \tag{3.4}$$

$$C_{im,1}\frac{dT_{im,1}(t)}{dt} = \frac{T_{im,1}(t) - T_{im,2}(t)}{R_{im,1}}A_{im} \tag{3.5}$$

$$C_{im,2}\frac{dT_{im,2}(t)}{dt} = \left(\frac{T_{im,1}(t) - T_{im,2}(t)}{R_{im,1}} - \frac{T_{im,2}(t) - T_{in}(t)}{R_{im,2}}\right)A_{im} + Q_{rad,im} \tag{3.6}$$

$$\begin{aligned} Q_{est} &= \sum_{i=1}^{n}\left[\frac{T_{ew,4}(t) - T_{in}(t)}{R_{ew,5}}A_{ew}\right] + \frac{T_{rf,4}(t) - T_{in}(t)}{R_{rf,5}}A_{rf} + \frac{T_{im,2}(t) - T_{in}(t)}{R_{im,2}}A_{im} \\ &+ \frac{T_{out}(t) - T_{in}(t)}{R_{win}}A_{win} - C_{in}\frac{dT_{in}(t)}{dt}A_{in} + \left(Q_{conv} + Q_{fr} + Q_{la}\right) \end{aligned} \tag{3.7}$$

where, $T$ and $Q$ are the temperature and heat gain respectively. $R$ and $C$ are thermal resistance and thermal capacitance respectively. $A$ is the effective surface area involved in the heat exchange process. $Q_{est}$ is the estimated cooling load. Thermal capacitances and resistances of building envelope can be obtained by comparing theoretical frequency response characteristics with that of the simplified building energy model using genetic algorithm (GA). The thermal capacitances and resistances of building internal masses can be obtained by minimizing error between actual (i.e., short-term historical operation data) and estimated cooling loads using genetic algorithm. Detailed procedures can be referred to previous study (Wang and Xu 2006).

Although the simplified building energy model can predict the building cooling load with a high accuracy, this kind of model is usually developed based on the constant indoor air temperature which cannot represent the thermal characteristics of building thermal masses when indoor air temperature varies during the office hours. Moreover, this simplified building energy model is still relatively complicated and difficult for dynamic application in smart grid. A more simple and effective model is therefore needed to represent the building cooling load variation (i.e., alteration) under different indoor temperature control strategies (e.g., precooling and temperature).

By observing the building cooling load alteration under different indoor temperature settings (by simulation tests), trends of the cooling load alteration were found very similar with the charging/discharging pattern of electrical battery. Therefore, a simplified building thermal storage model (also called “thermal battery” model in this study) is developed from the concept of electrical battery. An introduction on the charging/discharging performance of electrical battery is presented in the following section.

Figure 3.2 shows a typical schematic of RC circuit of an electrical battery for investigating the charging and discharging processes respectively. The electrical circuit contains several key electric devices such as resistances (i.e., $R_{charge}$ and $R_{discharge}$), capacitance (i.e., ), switch and power source.

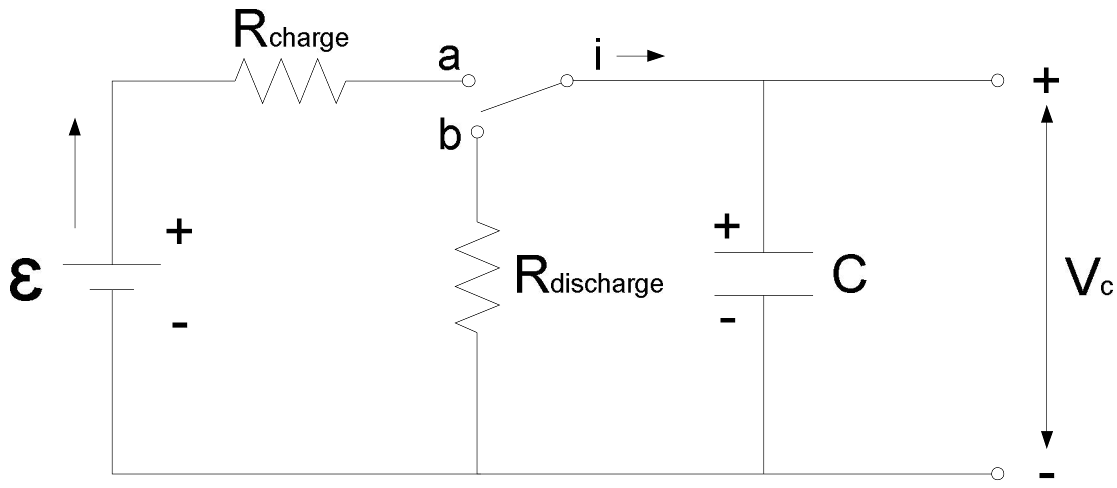



Figure 3.2 A typical schematic of RC circuit (electrical battery).

For this kind of RC circuit (electrical battery), two scenarios (i.e., charging process and discharging process) are discussed respectively.

(1) The charging process

When the switch is connected to point **a** at start (i.e., **t**=0) and the voltage of the capacitance is 0 (i.e., **q**=0) at same time. Equation (3.8) can be obtained according to the energy balance.

$$P_S = P_{R_{\mathrm{charge}}} + P_C \tag{3.8}$$

where,

$$P_S = i \cdot \varepsilon \tag{3.9}$$

$$P_{R_{\text{charge}}} = i \cdot V_{R_{\text{charge}}} = i^2 \cdot R_{\text{charge}} \tag{3.10}$$

$$P_C = i \cdot V_c = i \cdot \frac{q}{C} \tag{3.11}$$

$$i = \frac{dq}{dt} \tag{3.12}$$

As a result,

$$\varepsilon = R_{\text{charge}} \frac{dq}{dt} + \frac{q}{C} \tag{3.13}$$

By solving this equation, the characteristics of the charging process can be represented by Equations (3.14) and (3.15). Figure 3.3 also shows the changing trends of the charging current (i.e., **i**) and the stored energy (i.e., **q**).

$$q(t) = C \cdot \varepsilon(1 - e^{-\frac{t}{\tau_1}}) \tag{3.14}$$

$$i(t) = \frac{\varepsilon}{R_{\text{charge}}} e^{-\frac{t}{\tau_1}} \tag{3.15}$$

where,

$$\tau_1 = R_{\text{charge}} \cdot C \tag{3.16}$$

The $R_{charge}C$ (i.e., $\tau_1$) is so called capacitive time constant of the charging process.

When **t**= $\tau_1$,

$q(\tau_1)=C\varepsilon(1-e^{-1})=0.63\ C\varepsilon$;

$V_C(\tau_1)=\varepsilon(1-e^{-1})=0.63\varepsilon$;

$i(\tau_1)=(\varepsilon/R_{\text{charge}})e^{-1}=0.37(\varepsilon/R_{\text{charge}})$.

When **t**=∞,

$q(\infty)=C\varepsilon(1-1/e^{\infty})=C\varepsilon$;

$V_C(\infty)=\varepsilon(1-1/e^{\infty})=\varepsilon$;

$i(\infty)=(\varepsilon/R_{\text{charge}})(\ 1/e^{\infty})=0$.

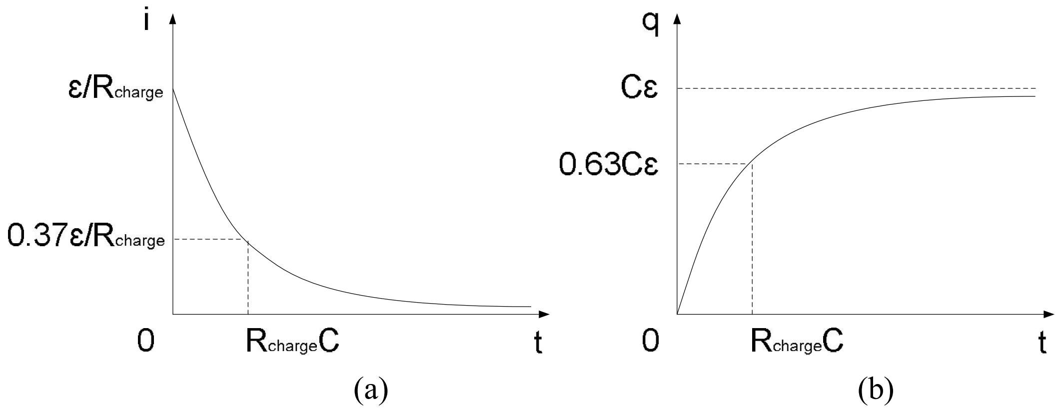



Figure 3.3 Variations of the charging current (a), and the stored energy (b) during the charging process.

(1) The discharging process

When the switch is connected to point **b** at start (i.e., **t**=0), the power source is disconnected (i.e., **ε**=0) and the voltage of the capacitance is assumed as $V_0$ (i.e., **q**=$q_0$) at same time. Then the Equation (3.13) can be rewritten as Equation (3.17).

$$0 = iR_{\text{discharge}} + \frac{q}{C} \tag{3.17}$$

By solving equation, the characteristics of the discharging process can be represented by Equations (3.18) and (3.19). Figure 3.4 also shows the changing trends of the discharging current (i.e., **i**) and the stored energy (i.e., **q**).

$$q(t) = q_0 e^{-\frac{t}{\tau_2}} = CV_0 e^{-\frac{t}{\tau_2}} \tag{3.18}$$

$$i(t) = \frac{dq(t)}{dt} = -\frac{V_0}{R_{\text{discharge}}} e^{-\frac{t}{\tau_2}} \tag{3.19}$$

The $R_{discharge}C$ (i.e., $\tau_2$) is so called capacitive time constant of the discharging process.

When **t**= $\tau_2$,

$q(\tau_2)=q_0e^{-1}=0.37q_0$;

$V_C(\tau_2)= V_0e^{-1}=0.37\ V_0$;

$i(\tau_2)=-(V_0/R_{discharge})e^{-1}=-0.37(V_0/R_{discharge})$.

When **t**=∞,

$q(\infty)=q_0/e^{\infty}=0;$

$V_C(\infty)=V_0/e^{\infty}=0;$

$i(\infty)=(V_0/R_{discharge})/e^{\infty}=0.$

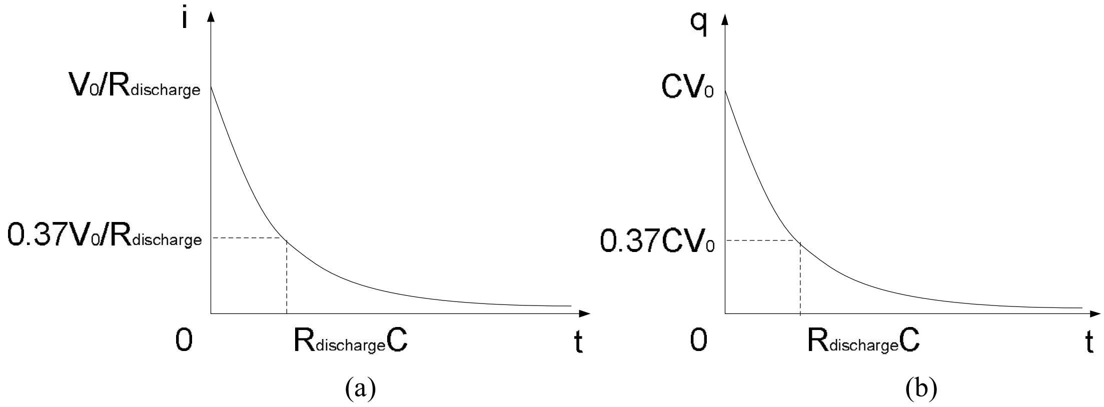



Figure 3.4 Variations of the discharging current (a), and the stored energy (b) during the discharging process.

The development of the simplified building thermal storage model (i.e., "thermal battery") is similar with the RC circuit (i.e., electrical battery) presented above due to they are based on the similar theories and the same trends.

## 3.2 Description of Simplified Building Thermal Storage Model

In this section, a building thermal storage model is developed in order to predict the heating/cooling load alteration potential of a building without active thermal storage (i.e., with building thermal masses only). As shown in Figure 3.5, a building (with its external and internal masses) is simplified to a lumped thermal mass and assumed to be homogeneous. An equivalent temperature ($\overline{T}_{bui}$) is introduced to represent the energy status of the building. In the thermal storage model, heat gains achieved in radiation, convection, sensible and latent heat processes, etc., are assumed not being affected by adopting active power demand control strategies. Building thermal characteristics can then be simply represented by the identified thermal capacitance and resistances. In reality, building heating/cooling load alteration potential is also influenced by the indoor air temperature set-point employed and the duration of the adopted power demand control. Such effects are considered by involving the building thermal mass ($C_{bui}$) and the equivalent temperature ($\overline{T}_{bui}$). The thermal mass of the indoor air volume is ignored as it is too small compared with the thermal mass of building structures.

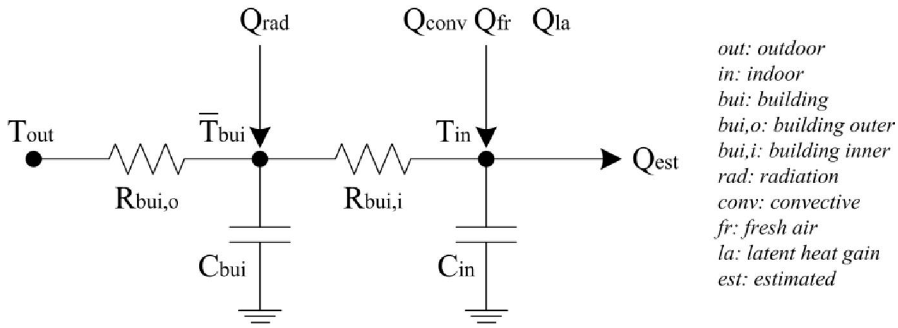



Figure 3.5 Schematic of the building thermal storage model for heating/cooling load alteration potential prediction.

A differential equation can be established according to energy balance in the thermal storage model, as shown in Equation (3.20). By solving the Equation (3.20), a function indicating the energy status of the building thermal masses can be written as Equation (3.21).

$$C_{bui}\frac{d\overline{T}_{bui}(t)}{dt}A_{bui} = \frac{T_{out} - \overline{T}_{bui}(t)}{R_{bui,o}}A_{bui} + \frac{T_{in} - \overline{T}_{bui}(t)}{R_{bui,i}}A_{bui} + Q_{rad} \tag{3.20}$$

$$\overline{T}_{bui}(t) = T_{ext}\left(1 - e^{-\frac{t}{\tau}}\right) + \overline{T}_{bui}(0)e^{-\frac{t}{\tau}} \tag{3.21}$$

where,

$$T_{ext} = \left( \frac{T_{out}}{R_{bui,o}} + \frac{T_{in}}{R_{bui,i}} + \frac{Q_{rad}}{A_{bui}} \right) R_{bui} \tag{3.22}$$

$$\tau = R_{bui} C_{bui} \tag{3.23}$$

$$R_{bui} = \frac{R_{bui,o} R_{bui,i}}{R_{bui,o} + R_{bui,i}} \tag{3.24}$$

where, $\overline{T}_{bui}(0)$ is the initial equivalent temperature of building thermal masses. $T_{ext}$ is the equivalent temperature of external heat sources (e.g., the outdoor and indoor air, radiation gains, etc.). $T_{out}$ and $T_{in}$ are the outdoor and indoor temperatures. $Q_{rad}$ is the radiation gains achieved by both outer and inner surfaces of the building.

The heat exchange between the building and the indoor air is particularly concerned because heating/cooling load alteration potential of the building is determined by the processes of energy store/release. By combining the Equation (3.20) and (3.21), the heat flux between the building and the indoor air can be written as Equation (3.25).

$$Q_{bui}(t) = \frac{\left\lfloor T_{ext} - \overline{T}_{bui}(0) \right\rfloor}{R_{bui,i}} e^{-\frac{t}{\tau}} A_{bui} + \frac{T_{in} - T_{out}}{\left( R_{bui,o} + R_{bui,i} \right)} A_{bui} - \frac{Q_{rad} R_{bui}}{R_{bui,i}} \tag{3.25}$$

Similar with the simplified building energy model mentioned previous, the predicted building heating/cooling load can be written as shown Equation (3.26) according to energy balance. The alteration potential of the building heating/cooling load can then be represented by Equation (3.27). It is worth to noticing that, as the gains of a building are assumed to be constant in the altered cases and the reference case, the gains due to radiation, convection, sensible and latent heat processes, etc. are canceled and do not appear in the mathematical formula of the thermal storage model.

$$Q_{est} = Q_{conv} + Q_{fr} + Q_{la} - Q_{bui} - C_{in} \frac{dT_{in}}{dt} A_{in} \tag{3.26}$$

$$\Delta Q_{est} = -\Delta Q_{bui} \tag{3.27}$$

where, $Q_{est}$ is the predicted heating/cooling load of the building. $Q_{conv}$, $Q_{fr}$, $Q_{la}$ are the convective heat gains, the heat gains from fresh air induction and air infiltration respectively. $C_{in}$, $T_{in}$, $A_{in}$ are thermal capacitance (per square meter), temperature, effective area of indoor air respectively. $\Delta Q_{est}$ and $\Delta Q_{bui}$ are the alteration of the building heating/cooling load and the changing/discharging rate of the building thermal masses.

The simplified thermal storage model can then be used to predict the charging/discharging rate of a building in the form of thermal energy as shown in Equation (3.28), and in the form of electrical power demand as shown in Equation (3.33). Effective storage capacity and storage efficiency of the building can also be predicted, as shown in Equations (3.34) and (3.35) respectively. A detailed description on the model development is given in the following section.

For the scenarios of adopting preheating/precooling and temperature set-point reset strategies, the charging/discharging rate (i.e., the heating/cooling load alteration potential) of building thermal masses can be summarized in Equations (3.28) to (3.32).

$$\Delta Q_{bui}(t) = \begin{cases} \Delta Q_{pre,c}(t), & t \in [0,\ t_c] \\ \Delta Q_{pre,d}(t) + \Delta Q_{set,d}(t), & t \in [0,\ t_d] \end{cases} \tag{3.28}$$

where,

$$\Delta Q_{pre,c}(t) = \frac{\Delta T_{in,c}}{\left(R_{bui,o} + R_{bui,i}\right)}\left(1 + \alpha e^{-\frac{t}{\tau}}\right)A_{bui} \tag{3.29}$$

$$\Delta Q_{set,d}(t) = \frac{\Delta T_{in,d}}{\left(R_{bui,o} + R_{bui,i}\right)}\left(1 + \alpha e^{-\frac{t}{\tau}}\right)A_{bui} \tag{3.30}$$

$$\Delta Q_{pre,d}(t) = -\alpha\frac{\Delta T_{in,c}}{\left(R_{bui,o} + R_{bui,i}\right)}\left(1 - e^{-\frac{t_c}{\tau}}\right)e^{-\frac{t}{\tau}}A_{bui} \tag{3.31}$$

$$\alpha = \frac{R_{bui,o}}{R_{bui,i}} \tag{3.32}$$

where, $\Delta Q_{pre,c}$, $\Delta Q_{set,d}$, $\Delta Q_{pre,d}$ are the heating/cooling load alterations corresponding to the preheating/precooling and the temperature set-point reset strategies during the charging and discharging periods respectively. $\Delta T_{in,c}$ and $\Delta T_{in,d}$ are the temperature set-point differences between the altered cases and the reference case during the charging and discharging periods respectively. $R_{bui,o}$ and $R_{bui,i}$ are the outer and inner thermal resistances of the building respectively. $\alpha$ is a ratio of the outer thermal resistance to the inner thermal resistance. $t_c$ and $t_d$ are the durations of charging and discharging. $\tau$ is the time constant of the building thermal masses. $t$ indicates the time. $A_{bui}$ is the effective building surface area involved in the heat exchange process.

The charging/discharging rate, storage capacity and storage efficiency are considered as the key indices of energy storages when integrated with a grid (Eyer and Corey 2010). The first important index for the building thermal storage is the charging/discharging rate. Given the overall COP of the HVAC system, the corresponding electrical power demand alteration can be expressed by Equation (3.33).

$$\Delta P_e(t) = \frac{\Delta Q_{est}(t)}{COP_{sys}} = \begin{cases} -\dfrac{\Delta Q_{pre,c}(t)}{COP_{sys}}, & t \in [0,\ t_c] \\ -\dfrac{\Delta Q_{pre,d}(t) + \Delta Q_{set,d}(t)}{COP_{sys}}, & t \in [0,\ t_d] \end{cases} \tag{3.33}$$

where, $\Delta P_e$ is the electrical power demand alteration of a building. $\Delta Q_{est}$ is the alteration of the building heating/cooling load of the building thermal masses. $COP_{sys}$ is the overall COP of the HVAC system. $Q_{pre,c}$, $\Delta Q_{set,d}$, $\Delta Q_{pre,d}$ are the heating/cooling load alterations corresponding to the preheating/precooling and the temperature set-point reset strategies during the charging and discharging periods respectively.

The other two indices of the building thermal storage are effective storage capacity and storage efficiency, which are determined by the thermal characteristics of the building and the performance of the HVAC system, as well as the duration of charging/discharging. These two indices are given by Equations (3.34) and (3.35).

$$E_{bui} = \frac{\int_0^{t_c} \Delta Q_{pre,c}(t)dt}{COP_{sys}} = \frac{\Delta T_{in,c}}{\left(R_{bui,o} + R_{bui,i}\right)COP_{sys}}\left[t_c + \alpha\tau\left(1 - e^{-\frac{t_c}{\tau}}\right)\right]A_{bui} \tag{3.34}$$

$$\eta_{bui} = \left|\frac{\int_0^{t_d} \Delta Q_{pre,d}(t)dt}{\int_0^{t_c} \Delta Q_{pre,c}(t)dt}\right| = \frac{\left(1 - e^{-\frac{t_c}{\tau}}\right)\left(1 - e^{-\frac{t_d}{\tau}}\right)}{\left(1 - e^{-\frac{t_c}{\tau}}\right) + \frac{t_c}{\alpha\tau}} \tag{3.35}$$

where, $E_{bui}$ is the effective storage capacity of the building thermal masses. $\eta_{bui}$ is the storage efficiency of the building thermal masses.

Although different types of commercial buildings (e.g., light weighted, medium weighted and heavy weighted) have different storage capabilities and energy performances, the thermal characteristics and the heating/cooling load alteration potentials of different types of buildings can be represented by the same thermal storage model as well. In the thermal storage model, the thermal capacitance ($C_{bui}$) and the thermal resistances ($R_{bui,o}$ and $R_{bui,i}$) of a building and the overall COP of the HVAC system are the key parameters and coefficient, which need to be identified. Identification of the parameters and validation of the thermal storage model will be discussed in the simulation case study. Once the parameters and coefficient are obtained, effective and reliable indices of the building thermal storage can be characterized accordingly for the day-ahead optimization/interaction and/or hour-ahead optimization/interaction of a smart grid.

It is worth noticing that the thermal storage model is considered to be too simple to represent the full characteristics of building heating/cooling load accurately and therefore it may be not suitable for predicting building heating/cooling loads. In this study, the thermal storage model is only used to predict the building heating/cooling load alterations (i.e., the changes of the heating/cooling load referring to corresponding reference case) when power demand control strategies are applied.

## 3.3 Specifications of Structures and Working Conditions

For the development of the simplified building thermal storage model, three types of building envelope (e.g., external walls and roof, etc.) were selected to investigate the performance of the thermal model. Except building envelopes, the other configurations of these buildings (i.e., lighted, medium and heavy weighted buildings) were all the same: each building has 40 floors with 4m height and 400 m$^2$ area per floor, and with window-to-wall ratio of 0.5. The external walls and roof of these three types of buildings were selected according to ASHRAE Handbook: Fundamentals (1997), as listed in the following Tables.

Table 3.1 Wall group 2 for composing the light weighted building

| Description | L (mm) | k (W/(m·K)) | ρ (kg/m3) | C (J/(kg·K)) | R (m$^2$·K/W) |
|---|---|---|---|---|---|
| Outside surface resistance (A0) | - | - | - | - | 0.059 |
| 13 mm finish (A6) | 13 | 0.415 | 1249 | 1090 | 0.031 |
| 25 mm insulation (B5) | 25 | 0.043 | 91 | 840 | 0.587 |
| 100 mm high density | 100 | 0.813 | 977 | 840 | 0.125 |

| | | | | | |
|---|---|---|---|---|---|
| concrete block (C3) | | | | | |
| Inside surface resistance (E0) | - | - | - | - | 0.121 |

Table 3.2 Wall group 17 for composing the medium weighted building

| Description | L (mm) | k (W/(m·K)) | ρ (kg/m3) | C (J/(kg·K)) | R ($m^2$·K/W) |
|---|---|---|---|---|---|
| Outside surface resistance (A0) | - | - | - | - | 0.059 |
| 150 mm insulation (B15) | 150 | 0.043 | 91 | 840 | 3.520 |
| 100 mm low density concrete block (C2) | 100 | 0.381 | 609 | 840 | 0.266 |
| 100 mm face brick (A2) | 100 | 1.333 | 2002 | 920 | 0.076 |
| Inside surface resistance (E0) | - | - | - | - | 0.121 |

Table 3.3 Wall group 41 for composing the heavy weighted building

| Description | L (mm) | k (W/(m·K)) | ρ (kg/m3) | C (J/(kg·K)) | R ($m^2$·K/W) |
|---|---|---|---|---|---|
| Outside surface resistance (A0) | - | - | - | - | 0.059 |
| 100 mm face brick (A2) | 100 | 1.333 | 2002 | 920 | 0.076 |
| 125 mm insulation (B14) | 125 | 0.043 | 91 | 840 | 2.933 |
| 300 mm high density concrete (C11) | 300 | 1.731 | 2243 | 840 | 0.176 |
| 20 mm plaster or gypsum (E1) | 20 | 0.727 | 1602 | 840 | 0.026 |
| Inside surface resistance (E0) | - | - | - | - | 0.121 |

A typical summer day with the weather data of Hong Kong (i.e., subtropical climate) was adopted for the tests, as shown in Figure 3.6. The overall COPs of the HVAC systems in buildings were assumed to be constant (i.e., 2.5). Precooling during non-office hours (e.g., precooling at 20°C) and temperature set-point reset during office hours (i.e., temperature set-point reset within [22.5°C, 25.5°C]) were selected as building power demand control strategies arbitrarily. Office hours were defined from 09:00 to 18:00, and early start-up (set from 08:30 to 09:00) for the HVAC systems was added as well.

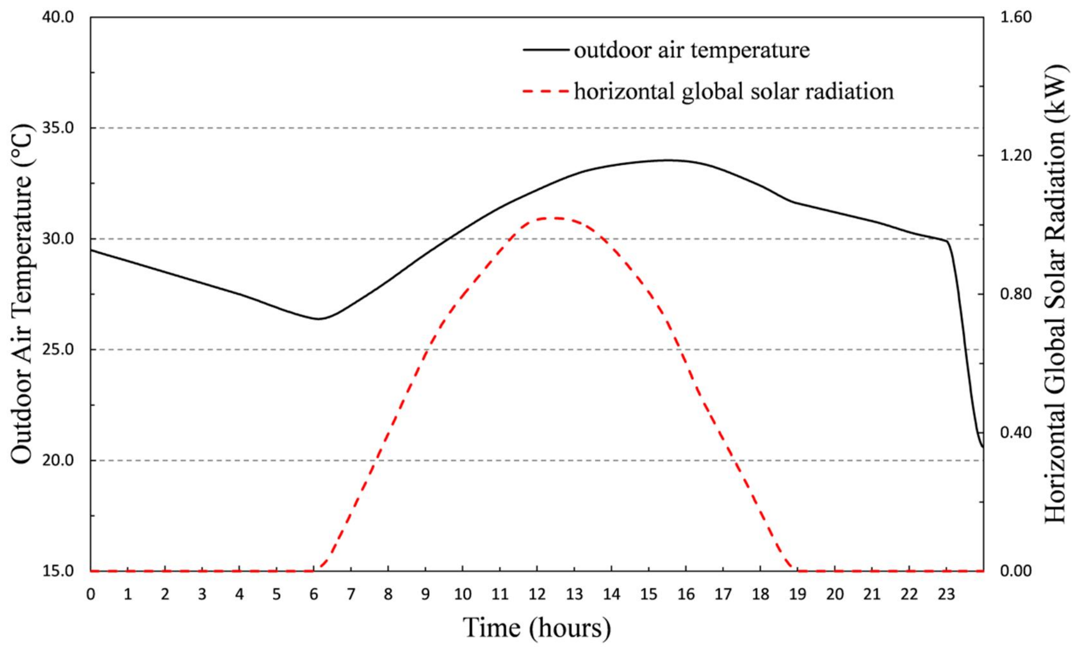



Figure 3.6 Outdoor air temperature and horizontal global solar radiation in a typical summer day of Hong Kong.

Actually, the charging and discharging rate for the building thermal masses are the power differences against the reference case corresponding to the increase and decrease power demand of the HVAC system. The reference case is that the indoor air temperature is fixed to 24°C during office hours and resumes free-floating during non-office hours. By comparing the predicted cooling loads of the altered cases and the reference case, the cooling load alteration potential of the building can then be obtained accordingly. Although there are many options for setting the altered cases (i.e., different power demand control strategies for the HVAC system), three scenarios are considered when adopting precooling and temperature set-point reset strategies: 1) precooling during non-office hours and discharging at the same temperature as the reference case (i.e., 24°C) during office hours; 2) no precooling and over-discharging at a higher reset temperature (i.e., set-point higher than 24°C) during office hours; 3) precooling during non-office hours and over-discharging at a higher reset temperature during office hours. A lower reset temperature (i.e., set-point lower than 24°C) during office hours is not considered due to the limited contribution to the cooling load alteration. The cooling load alteration potential of the building thermal masses has been summarized in Equations (3.28) to (3.32).

## 3.4 Parameters Identification of the Simplified Model

Parameters (i.e., $C_{bui}$, $R_{bui,o}$ and $R_{bui,i}$) in the thermal storage model are the key factors determining the effective indices and energy characteristics of a building. These parameters can be identified using building historical operation data (e.g., a daily operation data for the reference case and a daily operation data for the altered case, which have similar weather conditions and internal gains). In this case study, genetic algorithm-based (GA-based) method was employed to identify the parameters using the "actual" cooling load data simulated using TRNSYS. The objective function for GA-based parameter identification employed the integrated root-mean-square error for the predicted cooling load alteration, as defined in Equation (3.36).

$$J\left(C_{bui}, R_{bui,o}, R_{bui,i}\right) = \sqrt{\frac{\sum_{k=1}^{N}\left(\Delta Q_{act,k} - \Delta Q_{est,k}\right)^2}{N-1}} \tag{3.36}$$

Where, $J$ is the objective function of the thermal storage model in GA-based identification (i.e., minimization). $\Delta Q_{act}$ and $\Delta Q_{est}$ are the "actual" cooling load alteration of TRNSYS and the predicted cooling load alteration of the thermal storage model respectively. $C_{bui}$, $R_{bui,o}$ and $R_{bui,i}$ are the parameters of the thermal storage model. The searching ranges of thermal capacitance and resistances for the GA-based identification are recommended to be between zero and three times the properties of the external wall. A fitness function is also employed for the GA-based identification process, as shown in Equation (3.37).

$$f\left(C_{bui}, R_{bui,o}, R_{bui,i}\right) = \frac{1}{J\left(C_{bui}, R_{bui,o}, R_{bui,i}\right)} \tag{3.37}$$

Figure 3.6 shows the parameters identification procedure of the simplified building thermal storage model based on genetic algorithm. The stop criterion of the GA is according to the comparison of the best fitness values of two continuous running results. When the relative difference between the maximum fitness values ($d_f$) reaches a threshold value ($\varepsilon_f$), the GA then will stop.

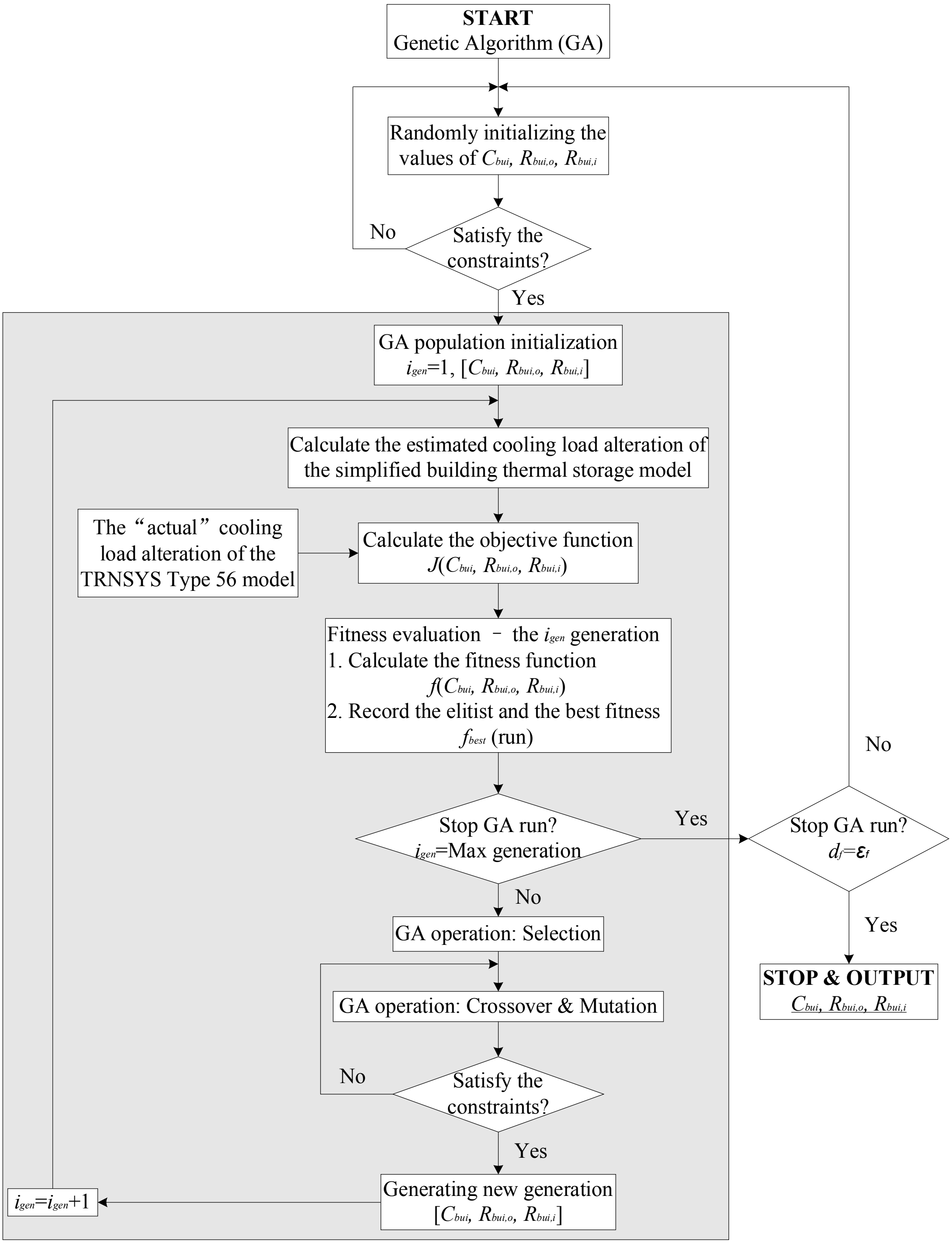



Figure 3.7 The procedure of GA-based parameters identification for the simplified building thermal storage model.

## 3.5 Results of Parameters Identification

Once the first three parameters (i.e., $C_{bui}$, $R_{bui,o}$ and $R_{bui,i}$) of the simplified model are identified, the rest parameters and coefficients can be calculated accordingly. Storage efficiencies can be calculated accordingly for different charging/discharging durations using Equation (3.35). It is worth mentioning that storage efficiency ($\eta_{bui}$) listed in table was the minimum one when the longest precooling time (i.e., 8 hours) is set. Light weighted buildings had the smallest thermal capacitance and the smallest time constant ($\tau$), and heavy weighted buildings had the biggest thermal capacitance and the largest time constant. It is worth noticing that medium weighted buildings had the highest storage efficiency due to their relatively bigger thermal capacitance and medium time constant. The results of parameters identification for three types of buildings are listed in Table 3.4.

Table 3.4 Identified parameters of the simplified building thermal storage model for different types of buildings

| Building type | $C_{bui}$ (J/m$^2$K) | $R_{bui,o}$ (m$^2$K/W) | $R_{bui,i}$ (m$^2$K/W) | $R_{bui}$ (m$^2$K/W) | $\tau$ *(hour)* | $\eta_{bui}$ *(-)* |
|---|---|---|---|---|---|---|
| Light weighted | 204775 | 0.3783 | 0.2303 | 0.1431 | 8.14 | 35.20% |
| Medium weighted | 248621 | 0.9236 | 0.2133 | 0.1733 | 11.97 | 41.61% |
| Heavy weighted | 400679 | 0.4333 | 0.2249 | 0.1481 | 16.48 | 26.47% |

## 3.6 Summary

This chapter presents the motivation, inspiration and formulation of developing a simplified building thermal storage model for estimating the load alteration potentials of passive buildings (i.e., building thermal masses as the only thermal storages). The simplified building model (i.e. the 2R1C model), consisting of two resistances ($R_{bui,o}$ and $R_{bui,i}$) and one capacitance (i.e., $C_{bui}$) was employed to represent thermal characteristics of the passive buildings. The specifications of building structures and working conditions for the development of the simplified thermal storage model were also presented.

Genetic algorithm-based method was employed to identify the model parameters on resistances and capacitance of the simplified 2R1C building model. The model parameters can be identified by minimizing the errors of the “actual” cooling load alteration of TRNSYS Type 56 building model and the predicted cooling load alteration of the simplified thermal storage model. In other words, it is recommended that GA-based parameters identification of 2R1C model to be performed by approaching a higher fitness. The procedure of the typical genetic algorithm was introduced.

# CHAPTER 4 VALIDATION OF SIMPLIFIED BUILDING THERMAL STORAGE MODEL

This chapter presents the validation of the simplified building thermal storage model developed in the previous chapter. A complicated building model (i.e., Type 56 as the "actual" building) of TRNSYS was employed as reference for this validation. If the thermal characteristics (i.e., the load alteration characteristics in this study) of these building models agree very well under the same outdoor and indoor conditions, then the developed thermal storage model is considered to be an effective model as the complicated one.

A total of twelve test cases, including different weighted structures (i.e., external walls and roofs) of buildings under different weather conditions (i.e., summer and spring) and indoor air temperature settings are conducted. The parameters of the simplified 2R1C building thermal model were identified using the Hong Kong weather data and shown as Figure3.6 in Chapter 3. Section 4.1 gives an introduction about the indoor temperature set points in the simulation tests. Section 4.2 presents the light weighted building validation cases. Section 4.3 presents the medium weighted building validation cases. Section 4.4 presents the heavy weighted building validation cases. Section 4.5 also briefs the application issues of simplified building thermal storage model. A summary of this chapter is given in Section 4.6.

## 4.1 Introduction

For summer identification and spring validation cases, the precooling time was set to 8 hours and the indoor air temperature set-point was set to 25.5°C during office hours. For summer 4 hours precooling validation case, the precooling time was set from 00:00 to 04:00, the indoor air temperature set-point was set to 25.5°C during office hours. For summer temperature set-point reset validation case, no precooling was adopted. The indoor air temperature set-point was set to 25.5°C from 08:30 to 11:00 and from 16:00 to 18:00, 23°C from 12:00 to 14:00, and 24°C for the rest of office hours. Comparisons between the "actual" and the predicted cooling load alterations for different scenarios are presented in the following sections.

## 4.2 Light Weighted Building Validation Cases

For the light weighted buildings, the physical parameters of the adopted external walls and roofs are presented in Table 3.1 of Chapter 3. Comparisons between the "actual" and the predicted cooling load alterations of the light weighted building are conducted under different demand response control strategies., as shown in Figure 4.1 to Figure 4.4. –It can be observed that the predicted cooling alterations are a little bit less than the "actual" cooling alteration during the precooling period (i.e., charging period) while the cooling alterations are a little bit bigger than the "actual" cooling alteration during the office hours (i.e., discharging period). The average errors of the simplified thermal storage model in predicting the load alteration for light weighted buildings was 14.40%.

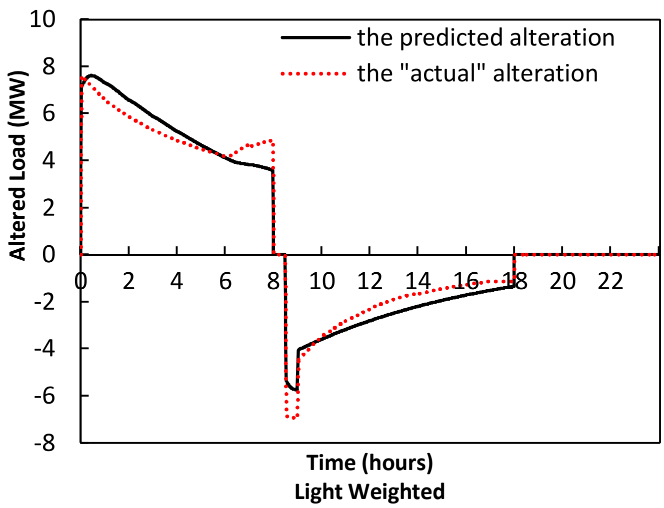



Figure 4.1 The “actual” and the predicted cooling load alterations of the light weighted building (parameter identification - Summer 8 hours precooling case).

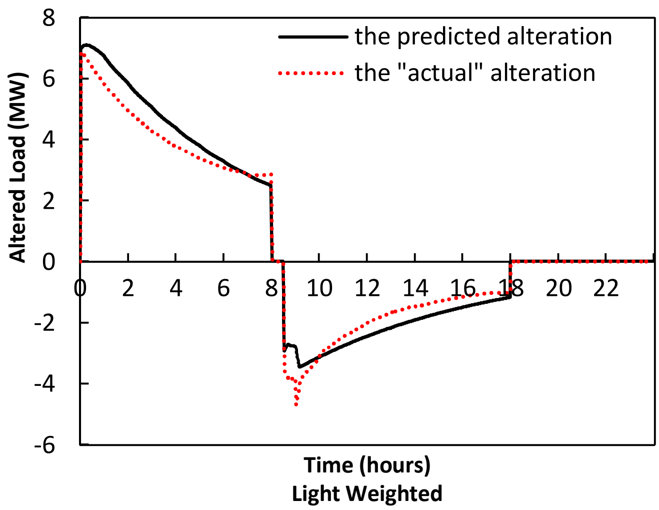



Figure 4.2 The “actual” and the predicted cooling load alterations of the light weighted building (validation - Spring 8 hours precooling case).

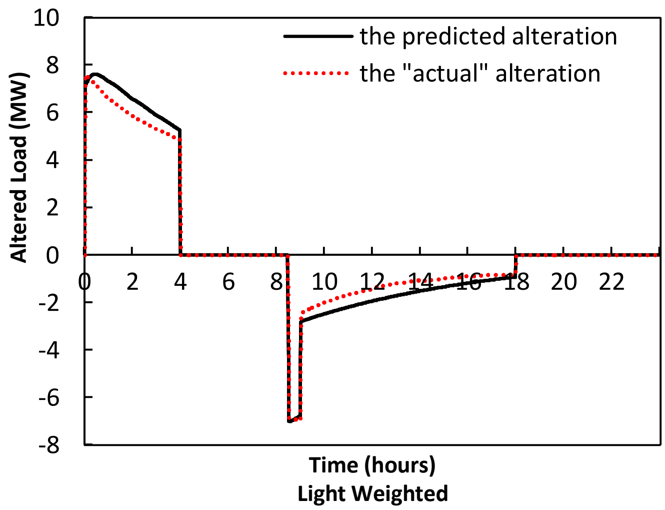



Figure 4.3 The “actual” and the predicted cooling load alterations of the light weighted building (validation - Summer 4 hours precooling case).

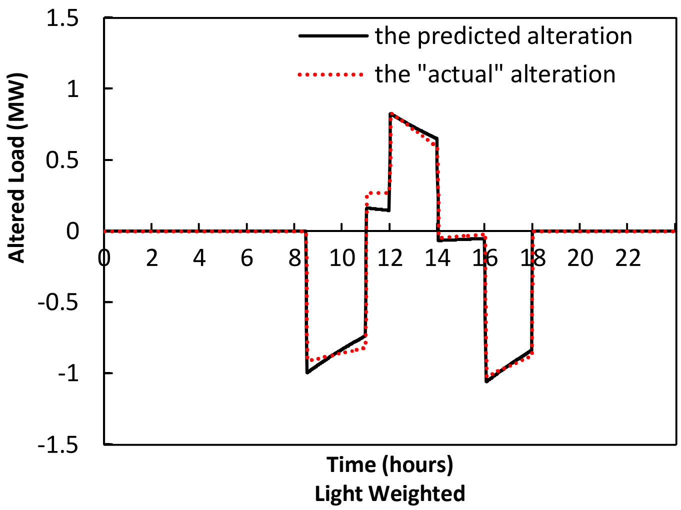



Figure 4.4 The “actual” and the predicted cooling load alterations of the light weighted building (validation - Summer temperature set-point reset case).

## 4.3 Medium Weighted Building Validation Cases

For the medium weighted buildings, the physical parameters of the adopted external walls and roofs are presented in Table 3.2 of Chapter 3. Comparisons between the “actual” and the predicted cooling load alterations of the medium weighted building are conducted under different demand response control strategies., as shown in Figure 4.5 to Figure 4.8. The predicted cooling alterations are a little bit less than the “actual” cooling alteration during the precooling period (i.e., charging period) while the cooling alterations are a little bit bigger than the “actual” cooling alteration during the office hours (i.e., discharging period). However, the load alterations of the medium buildings were more closed to the “actual” alterations that those of the light and heavy weighted buildings. The average errors of the simplified thermal storage model in predicting the load alteration for medium weighted buildings was 4.88%.

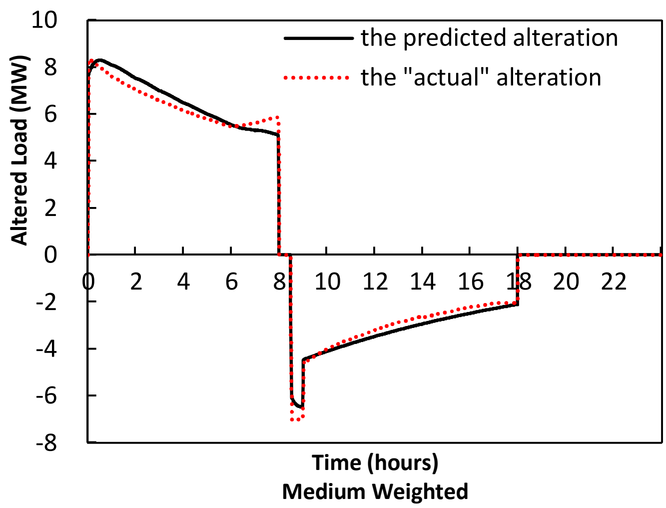



Figure 4.5 The “actual” and the predicted cooling load alterations of the medium weighted building (parameter identification - Summer 8 hours precooling case).

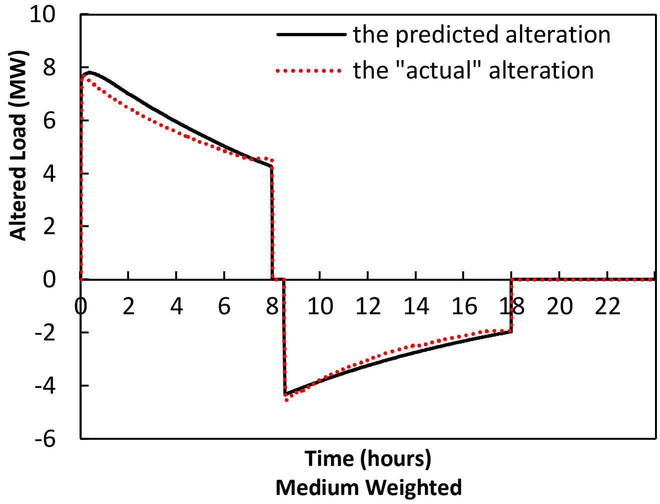



Figure 4.6 The “actual” and the predicted cooling load alterations of the medium weighted building (validation - Spring 8 hours precooling case).

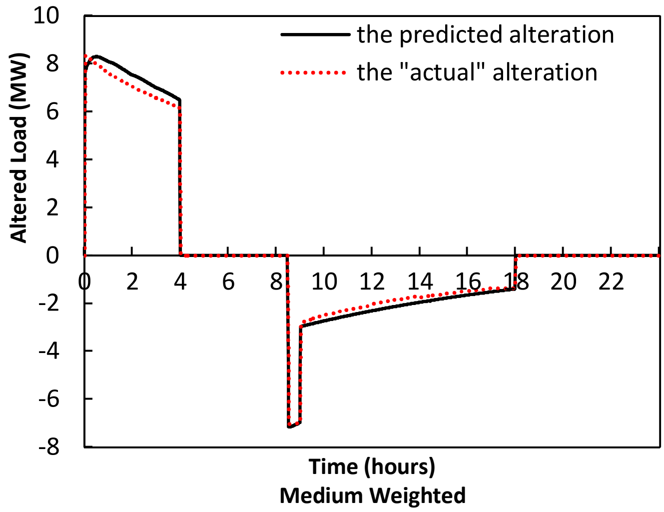



Figure 4.7 The “actual” and the predicted cooling load alterations of the medium weighted building (validation - Summer 4 hours precooling case).

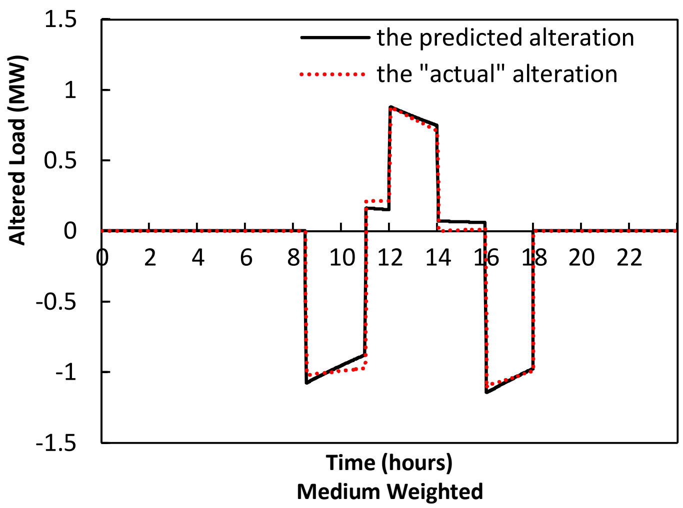



Figure 4.8 The “actual” and the predicted cooling load alterations of the medium weighted building (validation - Summer temperature set-point reset case).

## 4.4 Heavy Weighted Building Validation Cases

For the heavy weighted buildings, the physical parameters of the adopted external walls and roofs are presented in Table 3.3 of Chapter 3. The predicted cooling alterations are a little bit less than the “actual” cooling alteration during the precooling period (i.e., charging period) while the cooling alterations are a little bit bigger than the “actual” cooling alteration during the office hours (i.e., discharging period). However, the load alterations of the heavy buildings were more closed to the “actual” alterations that those of the light weighted buildings. The average errors of the simplified thermal storage model in predicting the load alteration for heavy weighted buildings was 6.37%.

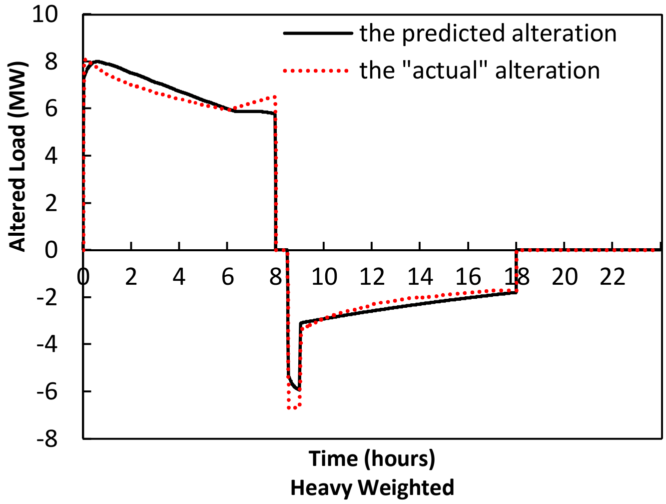



Figure 4.9 The “actual” and the predicted cooling load alterations of the heavy weighted building (parameter identification - Summer 8 hours precooling case).

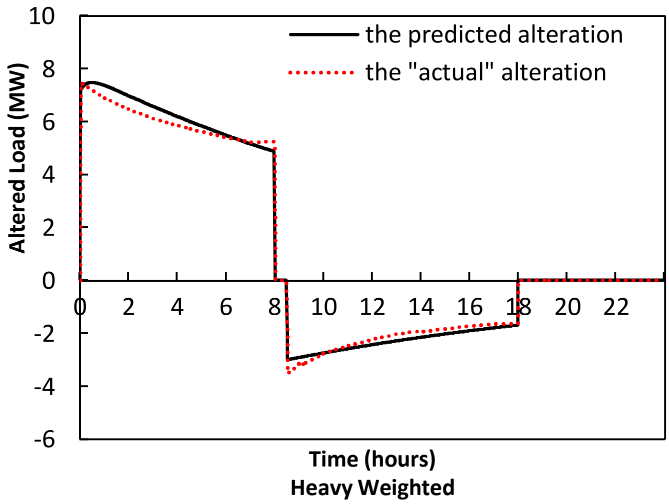



Figure 4.10 The “actual” and the predicted cooling load alterations of the heavy weighted building (validation - Spring 8 hours precooling case).

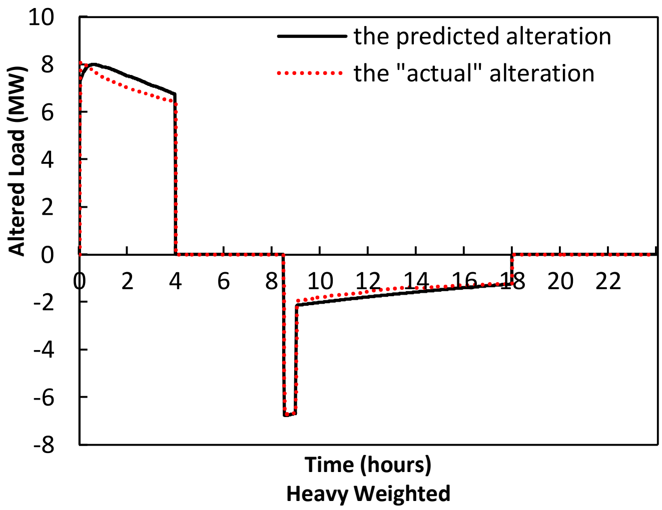



Figure 4.11 The “actual” and the predicted cooling load alterations of the heavy weighted building (validation - Summer 4 hours precooling case).

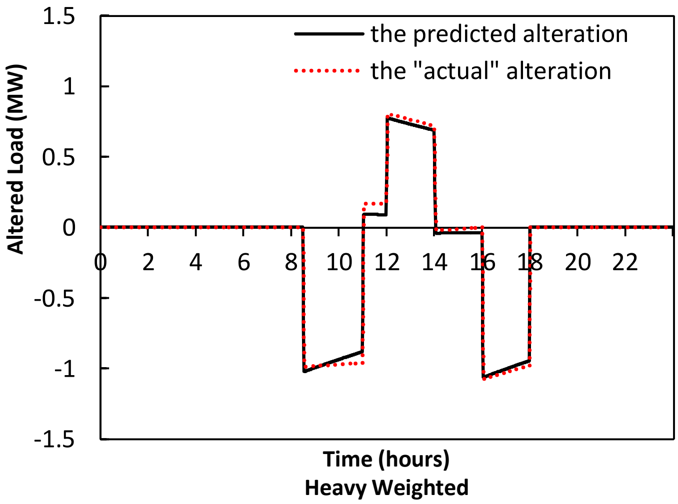



Figure 4.12 The “actual” and the predicted cooling load alterations of the heavy weighted building (validation - Summer temperature set-point reset case).

## 4.5 Application Issues of Simplified Building Thermal Storage Model

The simplified building thermal storage model is developed based on the building thermal masses (i.e., passive thermal storage) which are determined by the building constructions (e.g., external walls, roof, floors, internal walls and partitions, furniture, etc.), the application of this model is therefore affected by the configurations of the external walls (physical properties and window-wall ratio as well) as the external walls play important roles in external heat gain and indoor thermal energy storage. In this study, the default window-wall ratio is set to be 0.5, the building types consists of three weighted levels: light, medium and heavy. Except light weighted buildings (the average error is 14.40%), the model accuracy are quite high (the average errors are 4.88% for medium weighted buildings and 6.37% for heavy weighted buildings).

Actually, new constructed commercial buildings in the urban areas usually have high window-wall ratios and light weighted external walls due to the building architecture design (e.g., facade design). This kind of building design may result low storability of the external walls. The developed building thermal storage model may be not suitable for buildings with light building thermal masses (i.e., low amount of the total building thermal capacitance especial the thermal capacitance of the building envelope).

The simplified building thermal storage model can well represent thermodynamic performance (e.g., “charge” and “discharge” processes) of the building envelope and the internal thermal masses (the window-wall ratio is lower than 0.5, the average thermal capacitance is larger than 204775 J/m$^2$K). In addition, this simplified building thermal storage model is not suitable for predicting the whole building heating/cooling load because the node placement in this 2R1C model is too simple represent the thermodynamic of the building.

The indoor air temperature set point of the preheating/precooling strategy during the off-peak period (e.g., the night) should be carefully selected because the set point can significantly affect the power consumption of HVAC systems, as well as the storage efficiency (the energy loss of the building thermal masses is difficult to be controlled due to the building envelope has already been constructed). Although the simulation and validation cases of the simplified building thermal storage model were conducted with the subtropical weather data (e.g., Hong Kong), it is also suitable for the other weather conditions. It is worth mentioning that the dehumidification of indoor air (i.e., relative humidity control) is not considered in the developed storage model. It is necessary to modify the model if the prediction error of the heating/cooling load alteration cannot be ignored.

## 4.6 Summary

Twelve test cases are conducted for the validation of the developed simplified building thermal storage model through the comparisons of thermal characteristics between the predicted results from the model and the "actual" results of TRNSYS. Comparison results shown that the predicted cooling load alterations agreed well with the "actual" ones. The average errors of the thermal storage model for light weighted, medium weighted and heavy weighted buildings were 14.40%, 4.88% and 6.37% respectively. The simplified building thermal storage model can well represent the thermodynamic performance (i.e., heat transfers among the building, indoor and outdoor space) of different types of building envelopes (e.g., external walls and roofs) including light, medium and heavy weighted walls under different weather data. It is worth mentioning that, the simplified building thermal storage model is suitable for predicting the heating/cooling load alteration potentials of the passive building under different indoor air temperature settings while it is not suitable for predicting the building heating/cooling load. In addition, the simplified building thermal storage model is relatively simple in programming and has low computation load. It is therefore suitable for the applications of building load alteration estimation, system optimal control and smart grid interaction, etc.

# CHAPTER 5 BUILDING SYSTEMS AND DYNAMIC TEST PLATFORM

A dynamic simulation platform, based on TRNSYS and MATLAB, is constructed in this study for both the commercial buildings with complex building central chiller plant systems and the smart grid with the electricity pricing mechanism. The platform is used to demonstrate the interactive between buildings and the grid, and to evaluate the overall energy performance of buildings and the grid under the optimal control strategy developed in this study. Case studies focusing on active thermal storage systems are also conducted based on the EnergyPlus and this platform, respectively. Section 5.1 presents the introduction of the simulation platform for commercial buildings and the smart grid. Section 5.2 presents the development of the dynamic simulation platform. The major component models and their interconnections/interactions used to construct the complex dynamic simulation platform are also presented. Section 5.3 presents an electricity pricing mechanism adopted in this study. Section 5.4 introduces the test conditions and control strategies for the simulation platform. A summary of this chapter is given in Section 5.4.

## 5.1 Introduction

Power suppliers and consumers are located in power upstream and downstream of a traditional grid respectively. The power flow and information flow work in a unidirectional way which may cause power imbalance since the energy information cannot be exchanged in time. With increasing the integration of distributed generations (e.g. power generated by kinds of renewable energies) and the wide application of information technology, the smart grid enables both the power flow and the information flow to work in a bidirectional way which may bring energy optimization potentials by taking proper interactions within participants (e.g., power suppliers and consumers, etc.). Estimation and optimization of building electrical demand response potentials are based on a bidirectional operation infrastructure between the smart grid and buildings.

In order to estimate demand response potentials of buildings, building electricity sheddable load (e.g., building heating/cooling load) prediction is therefore becoming an important premise. As shown in Figure 5.1, individual buildings in different districts predict their own loads (e.g. a day-ahead) for further load aggregation. The aggregate load of an electrical grid can be expressed by the Equation (5.1). Actually, the aggregate load profile will affect electricity prices (e.g. marginal cost of generation and transmission) setting once dynamic pricing is adopted in smart grid. In reverse, electricity prices setting will also affect buildings to change their energy behaviors by considering operation cost.

$$P_{tot} = \sum_{j=1}^{M} p_{tot,j} \tag{5.1}$$

where, $P_{tot}$ and $p_{tot,j}$ indicate the aggregate load and the electricity load of individual buildings respectively. $M$ indicates the total number of buildings being aggregated. $j$ indicates the $j$th building. $p_{tot,j}$ consists of two parts of load: 1) controllable load ($P_{cont,j}$), and sheddable load ($P_{shed,j}$).

Figure 5.2 shows a process of building altering their electricity load with different control strategies when facing dynamic prices given in advance (e.g., a day-ahead). Dynamic load alteration of building and dynamic pricing mechanism of smart grid are need to be addressed for developing interactive control strategy and characterizing building thermal energy storages.

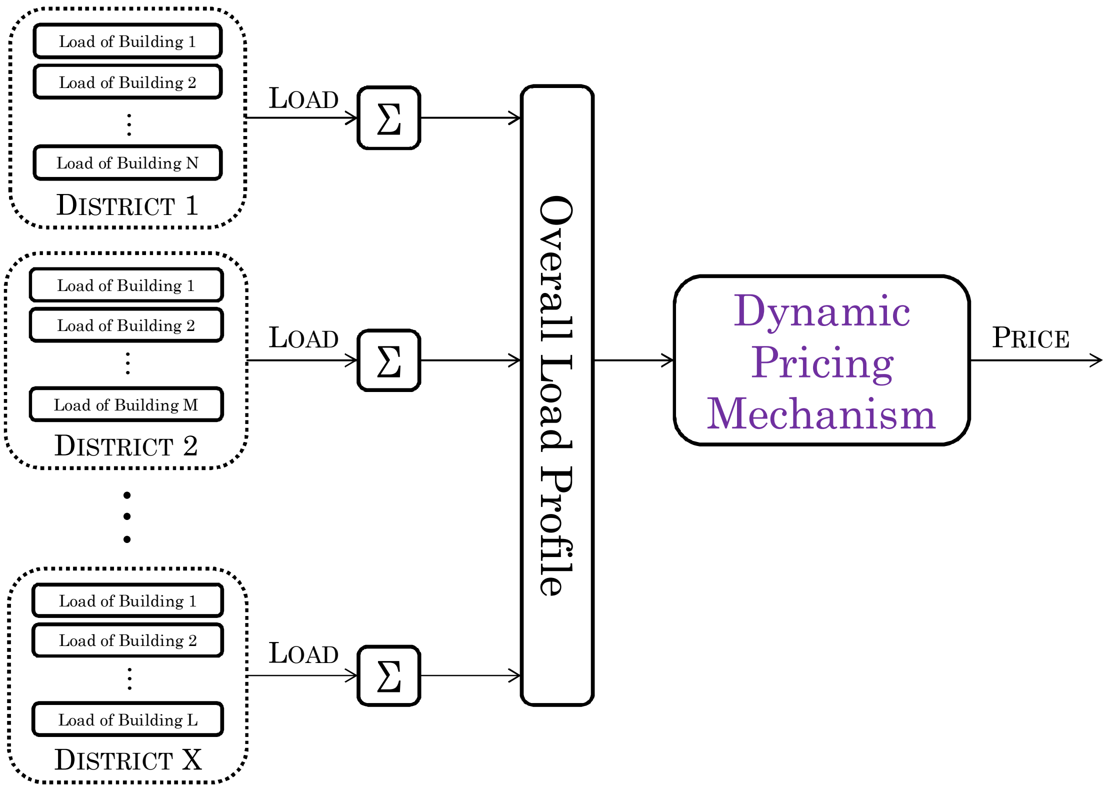



Figure 5. 1 Schematic of interactive framework between smart grid and commercial buildings - load aggregation for dynamic pricing.

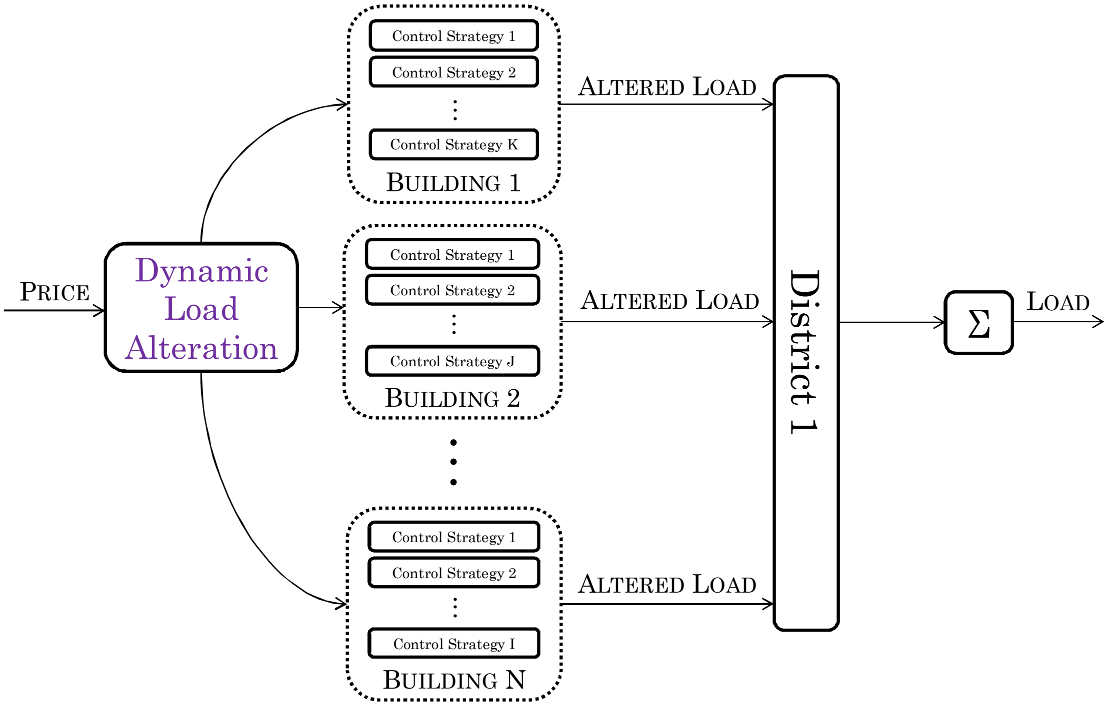



Figure 5.2 Schematic of interactive framework between smart grid and commercial buildings - demand response under dynamic prices.

Commercial buildings can benefit the grid with their thermal energy storages which can be treated as building thermal "batteries" (i.e. distributed storages). When power is surplus in the grid, these building thermal "batteries" can then be used to store the surplus power in the form of thermal energy by implementing proper control strategies. When power is inadequate in the grid, these building thermal "batteries" can then discharge the stored thermal energy to reduce their power demand from the grid. In the point of view of change/discharge processes, commercial buildings with their thermal energy storages can help relieve a critical issue of the grid: power imbalance. Compared with residential buildings, commercial buildings can contribute a significant ratio of total building load shifting, especially in urban areas (e.g. commercial buildings consume over 65% of total electricity in Hong Kong (Hong Kong EMSD 2012)). Numerous studies have been made on load management for commercial buildings by utilizing different thermal energy storage systems such as active thermal mass (e.g. ice storage), and passive thermal mass (e.g. building thermal mass). Load management of commercial buildings is focused on heating, ventilation, and air conditioning (HVAC) systems mainly because of two reasons: (1) the percentage consumption for HVAC systems is over 45% of total electricity in most commercial buildings (Lam et al. 2004), (2) the load management flexibility for HVAC systems can be controlled due to the extensive use of building automation systems (BAS). Proper control strategies of HVAC systems were developed and implemented under a certain electrical pricing for operation cost optimization. However, previous building load management was conducted in a passive and unidirectional way without interacting with electrical pricing. Moreover, study on integrating commercial buildings into smart grid was seldom found. This chapter therefore develops a simulation platform for the interactive load management of HAVC systems in commercial buildings by considering dynamic pricing, dynamic load management and the interactions between them, in order to achieve overall optimization of load management and operation cost for both power supply and demand sides. Building energy information, such as load shifting potentials of individual buildings and aggregated load profile of these buildings, have profound influence on power generation arrangement and electrical pricing at the supply side. Building energy information can generally be obtained by BAS. Meanwhile, BAS can also provide a communication platform for integrating commercial buildings into smart grid.

## 5.2 A Dynamic Simulation Platform for Buildings and Smart Grid

A simulation platform for simulating the complex chilling systems as mentioned previously is developed based on TRNSYS and MATAB. TRNSYS is a complete and extensible simulation environment for the transient simulation of systems, including multi-zone buildings. It is widely used by energy engineers and researchers to validate new energy concepts, from simple domestic hot water systems to the design and simulation of buildings and their equipment, including control strategies, occupant behavior, alternative energy systems (wind, solar, photovoltaic, hydrogen systems), etc. The TRNSYS library includes a great number of commonly used components of thermal and electrical energy systems, as well as component routines to handle inputs of weather data or other time-dependent forcing functions and outputs of simulation results. The modular nature of TRNSYS endows the program with tremendous flexibility, by which the mathematical models that are not included in the standard TRNSYS library can be developed and added into the program by users. One of the key factors in TRNSYS' is its open, modular structure. The source code of the kernel as well as the component models is delivered to the end users. This simplifies extending existing models to make them fit the user's specific needs. The DLL-based architecture allows users and third-party developers to easily add custom component models, using all common programming languages (C, C++, PASCAL, FORTRAN, etc.). In addition, TRNSYS can be easily connected to many other applications, for pre- or post-processing or through interactive calls during the simulation (e.g. Microsoft Excel, MATLAB, COMIS, etc.).

MATLAB (matrix laboratory) is a numerical computing environment and fourth-generation programming language. It allows matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs written in other languages, including C, C++, Java, and FORTRAN. In this study, MATLAB is employed to simulate the dynamic electricity pricing and compute the energy operation cost of individual buildings, as well as accomplish the interactions and communication between the buildings and the smart grid.

The commercial buildings, with the complex chilling systems constructed in the simulation platform, employ the detailed physical models of components including chillers, pumps, air handling units (AHU) and preliminary air handling units (PAU), controllers, etc. to represent the energy and power performance of the HVAC systems. As presented previously, the central chilling system consumes most of energy of the overall air-conditioning system. Therefore, the dynamic simulation platform constructed in this study is mainly concerning on the central chilling system. The multi-zone building model (i.e., Type 56) of TRNSYS 16 is employed to simulate the thermal behavior of the buildings. The heat load from the occupants, equipment and lighting system and weather data are also considered in the simulation as input files. The weather condition used is the data of the typical year in Hong Kong. Dynamic simulation of HVAC systems provides a convenient and low cost tool in testing, commissioning and evaluating the control strategies of HVAC systems or the control programs implemented in building automation systems (BAS). Dynamic models, which are convenient to use and well represent the dynamic characteristics in all the aspects of concern, are the basis for practical applications.

### 5.2.1 Building Model

The Type 56 multi-zone building model provides a more efficient way to calculate the interactions between external environment and internal zones, as well as within the internal zones by solving the coupled differential equations utilizing matrix inversion techniques. The effects of both short-wave and long-wave radiation exchange are accounted for with an area ratios method. The walls, ceilings, and floors are modeled according to the SHRAE transfer function approach. The building model also provides detailed description of a multi-zone building that is simplified with the use of the visual interface TRNBUILD in TRNSYS.

Due to the complexity of a multi-zone building the parameters of Type 56 are not defined directly in the TRNSYS input file. Instead, two files are assigned containing the required information, the building description (*.BLD) and the ASHRAE transfer function for walls (*.TRN). TRNBUILD (formerly known as PREBID) has been developed to provide an easy-to-use tool for creating the *.BLD and *.TRN files. Starting with some basic project data, the user describes each thermal zone in turn. Finally, the desired outputs are selected. All data entered are saved in a so called building file (*.BUI), a readable ASCII text file. The BUI file is very handy for checking data entered in TRNBUILD. It is worth mentioning that the thermal comfort calculation is a new feature in TRNBUILD 1.0 based on EN ISO 7730. The user can switch the comfort module on and define a comfort type for the zone by selecting a previously defined type or a new type.

### 5.2.2 Simplified Building Thermal Storage Model

The simplified building thermal storage model is developed based on the simplified building energy model developed by the Wang and Xu (2006). According to the equivalence principle, the simplified building energy model (3R2C+2R2C model as shown in Figure 5.1) can be transferred to the simplified building the model (2R1C model as shown in Figure 5.2).

For the simplified building energy model, 3R2C model is employed to represent building envelope (including external walls, roof and windows, etc.) and 2R2C model is employed to represent building internal masses (including internal walls, floors, ceilings, partitions and furniture, etc.). For the simplified building thermal storage model, a building (including its external and internal masses) is simplified to a lumped thermal mass and assumed to be homogeneous. An equivalent temperature ($T_{building}$ or $T_{bui}$) is employed to represent the energy status of the building. An operation temperature ($T_{operation}$ or $T_{opt}$) is employed to represent the indoor thermal environment of the building. Building thermal characteristics can then be simply represented by the overall building thermal capacitance ($C_{building}$ or $C_{bui}$), the overall external thermal resistance ($R_{external}$ or $R_{ext}$) and the overall external thermal resistance ($R_{internal}$ or $R_{int}$).

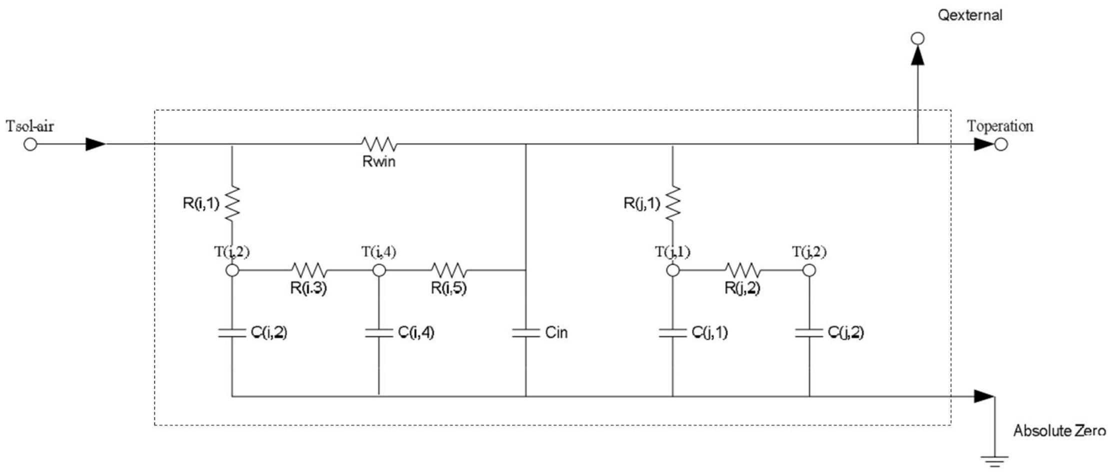



Figure 5.1 Restructuring of the simplified building energy model.

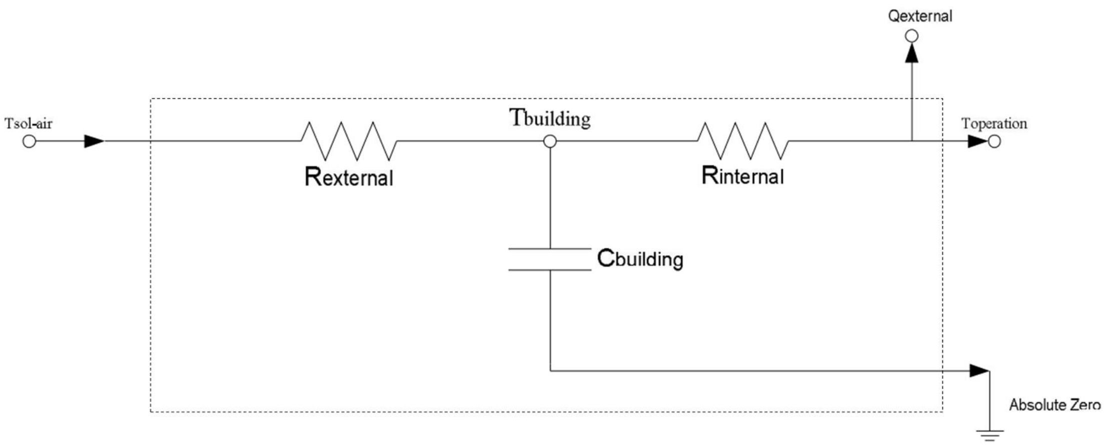



Figure 5.2 The simplified building thermal storage model based on equivalence principle.

The preliminary equivalence equation can be summarized as follows:

$$C_{bui} = \sum_{i=1}^{5}\left[C_{(i,2)} + C_{(i,4)}\right] + C_{(j,1)} + C_{(j,2)} + C_{in} \tag{5.1}$$

$$R_{ext} = \frac{T_{sol-air}(t) - T_{bui}(t)}{Q_{ext} + C_{bui}\dfrac{dT_{bui}(t)}{dt}} \tag{5.2}$$

$$R_{\text{int}} = \frac{T_{bui}(t) - T_{opt}(t)}{\sum_{i=1}^{5}\left[\dfrac{T_{(i,4)}(t) - T_{opt}(t)}{R_{(i,5)}}\right] + \dfrac{T_{(j,1)}(t) - T_{opt}(t)}{R_{(j,1)}} + \dfrac{T_{sol-air}(t) - T_{opt}(t)}{R_{win}} - C_{in}\dfrac{dT_{opt}(t)}{dt}} \tag{5.3}$$

where,

$$Q_{ext} = Q_{act} - Q_{\text{int}} - Q_{fresh} - Q_{\text{infil}} \tag{5.4}$$

According to the energy balance,

$$C_{bui}\frac{dT_{bui}(t)}{dt} = \frac{T_{sol-air}(t) - T_{bui}(t)}{R_{ext}} - \frac{T_{bui}(t) - T_{opt}(t)}{R_{\text{int}}} \tag{5.5}$$

Then,

$$T_{bui}(t) = \left[T_{bui}(0) - D\right]e^{-\frac{t}{\tau}} + D \tag{5.6}$$

where,

$$D = \frac{T_{sol-air}(t)R_{\text{int}} + T_{opt}(t)R_{ext}}{R_{ext} + R_{\text{int}}} \qquad \tau = \left[\frac{R_{ext}R_{\text{int}}}{R_{ext} + R_{\text{int}}}\right]C_{bui}$$

The detailed derivation process of the simplified building thermal storage model can refer to the Chapter 3. The thermal comfort is calculated according to the program developed by Håkan Nilsson (2005), more details of program code are listed in Appendix A.

### 5.2.3 Major Component Models of HVAC Systems

*Chillers*

The chiller model employed in this study is used to simulate the chiller dynamic performance under various working conditions, which is based on the model developed by Wang et al. (2000). The physical parameters of chillers such as the impeller tip speed ($u_2$), impeller exhaust area ($A$), impeller blades angle ($\beta$) and other coefficients/constants are considered in the chiller model. The compressor of chiller is modeled on the basis of mass conservation, Euler turbo-machine equation and energy balance equation. The Euler equation is modified by considering the impeller exit radial velocity ($c_{r2}$) distribution and derived as in Equation (5.7). Energy balance equations are applied to the compressor control volume and impeller control volume resulting in Equations (5.8) and (5.9), respectively. The hydrodynamic losses ($h_{hyd,com}$ and $h_{hyd,imp}$) in the two control volumes are considered to be composed of three elements, i.e., flow friction losses, inlet losses and incidence losses, as shown in Equations (5.10) and (5.11), respectively.

$$h_{th} = u_2\left[u_2 - \left(\frac{\pi^2}{8}\right)^2 c_{r2}\left(ctg\beta + B\frac{\upsilon_1}{\upsilon_i}tg\theta\right)\right] \tag{5.7}$$

$$h_{th} = h_{pol,com} + h_{hyd,com} \tag{5.8}$$

$$h_{th} = h_{pol,imp} + h_{hyd,imp} + \frac{c_i^2}{2} \tag{5.9}$$

$$h_{hyd,com} = \zeta\left[1 + \psi_1\left(\frac{\upsilon_1}{\upsilon_i}\frac{1}{\cos\theta}\right)^2 + \psi_2\left(\frac{\upsilon_1}{\upsilon_i}tg\theta\right)^2\right]c_{r2}^2 \tag{5.10}$$

$$h_{hyd,imp} = \zeta\left[\chi + \psi_1\left(\frac{\upsilon_1}{\upsilon_i}\frac{1}{\cos\theta}\right)^2 + \psi_2\left(\frac{\upsilon_1}{\upsilon_i}tg\theta\right)^2\right]c_{r2}^2 \tag{5.11}$$

where $h_{th}$ is the compressor theoretical head, $h_{hyd}$ is the hydrodynamic losses, $h_{pol}$ is the polytrophic compression work, $B$ is the ratio of the impeller channel depth at the intake to that at exhaust, $\upsilon_1$ and $\upsilon_i$ are the specific volumes at the impeller intake and exhaust, respectively, $c_i$ is the vapor velocity at the impeller exhaust, $\theta$ is the inlet guide vane angle, $\zeta$, $\psi_1$, $\psi_2$, $\chi$ are the introduced constants, and subscripts *com* and *imp* indicate compressor and impeller, respectively.

The evaporator and condenser are simulated using the classical heat exchanger efficiency method. The chiller power consumption ($W$) is calculated on the basis of the internal compression power ($W_{\text{inter}}$), as shown in Equation (5.12), which consists of three elements, i.e., internal compression power, a variable part of the losses proportional to the internal compression power and a constant part of the losses ($W_l$). Two thermal storage units (one at the cooling water inlet of the condenser and the other at the chilled water inlet of the evaporator) are used to represent the dynamic responses of the chiller to the changes of working conditions (inlet temperatures) and the dynamic effects of the working condition changes on the compressor load. They are mathematically represented by two first-order differential equations as shown in Equations (5.13) and (5.14), respectively.

$$W = \alpha W_{\text{inter}} + W_1 \tag{5.12}$$

$$C_{ev} \frac{dT'_{ev,in}}{dt} = c_{p,w} M_{w,ev} (T_{ev,in} - T'_{ev,in}) \tag{5.13}$$

$$C_{cd} \frac{dT'_{cd,in}}{dt} = c_{p,w} M_{w,cd} (T_{cd,in} - T'_{cd,in}) \tag{5.14}$$

where $\alpha$ is a coefficient, $T$ is the temperature, $T'$ is the temperature after introducing dynamic effects, and the subscript *in* indicates inlet.

*Pumps*

The variable speed pump is simulated by a steady-state pump, a steady-state frequency inverter and a dynamic actuator of the inverter (Wang 1998). The frequency at the outlet of the inverter is linear to the input signal from the actuator. The efficiency of the inverter is included within the model of the pump energy performance. The energy performance and pump characteristics at various speeds are simulated using fourth-order polynomial functions as shown in Equations (5.15) and (5.16), respectively. The coefficients in the equations can be determined by regression using the performance data from the manufacturer catalogues.

$$W_{pu}(Freq, M_{pu}) = \sum_{i=0}^{m} \sum_{j=0}^{n} G_{ij} Freq^i M_{pu}^j \tag{5.15}$$

$$p_{pu}(Freq, M_{pu}) = \sum_{i=0}^{m}\sum_{j=0}^{n} E_{ij} Freq^{i} M_{pu}^{j} \tag{5.16}$$

where $W_{pu}$ and $P_{pu}$ are the pump power consumption and pressure head, respectively, $Freq$ is the frequency input to the pump, $M_{pu}$ is the water flow rate through a pump, $G$ and $E$ are coefficients.

<u>AHU/PAU coils</u>

The AHU and PAU coil model is simulates the outlet water and outlet air states. In this study, the physical model developed by Wang (1998) is used. The AHU coil is modeled using a dynamic approach. A first-order differential equation, as shown in Equation (5.17), is used to represent the dynamics of a coil with lumped thermal mass. The dynamic equation based on the energy balance ensures that the energy is conserved. The outlet air and water temperatures ($t_{a,out}$, $t_{w,out}$) are computed using Equations (5.18) and (5.19) respectively, by the heat balances of both sides. The heat transfer calculation applies the classical number of transfer units (NTU) and heat transfer effectiveness methods. The classical method to calculate the effect of the fins in the air side on the thermal resistance is used.

$$C_c \frac{dT_c}{dt} = \frac{T_{a,in} - T_c}{R_1} - \frac{T_c - T_{w,in}}{R_2} \tag{5.17}$$

$$T_{a,out} = T_{a,in} - \frac{SHR(T_{a,in} - T_c)}{R_1 C_a} \tag{5.18}$$

$$T_{w,out} = T_{w,in} - \frac{T_c - T_{w,in}}{R_2 C_w} \tag{5.19}$$

where, $T_c$ is the mean temperature of the coil, $T_{a,in}$ and $T_{w,in}$ are the inlet air and water temperatures, $C_c$ is the overall thermal capacity of the coil, $C_a$ and $C_w$ are the capacity flow rates of air and water, $R_1$ and $R_2$ are the overall heat transfer resistances at air and water sides, *SHR* is the sensible heat ratio.

### 5.2.4 Smart Grid Model

MATLAB is employed to communicate the information of buildings and a smart grid, optimize the buildings power demands. MATLAB is also used to schedule the grid power generations and set the dynamic electricity prices. In the simulation, a small-scale smart grid is simulated for serving a total of 400 passive commercial buildings covering three different weighted buildings (including 100 light weighted buildings, 200 medium weighted buildings and 100 heavy weighted buildings). The power supply sources of the smart grid are assumed to consist of three categories (i.e., 1,000 MW of wind and solar generations, 1,000 MW of coal-fired generation and 500 MW of gas-fired generation. An optimal generation profile (i.e., the grid operates at a load level 1000 MW during non-office hours and 1,500 MW during office hours) is also defined. It is worth mentioning that, in the smart grid model, uncertainty and intermittence of renewable energies were not considered in detail for the overall power supply management.

The power characteristics of buildings such as power demands, power demand alterations and storage efficiencies are required for smart grid optimization. The smart grid is also required by the end-users (i.e., buildings) to set proper dynamic electricity prices in order to incent the power demand controls of individual buildings.

### 5.2.5 Electricity Pricing Mechanism

The cost of electricity (i.e., electricity price) depends on many factors including cost of fuels, marginal cost of generation, maintenance and transmission, profits, economics, etc. In fact, there are already many pricing mechanisms applied in the reality such as time-of-use pricing (TOU), critical peak pricing (CPP), real time pricing (RTP), etc. The basic idea of these pricing mechanisms is that, the electricity price is used to represent the marginal cost of electricity and the balance status of power supply and demand, and aims to maximize the overall economic benefits. Schweppe et al. (1988) developed a classic electricity pricing principle and pointed out the relationship between the electricity price and the power demand. The relationship is represented and compromised by two curves: supply curve and demand cure. The details will be described in Chapter 6 and shown in Figure 6.3.

Although dynamic pricing is a very complicated process related to many factors (e.g., technical, economic, and operational, etc.), a simple dynamic pricing mechanism is developed and adopted in the simulation platform, as shown in Equation (5.20).

$$r(t) = \begin{cases} r_1 \dfrac{P(t)}{P_1}, & P(t) \in [0,\ P_1] \\ \dfrac{\left[\sum_{i=1}^{n-1}\left(r_i P_i\right)\right] P_n + r_n \left[P(t) - \sum_{i=1}^{n-1} P_i\right]^2}{P(t) P_n}, & P(t) \in [\sum_{i=1}^{n-1} P_i,\ \sum_{i=1}^{n} P_i] \end{cases} \tag{5.20}$$

where, $r$ is the dynamic price of electricity. $P$ is the aggregate electricity load of end-users. $r_i$ is the pricing factor of the *ith* power supply source. $P_i$ is the generation capability of the *ith* power supply sources. The power supply sources are arranged to generate at a specific sequence (i.e., the number order from *1* to *n*) by considering their availabilities and marginal costs. In other words, the grid prefers to consume the energy sources with lower cost and/or lesser controllability (e.g., renewable energy sources). The dynamic pricing mechanism can be described as follows: The electricity price decreases when the power supply is surplus and/or the supply cost is cheap while the electricity price increases when the power supply is inadequate and/or the supply cost is expensive. It is worth mentioning that, in order to incent the activities of end-users in specific cases, the factors of power supply sources in determining the price should be set very carefully.

## 5.3 Test Conditions and Control Strategies

For the commercial buildings simulated in TRNSYS, the schedule of internal heat gains come from the occupancy, lighting, equipment, fresh air and infiltration air, etc., as shown in the Figure 5.3. The peak of heat gains usually falls in the office hours, and results a peak cooling load in the buildings combined with the external heat gains.

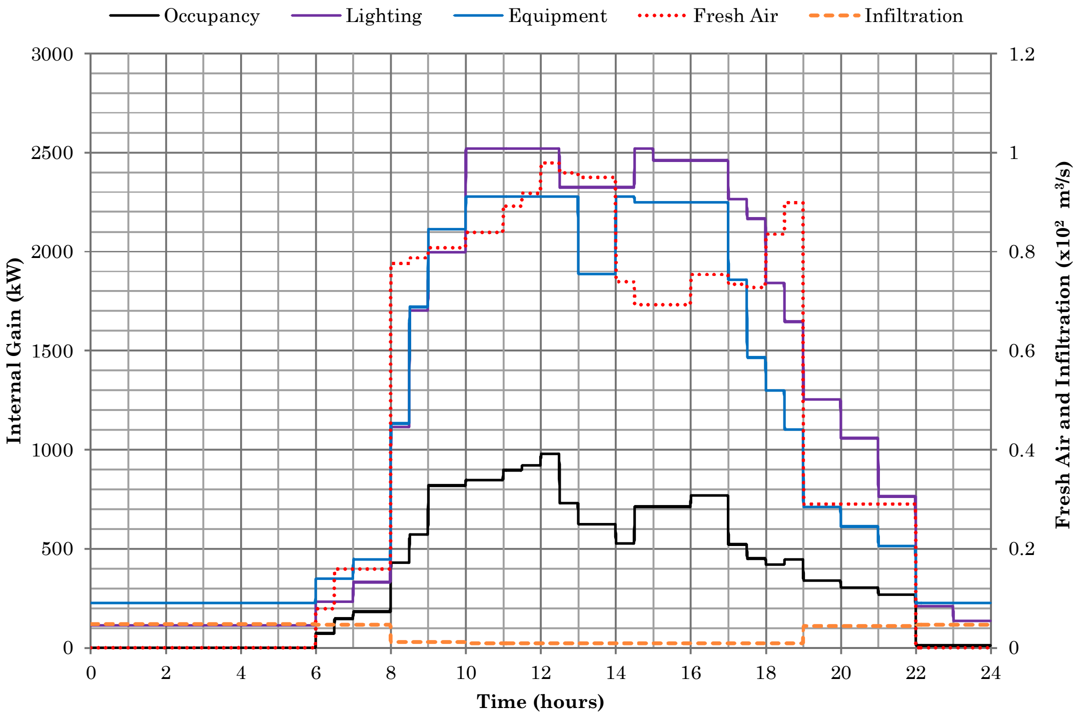



Figure 5.3 The daily schedule of different heat internal gains.

In order to find out the charging/discharging trends and the thermal characteristic of building thermal masses (i.e., the passive storage), nine sets precooling control strategies are proposed for individual buildings against reference control strategy (i.e. night setback) in a typical summer day in Hong Kong. Temperature setting of night setback is 23.0°C during office hours (from 9:00 a.m. to 6:00 p.m.), and 26.5°C during non-office hours (from 6:00 p.m. to 9:00 a.m.). Settings for precooling control strategies are listed in Table 5.1, which consists of three precooling modes (light, moderate, and deep precooling respectively) and three precooling temperature set points (20.5°C, 19.5°C and 18.5°C respectively). Temperature remains 23.0°C during office hours and is accordingly set to different precooling patterns during non-office hours for precooling control strategies. For instance, column of moderate precooling at 19.5°C means temperature is set to 19.5°C from 3:00 a.m. to 9:00 a.m. (6 hours precooling before office hours), and then set to 23.0°C during office hours and set back to 26.5°C during the rest hours. The results of the simulation tests showing the energy performance for different indoor air temperature control strategies are listed in Table 5.2.

Table 5.1 Indoor air temperature control strategies for charging/discharging of building thermal masses

| **Indoor Air Temperature Set Point during Precooling (°C)** | **Precooling Modes** | | |
|---|---|---|---|
| | *Light Precooling* (hours) | *Moderate Precooling* (hours) | *Deep Precooling* (hours) |
| 20.5 | 3.0 ($CS_7$) | 6.0 ($CS_8$) | 9.0 ($CS_9$) |
| 19.5 | 3.0 ($CS_4$) | 6.0 ($CS_5$) | 9.0 ($CS_6$) |
| 18.5 | 3.0 ($CS_1$) | 6.0 ($CS_2$) | 9.0 ($CS_3$) |

Table 5.2 Energy performance of building thermal masses under different indoor air temperature control strategies

| **Control Strategies of Precooling** | **Energy Performance of Building Thermal Mass** |
|---|---|

| Set Point and Precooling Time | | *Storage Efficiency* | *Energy Increase* | *Load Shift* |
|---|---|---|---|---|
| 20.5°C | 3 hours | 80.66% | 1.00% | 3.77% |
| | 6 hours | 64.32% | 2.96% | 4.78% |
| | 9 hours | 54.38% | 4.94% | 5.32% |
| 19.5°C | 3 hours | 79.60% | 1.24% | 4.32% |
| | 6 hours | 63.43% | 3.54% | 5.50% |
| | 9 hours | 53.70% | 5.84% | 6.13% |
| 18.5°C | 3 hours | 81.05% | 1.30% | 5.03% |
| | 6 hours | 64.51% | 3.92% | 6.37% |
| | 9 hours | 54.52% | 6.54% | 7.10% |

## 5.4 Summary

This chapter describes a dynamic simulation platform based on TRNSYS and MATLAB programs. Building models, major components of HVAC systems models and smart grid model are also introduced in this chapter. A simple dynamic pricing mechanism is developed for the interactions between buildings and smart grid. Different indoor air temperature control strategies are developed to investigate the energy performance especially the energy storage characteristics of building thermal masses. The interactive power demand management strategy of the passive buildings for smart grid application, the chiller demand limit control strategy are developed, tested and validated based on this dynamic simulation platform.

# CHAPTER 6 AN INTERACTIVE BUILDING POWER DEMAND MANAGEMENT STRATEGY

With the increasing use and integration of renewable energies, the power imbalance between the supply side and demand side has become one of the most critical issues in the developing smart grid. As the major power consumers at the demand side, buildings can perform as distributed thermal storages to help relieving power imbalance of a grid. However, power demand alteration potentials of buildings and energy information of grids might not be effectively predicted and communicated for interaction and optimization. This chapter presents an interactive building power demand management strategy for the interaction of commercial buildings with a smart grid and facilitating the grid optimization. The simplified building thermal storage model is employed for predicting and characterizing the power demand alteration potentials of individual buildings together with a model for predicting the normal power demand profiles of buildings. The simulation test results show that commercial buildings can contribute significantly and effectively in power demand management or alterations with building power demand characteristics identified properly.

Section 6.1 presents an introduction of the existing studies on smart grid and discusses the feasibility of developing an interactive building power demand management strategy. Section 6.2 presents the concept and formation of interactive building power demand management strategy. The developed interactive management strategy consists of three parts: interaction with grid by adopting dynamic pricing, optimization of building power demand management, and implementation structure of the interactive strategy. Section 6.3 presents the validation of the interactive strategy with a case study. A summary of this chapter is given in Section 6.4.

## 6.1 Introduction

Smart grid is considered as a promising solution concerning its improvements and benefits in power reliability, energy efficiency, economics and sustainability (DOE 2003; European Commission 2006; Yuan and Hu 2011). In recent years, many efforts have been made on different aspects of smart grid including but not limited to micro-grid (California Energy Commission 2003), distributed generation and distributed storage (Toledo et al. 2010), smart meter (Depuru et al. 2011), information and communication technologies (Wissner 2011), advanced metering infrastructure (RG&E 2007), supervisory control and data acquisition (Kang et al. 2011), demand response (Faria and Vale 2011) and energy management system (Kokai et al. 1998). By conducting efficient acquisition of energy information and optimal controls of operation, smart grid can achieve a better power reliability and a higher overall energy performance when integrating different energy sources, storages and loads.

Although smart grid researches and applications have involved end-users (e.g., buildings) in the form of demand response (i.e., incentive-based and price-based (Albadi and El-Saadany 2008)), buildings can only conduct their power demand controls in a passive and static means by receiving signals (e.g., electricity prices) and controls (e.g., direct load controls) from the grid. Moreover, attention has been seldom paid on the considerable thermal energy capacities of buildings, which can be considered as distributed storages to help relieving power imbalance caused by renewable generations or other scenarios. Actually, buildings have been becoming the major energy consumers with consuming around 40% of total end-use energy all over the world (Kolokotsa et al. 2011) and over 90% of total electricity in some urban areas, such as Hong Kong (Hong Kong EMSD 2012). Buildings can help improving energy performance of an electrical grid by shifting loads and reducing peak demands. Previous studies mainly focused on the impacts and benefits of adopting different power demand control strategies under specific electricity prices in buildings (Braun et al. 2001; Henze 2005; Sun et al. 2010). However, characterization of power demand alteration potentials of buildings and their aggregate effect for grid dynamic optimization have rarely been addressed.

With the development and extensive use of building automation systems, information and communication technologies and grid energy management system, a bidirectional communication between buildings and a grid can be widely established and used for interacting and optimizing the power supply and the demand. It is worth mentioning that, power demands of end-users and electricity prices of the grid are the key information for interaction and optimization between power supply and demand sides (Schweppe et al. 1988). Buildings, as one of the most important participants involved in a smart grid, can provide useful information such as energy behaviors, power demand and the corresponding alteration potentials for grid optimal arrangement. In fact, smart meters have been successfully applied for residential buildings in many countries for collecting detailed energy data (Olmos et al. 2011). However, energy behaviors and power demand alteration potentials of commercial buildings have not been studied and quantified for grid scale interaction and optimization (Guan et al.

2010).

This chapter therefore proposes an interactive building power demand management strategy, which includes three major parts/steps: 1) prediction of building power demand and characterization of the corresponding alteration potential, 2) interaction with grid by adopting dynamic pricing, 3) optimization of building power demand control. The interactive strategy quantifies the thermal characteristics and power demand alteration potentials of passive buildings (i.e., buildings without active thermal energy storages) by adopting a building thermal storage model developed in Chapter 3. Simulation case study is also conducted for testing the interaction and optimization between a group of commercial buildings and a small-scale smart grid.

## 6.2 The Interactive Building Power Demand Management Strategy

Buildings are the major energy (especially power) consumers today and their shares are still increasing due to the urbanization. Buildings can benefit an electrical grid by relieving the pressure of power imbalance during different energy processes, particularly with the application of energy storages. Compared with traditional grids, smart grids enable a bidirectional operation (i.e., "two-way" connection with power flow and information flow) to improve power reliability and energy performance. A generic interactive framework is proposed in this chapter for establishing the bidirectional communication between supply and demand sides of a smart grid, as shown in Figure 6.1. Different participants such as power suppliers, deliverers and consumers are involved and connected by an information and data communication network. An information management and control center is employed by the smart grid for data and information collection, reliability and performance analysis, generation management and optimal control. It is worth mentioning that, the bidirectional connection and communication between smart meter and building automation system of commercial building are more complicated than that of the other two sectors. The requirements of information exchange and control logics for integrating building automation system and smart metering system need to be further addressed due to their different system configurations, communication protocols and time delays, etc. A generic integration framework, obtaining building automation system and smart metering system, therefore needs to be developed for involving commercial buildings in smart grid.

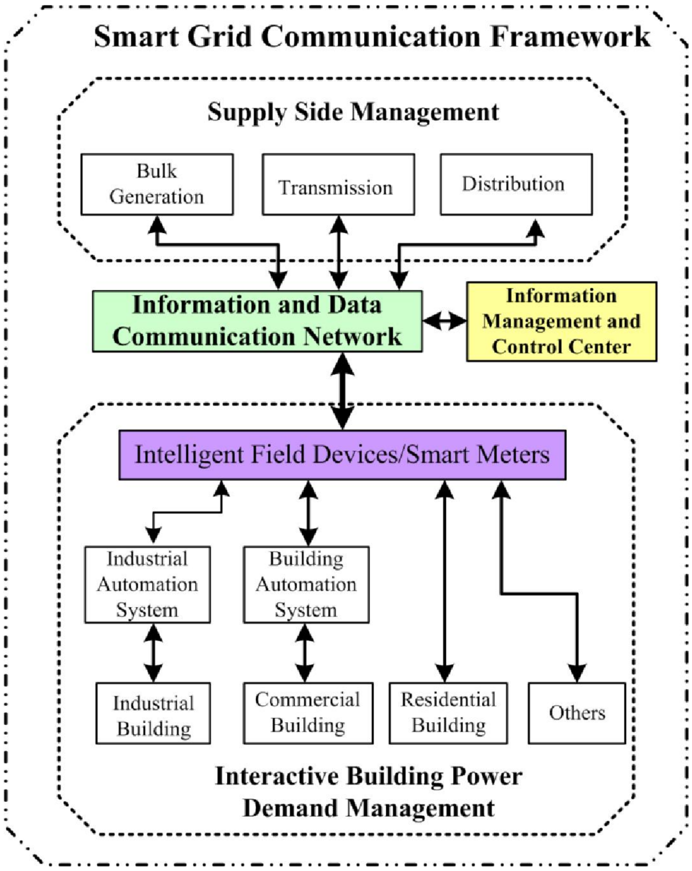



Figure 6.1 Communication framework for power supply and demand sides of the smart grid.

Commercial buildings and their thermal masses are investigated by considering the availabilities of thermal storage capability, energy information acquisition and control strategy implementation. Figure 6.2 illustrates a bidirectional power and information connections of suppliers and consumers (i.e., commercial buildings). Commercial buildings and their thermal masses are considered as thermal storages storing/releasing energy in form of thermal energy. By having power information (e.g., generation capabilities and power demand alteration potentials) and incentive programs (e.g., dynamic prices) of power supply and demand sides, the overall energy performance can be improved with active participant of buildings. It is worth noticing that only simple pricing algorithm and generation capability profile are adopted in this study to test the buildings-grid interactive operation particularly the potentials and effects of buildings.

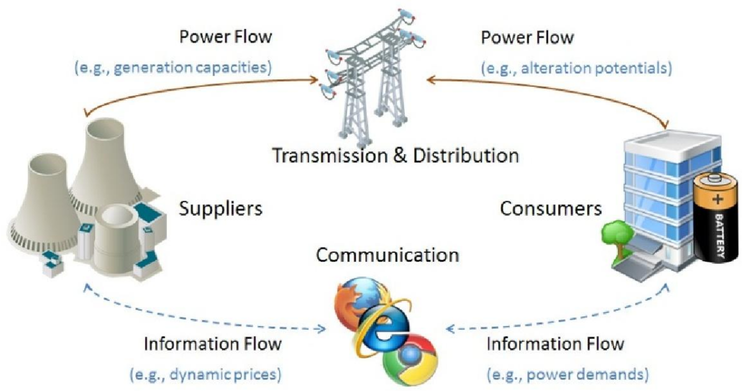
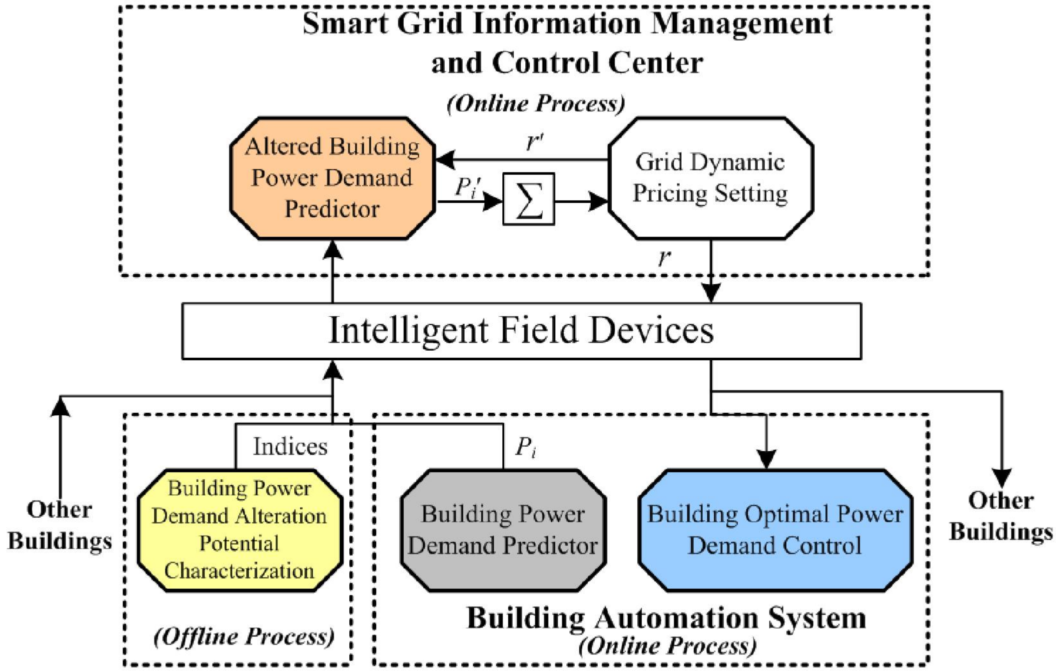



Figure 6.2 Schematic of interaction between commercial buildings and the smart grid.

The interactive building power demand management strategy is proposed for integrating commercial buildings into the smart grid involving four main steps: 1) prediction of building power demand, 2) characterization of the building demand alteration potential and associated efficiency degradation, 3) grid dynamic prices accomplishment, and 4) optimization of building power demand control, as shown in Figure 6.3.




$P_i$: the reference power demand prediction of the $i^{th}$ building
$P_i'$: the altered power demand prediction of the $i^{th}$ building
$r$: the finalized electricity prices
$r'$: the trial electricity prices

Figure 6.3 Schematics of the interactive power demand management strategy for commercial buildings.

In this interactive strategy, predictions of reference and altered building power demands are accomplished by the following three schemes: building power demand predictor, characterization of building power demand alteration potential and altered building power demand predictor. Building power demand predictor is employed online to predict the reference electricity load profiles of buildings ($P_i$) (i.e., the original power demand without active power demand controls). Characterization of building power demand alteration potential is performed offline to identify the parameters of the simplified building thermal storage model. Altered building power demand predictor is employed online to predict the altered electricity load profiles of buildings ($P_i'$) when adopting given active power demand controls.

The interaction between buildings and the smart grid results in the optimized incentive dynamic prices based on the possible altered power demand profiles and the available power generations including efficiency issues. Optimization of the grid incentive dynamic prices is accomplished when a compromised balance between the power supply and the demand is established. Finally, having the incentive prices determined by the grid through interacting the buildings and the grid, optimal building power demand control aims to achieve maximum operation energy cost savings of individual buildings.

### 6.2.1 Estimation of Building Power Demand and Its Alteration

Smart grid requires effective and reliable predictions of the power demands and their alteration potentials, as well as the corresponding realization costs of a large number of buildings for the grid generation management and energy optimization. Therefore, these prediction methods or models should be generic, simple and suitable for online applications when a large number of buildings are involved in a grid. Convenience in using the models and identifying the model parameters (i.e., building characteristic indices) is crucial when implementing the interactive strategy.

There are many methods available for both supply and demand sides to obtain the power demands of end-users (e.g., buildings). In this study, power demand characteristics of commercial buildings in an interactive smart grid are quantitatively represented by the reference power demands and the corresponding alteration potentials.

*Building power demand prediction using the simplified building energy model*

The total power demand (i.e., electricity load) of a commercial building can be divided into two parts: the sheddable power demand and controllable power demand. Generally, the electricity load of a commercial building is contributed by building service systems including heating, ventilation and air-conditioning (HVAC) systems, lighting and electrical equipment, lifts and elevators, etc. Electricity loads of lighting, electrical equipment, transportation and other appliances can be considered as the sheddable demands, which can be conveniently obtained according to their operation schedules. By contrast, electricity loads of HVAC systems are controllable loads which are possible to be altered by power demand controls. They are complex to be predicted due to the dynamic nature of their working conditions. The total power demand of a commercial building can then be represented by Equation (6.1).

$$P_{tot} = P_{cont} + P_{shed} \tag{6.1}$$

where, $P_{tot}$ is the total power demand of a building. $P_{cont}$ is the controllable power demand of the building which is mainly contributed by HVAC systems. $P_{shed}$ is the sheddable power demand of the building which is contributed by the building service systems other than HVAC systems and other electrical appliances.

The thermal storage of a building (e.g., building thermal masses, phase change materials, water/ice storages, etc.) is the major contributor of the power demand alteration potential. Different power demand control strategies of the HVAC system result in different electricity load profiles. The predicted power demand of a HVAC system is the function of the predicted heating/cooling load of the building and the HVAC overall coefficient of performance (COP), as shown in Equation (6.2).

$$P_{cont} = \frac{Q_{est}}{COP_{sys}} \tag{6.2}$$

where, $Q_{est}$ is the predicted heating/cooling load of a building. $COP_{sys}$ is the overall COP of the HVAC system. It is because buildings may purchase heating and cooling in other ways such as heating/cooling from the district heating/cooling system. Many methods and models are developed for building load prediction, including physical model, black box model and grey box model. In this study, a simplified building energy model (i.e., grey box model) was selected and employed for predicting the heating/cooling load of a building without active thermal storage (Wang and Xu 2006), as shown in Equation (6.3). Model details were already presented in Chapter 3.

$$\begin{aligned} Q_{est} = & \sum_{i=1}^{n}\left[\frac{T_{ew,4}(t) - T_{in}(t)}{R_{ew,5}} A_{ew}\right] + \frac{T_{rf,4}(t) - T_{in}(t)}{R_{rf,5}} A_{rf} + \frac{T_{im,2}(t) - T_{in}(t)}{R_{im,2}} A_{im} \\ & + \frac{T_{out}(t) - T_{in}(t)}{R_{win}} A_{win} - C_{in}\frac{dT_{in}(t)}{dt} A_{in} + \left(Q_{conv} + Q_{fr} + Q_{la}\right) \end{aligned} \tag{6.3}$$

where, $T$ and $Q$ are the temperature and heat gain respectively. $R$ and $C$ are thermal resistance and thermal capacitance respectively. $A$ is the effective surface area involved in the heat exchange process.

*Building power demand alteration potential prediction using the simplified building thermal storage model*

In this chapter, the simplified building thermal storage model developed in Chapter 3 is used to predict the power demand alteration potential of the passive buildings.

For the scenarios of adopting preheating/precooling and temperature set-point reset strategies, the corresponding electrical power demand alteration (i.e., charging/discharging rate) of a passive building (i.e., a building with building thermal masses only) can be expressed by Equation (3.33). More details can refer to the development and the validation of the simplified building thermal storage model in Chapter 3 and Chapter 4, respectively.

### 6.2.2 Interaction with Grid by Adopting Dynamic Pricing

As the energy behaviors of electricity end-users (e.g., power demands of buildings) could be dramatically influenced by electricity pricing, electricity pricing is the other key factor in an interactive strategy for grid interaction and optimization. The electricity pricing is affected by many factors including cost of fuels, marginal cost of generation, transmission and maintenance, utility profits, economics, etc. There are already many pricing mechanisms applied such as time-of-use pricing (TOU), critical peak pricing (CPP), real time pricing (RTP, i.e., dynamic pricing), etc. Schweppe et al. (1988) developed a classic pricing model named spot pricing (i.e., dynamic pricing) and pointed out the relationship between the electricity price and the power demand. Figure 6.4 shows two curves with a simple compromising process. Supply curve indicates that the electricity price increases when the power supply increases. Demand curve indicates that the power demand decreases when the electricity price increases. The basic idea of dynamic pricing is that the electricity price is used to represent the marginal cost of electricity and the balance status of power supply and demand, and aims to maximize the overall economic benefits.

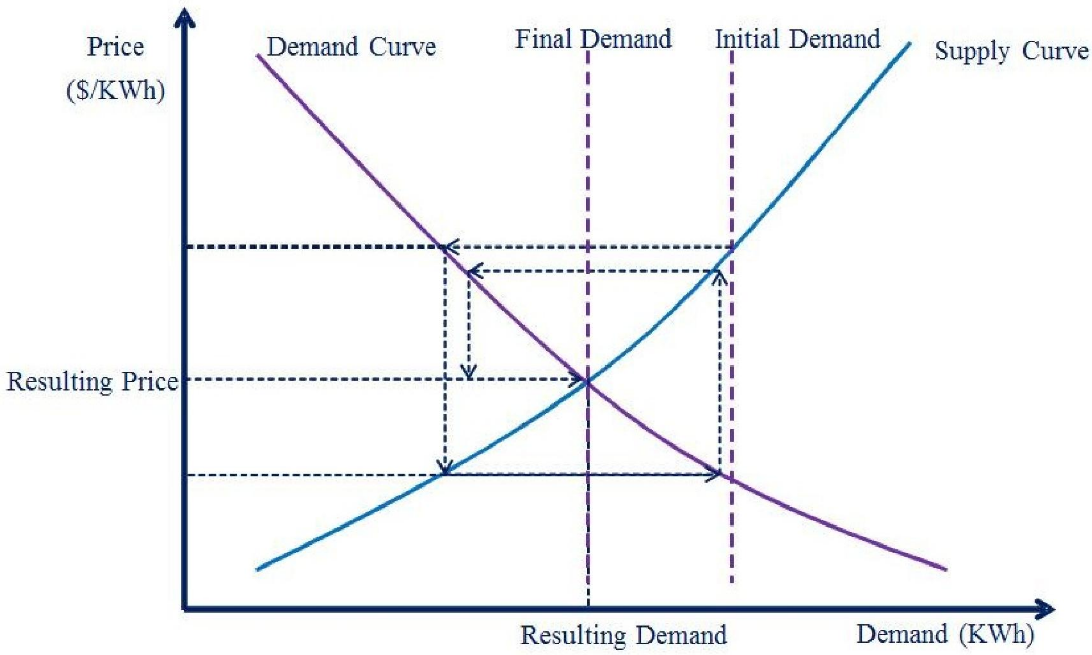


Figure 6.4 Dynamic pricing principle for interaction between power supply and demand (Schweppe et al. 1988).

The interactive strategy proposed in this chapter aims at developing an effective approach in communicating the quantitative power demand potentials of buildings to a smart grid, which can help the grid in relieving the stress of power imbalance and maximizing the overall economic benefits. Generally, an electrical grid desires to operate with an optimal operation profile (e.g., a daily profile), which is drawn by comprehensively considering power reliability, operation cost and energy performance, etc. Figure 6.5 illustrates an interaction process between power supply and demand with adopting incentive prices. The grid encourages end-users to help altering the aggregate electricity load profile by setting proper electricity prices. End-users change their energy behaviors and alter individual electricity load profiles according to their own considerations (e.g., minimizing operation energy cost). A win-win situation (i.e., energy saving of the grid and cost saving of end-users) can be achieved when the aggregate electricity load profile is approaching to the optimal operation profile.

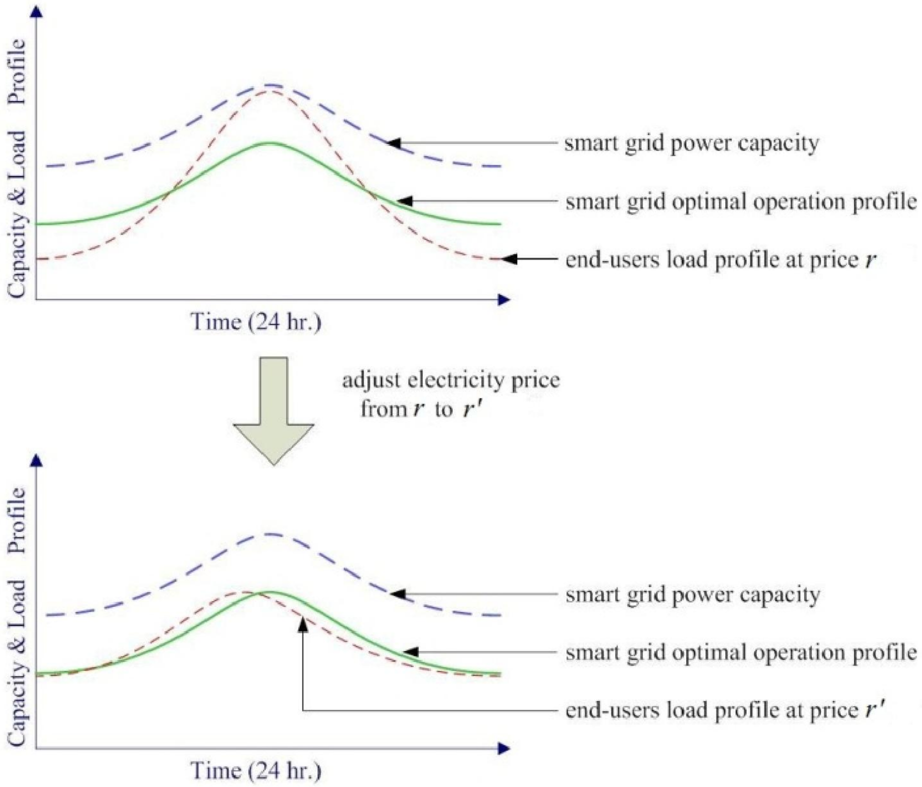



Figure 6.5 Illustration of interaction between the grid and end-users when adopting incentive prices.

In order to demonstrate the interactive strategy with focus on alteration potential of building power demand, complex electricity market is not considered in this study. A simple dynamic pricing mechanism was adopted in the validation tests, which was based on the theory of spot pricing (Schweppe et al. 1988), as shown in Equation (5.20) of Chapter 5.

### 6.2.3 Optimization of Building Power Demand Management

Commercial buildings generally conduct their optimal power demand controls or management in order to achieve the minimum operation energy cost. On the premise of ensuring expected building services functions and indoor environment, buildings can alter their power demands as needed using building automation systems. An operation energy cost function is employed for setting the optimal power demand control strategy, as shown in Equation (6.4).

$$B_{tot} = \sum_{t=1}^{N} \left[ r(t) \times P_{tot}(t) \right], \ (t = 1, 2, 3, \ldots\ldots, \mathrm{N}) \tag{6.4}$$

where, $B_{tot}$ is the total operation energy cost of a building. $r(t)$ is the electricity price during time interval. $P_{tot}(t)$ is the total power demand of the building during time interval. $N$ is the total number of dynamic pricing time intervals. Comparing the costs resulted by different power demand control strategies, the optimal one (i.e., the control strategy corresponding to the lowest operation energy cost) can be identified for building system controls for the next day).

An interactive relationship between commercial buildings and the smart grid can then be established. The power demand alterations of buildings are influenced by electricity pricing while the electricity pricing is also influenced by the altered aggregate power demand of buildings conversely. Figure 6.6 shows an optimization process between commercial buildings and a smart grid under dynamic pricing. Having the reference electricity load profiles, buildings can predict their altered electricity load profiles accordingly by predicting their power demand alterations. The altered electricity load profile of each building is then aggregated and used by the grid to set proper electricity prices. Further adjustments on the electricity prices and the altered electricity load profiles will continue until a near optimal operation profile of the grid is approached. It is worth mentioning that the electricity load profiles of buildings will be altered when operation energy cost savings can be achieved. Otherwise no changes will be made.

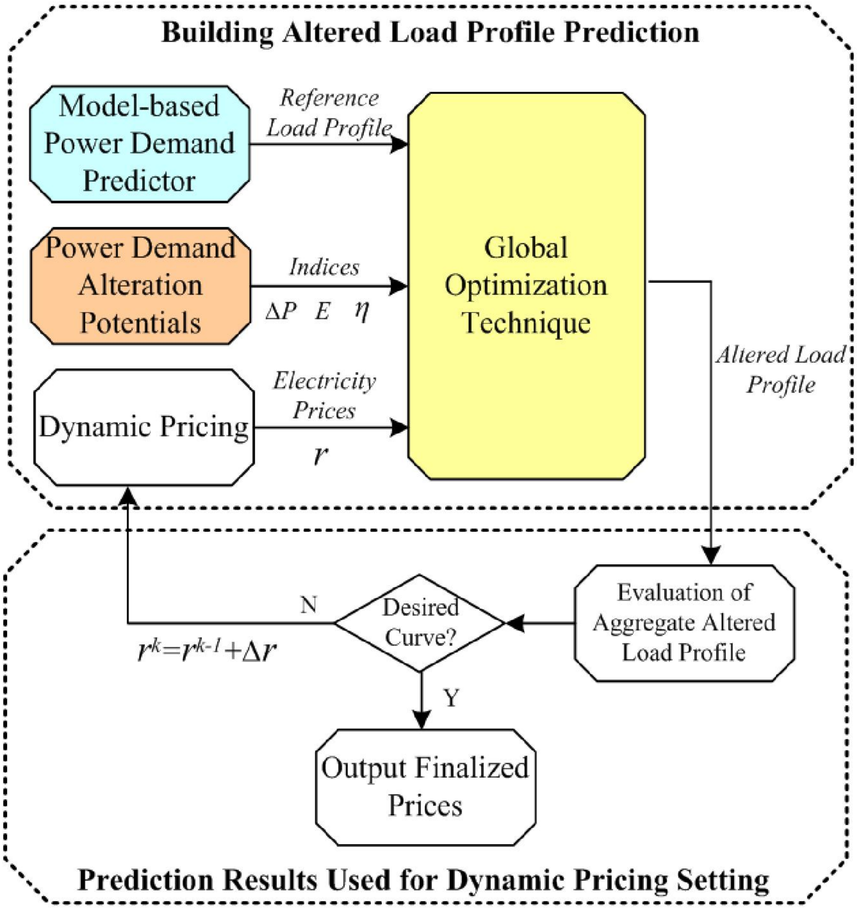



Figure 6.6 Optimization process of commercial buildings and a smart grid under dynamic pricing.

### 6.2.4 Implementation Structure of the Interactive Strategy

The proposed interactive building power demand management strategy relies on an information and communication platform, which can communicate energy information and implement control strategies effectively. Although the bidirectional communication between smart meters and grids has been established and demonstrated in several trial projects for residential buildings, the development of communication and interaction between commercial buildings and a smart grid has rarely been reported.

Based on the latest available technologies such as building automation systems, smart meters, and grid energy management system, this case study proposes an implementation structure for the interactive strategy by integrating smart meters into building automation systems, as shown in Figure 6.7. The building automation system provides various energy information of a building (e.g., HVAC systems, lighting systems, etc.), and conducts controls and optimizations for building service systems. The smart meter collects useful information from both power supply and demand sides (e.g., electricity prices and building power demands), and communicates the information (e.g., day-ahead and/or hour-ahead) for further interaction and optimization. Furthermore, open protocols (e.g., TCP/IP, BACnet, etc.) are also recommended for establishing the information and communication platform by considering the compatibility and convenience of the Internet.

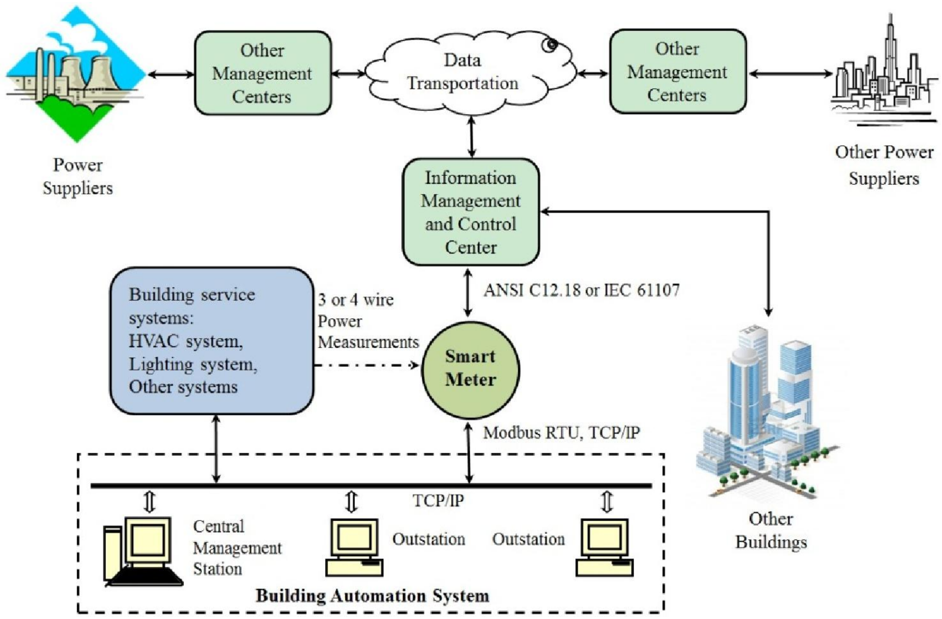



Figure 6.7 Implementation structure of the interactive building power demand management strategy.

## 6.3 Validation of the Interactive Strategy

### 6.3.1 Simulation Test Setup

Simulation software TRNSYS (2004) and MATLAB (2006) were employed to establish a virtual communication and control platform for the interactive building power demand management strategy. TRNSYS was used to simulate the "actual" heating/cooling loads of buildings and validate the developed building thermal storage model in this study. MATLAB was used to communicate the information of both commercial buildings and a small-scale smart grid, and optimize the power demands of buildings and the electricity prices of the grid. Power generation scheduling of the grid and the dynamic pricing mechanism were programmed in MATLAB. MATLAB also obtained the building loads and possible power demand alterations from TRNSYS for setting dynamic prices according to the desired generation profile. The interaction process was completed in MATLAB and the communication was assumed to be instant without any time delay.

In the simulation, three types of total 400 passive commercial buildings including 100 light weighted buildings, 200 medium weighted buildings and 100 heavy weighted buildings were simulated. The configurations of these buildings are all the same: 40 floors with 4m height and 400 $m^2$ area per floor, window-to-wall ratio was set to 0.5. The overall COPs of the HVAC systems in buildings were assumed to be constant (i.e., 2.5). Except HVAC systems, the electricity loads of the rest building service systems were added to represent the basic electricity load (i.e. uncontrollable load) for each individual building. The building power demand control strategies and office hours and the operation schedule of HVAC systems were presented in Chapter 3. Power demands of buildings were assumed to be provided by the smart grid, which had three different kinds of energy sources (i.e., wind/solar, coal-fired and gas-fired power plants). According to the proposed dynamic pricing mechanism, Equation (5.20) can then be rewritten as Equation (6.5).

$$r(t) = \begin{cases} r_1 \dfrac{P(t)}{P_1}, & P(t) \in [0,\ P_1] \\ \dfrac{r_1P_1P_2 + r_2[P(t) - P_1]^2}{P(t)P_2}, & P(t) \in [P_1,\ (P_1 + P_2)] \\ \dfrac{r_1P_1P_3 + r_2P_2P_3 + r_3[P(t) - P_1 - P_2]^2}{P(t)P_3}, & P(t) \in [(P_1 + P_2),\ (P_1 + P_2 + P_3)] \end{cases} \tag{6.5}$$

where, $P_1$, $P_2$, $P_3$ are the generation capacities of renewable generation (i.e., wind/solar), general generation (i.e., coal-fired) and extra generation (i.e., gas-fired) respectively. $r_1$, $r_2$, $r_3$ are the pricing factors of renewable generation, general generation and extra generation respectively. The pricing factor $r_i$ can be obtained from the initial and operation costs of the corresponding generation and power supply. It also depends on the availability and controllability of the generation (e.g., generation for operating reserves has a higher pricing factor compared with the regular generation). In the tests, the uncertainty and intermittence of renewable energies (i.e., wind and solar) were not considered in this study. Constant capacities of different generations in the grid were assumed to be 1,000 MW of wind and solar generations ($P_1$), 1,000 MW of coal-fired generation ($P_2$), and 500 MW of gas-fired generation ($P_3$). An optimal generation profile was also assumed to operate at 1000 MW during non-office hours and 1,500 MW during office hours. The simplified building energy model was employed to predict the cooling loads of reference buildings, and the developed building thermal storage model was used to predict cooling load alteration potentials of buildings. Building energy characteristic information including power demands, power demand alteration potentials and realization costs (e.g., storage efficiency) are required for grid optimization. The grid is also required to set proper electricity prices in order to incent the power demand controls of buildings.

### 6.3.2 Validation of The Interactive Strategy

The identified parameters of thermal storage model for different types of buildings were presented in Table 3.4. $COP_{sys}$ was assumed to be unchanged during the charging/discharging process.

These parameters are the essential information for obtaining the effective indices of buildings. Table 6.1 lists an example of power demand alterations for three types of buildings when different precooling durations (i.e., no precooling, 4 and 8 hours precooling) were applied. The power demand alteration and the total altered electricity energy increased when the precooling duration increased while the longer precooling duration was, the lower energy efficiency building had.

Table 6.1 Power demand alterations of buildings during office hours

| Building type | Precooling Time (hours) | Power demand alterations (kW) | | | | | | | | | | Total altered energy (kWh) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 08:30 09:00 | 09:00 10:00 | 10:00 11:00 | 11:00 12:00 | 12:00 13:00 | 13:00 14:00 | 14:00 15:00 | 15:00 16:00 | 1600 17:00 | 17:00 18:00 | |
| Light weighted | 0 | 924 | 371 | 313 | 277 | 245 | 216 | 191 | 169 | 150 | 132 | 2527 |
| | 4 | 1674 | 1079 | 940 | 831 | 735 | 650 | 575 | 508 | 450 | 398 | 7002 |
| | 8 | 2171 | 1549 | 1355 | 1199 | 1060 | 938 | 829 | 733 | 649 | 574 | 9971 |
| Medium weighted | 0 | 1098 | 417 | 365 | 336 | 309 | 284 | 262 | 241 | 221 | 204 | 3189 |
| | 4 | 1867 | 1165 | 1053 | 968 | 891 | 819 | 754 | 693 | 638 | 587 | 8501 |
| | 8 | 2457 | 1739 | 1581 | 1454 | 1337 | 1230 | 1132 | 1041 | 957 | 881 | 12579 |
| Heavy weighted | 0 | 1377 | 414 | 363 | 341 | 321 | 302 | 285 | 268 | 252 | 237 | 3472 |
| | 4 | 1828 | 861 | 783 | 737 | 694 | 653 | 615 | 578 | 544 | 512 | 6892 |
| | 8 | 2204 | 1232 | 1133 | 1066 | 1003 | 944 | 889 | 836 | 787 | 741 | 9733 |

The thermal characteristics of buildings with different ratios of internal masses were also investigated. Table 6.2 and Table 6.3 show the details of parameters and power demand alterations for medium weighted buildings with different ratios of internal masses. Results shown that buildings with higher ratios of internal masses were identified having higher thermal capacitances. Buildings with lower ratio of internal masses had higher storage efficiency due to the smaller time constant. In other words, buildings with smaller time constant could store and release energy more effectively due to their less thermal inertia. However, buildings with higher ratios of internal masses had more power demand alterations.

Table 6.2 Identified parameters and coefficients of the thermal storage model for different types of buildings with different ratios of internal masses

| Building type | Internal masses ratio | $C_{bui}$ (J/m$^2$K) | $R_{bui,o}$ (m$^2$K/W) | $R_{bui,i}$ (m$^2$K/W) | $R_{bui}$ (m$^2$K/W) | $\tau$ (hour) | $COP_{sys}$ (-) | $\eta_{bui}$ (-) |
|---|---|---|---|---|---|---|---|---|
| Medium weighted | Low | 248621 | 0.9236 | 0.2133 | 0.1733 | 11.97 | 2.5 | 41.61% |
| | Middle | 467878 | 0.6551 | 0.1477 | 0.1205 | 15.66 | 2.5 | 35.31% |
| | High | 696082 | 0.5266 | 0.1134 | 0.0933 | 18.03 | 2.5 | 32.33% |

Table 6.3 Power demand alterations of buildings with different ratios of internal masses during office hours

| Building type | Internal Masses ratio | Power demand alterations (kW): 8 hours precooling case | | | | | | | | | | Total altered energy (kWh) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 8:30 9:00 | 9:00 10:00 | 10:00 11:00 | 11:00 12:00 | 12:00 13:00 | 13:00 14:00 | 14:00 15:00 | 15:00 16:00 | 1600 17:00 | 17:00 18:00 | |
| Medium weighted | Low | 2457 | 1739 | 1581 | 1454 | 1337 | 1230 | 1132 | 1041 | 957 | 881 | 12579 |
| | Middle | 3216 | 2126 | 1967 | 1845 | 1731 | 1624 | 1523 | 1429 | 1341 | 1258 | 16451 |
| | High | 3962 | 2547 | 2374 | 2246 | 2125 | 2010 | 1902 | 1799 | 1702 | 1610 | 20296 |

The grid obtained the reference aggregate load of buildings by giving the trial electricity prices (i.e., a fixed electricity price in this test). In order to encourage the aggregate load profile of buildings to approach the optimal operation profile of the grid, dynamic prices of next day were finalized by setting the pricing factors at $r_1$=0.5 HKD/kWh, $r_2$=0.5 HKD/kWh, $r_3$=25 HKD/kWh. As shown in Figure 6.8, the fixed electricity price (i.e., 2.28 HKD/kWh) was obtained by calculating the average marginal cost of total power generations in the next day. Dynamic prices were much lower than the fixed price because significant reduction in the marginal cost of total power generations was achieved when adopting the interactive strategy.

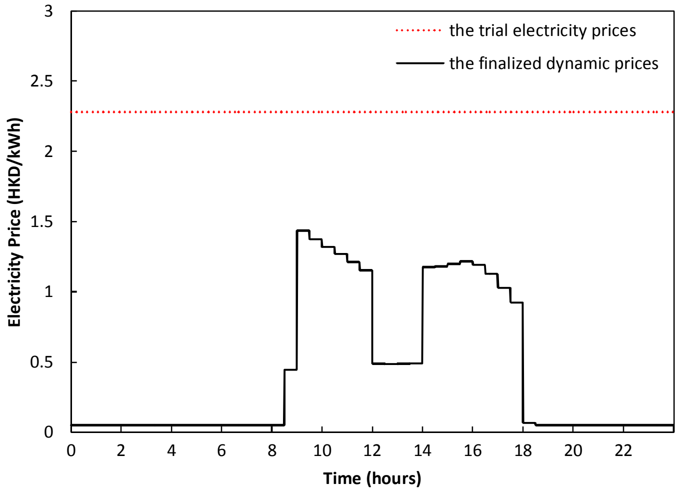



Figure 6.8 The trial electricity prices and the finalized dynamic prices in the interactive strategy.

In this simulation test, power was surplus during non-office hours due to sufficient renewable generation, and power was inadequate during office hours when renewable generation could not afford power demand and extra power plants (e.g., coal-fired and/or gas-fired) needed to be turned on. Actually, off-peak period always falls in non-office hours while peak demand usually happens during office hours in urban areas. In off-peak period, end-users (e.g., buildings) are encouraged to consume renewable energies as much as possible in efficient means due to the difficulties and the high cost of electricity storage.

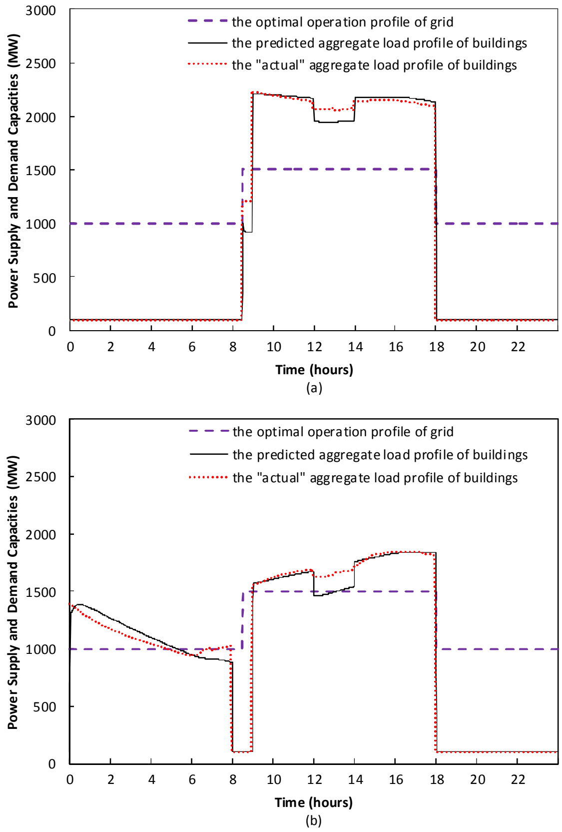



Figure 6.9 Aggregate electricity load profiles of buildings under (a) the trial electricity prices, (b) the finalized dynamic prices

Figure 6.9 shows the test results of commercial buildings and the grid when adopting the interactive strategy. The aggregate electricity load profile of buildings was approaching to the optimal profile, as indicated by approaching from (a) to (b). Building thermal storage model can predict power demand alterations of buildings with acceptable accuracy. The difference between the predicted and the “actual” loads during lunch hours (i.e., 12:00-14:00) might be resulted from the errors between the simplified and the complex building energy models, while operation data of internal gains had not been trained individually. Energy saving for the grid and cost saving for commercial buildings can be achieved by adopting the interactive power demand management strategy. Compared with the reference case (i.e., the case without interaction), 2,979 MWh energy was saved per day for the grid in a daily operation.

50,274 HKD, 47,311 HKD, 50,021 HKD (note: 1 USD = 7.8 HKD) operation energy costs were saved per day for each light weighted, medium weighted and heavy weighted building respectively. In other words, the cheaper and surplus renewable generation was properly utilized during non-office hours, while the expensive and extra generation was dramatically reduced during office hours. It is worth mentioning that, different pricing mechanisms (e.g., time of use pricing, critical peak pricing, dynamic pricing, etc.) may lead to different optimal results when implementing the proposed interactive strategy. It is because different building thermal storages have different capabilities (e.g., storage capacity, efficiency and charging/discharging rate, etc.) in responding to the electricity prices. However, the dynamic pricing is considered as the most reasonable one to represent the power supply cost and power balance status especially in developing a smart grid. Indoor thermal comfort was still acceptable during office hours when adopting the interactive strategy (i.e., temperature was reset to 25.5°C in the test). Figure 6.10 shows predicted mean vote (PMV) values of a medium weighted building, which indicates that the indoor thermal comfort level after demand control was not affected significantly compared with that before demand control.

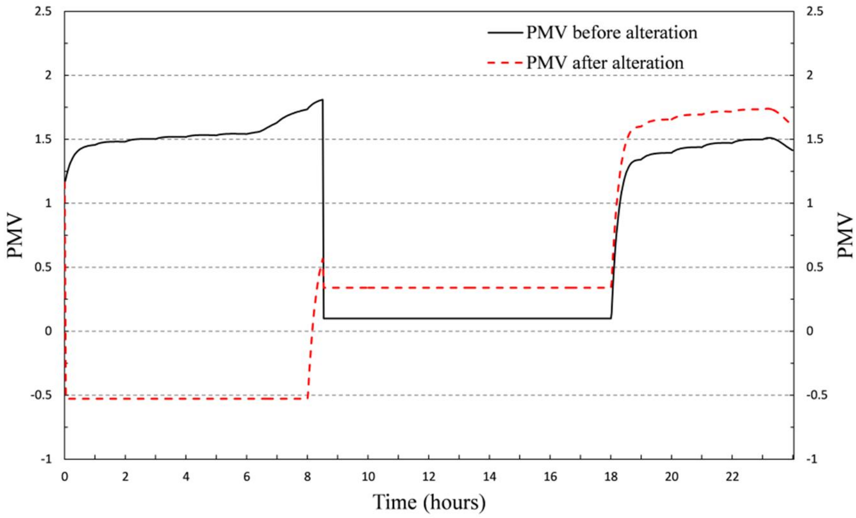



Figure 6.10 Comparison of indoor thermal comfort before and after demand control.

## 6.4 Summary

This chapter proposed an interactive building power demand management strategy for communicating effective power demand alteration information of commercial buildings to facilitate grid scale optimization. The simulation test results shown that the power imbalance could be significantly reduced when the effective interaction between the power supply and the demand was established. The energy storage efficiency of building thermal masses for commercial buildings was up to 41.61% which was considerable for practical application in the smart grid.

The simplified building thermal storage model was employed to provide effective and very simple indices of buildings for the use of grid interaction and optimization. Tests results also shown that building thermal masses, as the ubiquitous thermal storage, can be utilized to help relieving grid power imbalance caused by renewable generations or other scenarios. In order to achieve higher energy storage efficiency, high thermal resistances for the outer construction materials and low thermal resistances for the inner construction materials are recommended for new building constructions and existing building renovations.

# CHAPTER 7 A FAST CHILLER POWER DEMAND RESPONSE CONTROL STRATEGY

In order to maintain the balance between power supply and demand, extra generation capacities of power plants are usually reserved by the grid at the supply side. The possibility of providing operating reserves at power demand side (i.e., industrial and residential sectors) has been discussed and approved in previous studies. However, the alteration potential and the control strategy of large-scale power demand systems (e.g., HVAC systems) in commercial buildings are seldom studied. This chapter therefore investigates the cooling demand alternation potential of commercial buildings and estimates the power demand reduction potential of the chiller(s) aiming at providing effective power information for grid operation. On the premise of indoor thermal comfort, a fast chiller power demand response control strategy is developed based on building thermal models. Compared with conventional indoor temperature set-point reset strategy, the developed strategy can provide an accurate estimation of power demand reduction in advance, and enable a fast response fulfilling the operation requirements of the grid. Simulation tests have been conducted to estimate the potential of reserve and investigate the impact on the thermal comfort when adopting the developed strategy. Imbalance issues of chilled water flow and indoor air temperature are also investigated and solved.

Section 7.1 presents an introduction of the operating reserve in smart grid and the background of developing a fast chiller power demand response control strategy at building demand side for smart grid application. Section 7.2 presents the concept and formation of a fast chiller power demand response control strategy with addressing the demand reduction and limiting duration. Section 7.3 presents the impact of the developed limiting strategy on the water side and air side of the HVAC systems and the corresponding solutions. Section 7.4 presents the simulation test results of addressing the water deficit flow and indoor air temperature unevenness issues. A summary of this chapter is given in Section 7.5.

## 7.1 Introduction

As peak load and power imbalance are the critical issues concerned in an electrical grid, operating reserve avoiding power shortage (e.g., generator random outages, load fluctuations, etc.) becomes an essential part in power systems (Wang et al. 2005). Operating reserve can provide a certain generating capacity available to the grid within a short interval of time in order to meet demand when the normal power supply is insufficient. Operating reserve is generally composed of four types of reserves (i.e., frequency controlled, spinning, non-spinning, and replacement) classified by different time scales (i.e., seconds, minutes and hours). The cost of operating reserve is extremely high due to extra generators should be turned on during peak hours and/or imbalance periods. In addition, the cost increases dramatically when the shorter response time is required. Kirby (2013) pointed out that responsive load can be treated as spinning reserve in the electrical grid and listed the desired characteristics (e.g., storage, control capability, response speed and restoration, etc.). In order words, end-users (e.g., building sectors) at power demand side can contribute their effort in operating reserve. For instance, the industrial sectors conventionally contributed their responses to the grid by direct load control. Xu et al. (2011) proposed that the generation and demand can contributed equally to the frequency control as reserves. The test results shown that the considerable frequency controlled responses of residential sectors can be achieved by adopting temperature reset or on/off control of house appliances. Similarly, commercial buildings with air-conditioning system as the major responsive loads have significant potentials in contributing as operating reserve due to their preferred characteristics of thermal systems.

Smart grid has involved end-users (e.g., buildings) in the form of the demand response (e.g., time-based and incentive-based), which can contribute their efforts by shifting/reducing loads to help improve grid performance. Henze (2005) investigated the energy and cost benefits of adopting active and passive thermal storage in buildings under specific electricity tariff. With a certain incentive, buildings can achieve their own benefits by properly charging/discharging the thermal energy. Lee and Braun (2008) developed kinds of methods to determine indoor air temperature set-point concerning peak demand limiting. Sun et al. (2010) conducted case studies concerning on the peak demand reduction to compromise energy cost and peak demand charge using indoor air temperature set-point reset strategy. However, previous studies mainly focused on the impacts and benefits of different load control strategies from the point of view of building side, which did not consider the high requirements and huge benefits of fast demand response to the electrical grid. Due to the uncertainty and intermittence of renewable energies (e.g., wind and solar), operating reserve (especially the frequency controlled reserve responding in seconds and minutes) needs more and more participant from power demand side, particularly when a large amount of renewable generations integrated into the smart grid. Chiller, as the major energy consumer of air-conditioning system in commercial buildings, can be treated as a responsive load in frequency controlled reserve due to its considerable power demand alteration ability.

This chapter therefore aims to develop a fast chiller power demand response control strategy for enabling chiller demand as frequency controlled reserve. The simplified building energy model is employed for estimating building cooling demand, while the simplified building thermal storage model is employed for estimating chiller demand reduction and the corresponding limiting period. The demand limiting strategy is designed not only fulfilling the grid operation requirement but also considering the indoor thermal comfort. Compared with the conventional demand limiting strategy (i.e., indoor air temperature set-point reset), the developed strategy has an immediate response and relative stable power demand reduction (i.e., serving as frequency controlled reserve).

## 7.2 The Fast Chiller Power Demand Response Control Strategy

In commercial buildings, the power demand limiting measures includes passive improvement (e.g., adopting electrical equipment with high energy efficiency) and active control (e.g., shifting load within different periods, limiting demand with sacrificing convenience/comfort of end-users). In order to respond dynamically to the needs of an electrical grid in specific periods, cooling demand of commercial buildings can be shifted or limited due to thermal characteristics of building and its systems by adopting active control properly. Actually, a significant ratio of power demand is contributed by heating, ventilation and air-conditioning (HVAC) systems in commercial buildings. Specially, chiller is the major component of HVAC systems having great potential in power demand limiting control due to its large power capacity. The active control for chiller demand limiting therefore becomes very important when its demand response is designed for real time application of the electrical grid. Figure 7.1 shows a typical power demand profile of a chiller plant in a commercial building. For workdays, the chiller was requested to switch on at 8:00 a.m. for precooling down the indoor space although the office hour of building starts from 9:00 a.m. During the morning start period, a significant increment of chiller power demand appeared (from 8:40 a.m. to 9:20 a.m.) until the power demand become stable and the indoor air temperature reached the set-point (after 9:20 a.m.). In other words, a visible time delay (around 40 minutes) exits between the time of chiller power reduction (demand response) and the time of indoor air temperature variation (i.e., from the free floating status to approaching the set-point). Not only the chiller(s) but the other components in HVAC systems concerning on power demand response have a relatively long time delay which cannot fulfill the requirement of frequency controlled reserved.

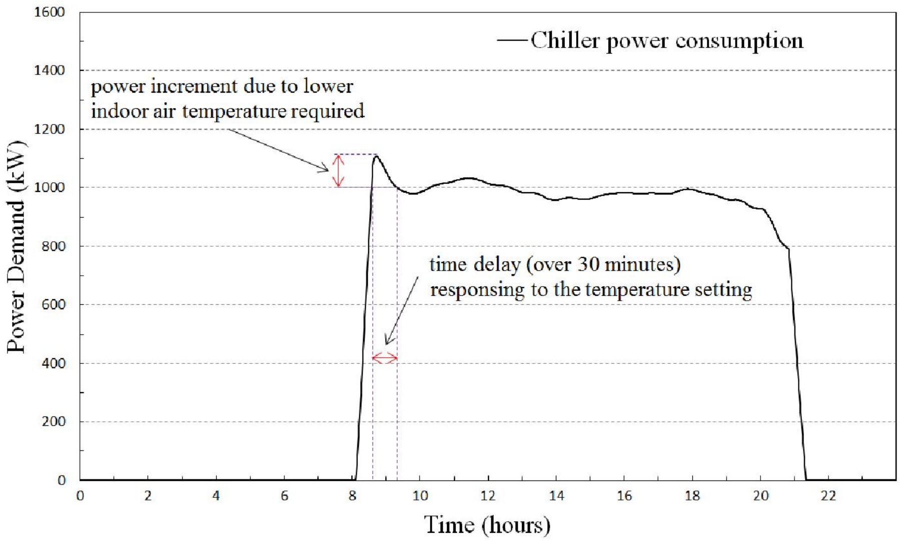



Figure 7.1 Power demand of a chiller responding to indoor air temperature setting in a real commercial building.

In this chapter, a reverse concept in active control is therefore developed for enabling a fast power demand of chiller(s) as frequency controlled reserve. The major difference between the conventional strategy (i.e., the indoor air temperature set-point reset strategy) and the reverse demand limiting strategy is the responding sequence: responding from the "cooling supply" or the "cooling demand" side. Once building receives the signal from the electrical grid (e.g., dynamic prices, direct load control signal), the conventional method is to reset indoor air temperature set-point (i.e. responding from the demand side) and result power demand reduction of chiller(s) with a certain time delay, while the reverse method is to switch off chiller(s) directly (i.e. responding from the supply side) to generate an immediate demand reduction without any delay. As shown in Figure 7.2, the chiller control panel, which can directly control the chiller(s), is responsible for receiving the signal from the electrical grid (i.e., power shortage signal) and results power demand reduction with proper estimations. The estimations include two main steps: 1) estimation of building cooling demand reduction based on indoor thermal comfort limitation (i.e., indoor air temperature upper boundary); and 2) estimation of chiller power demand reduction with calculated COP. The final estimated results will send to chiller control panel for chiller operation including on/off and duration controls when responding to the request of the grid.

It is no difficult in directly implementing on/off control of chiller(s). However, the estimation of the reduced building cooling demand and the duration of demand limiting period are very difficult. In order to ensure indoor thermal comfort and solve mentioned issues, a simplified building model is employed to estimate the original cooling demand of building and a simplified building thermal storage model is developed to estimate the additional cold energy released from building thermal masses with the increase of indoor air temperature. The variation of COP of chiller(s) and the thermal characters of HVAC systems are also considered during the power demand limiting period since they are different from the normal operation.

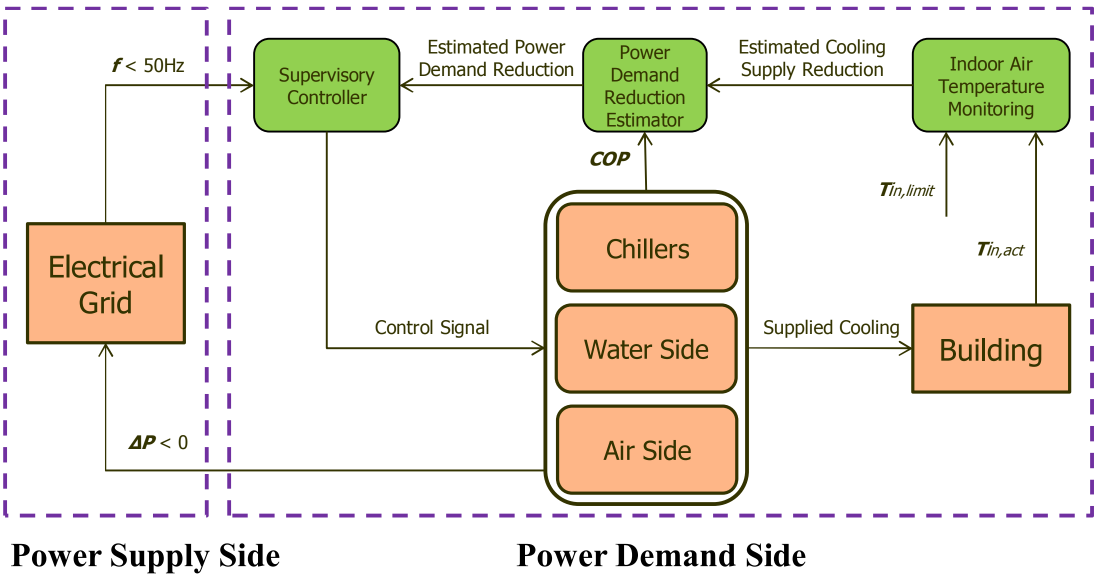



Figure 7.2 Schematic of the developed chiller demand limiting strategy.

### 7.2.1 Chiller Power Demand and Possible Reduction

*Estimation of building power demand*

On the premise of indoor thermal comfort, cooling demand of a commercial building therefore should be estimated in advance for conducting demand limiting. By considering computing time and operation data availability, a simplified building energy model (i.e., grey box model presented in Chapter 3) is employed to estimate cooling demand of a commercial building (Wang and Xu 2006). As shown in Figure 3.1, building cooling demand can be obtained by Equation (3.7) according to the energy balance.

As the cooling supplied for the building is generated by chiller(s) and delivered by the whole HVAC systems, the supplied cooling need to cover the cooling demand of building in order to main an acceptable indoor thermal comfort (e.g., a constant indoor air temperature during office hours). The supplied cooling and cooling demand should be equal in principle (i.e., $Q_{sup}=Q_{est}$). A relationship between power demand(s) of chiller(s), and supplied cooling can then be descripted as $P_{chi}= Q_{sup}/COP$. $Q_{\mathrm{sup}}$ is the supplied cooling provided by chiller(s). $Q_{est}$ is the estimated cooling demand of a building. COP is coefficient of performance of chiller. $P_{chi}$ is the estimated power demand of chiller. While the COP of chiller(s) can be obtained from catalogue or calculated by Equation (7.1) using regression method.

$$COP = a_0 PLR^4 + a_1 PLR^3 + a_2 PLR^2 + a_3 PLR + a_4 \tag{7.1}$$

where, $a_0, a_1, a_2, a_3, a_4$ are the coefficients which can be identified using historical operation data, $PLR$ is part load ratio of a chiller which is defined as $PLR=Q_{sup}/Q_{rated}$. $Q_{rated}$ is the rated cooling capacity of a chiller. It is worth mentioning that $PLR$ is normally a value between zero and one, however, $PLR$ might exceed one in some special cases when supplied cooling is more than the rated cooling capacity.

*Estimation of building power demand reduction*

In order to estimate the load-shifting capability of building thermal masses, the simplified building thermal storage model is employed for investigating the effect of load variation responding to the change of indoor air temperature. The details of the simplified thermal storage model and the estimation method were presented in Chapter 3.

### 7.2.2 Chiller Power Demand as Operating Reserves

Estimation of chiller power demand reduction is the major objective of the developed demand limiting strategy. The situation of demand limiting period in this chapter is a little different with the case in developing the building thermal storage model as present in Chapter 3 and 4 due to the indoor latent heat load decrease (i.e., the indoor air moisture increase) with insufficient cooling capacity provided by limiting power demand of chiller(s). At the same time, the indoor air temperature will vary if the supplied cooling capacity cannot maintain a constant temperature set-point. Then a relationship between supplied cooling capacity and cooling demand can be modified based on Equation (3.26) and Equation (3.27), and as shown in Equation (7.3). The trajectory of indoor air temperature can then be calculated by solving Equation (7.3) and used for estimating demand limiting period on the premise of indoor thermal comfort.

$$\Delta Q_{tot} = Q_{N.\sup} - Q_{L.\sup} \tag{7.2}$$

$$\Delta Q_{est} = \Delta Q_{la} - \Delta Q_{bui} - C_{in} \frac{dT_{in}}{dt} A_{in} \tag{7.3}$$

where, $T_{in}$ is the indoor air temperature during the demand limiting period. $C_{in}$ is the thermal capacity of the indoor air. $Q_{N.sup}$ is the cooling supply capacity provided by chillers under normal operation. $Q_{L.sup}$ is the cooling supply capacity provided by chillers in cooling supply limiting operation. $M_{in}$ is the mass of the indoor air.

During demand limiting period, $PLR$ always exceeds one due to the high return chiller water temperature and the consequent overdrawing of the rated cooling capacity. However, $PLR$ during demand limiting period can be regressed by operation data (i.e., $PLR_{avg}$=1.234 in this study). Finally, the chiller power demand reduction and the duration of demand limiting period can be summarized by Equations (7.4) and (7.5) respectively.

$$\Delta P_{chi} = \frac{Q_{N.\sup}}{COP_{N.\sup}} - \frac{Q_{L.\sup}}{COP_{L.\sup}} \tag{7.4}$$

$$t = \int_{T_{in}(0)}^{T_{in,upper}} - \frac{C_{in}A_{in}}{\Delta Q_{bui} + \Delta Q_{tot}} dT_{in} \tag{7.5}$$

where, $\Delta P_{chi}$ is the power demand reduction. $COP_{N.\sup}$ and $COP_{L.\sup}$ are the COPs of chillers under normal operation and cooling supply limiting operation respectively. $t$ is the allowed duration of demand limiting. $T_{in}(0)$ and $T_{in,upper}$ are the initial indoor air temperature and its upper limit respectively.

### 7.2.3 Results of Case Study

In this case study, simulation software TRNSYS is employed to simulate the "actual" cooling demand and associated cooling demand alteration of a commercial building and validate the developed building thermal storage model. A typical summer day with weather data of Hong Kong (i.e., subtropical weather) is adopted in the tests, as shown in Figure 7.3. The upper boundary of the indoor air temperature set-point is 25.5°C. Office hours of the commercial building are defined from 9:00 a.m. to 7:00 p.m.

Parameters of the thermal storage model for the adopted commercial building (i.e., a medium weighted building) were identified as: $C_{bui}$=263,141 J/m$^2$K, $R_{bui,o}$=0.3783 m$^2$K/W, $R_{bui,i}$=0.2303 m$^2$K/W, and the rest calculated coefficients are listed in Table 7.1.

Table 7.1 Identified parameters and coefficients of the thermal storage model for a commercial building

| Building type | $C_{bui}$ (J/m$^2$K) | $R_{bui,o}$ (m$^2$K/W) | $R_{bui,i}$ (m$^2$K/W) | $R_{bui}$ (m$^2$K/W) | $\alpha$ (-) | $\tau$ (hour) |
|---|---|---|---|---|---|---|
| Medium weighted | 263141 | 0.3783 | 0.2303 | 0.1501 | 0.8783 | 10.97 |

Table 7.2 Identified coefficients for estimating COP and PLR of chiller(s)

| Identified coefficients | $a_0$ | $a_1$ | $a_2$ | $a_3$ | $a_4$ |
|---|---|---|---|---|---|
| Value | 3.6667 | -4.5387 | -7.3603 | 12.668 | 0 |

For the relationship between the COP and PLR of chiller(s), coefficients were identified using historical operation data, as listed in Table 7.2. It is worth mentioning that, PLR exceeded one ($PLR_{avg}$=1.234) when implement chiller power demand limiting strategy during the tests. Figure 7.3 shows a comparison of the chiller power demands of normal operation and demand limiting operation. Immediate (i.e., respond in seconds) power demand reductions (average value listed here) can be achieved for the specific periods: 556 kW from 10:00 a.m. to 11:00 a.m., 771 kW from 12:00 a.m. to 3:00 p.m., 551 kW from 4:00 p.m. to 5:00 p.m. However, a significant power rebound is always followed after each power demand reduction since the limited cooling demands need to be restored for the use of next time. The total power demand of the HVAC systems (including pumps, AHU fans, chillers, etc.) was almost unchanged after adopting the chiller power demand strategy (e.g., a difference within 1%).

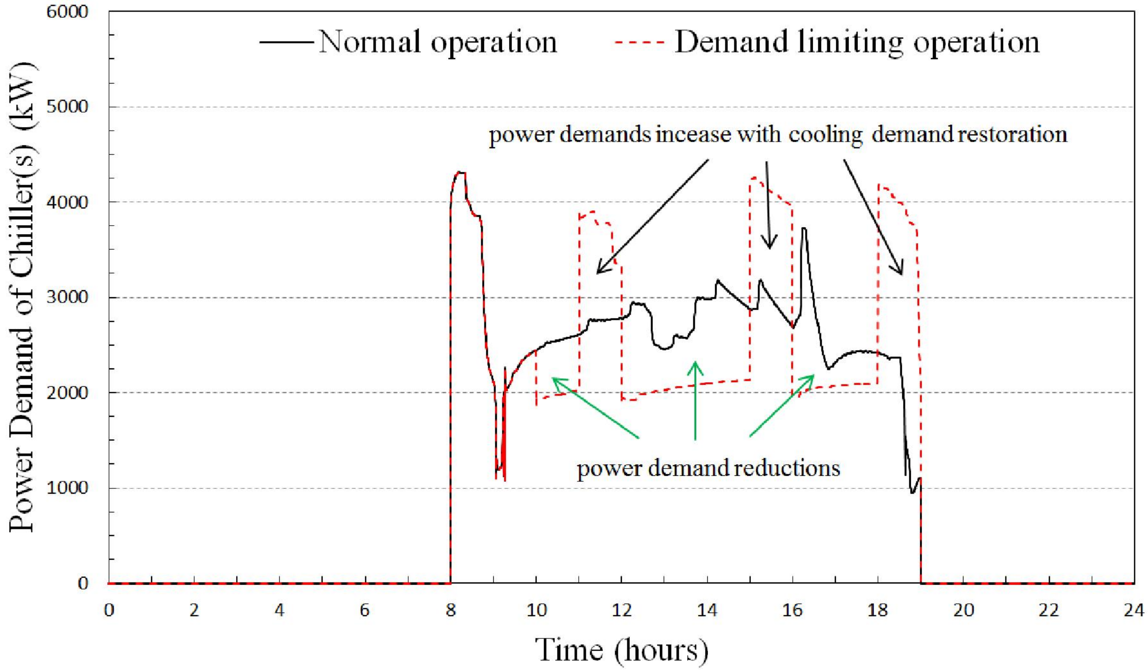



Figure 7.3 A power demand comparison of chiller(s) in normal operation and demand limiting operation.

A comparison of between "actual" and estimated power demand reductions of chiller(s) during the limiting period has also been made, as shown in of Figure 7.4. The chiller demand limiting strategy can estimate the reduction potential of chiller power demand quite well. Meanwhile, in order to estimate the demand limiting duration which is mainly based on indoor thermal comfort (i.e., only considering the constraint of indoor air temperature in this study), estimation of indoor air temperature variation is therefore the another important job in the developed chiller demand limiting strategy. Figure 7.5 shows the estimated result of indoor air temperature variation during a demand limiting period (i.e., from 12:00 a.m. to 3:00 p.m.). The chiller demand limiting strategy is also suitable for real application with acceptable accuracy compared with the "actual" indoor air temperature. As indoor thermal comfort is especially concerned in the chiller demand limiting strategy, predict mean vote (PMV) values were also monitored before and after adopting the strategy. As shown in Figure 7.6, the indoor thermal comfort level after adopting active control (i.e., demand limiting) was not affected significantly compared with that before active control.

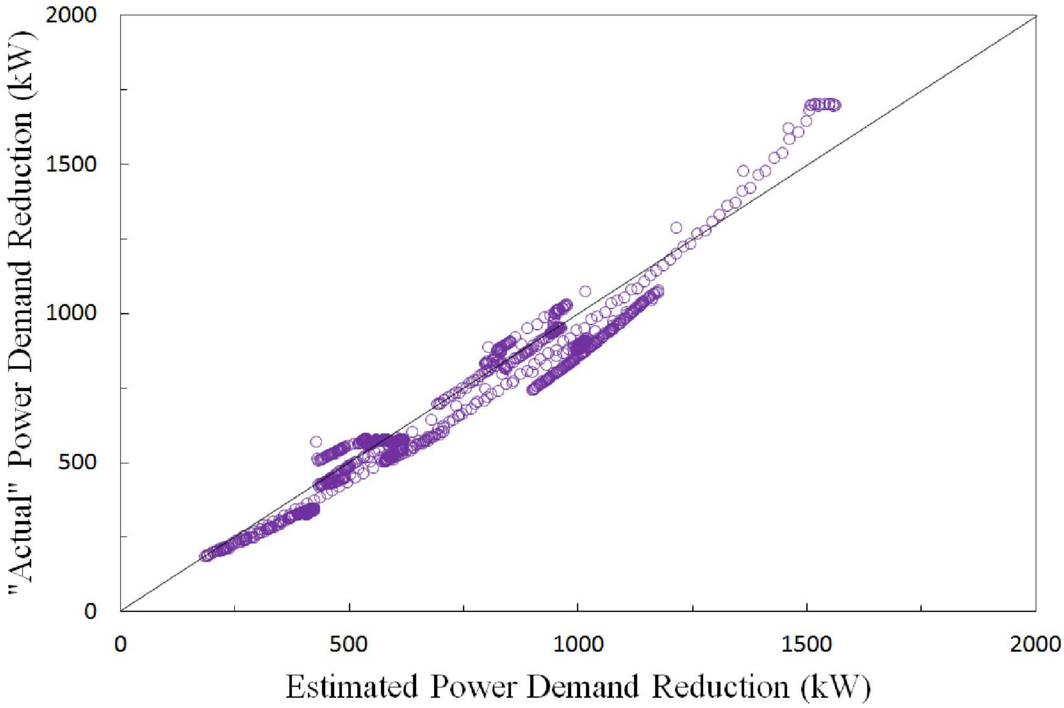



Figure 7.4 Comparisons between the "actual" and the estimated power demand reductions of chiller(s).

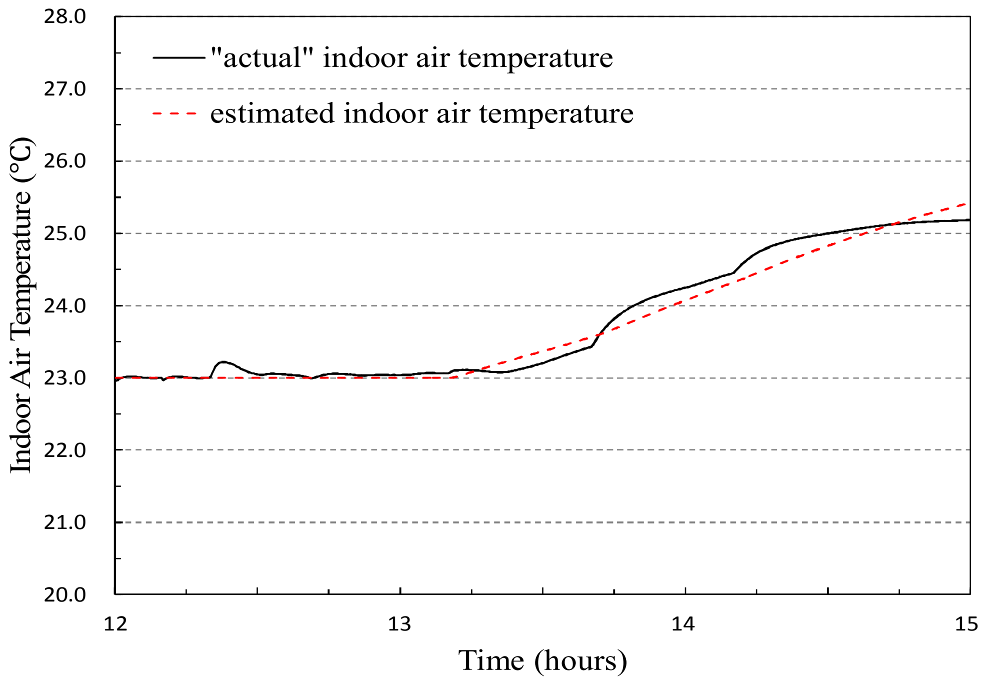



Figure 7.5 Comparisons between the "actual" and the estimated indoor air temperature variation during the demand limiting period.

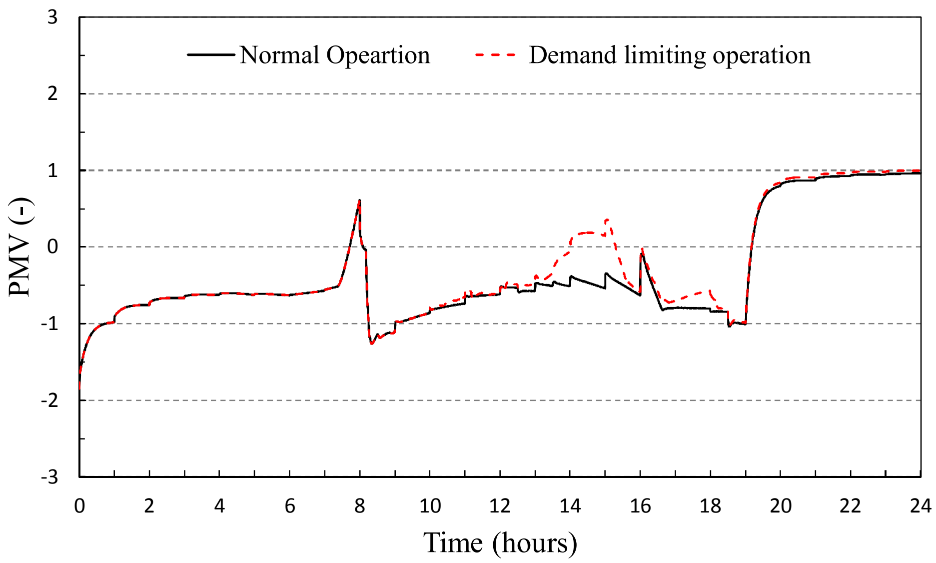



Figure 7.6 Comparison of the indoor thermal comfort (e.g., PMV) between the normal operation and demand limiting.

## 7.3 Imbalance Issues Caused by The Demand Limiting Strategy

As mentioned before, the distribution of the chilled water flowing into the air-conditioning terminals (e.g., AHUs) will be disturbed once implementing the demand limiting strategy (i.e., shutting down a certain number of the chillers).

Because the total cooling capacity provided by the central chilling systems under the demand limiting strategy is not enough compared with the normal working conditions, the air-conditioning terminals will strive for more chilled water by opening the valves in order to achieve the indoor air temperature set points. The actual indoor air temperatures of different zones (e.g., near zones and remote zones) may have big difference with each other and result different tolerances for each zone. As a result, the overall demand limiting amount and duration will be influenced by these imbalance effects.

As water deficit flow and indoor air temperature unevenness can result low performance of HVAC systems during the demand limiting period (e.g., lower pump efficiency, shorter limiting duration), the developed control strategy also includes the supplementary manners to solve these problems caused by the directly shutting down of chiller(s).

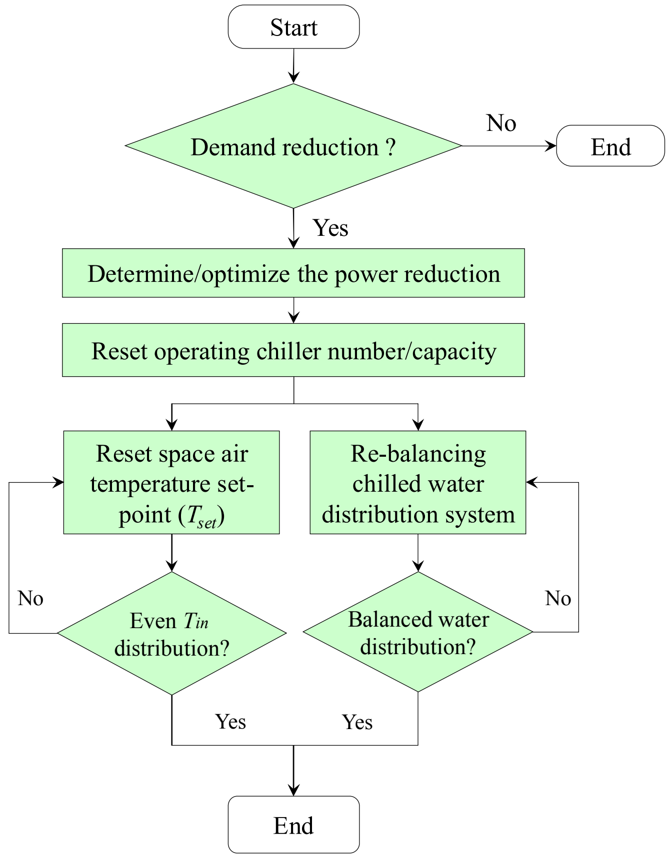



Figure 7.7 Flow chart of the fast building power demand response control strategy.

The basic idea of the fast chiller power demand response control strategy is to limit the cooling supply of chiller plants (e.g., shut off some of the operating chillers) so as to achieve immediate power reduction. The operating capacities of the other air-conditioning components will be modulated to match the limited cooling supply in a manner which will achieve stable control and evenly spread to thermal environment degradation throughout the building. Figure 7.7 shows a flow chart of the proposed fast chiller power demand response control strategy. On receiving a demand reduction request, an optimized power reduction threshold will be determined by compromising between cost benefit and comfort sacrifice. The operating chiller number/capacity is then reduced, resulting in immediate power demand reductions and reduced cooling supply. The other main task of the control strategy is to maintain stable control of the entire air-conditioning system to achieve proper cooling distribution and even indoor thermal comfort reduction.

Actually, when the chiller(s) are switched off which is activated by the demand response events, the normal operation of the whole HVAC systems will be disordered due to the abnormal sequence control of the chillers. As shown in the Figure 7.8, water deficit flow will happen due to the chiller(s) are shut down where the dedicated constant speed pump(s) are also shut down accordingly. At the same time, the secondary pumps will keep their running speed as much as possible due to the pressure difference is becoming lower in the terminals (i.e., AHUs) as they are all requesting more chilled water by their own setting during the demand response events (actually, a kind of energy valve has already been available for this scenario in practice). Then, the water deficit flow between primary pumps and secondary pumps will happen. Water deficit flow will waste a lot of pump energy which actually can be avoided by proper control (Gao et al. 2011).

Besides water deficit flow, the air temperature unevenness may be happened in different air-conditioning zones as the system resistance are different for different routes (this effect are more obviously for the direct return system compared with revised return system). As the power reduction during the demand response events are estimated and implemented based on sacrificing a certain level of the indoor thermal comfort, the indoor air temperature (i.e., dry bulb) is most important factor to indicate the indoor thermal comfort. If the air temperature unevenness happened, it means the power reduction duration has to become shorter than expected due to the indoor thermal comfort in some air-conditioning zones may exceed the preset threshold.

In order to improve the energy performance of HVAC system during the demand response events and achieve the estimated power reduction for a certain period in the practical applications, the two issues mentioned above should also be solved in the fast chiller power demand response control strategy. There for two additional strategies are developed and adopted to eliminate these negative impacts.

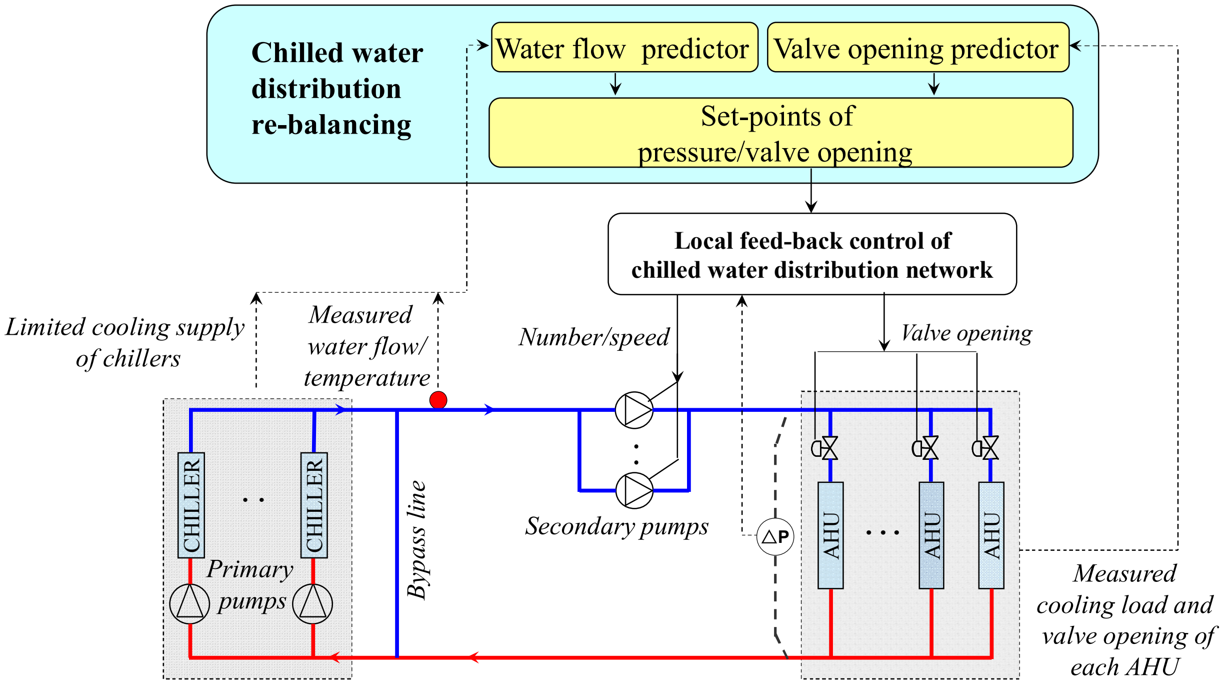



Figure 7.8 Schematic of chilled water distribution re-balancing.

Figure 7.8 shows the system control configurations of HVAC systems on water side for the operation arrangement during the demand response events. When the fast chiller power demand response control strategy is implemented during specific periods, cooling supply of chillers will be limited. On one hand, information of the supply chilled water (e.g., measured water flow rate and supply water temperature) will be measured and transferred to the water flow predictor for resetting the pressure drop set point of the chiller water loop, which indirectly decreases the operation number/speed of the secondary pumps. On the other hand, information of the demand cooling side (e.g., estimated cooling capacity of each AHU, measured chilled water flow rate, supply and return water temperature) will be predicted and collected accordingly, and then transferred to the valve opening predictor for resetting valve opening set point of each AHU. A local feed-back control of chilled water distribution network is also adopted and responsible for the information collection and local controls of the secondary pumps and AHU valves.

The chilled water distribution re-balancing measure is to ensure the proportional distribution of chilled water to individual air-handling units (AHU) with reduced cooling supply. A water flow predictor is used to predict the proper upper limit of chilled water flow corresponding to the available operating chiller capacity. Then the number/speed of operating pumps and the differential pressure set-point are reset for energy efficient operation particularly to avoid excessive water supply (i.e., the cause of water deficit flow) when chiller cooling supply is limited. In addition, when some water unbalance phenomenon occurs (e.g. over-supplies of water flow to near AHUs), additional controls will be activated interfere with the AHUs. A valve opening predictor is therefore employed to determine the proper ranges and set the limits of the valve openings of individual AHUs.

Space temperature set-point reset measure allows the air temperature set-point of the indoor spaces to be set to rise progressively while the total cooling consumed by the terminal units is controlled proximately at the pre-determined cooling capacity and keeping the same temperature rising profile in all indoor spaces (e.g., near, medium and remote zones). If the set-point increases too quickly, the preset cooling capacity is not fully used and the space comfort level cannot be maintained within expected levels for the specific period, with resulting in the failure of power limiting control (e.g., the demand response period). If the set-point rises too slowly, temperatures of some spaces cannot be maintained at the set-point and increase faster than in other spaces resulting in destructive competition and uneven distribution of cooling and eventually the breakdown of control.

### 7.3.1 Measures on The Distribution of Chilled Water Flow

In the central chilling systems, the chilled water is distributed to the terminal units by variable speed pumps (i.e., the secondary pumps) which are controlled by keeping the pressure differential between the main supply and return pipelines or the pressure differential in the critical loop (e.g., the most remote loop for the direct-return system). The pressure differential set-point can be fixed or varied according to the practical requirements. The set-point is usually recommended to adjust properly to maintain the desired supply air temperature set-points of the terminals with just one control valve in a fully open position.

Figure 7.9 and Figure 7.10 show the general structures of the speed control strategies for variable speed pumps distributing water to terminal units for direct-return and reverse-return systems respectively.

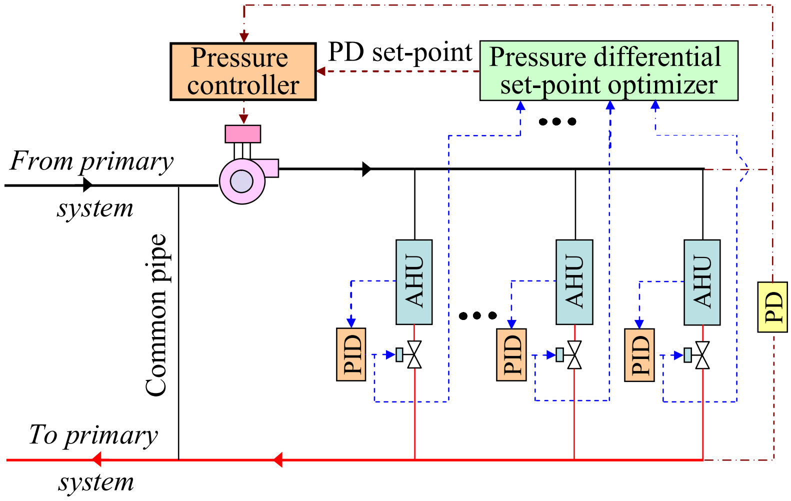


Figure 7.9 The speed control strategy for variable speed pumps distributing water to terminal units in direct-return systems (Gao 2012).

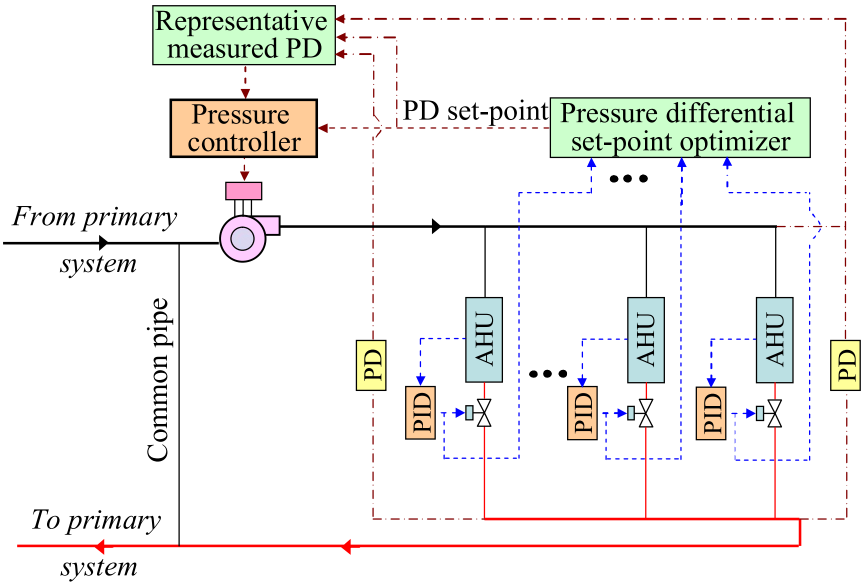


Figure 7.10 The speed control strategy for variable speed pumps distributing water to terminal units in reverse-return systems (Gao 2012).

As illustrated in the above figures, the imbalance issues of reverse-return systems are less serious than those of direct-return systems because of the similar resistances in each loop. The possible solution for the imbalance distribution of chilled water is to overwrite the original control strategies (e.g., replace the original PID settings by calculating the dedicated chilled water flow corresponding to cooling capacity reduction). The possible solutions should coordinate with the controls of the secondary pumps. For instance, the speed and number of the secondary pumps can be properly reduced when chillers are shut down under the demand limiting strategy.

### 7.3.2 Measures on The Distribution of Indoor Air Temperature

The major reason of resulting indoor air temperature unevenness is that, the indoor air temperature is free-controlled under the demand limiting strategy as pervious designed and the resulted cooling capacity reductions are not proportional as expected in different zones due to the imbalance distribution of chilled water flow. According to the principle of the demand limiting strategy, the chillers are switched off for a certain period responding to the grid emergency events, the indoor air temperature of the building can free float in the comfortable range as the estimated in advance. However, the air temperature unevenness in different zones (i.e., different trajectories of temperature rising) may still happen if no further controls implemented after carrying out the demand limiting strategy.

Besides the additional controls at water side (i.e., chilled water flow control), the possible solution for the indoor air temperature unevenness issue is that, dynamically resetting the indoor air temperature set point of each zone at same time during the demand limiting periods. The basic idea of indoor air temperature set point reset strategy is to make sure the indoor air temperatures of individual zones rise synchronously, which is convenient for accurately estimating the power reduction and its duration of the demand limiting.

## 7.4 Simulation Tests

Since validation experiments on real buildings in real smart grid is nearly impossible, computer-based simulation for validation seems the only choice. In this study, simulation software TRNSYS is employed to build a virtual to test the fast chiller power demand response control strategy. This platform will employ detailed models of the building envelope and the main components of a central air-conditioning system (e.g. chillers, pumps, air-handling units, etc.). The process of heat transfer, mass transfer, energy conversion and controls among building systems will be accurately simulated. The “actual” cooling demand/associated cooling demand alteration of a commercial building can be estimated as well. A typical summer day with weather data of Hong Kong (i.e., subtropical weather as shown in Figure 3.6) is adopted in the tests. The upper boundary of the indoor air temperature set-point is set to 26.5°C. Office hours of the commercial building are defined from 08:00 to 19:00. Three demand response periods are selected in advance for the test (i.e., 09:00 to 10:00, 12:00 to 13:00, 15:00 to 16:00). It is worth mentioning that the water network pressure drop model (Ma 2008) is employed in the simulation. The overall pressure drop of the water loop can be modelled and calculated by counting the pressure drops of the pipelines, fittings, pumps, sub-branches and AHUs, etc. respectively.

Figure 7.11 shows a comparison of the chiller power demands of normal operation and the operation adopting the fast chiller demand response strategy. The immediate response (i.e., respond within seconds) in power demand reductions (average value listed here) can be achieved for the specific periods: 4,018 kW (61.68%) from 09:00 to 10:00, 2,611 kW (32.04%) from 12:00 to 13:00, 3,112 kW (35.50%) from 15:00 to 16:00, however, the limited cooling demands need to be restored for the use of next time. Actually, the total power consumption of the HVAC systems (including pumps, AHU fans, chillers, etc.) was also saved about 5.48% after adopting the chiller power demand strategy. The fast chiller power demand response control strategy not only can give a quick and valuable power response to the grid which allows the owner achieve a significant incentive benefits in power demand, but also can save energy cost from the overall electricity consumption.

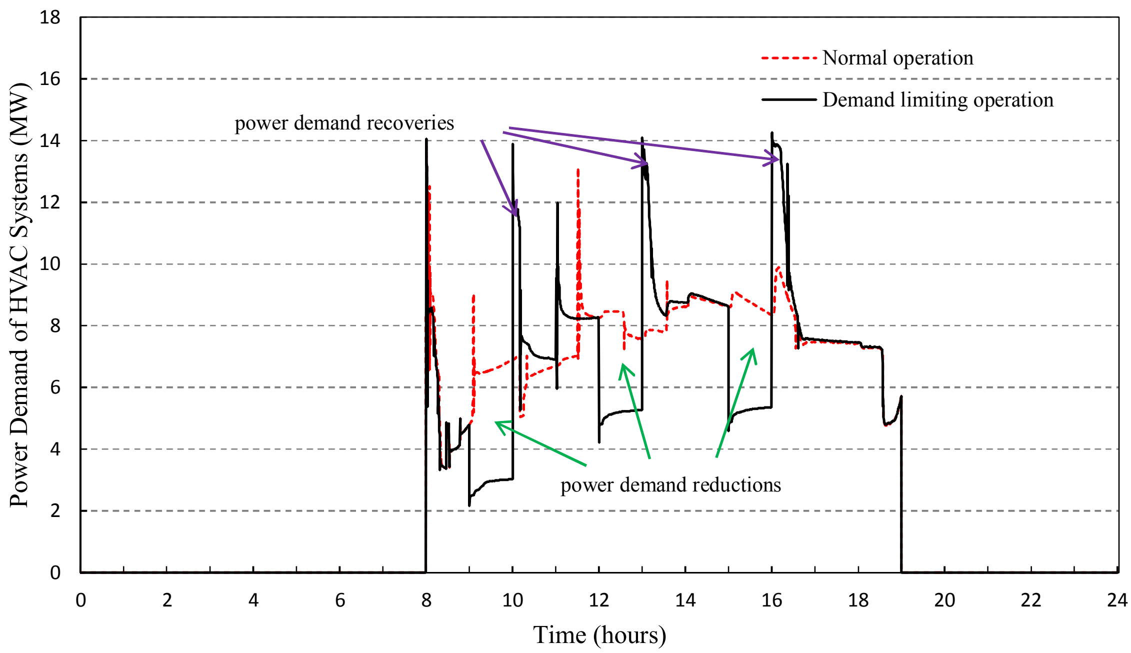



Figure 7.11 Comparison between power demands of chillers in normal operation and the demand response - Conventional controls at water and air sides.

Table 7.3 lists a comparison of power demand reductions of total six studies cases, without additional measures on water and air sides, the fast chiller demand response strategy achieve the lowest power reductions in specific periods. The additional water side control can help increase power demand reductions due to energy saving in secondary pumps. While the exponent air temperature reset strategy on air side can achieve the highest power reductions in different demand response periods due to the lower cooling capacity required by the indoor spaces. In addition, the water side control can also eliminate water deficit flows which may also cause pump energy waste. Figure 7.12 shows a comparison of water flow in bypass pipe in free control case and water side control case during the demand response events. For the free control case, water deficit flow happened in the morning demand response, however, the major energy saving resulted by water side control are mainly contributed by reducing the operation number/speeds of the secondary pumps.

Table 7.3 presents a comparison between power demand reductions of total six test cases with different options of chilled water side and air side controls after limiting the chiller cooling supply, including:

Test Case #1: conventional control, without any measures adopted at water side or air side;

Test Case #2: adopting flow limiting control of secondary pumps at water side only;

Test Case #3: adopting indoor air temperature set point reset (linear trajectory) at air side only;

Test Case #4: adopting flow limiting control of secondary pumps at water side, and indoor air temperature set point reset (linear trajectory) at air side;

Test Case #5: adopting indoor air temperature set point reset (exponent trajectory) at air side only;

Test Case #6: adopting flow limiting control of secondary pumps at water side, and indoor air temperature set point reset (exponent trajectory) at air side.

Table 7.3 Power demand reductions of HVAC systems in different studied case during the demand response periods

| Studied cases | 09:00-10:00 | 12:00-13:00 | 15:00-16:00 |
|---|---|---|---|
| **Test Case #1** | 4,018 kW | 2,611 kW | 3,112 kW |
| **Test Case #2** | 4,107 kW | 2,963 kW | 3,491 kW |
| **Test Case #3** | 4,020 kW | 2,743 kW | 3,181 kW |
| **Test Case #4** | 4,133 kW | 3,128 kW | 3,599 kW |
| **Test Case #5** | 4,227 kW | 2,967 kW | 3,415 kW |
| **Test Case #6** | 4,329 kW | 3,335 kW | 3,812 kW |

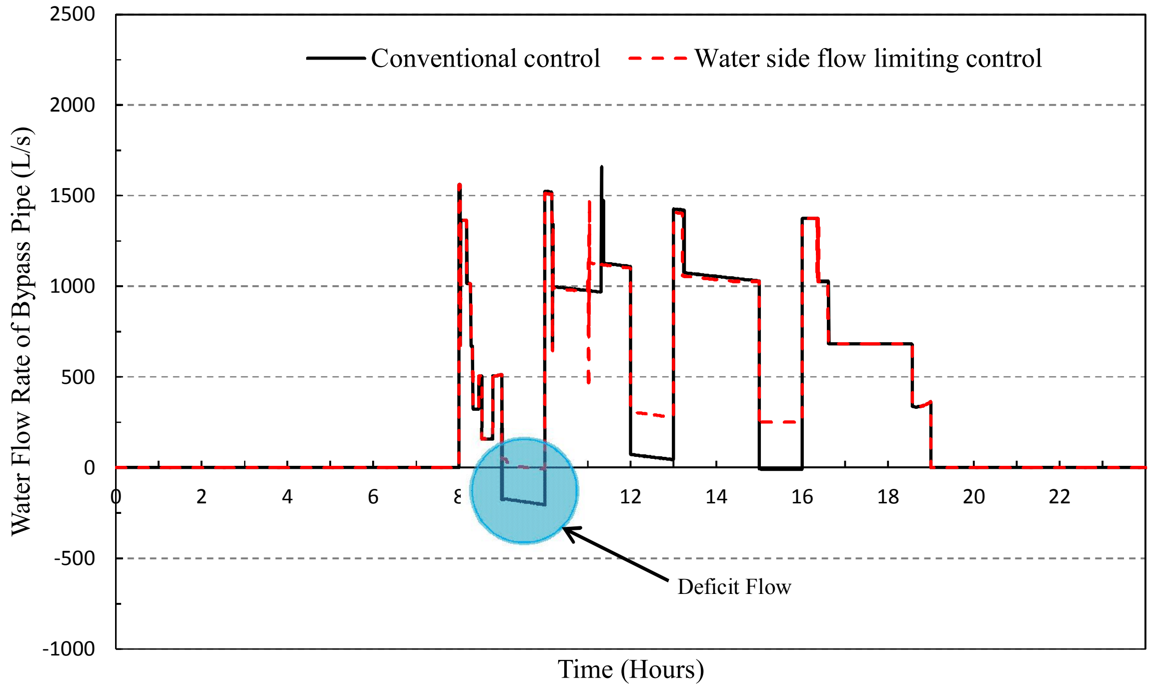
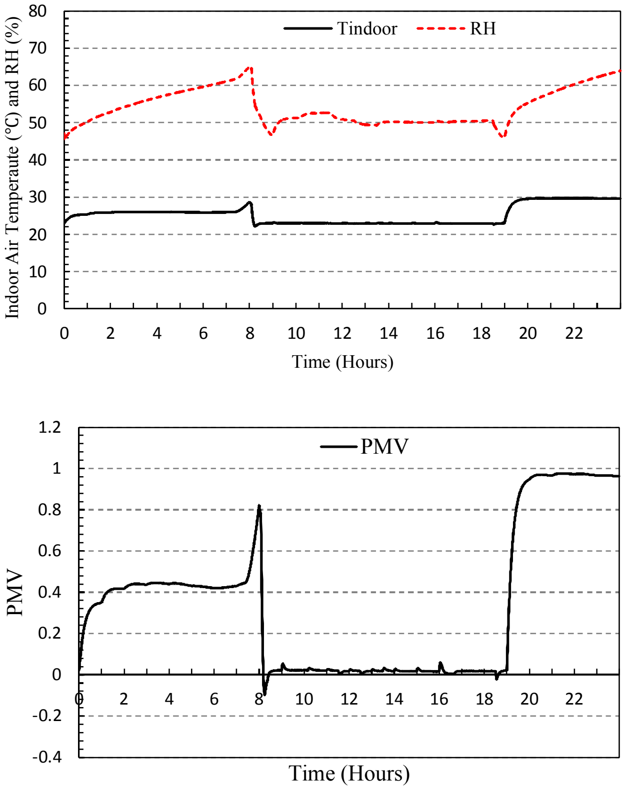
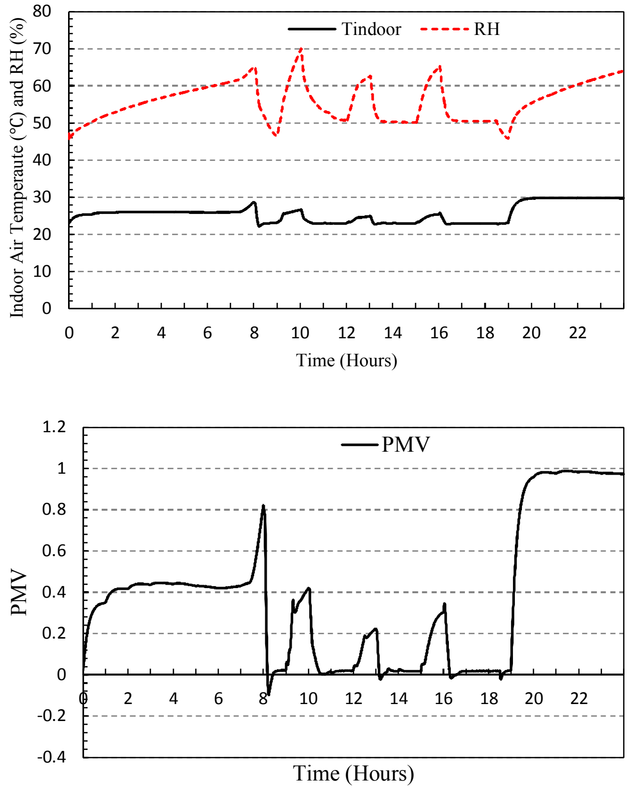



Figure 7.12 A comparison between water flows in bypass in conventional control case and water side flow limiting control case in demand response.

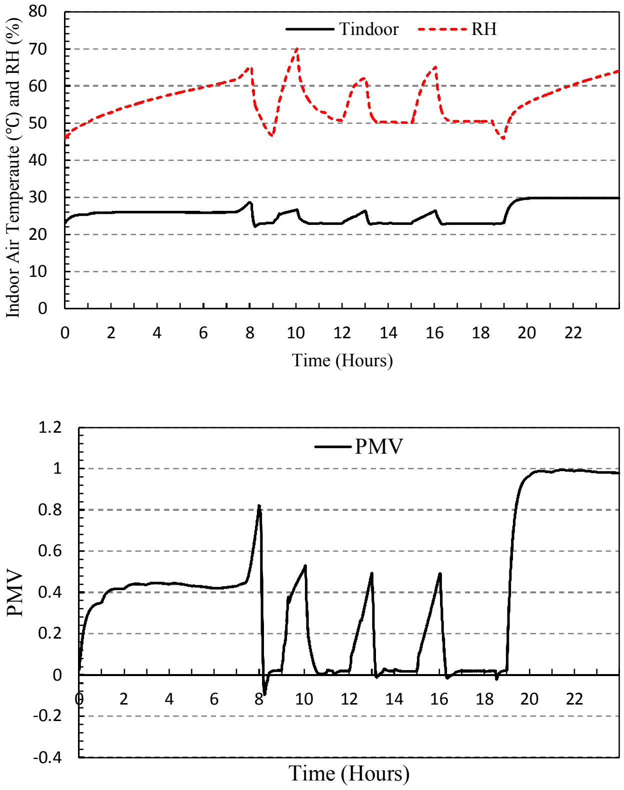
As mentioned in Section 7.2, through the fast chiller power demand response control strategy, the power demand reductions are achieved by scarifying a certain level of thermal comfort. As the indoor thermal comfort is an important factor and especially concerned by the end-users, predict mean vote (PMV) values were also monitored before and after adopting different strategies. As shown in Figure 7.13, the indoor thermal comfort level after adopting demand response control (including free control, linear and exponent air temperature set point reset) was not affected significantly (i.e., the thermal comfort still falls in the acceptable range).



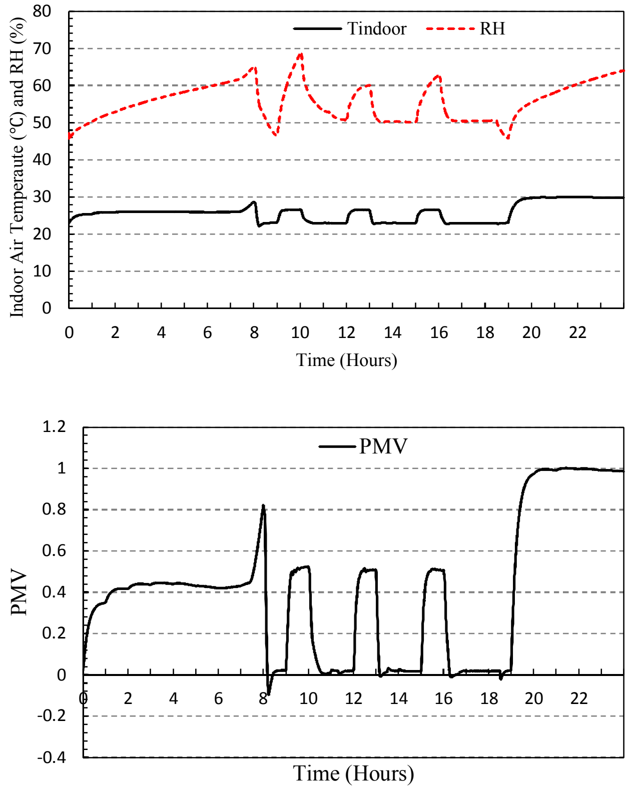

(a) normal operation




(b) demand response with conventional control




(c) demand response with
linear temperature set point reset




(d) demand response with
exponent temperature set point reset

Figure 7.13 Indoor thermal comfort comparisons in different cases.

The simulation results show that the developed fast chiller demand response control strategy can effectively respond to the requirement of grid immediately with a considerable amount of power demand reductions which are about 32.04%-66.45% of the overall power demand of HVAC systems. Such power demand reduction is significant and meaningful which can be estimated in advance and used as a kind of cost-effective operating reserve for future smart grid. The additional measures adopted on water side and air side can further save the energy of secondary pumps and eliminate the unevenness of the air temperature in different zones. Moreover, the indoor thermal comfort can be maintained in an acceptable range during the demand response periods.

## 7.5 Summary

With the development of smart grid, critical issues such as peak load and power imbalance need more efforts from power demand side (e.g., buildings). This chapter presented a fast chiller power demand response control strategy for enabling chiller demand as frequency controlled reserve, which can respond to the electrical grid rapidly compared with conventional indoor air temperature set-point reset strategy. Chiller power demand reduction and duration of the limiting period were estimated respectively based on the building thermal models. The simulation results shown that the power demand reduction of chiller(s) can be estimated with an acceptable accuracy by the developed strategy. The indoor thermal comfort level was not affect significantly when conducting the chiller demand limiting strategy. However, it is worth mentioning that, possible problems (e.g., deficit flow of chilled water and uneven temperature distribution in different air conditioned zones) may be caused due to the direct control on chiller(s) rather than the setting of indoor air temperature set-point. Possible solutions are also recommended to solve these problems.

# CHAPTER 8 CONCLUSIONS AND FUTURE WORK

In this PhD project, an interactive building energy demand management strategy was developed to enable the interaction between commercial buildings and the smart grid. A simplified building thermal storage model is developed for characterizing the power demand alteration potentials of passive buildings (i.e., with thermal masses only). Genetic algorithm-based (GA-based) method was employed to identify the model parameters. Test results shown that the GA-based method is an effective approach in identifying the model parameters, and the simplified building thermal storage model can be used to estimate the load alteration potentials of different weighted buildings with high accuracy.

The interactive building energy demand management strategy consists of four main parts: 1) the prediction of building power demand, 2) the characterization of building demand alteration potential and associated efficiency degradation, 3) the accomplishment of grid dynamic prices, and 4) the optimization of building power demand management.

A fast chiller power demand response control strategy was also developed for practical application in building HVAC systems towards smart grid. The possible power demand reduction of chiller can be treated as the operating reserves for handling smart grid emergency situations. The impact of implementing the demand limiting strategy on the thermal comfort was also concerned. The caused imbalance issues (e.g., imbalances in chilled water flow and indoor air temperature are) were considered and solved.

Besides the passive thermal storage systems, the active thermal storage systems (i.e., the chilled water storage system and the PCM storage tank) in commercial buildings are also presented for demonstrating the online and offline in smart grid. Energy and cost savings can be achieved by interacting and optimizing the power demand alteration potentials of buildings and energy information of a smart grid.

## 8.1 Conclusions

<u>*The Simplified Building Thermal Storage Model*</u>

A passive building (with its external and internal masses) can be simplified to a lumped thermal mass and assumed to be homogeneous. An equivalent temperature ($\overline{T}_{bui}$) is introduced to represent the thermal energy status of the building. The simplified 2R1C building thermal storage model consisting of two resistances ($R_{bui,\mathrm{o}}$ and $R_{bui,i}$) and one capacitance (i.e., $C_{bui}$) was employed to represent the thermal characteristics of the building. Test results show that the simplified building thermal storage model (2R1C) can accurately estimate the thermal demand alteration potentials of passive buildings. A genetic algorithm-based (GA) method is employed to identify the parameters of the simplified building thermal storage model. These parameters were identified by minimizing the deviations between the “actual” cooling load alteration of TRNSYS Type 56 building model (i.e., $\Delta Q_{act}$) and the predicted cooling load alteration of the simplified thermal storage model (i.e., $\Delta Q_{est}$). Therefore, it is suggested that parameters identification of the simplified building thermal storage model should be performed by minimizing objective function $J$ as it is simpler and gives a higher fitness. The simplified building model can well represent thermodynamic performance of different weighted building (light, medium and heavy weighted buildings which mainly defined by the physical properties of the external structures). The average errors of the simplified thermal storage model in predicting the load alteration for light, medium and heavy weighted buildings were14.40%, 4.88% and 6.37% respectively.

*The Interactive Control Strategies*

The interactive building power demand management strategy was developed for enabling the demand alteration potentials of commercial buildings to further facilitating smart grid optimization. Commercial buildings can contribute significantly and effectively in power demand management or alterations with building power demand characteristics identified properly. The simulation test results shown that the power imbalance could be significantly reduced when the effective interaction between the power supply and the demand was established. The energy storage efficiency of building thermal masses for commercial buildings was up to 41.61% which was considerable for practical application in the smart grid.

A simple dynamic electricity pricing mechanism was also developed based on the spot pricing theory. The basic idea of dynamic pricing is that the electricity prices represent the marginal costs of electricity and the power balance status, and aims to maximize the overall social benefits.

In order to maintain the balance between power supply and demand, a fast chiller power demand response control strategy was developed to treat the power demands of chillers as cost-effective operating reserves instead of extra generation capacities of power plants. Compared with conventional indoor temperature set-point reset strategy, the developed strategy can provide an accurate estimation of power demand reduction in advance, and enable a fast response fulfilling the operation requirements of the grid on the premise of indoor thermal comfort. The chiller sequence control and the control logic of the building central chilling systems have been rearranged.

With the available and mature technologies such as information and communication technologies, advanced metering infrastructure, smart meters, home energy management system and building automation systems, bidirectional connections and communication/interaction between the building end-users and the smart grid can be effectively built for the overall optimization of both power supply and demand sides. The possibility of online and offline applications of building active thermal storages for smart grid were also discussed and tested in the simulation platform.

## 8.2 Further Work

*The Simplified Building Thermal Storage Model*

The simplified building thermal storage model is suitable for estimating the heating/cooling load alteration of the passive building rather than the building heating/cooling load. Moreover, the accuracies of the model for light weighted buildings are not as good as those of the medium and heavy weighted buildings. There is a need to analyze if the simplified building thermal storage model can be improved to be suitable for lighted heavy walls.

As the development of the simplified building thermal storage model is focused on the building thermal masses only, the model may not suitable for the applications of the other thermal storages (e.g., internal walls integrated with PCM). The simplified model needs to be further adjusted when applied to the combination of the passive thermal storages and the active thermal storages.

Actually, the parameters of the simplified building thermal storage model are identified by two scenarios (i.e., the precooling control strategy and the demand limiting control strategy) under different weather condition. For future study, the model can be further improved for estimating the energy performance of both the precooling control strategy (i.e., the charging process) and the demand limiting control strategy (i.e., the discharging process).

In the simplified thermal storage model, the prediction average error of the light weighted buildings was 14.40%, which was higher than the medium and heavy weighted buildings. The main reason may be due to the conflict between the selected window-to-wall ratio (i.e., 0.5 in this study)/wall type (i.e., wall group 2 according to the ASHRAE, which has a thin thickness, low thermal resistances and low thermal capacitances) and the more simplified building thermal storage model (i.e., 2R1C model is employed to represent a whole building). However, the simplified thermal storage model is capable to predict the medium and heavy weighted buildings, as well as the lighted weighted buildings with a lower window-to-wall ratio (e.g., less than 0.5) and/or more heavy building walls (i.e., more thermal masses than wall group 2). The major application of this simplified thermal storage model can be used to represent the thermal characteristics of residential/commercial buildings (e.g., with an average building thermal masses more than 204775 J/m$^2$K). While the limitation of this simplified thermal storage model is the parameter identification. The parameters of the simplified thermal storage model need to be identified by training the operation data of at least two similar days, which have the similar external and internal conditions (e.g., solar radiation and internal gains).

*The Interactive Control Strategies*

For the interactive building power demand management strategy, the current study is mainly focused on the power demand potentials of the HVAC systems. Actually, the interactive concept for smart grid is also suitable for the other building services systems (e.g., the artificial lighting systems). In addition, this interactive management strategy can also be modified for the applications in the thermal grid (e.g., the district heating/cooling system).

The simplified building thermal storage model is very important for the interactive strategy because of the model provides effective and very simple indices of buildings for the use of grid interaction and optimization. Tests results also shown that building thermal masses, as the ubiquitous thermal storage, can be utilized to help relieving grid power imbalance caused by renewable generations or other scenarios. In order to achieve higher energy storage efficiency, high thermal resistances for the outer construction materials and low thermal resistances for the inner construction materials are recommended for new building constructions and existing building renovations. The interactive control strategy therefore can be further developed for the applications of different thermal storages in buildings.

Although the chiller demand limiting strategy proved the possibility of treating the power demands of chillers as the operating reserves especially the frequency controlled reserve for smart grid, the estimated chiller power demand reduction is not controlled at a constant value which is not convenience for grid optimization. Actually, electrical grid prefers the end-users to provide a fixed demand response (i.e., give a fixed power demand reduction during the specific period). Therefore, the chiller demand limiting strategy should be further revised especially modified to be applicable for both the passive and active thermal storages. Furthermore, the power demand restoration (resulting from the heating/cooling load restoration) should be carefully controlled after the power demand limiting period. Indoor air temperature control and the central chilled water system control can be considered for solving the restoration issue. For the water side of HVAC systems, the centralized thermal storage system and the associated control strategy can be applied for improving the performance of the chiller power demand response control strategy. For the air side of HVAC systems, the indoor air temperature set points can be optimized in the acceptable range for the needs of the power profile regulation. It is interesting and needed to study the effects and impacts of the indoor air temperature set-point trajectory. More importantly, the optimization on the indoor air temperature set-point can be used to achieve the energy/cost savings especially for online applications in smart grid.

*Air-Conditioning System With Proactive Demand Control*

The building online and offline applications for smart grid are possible thanks to the available and mature technologies including as information and communication technologies, smart meters and building automation systems. The building end-users and the smart grid can be effectively interacted and optimized with each other especially when the bidirectional connections and real time communication are established. Effective information is exchanged within the power and information flows at both power supply and demand sides.

As the power reliability and quantity are especially concerned by the smart grid (e.g., the peak load and power imbalance issues), power demand responses at demand side are suggested to be applicable for the different time scales: offline power demand response (e.g., day-ahead application) and online power demand response (e.g., hour-ahead/15 minutes-ahead). The offline power demand response is scheduled to improve the grid load factor in the coming daily operation (i.e., the coarse tuning), while the online power demand response is used to improve the grid reliability and quality by treating the power demands as the transient "operating reserves" (i.e., the fine tuning) and serving for emergency events. This chapter respectively introduces the offline and online applications of the active thermal storage systems in commercial buildings. The energy performance of the systems and the practical effects of the demand responses will also be investigated.

*PCMs Storage System for Smart Grid Application*

Spinning reserves, as important parts of the ancillary services, are designed to maintain the electric grid stability in response to system shocks such as generation and transmission outage. They are typically required to respond within a minute of notification and ramp up to deliver the full resource within 10 minutes (Josh et al. 2012). Demand response resources (DRRs) can provide a lower cost alternative to spinning reserves. Loads with control devices can also respond more quickly than most generation facilities and ramp up to full capacity in usually less than 5 minutes. Some Regional Transmission Operators (RTOs), such as PJM, NYISO, ISO-NE, Midwest ISO et al, have already allowed DRRs to participate in the energy and ancillary service markets. Midwest ISO divides the responsive loads into two categories: Type-1 DRR and Type-2 DRR.

Actually, HVAC loads can be the ideal suppliers of spinning reserves. As a kind of DRRs, the HVAC loads are capable of suffering numerous, short and infrequent curtailments. These responsive loads do not have the constraints of the traditional generators (e.g., ramping time, minimum on/off time, etc.). The required load curtailment is usually instantaneous, while traditional power generation needs a relatively long time (e.g., 10 minutes) to fully respond the grid (Kirby et al. 2008). Several programs have demonstrated how to use the existing HVAC load as DRRs to provide spinning reserves. The control of HVAC load can quickly respond to the grid curtailment request, and result little impact on customers at the same time. These programs encourage the customers to provide spinning reserve services (i.e., the load curtailment of HVAC systems) by providing incentives (Eto et al. 2007).

An optimal control strategy of HVAC systems aiming to provide spinning reserve services by comprehensively utilizing building passive and active storages can be further developed for the smart grid application. On the premise of shutting a certain number of chillers down, the power demand-shifting and demand-shedding potentials of buildings with the cold storages have been also investigated. Compared with conventional passive-only and active storage control strategies, the developed strategy can provide a fast and stable power demand reduction once receive the curtailment notification from a RTO company.

The Midwest Independent System Operator (MISO) defines two types of DRR:

Type-1 DRR and Type-2 DRR (Chen and Li 2011). The type-1 DRR can be defined as supplying energy with a fixed target reduction at MW level when committed, or to provide spinning or supplemental reserves when not committed. Type-1 DRRs are mainly the interruptible loads, which can be qualified as spinning reserves. The customers will receive credits or debits from MISO for their power demand reduction which is specified in the previous service agreement. The duration of spinning reserves provided by DRRs is required to be 2 hours and the full response time is required less than 10 minutes.

In order to respond dynamically and rapidly to the curtailment notification from MISO, the cooling demand of commercial buildings has to be shifted and shed accordingly due to the thermal characteristics of building and its storage systems. Chiller(s), as the major component in HVAC systems taking a large amount of power demand, can be shut down once the buildings receive the curtailment notification from the grid. The active storage system can then be activated in order to keep a fixed power demand reduction, and make sure the building indoor temperature rising on the range of indoor thermal comfort.

Extra energy is usually needed after the DR events in order to bring the building and its systems back to normal conditions. The post DR event spike in demand is generally known as "rebound". To eliminate the negative effects on the electric grid, rebound avoidance should be considered. The developed strategy allows the HVAC systems to slowly ramp up, and limits the power demand rising after the DR event. The method for estimation of cooling demand reduction and power demand reduction after switching off chiller(s) without employing the active storage system has been developed by Xue et al. (2013). However, the profile of the power reduction amount can be changed by utilizing the controllability of active storage (e.g., by adjusting the discharge flow rate of PCM tank in this study). Furthermore, the use of active storage system can obviously increase the amount of power demand reduction and extend the dedicated DR duration.

# APPENDIX A MATLAB M. FILE CODE FOR THERMAL COMFORT ESTIMATION

```
function [PMV,PPD]=ThermalComfort (CLO,TA,TR,MET,VEL,RH)
% Choose "Tools-Macro-Security-Mean".
% This version is scanned with Symantec Antivirus Definition File 2005-09-15 rev.23
% Modified by Håkan Nilsson
% Department of Technology and Built Environment
% Laboratory of Ventilation and Air Quality
% University of Gävle
% Re-coded in m.file by Xue Xue
% ***************Input Parameters****************
% CLO=1.10; % variable, clothing (Closing, clo, range in [0, 2])
% TA=24.0; % variable, indoor air temperature (Celsius, C, range in [10, 30])
% TA=Tin(i);
% TR=22.0; % variable, mean radiation temperature Celsius, C, range in [10, 40])
% MET=1.0; % variable, activity (Metabolic, met, range in [0.8, 4])
% VEL= 0.15; % variable, air velocity (m/s, range in [0, 1])
% RH=50.0; % variable, relative humidity (%, range in [30, 70])
% RH=55.0; % variable, relative humidity (%, range in [30, 70]), recommend RH value is 55.0
% ***************Calculation Processes***************
FNPS=exp (16.6536-4030.183/(TA+235));
```

```
PA=RH*10*FNPS;
ICL=0.155*CLO;
M=MET*58.15;
if (ICL<0.078)
        FCL=1+1.29*ICL;
else
        FCL=1.05+0.645*ICL;
end
HCF=12.1*VEL^0.5;
TAA=TA+273.15;
TRA=TR+273.15;
TCLA=TAA+(35.5-TA)/(3.5*(6.45*ICL+0.1));
P1=ICL*FCL;
P2=P1*3.96;
P3=P1*100;
P4=P1*TAA;
P5=308.7-0.028*M+P2*(TRA/100)^4;
XN=TCLA/100;
XF=TCLA/50;
%    XF = XN
N=0;
EPS=0.0015;
while (abs(XN-XF)>EPS)
```

```
    XF=(XF+XN)/2;
    HCF=12.1*VEL^0.5;
    HCN=2.38*abs(100*XF-TAA)^0.25;
    if (HCF>HCN)
        HC=HCF;
    else
        HC=HCN;
    end
    XN=(P5+P4*HC-P2*(XF^4))/(100+P3*HC);
    N=N+1;
end
TCL=100*XN-273.15;
% skin diff loss
HL1=3.05*0.001*(5733-6.99*M-PA);
% sweat loss
if (M>58.15)
    HL2=0.42*(M-58.15);
else
    HL2=0;
end
% latent respiration loss
HL3=1.7*0.00001*M*(5867-PA);
% dry respiration loss
```

```
HL4=0.0014*M*(34-TA);
% radiation loss
HL5=3.96*FCL*(XN^4-(TRA/100)^4);
% convection loss
HL6=FCL*HC*(TCL-TA);
% thermal sensation to skin tran coef
TS=0.303*exp(-0.036*M)+0.028;
if (VEL<0.2)
    TPO=0.5*TA+0.5*TR;
else
    if (VEL<0.6)
        TPO=0.6*TA+0.4*TR;
    else
        TPO=0.7*TA+0.3*TR;
    end
end
% ***************Output Results***************
PMV=TS*(M-HL1-HL2-HL3-HL4-HL5-HL6); % output, thermal comfort index (Predicted Mean Vote, PMV, -)
PPD=100-95*exp(-0.03353*PMV^4-0.2179*PMV^2); % output, thermal comfort index (Predicted Percentage Dissatisfied, PPD, %)
```

# REFERENCES


Abdelaziz, E.A., R. Saidur, and S. Mekhilef. 2011. A review on energy saving strategies in industrial sector. Renewable and Sustainable Energy Reviews 15(1):150-168.

Albadi, M.H., and E.F. El-Saadany. 2008. A summary of demand response in electricity markets. Electric Power Systems Research 78(11):1989-1996.

Alfares, H.K., and M. Nazeeruddin. 2002. Electric load forecasting: Literature survey and classification of methods. International Journal of Systems Science 33(1):23-34.

Al-Hamadi, H.M., and S.A. Soliman. 2004. Short-term electric load forecasting based on Kalman filtering algorithm with moving window weather and load model. Electric Power Systems Research 68(1):47-59.

Al-Hamadi, H.M., and S.A. Soliman. 2005. Long-term/mid-term electric load forecasting based on short-term correlation and annual growth. Electric Power Systems Research 74(3):353-361.

AlRashidi, M.R., and K.M. EL-Naggara. 2010. Long term electric load forecasting based on particle swarm optimization. Applied Energy 87(1):320-326.

Alsayegh, O., S. Alhajraf, and H. Albusairi. 2010. Grid-connected renewable energy source systems: Challenges and proposed management schemes. Energy Conversion and Management 51(8):1690-1693.

Amjady, N., and F. Keynia. 2008. Mid-term load forecasting of power systems by a new prediction method. Energy Conversion and Management 49(10):2678-2687.

Amjady, N., and F. Keynia. 2009. Short-term load forecasting of power systems by combination of wavelet transform and neuro-evolutionary algorithm. Energy 34(1):46-57.

Andrews, C.J., and U. Krogmann. 2009. Technology diffusion and energy intensity in US commercial buildings. Energy Policy 37(2):541-553.

Antonopoulos, K.A., and E. Koronaki. 1998. Apparent and effective thermal capacitance of buildings. Energy 23(3):183-192.

Antonopoulos, K.A., and E. Koronaki. 1999. Envelope and indoor thermal capacitance of buildings. Applied Thermal Engineering 19(7):743-756.

Antonopoulos, K.A., and E. P. Koronaki. 2000. Effect of indoor mass on the time constant and thermal delay of buildings. International Journal of Energy Research 24(5):391-402.

Aquino-Lugo, A.A., R. Klump, and T.J. Overbye. 2011. A Control Framework for the Smart Grid for Voltage Support Using Agent-Based Technologies. IEEE Transactions on Smart Grid 2(1):173-180.

Arnulf, J.W., S. Márta, S. Nicolae, and M.F. Fabio. 2011. Renewable electricity in Europe. Renewable and Sustainable Energy Reviews 15(8):3703-3716.

Arteconi, A., N.J. Hewitt, and F. Polonara. 2012. State of the art of thermal storage for demand-side management. Applied Energy 93:371-389.

Arteconi, A., N.J. Hewitt and F. Polonara. 2013. Domestic demand-side management (DSM): Role of heat pumps and thermal energy storage (TES) systems. Applied Thermal Engineering. 51(1-2):155-165.

Ashok, S. 2006. Peak-load management in steel plants. Applied Energy

83(5):413-424.

Ashok, S., and R. Banerjee. 2000. Load-management applications for the industrial sector. Applied Energy. 66(2):105-111.

Athanasios, A.D., B. Markus, D. Javier, F. Giulia, G. Sabine, G. Edgard, G. Giorgio, K. Avraam, P. Luis, P. Irene, and R. Michela. 2011. Methods and tools to evaluate the availability of renewable energy sources. Renewable and Sustainable Energy Reviews 15(2):1182-1200.

Aung, Z., M. Toukhy, J. Williams, A. Sanchez, and S. Herrero. 2012. Towards Accurate Electricity Load Forecasting in Smart Grids. DBKDA 2012 : The Fourth International Conference on Advances in Databases, Knowledge, and Data Applications. page:51-57.

Aung, Z., M. Toukhy, J.R. Williams, A. Sanchez, and S. Herrero. 2011. Towards accurate electricity load forecasting in smart grids. DBKDA 2012: The Fourth International Conference on Advances in Databases, Knowledge, and Data Applications. ISBN: 978-1-61208-185-4. page:51-57.

Avci, M., M. Erkoc, A. Rahmani, and S. Asfour. 2013. Model predictive HVAC load control in buildings using real-time electricity pricing. Energy and Buildings 60:199-209.

Ayompe, L.M., and A. Duffy. 2013. Feed-in tariff design for domestic scale grid-connected PV systems using high resolution household electricity demand data. Energy Policy 61:619-627.

Baetens, R., B.P. Jelle, and A. Gustavsen. 2010. Properties, requirements and possibilities of smart windows for dynamic daylight and solar energy control in buildings: A state-of-the-art review. Solar Energy Materials and Solar Cells 94(2):87-105.

Bailey, M. 1998. Provision of frequency responsive power reserve from disconnectable load. IEE Colloquium on Economic Provision Of A Frequency Responsive Power Reserve Service (98/190). page:1-5.

Baladi, S.M., J.A. Herriges, and T.J. Sweeney. 1998. Residential response to voluntary time-of-use electricity rates. Resource and Energy Economics 20(3):225-244.

Balaras, C.A., A.G. Gaglia, E. Georgopoulou, S. Mirasgedis, Y. Sarafidis, and D.P. Lalas. 2007. European residential buildings and empirical assessment of the Hellenic building stock, energy consumption, emissions and potential energy savings. Building and Environment 42(3):1298-1314.

Ban, M., G. Krajačić, M. Grozdek, T. Ćurko, and N. Duić. 2012. The role of cool thermal energy storage (CTES) in the integration of renewable energy sources (RES) and peak load reduction. Energy 48(1):108-117.

Batista, N.C., R. Melício, J.C.O. Matias, and J.P.S. Catalão. 2013. Photovoltaic and wind energy systems monitoring and building/home energy management using ZigBee devices within a smart grid. Energy 49:306-315.

Bazmi, A.A., and G. Zahedi. 2011. Sustainable energy systems: Role of optimization modeling techniques in power generation and supply-A review. Renewable and Sustainable Energy Reviews 15(8): 3480-3500.

Beaudin, M., H. Zareipour, A. Schellenberglabe, and W. Rosehart. 2010. Energy storage for mitigating the variability of renewable electricity sources: An updated review. Energy for Sustainable Development 14(4):302-314.

Behl, M., T.X. Nghiem, and R. Mangharam. 2012. Green Scheduling for Energy-Efficient Operation of Multiple Chiller Plants. TSS '12 Proceedings of the 2012 IEEE 33rd Real-Time Systems Symposium. page:195-204.

Berredo, R.C., P.Ya. Ekel, J.S.C. Martini, R.M. Palhares, R.O. Parreiras, and J.G. Pereira Jr. 2011. Decision making in fuzzy environment and multicriteria power engineering problems. International Journal of Electrical Power & Energy Systems 33(3):623-632.

Bianchi, M., A. De Pascale, and F. Melino. 2013. Performance analysis of an integrated CHP system with thermal and Electric Energy Storage for residential application. Applied Energy http://dx.doi.org/10.1016/j.apenergy.2013.01.088.

Boehm, R.F. 2012. An approach to decreasing the peak electrical demand in residences. Energy Procedia 14:337-342.

Boonnasa, S., and P. Namprakai. 2010. The chilled water storage analysis for a university building cooling system. Applied Thermal Engineering 30(11-12):1396-1408.

Borg, S.P., and N.J. Kelly. 2011. The effect of appliance energy efficiency improvements on domestic electric loads in European households. Energy and Buildings 43(9):2240-2250.

Bouhouras, A.S., G.T. Andreou, and D.P. Labridis. 2010. Feasibility study of the implementation of A.I. automation techniques in modern power distribution networks. Electric Power Systems Research 80(5):495-505.

Braun, J.E. 2003. Load control using building thermal mass. Journal of Solar Energy Engineering 125:292-301.

Braun, J.E., and N. Chaturvedi. 2002. An Inverse Gray-Box Model for Transient Building Load Prediction. HVAC&R Research 8(1):73-99.

Braun, J.E., K.W. Montgomery, and N. Chaturvedi. 2001. Evaluating the Performance of Building Thermal Mass Control Strategies. HVAC&R Research 7(4):403-428.

Brazier, F.M.T., F. Cornelissen, R. Gustavsson, C. M. Jonker, O. Lindeberg, B. Polak, and J. Treur. 2002. A multi-agent system performing one-to-many negotiation for load balancing of electricity use. Electronic Commerce Research and Applications 1(2):208-224.

Broeer, T., J. Fuller, F. Tuffner, D. Chassin, and N. Djilali. 2014. Modeling framework and validation of a smart grid and demand response system for wind power integration. Applied Energy 113:199-207.

California Energy Commission. 2003. Integration of Distributed Energy Resources: The CERTS MicroGrid Concept. http://certs.lbl.gov/pdf/50829-app.pdf.

Cao, S.L., A. Hasan, and K. Sirén. 2014. Matching analysis for on-site hybrid renewable energy systems of office buildings with extended indices. Applied Energy 113:230-247.

Cappers, P., C. Goldman, and D. Kathan. 2010. Demand response in U.S. electricity markets: Empirical evidence. Energy 35(4):1526-1535.

Castillo-Cagigal, M., E. Caamaño-Martín, E. Matallanas, D. Masa-Bote, A. Gutiérrez, F. Monasterio-Huelin, and J. Jiménez-Leube. 2011. PV self-consumption optimization with storage and Active DSM for the residential sector. Solar Energy 85(9):2338-2348.

Chakrabortty, A. 2012. Control and optimization methods for electric smart grids. Vol.

3. Springer.

Chan, Z.S.H., H.W. Ngan, A.B. Rad, A.K. David, and N. Kasabov. 2006. Short-term ANN load forecasting from limited data using generalization learning strategies. Neurocomputing 70(1-3):409-419.

Charles River Associates. 2005. Primer on Demand-Side Management: With an Emphasis on Price-Responsive Programs. http://siteresources.worldbank.org/INTENERGY/Resources/PrimeronDemand-SideManagement.pdf.

Chen, T.Y. 2001. Real-time predictive supervisory operation of building thermal systems with thermal mass. Energy and Buildings 33(2):141-150.

Chen, X.P., Y.D. Wang, H.D. Yu, D.W. Wu, Y.P Li, and A.P. Roskilly. 2012. A domestic CHP system with hybrid electrical energy storage. Energy and Buildings 55:361-368.

Chen, Y.H., and J. Li. 2011. Comparison of security constrained economic dispatch formulations to incorporate reliability standards on demand response resources into Midwest ISO co-optimized energy and ancillary service market. Electricity Power Systems Research 81:1786-1795.

Chua, K.J., W.M. Yang, T.Z. Wong, and C.A. Ho. 2012. Integrating renewable energy technologies to support building trigeneration - A multi-criteria analysis. Renewable Energy 41:358-367.

Cleveland, F. 2007. Enhancing the reliability and security of the information infrastructure used to manage the power system. Proceedings of IEEE Power Engineering Society General Meeting. 24-28 June 2007. Cleveland, Frances.

DOI: 10.1109/PES.2007.386013. pages:1-8.

Cui, J.T., and S.W. Wang. 2005. A model-based online fault detection and diagnosis strategy for centrifugal chiller systems. International Journal of Thermal Sciences 44(10):986-999.

Dalton, G.J., D.A. Lockington, and T.E. Baldock. 2009. Feasibility analysis of renewable energy supply options for a grid-connected large hotel. Renewable Energy 34(4):955-964.

Darby, S.J., and E. McKenna. 2012. Social implications of residential demand response in cool temperate climates. Energy Policy 49:759-769.

Dave, S., M. Sooriyabandara, and M. Yearworth. 2013. System behaviour modelling for demand response provision in a smart grid. Energy Policy 61:172-181.

DeGroff, D. 2010. Green Environment: Decision-Making and Power Utility Optimization towards Smart-Grid Options. Smart Grid and Renewable Energy 1:32-39.

Depuru, S.S.S.R., L.F. Wang, and V. Devabhaktuni. 2011. Smart meters for power grid: Challenges, issues, advantages and status. Renewable and Sustainable Energy Reviews 15(6):2736-2742.

Deshmukh, M.K., and S.S. Deshmukh. 2008. Modeling of hybrid renewable energy systems. Renewable and Sustainable Energy Reviews 12(1):235-249.

Diaconu, B.M. 2011. Thermal energy savings in buildings with PCM-enhanced envelope: Influence of occupancy pattern and ventilation. Energy and Buildings 43(1):101-107.

Dlamini, N.G., and F.Cromieres. 2012. Implementing peak load reduction algorithms for household electrical appliances. Energy Policy 44:280-290.

Doostizadeh, M., and H. Ghasemi. 2012. A day-ahead electricity pricing model based on smart metering and demand-side management. Energy 46(1):221-230.

Drees, K.H., and J.E. Braun. 1996. Development and Evaluation of a Rule-Based Control Strategy for Ice Storage Systems. HVAC&R Research 2(4):312-334.

Druitt, J., and W.G. Früh. 2012. Simulation of demand management and grid balancing with electric vehicles. Journal of Power Sources 216:104-116.

Du, P.W., and N. Lu. 2011. Appliance Commitment for Household Load Scheduling. IEEE Transactions on Smart Grid 2(2):411-419.

Dussault, J.M., L. Gosselin, and T. Galstian. 2012. Integration of smart windows into building design for reduction of yearly overall energy consumption and peak loads. Solar Energy 86(11):3405-3416.

Earle, R., E.P. Kahn, and E. Macan. 2009. Measuring the Capacity Impacts of Demand Response. The Electricity Journal 22(6):47-58.

Electric Power Research Institute (EPRI). 1985. Commercial cold storage design guide. Technical report.

Electrical and Mechanical Services Department of Hong Kong. 2012. Hong Kong Energy End-use Data. www.emsd.gov.hk/emsd/e_download/pee/HKEEUD2012.pdf.

El-Ferik, S., S.A. Hussain, and F.M. Al-Sunni. 2006. Identification and weather sensitivity of physically based model of residential air-conditioners for direct load control: A case study. Energy and Buildings 38(8):997-1005.

EN ISO 7730. 2005. Ergonomics of the thermal environment - analytical determination and interpretation of thermal comfort using calculation of the PMV and PPD indices and local thermal comfort criteria, CEN (European Committee for Standardization).

Ericson, T. 2009. Direct load control of residential water heaters. Energy Policy 37(9):3502-3512.

Erol-Kantarci, M., and H.T. Mouftah. 2011. Wireless Sensor Networks for Cost-Efficient Residential Energy Management in the Smart Grid. IEEE Transactions on Smart Grid 2(2):314-325.

Escrivá-Escrivá, G. 2011. Basic actions to improve energy efficiency in commercial buildings in operation. Energy and Buildings 43(11):3106-3111.

Eto, J.H., J. Nelson-Hoffman, C. Torres, S. Hirth, B. Yinger, J. Kueck, B. Kirby, C. Bernier, R. Wright, A. Barat, and D.S. Watson. 2007. Demand response spinning reserve demonstration. Lawrence Berkeley National Laboratory. LBNL-62761.

European Commission. 2006. Vision and strategy for Europe’s electricity networks of the future. www.smartgrids.eu/documents/vision.pdf.

Eyer, J., and G. Corey. 2010. Energy Storage for the Electricity Grid: Benefits and Market Potential Assessment Guide. http://prod.sandia.gov/techlib/access-control.cgi/2010/100815.pdf.

Fan, S., and R.J. Hyndman. 2011. The price elasticity of electricity demand in South Australia. Energy Policy 39(6):3709-3719.

Fanger, P. O. 1970. Thermal Comfort. Danish Technical Press (Republished by McGraw-Hill, New York, 1973).

Faria, P., and Z. Vale. 2011. Demand response in electrical energy supply: An optimal real time pricing approach. Energy 36(8):5374-5384.

Faruqui, A., D. Harris, and R. Hledik. 2010. Unlocking the €53 billion savings from smart meters in the EU: How increasing the adoption of dynamic tariffs could make or break the EU's smart grid investment. Energy Policy 38(10):6222-6231.

Finn, P., C. Fitzpatrick, and D. Connolly. 2012. Demand side management of electric car charging: Benefits for consumer and grid. Energy 42(1):358-363.

Finn, P., M. O'Connell, and C. Fitzpatrick. 2013. Demand side management of a domestic dishwasher: Wind energy gains, financial savings and peak-time load reduction. Applied Energy 101:678-685.

Fitzgerald, N., A.M. Foley, and E. McKeogh. 2012. Integrating wind power using intelligent electric water heating. Energy 48(1):135-143.

Foucquier, A., S. Robert, F. Suard, L. Stéphan, and A. Jay. 2013. State of the art in building modelling and energy performances prediction: A review. Renewable and Sustainable Energy Reviews 23:272-288.

Gans, W., A. Alberini, and A. Longo. 2013. Smart meter devices and the effect of feedback on residential electricity consumption: Evidence from a natural experiment in Northern Ireland. Energy Economics 36:729-743.

Gao, D.C. 2012. Diagnosis and Robust Control of Complex Building Central Chilling Systems for Enhanced Energy Performance. PhD thesis. Pao Yue-kong Library. The Hong Kong Polytechnic University

Gao, D.C., S.W. Wang, and Y.J. Sun. 2011. A fault-tolerant and energy efficient control strategy for primary–secondary chilled water systems in buildings, Energy and Buildings 43(12): 3646-3656.

Gao, J.C., Y. Xiao, J. Liu, W. Liang, and C.L.P. Chen. 2011. A survey of communication/networking in Smart Grids. Future Generation Computer Systems 28(2):391-404.

Gellings, C.W. 1985. The concept of demand-side management for electric utilities. PROCEEDINGS OF THE IEEE 73(10):1468-70.

George, M., and R. Banerjee. 2011. A methodology for analysis of impacts of grid integration of renewable energy. Energy Policy 39(3):1265-1276.

Ghiassi, M., D.K. Zimbra, and H. Saidane. 2006. Medium term system load forecasting with a dynamic artificial neural network model. Electric Power Systems Research 76(5):302-316.

Gilbraith, N., and S.E. Powers. 2013. Residential demand response reduces air pollutant emissions on peak electricity demand days in New York City. Energy Policy 59:459-469.

Giorgio, A.D., and L.P. Pimpinella. 2012. An event driven Smart Home Controller enabling consumer economic saving and automated Demand Side Management. Applied Energy 96:92-103.

Glasnovic, Z., and J. Margeta. 2011. Vision of total renewable electricity scenario. Renewable and Sustainable Energy Reviews 15(4):1873-1884.

Goh, H.H., B.C. Kok, H.T. Yeo, S.W. Lee, and A.A.M. Zin. 2013. Combination of TOPSIS and AHP in load shedding scheme for large pulp mill electrical system. International Journal of Electrical Power & Energy Systems 47:198-204.

Goldman, C.A., and M.S. Kito. 1995. Review of US utility demand-side bidding programs: Impacts, costs, and cost-effectiveness. Utilities Policy 5(1):13-25.

Goldman, C.A., M. Farber, and R. Scheer. 1997. Impact of information and communication technologies on residential customer energy services. Utilities Policy 6(2):151-161.

Goto, K., C. Suzuki, K. Takada, T. Hasegawa, N. Kashima, and S. Nagaya. 2001. Development of HTS cable with Bi-2223 transposed segment conductors. Physica C: Superconductivity 357-360(2):1255-1258.

Gottwalt, S., W. Ketter, C. Block, J. Collins, and C. Weinhardt. 2011. Demand side management-A simulation of household behavior under variable prices. Energy Policy 39(12):8163-8174.

Grynning, S., A. Gustavsen, B. Time, and B.P. Jelle. 2013. Windows in the buildings of tomorrow: Energy losers or energy gainers? Energy and Buildings 61:185-192.

Gulez, K. 2008. Neural network based switching control of AC-AC converter with DC-AC inverter for voltage sags, harmonics and EMI reduction using hybrid filter topology. Simulation Modeling Practice and Theory 16(6):597-612.

Gungor, V.C., and F.C. Lambert. 2006. A survey on communication networks for electric system automation. Computer Networks 50(7):877-897.

Gyamfi, S., and S. Krumdieck. 2012. Scenario analysis of residential demand response at network peak periods. Electric Power Systems Research 93:32-38.

Gyamfi, S., S. Krumdieck, and T. Urmee. 2013. Residential peak electricity demand response-Highlights of some behavioural issues. Renewable and Sustainable Energy Reviews 25:71-77.

Ha, M.K., and T. Nakata. 2006. Analysis of the impact of electricity grid interconnection between Korea and Japan - Feasibility study for energy network in Northeast Asia. Energy Policy 34(9):1015-1025.

Hajiah, A., and M. Krarti. 2012. Optimal control of building storage systems using both ice storage and thermal mass - Part I: Simulation environment. Energy Conversion and Management 64:499-508.

Hajiah, A., and M. Krarti. 2012. Optimal controls of building storage systems using both ice storage and thermal mass - Part II: Parametric analysis. Energy Conversion and Management 64:509-515.

Halford, C.K., and R.F. Boehm. 2007. Modeling of phase change material peak load shifting. Energy and Buildings 39(3):298-305.

Hamidi, V., F.R. Li, and F. Robinson. 2009. Demand response in the UK's domestic sector. Electric Power Systems Research 79(12):1722-1726.

Hammer, A., D. Heinemann, E. Lorenz, and B. Lückehe. 1999. Short-term forecasting of solar radiation: a statistical approach using satellite data. Solar Energy 67(1-3):139-150.

Hammons, T.J. 2008. Integrating renewable energy sources into European grids. International Journal of Electrical Power & Energy Systems 30(8):462-475.

Hao, H., A. Kowli, Y. Lin, P. Barooah, and S. Meyn. 2013. Ancillary Service for the Grid via Control of Commercial Building HVAC Systems. American Control Conference (ACC), 2013. page:467-472.

Hart, D.G. 2008. Using AMI to realize the smart grid. IEEE Power and Energy Society General Meeting - Conversion and Delivery of Electrical Energy in the 21st Century. 20-24 July 2008. Pittsburgh, PA. DOI: 10.1109/PES.2008.4596961. pages:1-2.

Hartway, R., S. Price, and C.K. Woo. 1999. Smart meter, customer choice and profitable time-of-use rate option. Energy 24(10):895-903.

He, Y.X., B. Wang, J.H Wang, W. Xiong, and T. Xia. 2012. Residential demand response behavior analysis based on Monte Carlo simulation: The case of Yinchuan in China. Energy 47(1):230-236.

Henze, G.P. 2005. Energy and Cost Minimal Control of Active and Passive Building Thermal Storage Inventory. Journal of Solar Energy Engineering 127(3):343-351.

Henze, G.P., C. Felsmannb, and G. Knabeb. 2004. Evaluation of optimal control for active and passive building thermal storage. International Journal of Thermal Sciences 43(2):173-183.

Henze, G.P., D. Kalz, C. Felsmann, and G. Knabe. 2004. Impact of forecasting accuracy on predictive optimal control of active and passive building thermal storage inventory. HVAC&R Research 10(2):153-178.

Henze, G.P., D. Kalz, S. Liu, and C. Felsmann. 2005. Experimental analysis of model-based predictive optimal control for active and passive building thermal storage inventory. HVAC&R Research 11(2):189-213.

Henze, G.P., R.H. Dodier, and M. Krarti. 1997. Development of a Predictive Optimal Controller for Thermal Energy Storage Systems. HVAC&R Research 3(3):233-264.

Herter, K. 2007. Residential implementation of critical-peak pricing of electricity. Energy Policy 35(4):2121-2130.

Herter, K., P. McAuliffe, and A. Rosenfeld. 2007. An exploratory analysis of California residential customer response to critical peak pricing of electricity.

Energy 32(1):25-34.

Heyd, G.T. 2010. The Next Generation of Power Distribution Systems. IEEE Transactions on Smart Grid 1(3):225-235.

Hingorani, N.G., and L. Gyugyi. 2000. Understanding FACTS-Concepts and Technology of Flexible AC Transmission Systems. IEEE Press, New York.

Hong, Y.Y., H.M. Hsieh, and S.Y. Ho. 2007. Determination of locations for static transfer switches using Genetic Algorithms and fuzzy multi-objective programming. International Journal of Electrical Power & Energy Systems 29(6):480-487.

Hor, C.L. and P.A. Crossley. 2006. Substation event analysis using information from intelligent electronic devices. International Journal of Electrical Power & Energy Systems 28(6):374-386.

Hu, N., M. Toda, A.N. Ozcivan, T. Yagai, M. Tsuda, and T. Hamajima. 2010. Design of HTS tri-axial cable in steady-state operation. Physica C: Superconductivity 470(20):1584-1587.

Igure, V.M., S.A. Laughter, and R.D. Williams. 2006. Security issues in SCADA networks. Computers & Security 25(7):498-506.

International Energy Agency. 2010. Transforming global markets for clean energy products. Technical report. http://www.iea.org/papers/2010/global%5market%5transformation.pdf.

Järventausta, P., S. Repo, A. Rautiainen, and J. Partanen. 2010. Smart grid power system control in distributed generation environment. Annual Reviews in Control 34(2):277-286.

Javed, F., N. Arshad, F. Wallin, I. Vassileva, and E. Dahlquist. 2012. Forecasting for demand response in smart grids: An analysis on use of anthropologic and structural data and short term multiple loads forecasting. Applied Energy 96:150-160.

Jiang, B.N., and Y.S. Fei. 2011. Dynamic Residential Demand Response and Distributed Generation Management in Smart Microgrid with Hierarchical Agents. Energy Procedia 12:76-90.

Jin, T.D., and M. Mechehoul. 2010. Ordering Electricity via Internet and its Potentials for Smart Grid Systems. IEEE Transactions on Smart Grid 1(3):302-310.

Joe, J., W. Choi, H. Kwon, and J.H. Huh. 2013. Load characteristics and operation strategies of building integrated with multi-story double skin facade. Energy and Buildings 60:185-198.

Josh, B., M.J. Sullivan, and J.H. Eto. 2012. Measuring short-term air conditioner demand reductions for operations and settlement. Lawrence Berkeley National Laboratory. LBNL-5330E.

Josh, B., M.J. Sullivan, and J.H. Eto. 2012. Measuring short-term air conditioner demand reductions for operations and settlement. Lawrence Berkeley National Laboratory. LBNL-5330E.

Kailas, A., V. Cecchi, and A. Mukherjee. 2013. Handbook of Green Information and Communication Systems. Chapter 2 - A Survey of Contemporary Technologies for Smart Home Energy Management. Page:35-56.

Kamel, R.M., A. Chaouachi, and K. Nagasaka. 2010. Wind power smoothing using fuzzy logic pitch controller and energy capacitor system for improvement

Micro-Grid performance in islanding mode. Energy 35(5):2119-2129.

Kamel, R.M., A. Chaouachi, and K. Nagasaka. 2011. Enhancement of micro-grid performance during islanding mode using storage batteries and new fuzzy logic pitch angle controller. Energy Conversion and Management 52(5):2204-2216.

Kandil, M.S., S.M. El-Debeiky, and N.E. Hasanien. 2001. Overview and comparison of long-term forecasting techniques for a fast developing utility: part I. Electric Power Systems Research 58(1):11-17.

Kandil, M.S., S.M. El-Debeiky, and N.E. Hasanien. 2001. The implementation of long-term forecasting strategies using a knowledge-based expert system: part-II. Electric Power Systems Research 58(1):19-25.

Kang, D.J., J.J. Lee, B.H. Kim, and D. Hur. 2011. Proposal strategies of key management for data encryption in SCADA network of electric power systems. International Journal of Electrical Power & Energy Systems 33(9):1521-1526.

Keeney, K.R., and J.E. Braun. 1997. Application of Building Precooling to Reduce Peak Cooling Requirements. ASHRAE Transactions 103(1):463-469.

Khan, K.H., M.G. Rasul, and M.M.K. Khan. 2004. Energy conservation in buildings: cogeneration and cogeneration coupled with thermal energy storage. Applied Energy 77(1):15-34.

Khan, R.H., and J.Y. Khan. 2013. A comprehensive review of the application characteristics and traffic requirements of a smart grid communications network. Computer Networks 57(3):825-845.

Khattam, W.E., and M.M.A. Salama. 2004. Distributed generation technologies, definitions and benefits. Electric Power Systems Research 71(2):119-128.

Kiliccote, S., M.A. Piette, E. Koch, and D. Hennage. 2011. Utilizing Automated Demand Response in Commercial Buildings As NonSpinning Reserve Product for Ancillary Services Markets. 50th IEEE Conference on Decision and Control and European Control Conference. page:4354-4360.

Kim, Y.M., J.H. Lee, S.M. Kim, and S. Kim. 2011. Effects of double skin envelopes on natural ventilation and heating loads in office buildings. Energy and Buildings 43(9):2118-2126.

Kirby, B., J. Kueck, T. Laughner, and K. Morris. 2008. Spinning Reserve from Hotel Load Response. The Electricity Journal 21(10):59-66.

Kirby, B.J. 2003. Spinning Reserve From Responsive Loads. http://certs.lbl.gov/pdf/spinning-reserves.pdf.

Klein, L., J.Y. Kwak, G. Kavulya, F. Jazizadeh, B. Becerik-Gerber, P. Varakantham, and M. Tambe. 2012. Coordinating occupant behavior for building energy and comfort management using multi-agent systems. Automation in Construction 22:525-536.

Kokai, Y., F. Masuda, S. Horiike, and Y. Sekine. 1998. Recent development in open systems for EMS/SCADA. International Journal of Electrical Power & Energy Systems 20(2):111-123.

Kolokotsa, D., D. Rovas, E. Kosmatopoulos, and K. Kalaitzakis. 2011. A roadmap towards intelligent net zero- and positive-energy buildings. Solar Energy 85:3067-3084.

Kondoh, J., N. Lu, and D.J. Hammerstrom. 2011. An Evaluation of the Water Heater Load Potential for Providing Regulation Service. IEEE Transactions on Power

Systems 26(3):1309-1316.

Korres, G.N. 2011. An integer-arithmetic algorithm for observability analysis of systems with SCADA and PMU measurements. Electric Power Systems Research 81(7):1388-1402.

Kostková, K., Ľ. Omelina, P. Kyčina, and P. Jamrich. 2013. An introduction to load management. Electric Power Systems Research 95:184-191.

Kriett , P.O., and M. Salani. 2012. Optimal control of a residential microgrid. Energy 42(1):321-330.

Kueck, J.D., B.J. Kirby, J. Eto, R.H. Staunton, C. Marnay, C.A. Martinez, and C. Goldman. 2001. Load as a Reliability Resource in Restructured Electricity Markets. http://eaei.lbl.gov/sites/all/files/lbnl-47983_0.pdf.

Kueck, J.D., B.J. Kirby, M.R. Ally, and K. Rice. 2009. Using Air Conditioning Load Response for Spinning Reserve. http://certs.lbl.gov/pdf/air-conditioning-load.pdf.

Kume, N., and M.J. Rissanena. 2011. Towards ambient communication support for power grid maintenance and repair. Procedia Computer Science 5:98-105.

Kyriakarakos, G., D.D. Piromalis, A.I. Dounis, K.G. Arvanitis, and G. Papadakis. 2013. Intelligent demand side energy management system for autonomous polygeneration microgrids. Applied Energy 103:39-51.

Laghari, J.A., H. Mokhlis, A.H.A. Bakar, and H. Mohamad. 2013. Application of computational intelligence techniques for load shedding in power systems: A review. Energy Conversion and Management 75:130-140.

Lallement, D.M., E.N. Terrado, and Y.B. Zhang. 2006. Empowering information and communication technologies in isolated areas: learning from the solar-net villages program in honduras. Renewable and Sustainable Energy Reviews 10(1):46-53.

Lam, J.C. 2000. Energy analysis of commercial buildings in subtropical climates. Building and Environment 35(1):19-26.

Lam, J.C. 2000. Residential sector air conditioning loads and electricity use in Hong Kong. Energy Conversion and Management 41(16):1757-1768.

Lam, J.C., R.Y.C. Chan, C.L. Tsang, and D.H.W. Li. 2004. Electricity use characteristics of purpose-built office buildings in subtropical climates. Energy Conversion and Management 45:829-844.

Leadbetter, J., and L. Swan. 2012. Battery storage system for residential electricity peak demand shaving. Energy and Buildings 55:685-692.

Lee, H., J. Bush, Y. Hwang, and R. Radermacher. 2013. Modeling of micro-CHP (combined heat and power) unit and evaluation of system performance in building application in United States. Energy 58:364-375.

Lee, K., and J.E. Braun. 2008. Development of methods for determining demand-limiting setpoint trajectories in buildings using short-term measurements. Building and Environment 43(10):1755-1768.

Lee, K., and J.E. Braun. 2008. Model-based demand-limiting control of building thermal mass. Building and Environment 43(10):1633-1646.

Lee, T.Y., and C.L. Chen. 2007. Iteration particle swarm optimization for contract capacities selection of time-of-use rates industrial customers. Energy Conversion and Management 48(4):1120-1131.

Lee, W.S., Y.T. Chen, and T.H. Wu. 2009. Optimization for ice-storage air-conditioning system using particle swarm algorithm. Applied Energy 86(9):1589-1595.

Leow, W.L., R.C. Larson, and J.L. Kirtley. 2013. Occupancy-moderated zonal space-conditioning under a demand-driven electricity price. Energy and Buildings 60:453-463.

Li, G.D., C.H. Wang, S. Masuda, and M. Nagai. 2011. A research on short term load forecasting problem applying improved grey dynamic model. International Journal of Electrical Power & Energy Systems 33(4):809-816.

Li, G.J., Y.Z. Sun, Q. Wang, S.S. Choi, and S.Y. Ruan. 2010. Design of a Photo-Voltaic System to Enhance Network Dynamic Stability. Smart Grid and Renewable Energy 1:1-6.

Li, X.J., Y.J. Song, and S.B. Han. 2008. Frequency control in micro-grid power system combined with electrolyzer system and fuzzy PI controller. Journal of Power Sources 180(1):468-475.

Lijesen, M.G. 2007. The real-time price elasticity of electricity. Energy Economics 29(2):249-258.

Lin, F., and J. Yi. 2000. Optimal operation of a CHP plant for space heating as a peak load regulating plant. Energy 25(3):283-298.

Liu, S., and G.P. Henze. 2004. Impact of modeling accuracy on predictive optimal control of active and passive building thermal storage inventory. ASHRAE Transactions 110(1):151-163.

Luis, P.L., J. Ortiz, and C. Pout. 2008. A review on buildings energy consumption information. Energy and Buildings 40(3):394-398.

Lujano-Rojas, J.M., C. Monteiro, R. Dufo-López, and J.L. Bernal-Agustín. 2012. Optimum residential load management strategy for real time pricing (RTP) demand response programs. Energy Policy 45:671-679.

Lund, P. 2012. Large-scale urban renewable electricity schemes - Integration and interfacing aspects. Energy Conversion and Management 63:162-172.

Mago, P.J., and A.D. Smith. 2012. Evaluation of the potential emissions reductions from the use of CHP systems in different commercial buildings. Building and Environment 53:74-82.

Mago, P.J., and A.K. Hueffed. 2010. Evaluation of a turbine driven CCHP system for large office buildings under different operating strategies. Energy and Buildings 42(10):1628-1636.

Majumdar, S., D. Chattopadhyay, and J. Parikh. 1996. Interruptible load management using optimal power flow analysis. IEEE Transactions on Power Systems 11(2):715 - 720.

Mamlook, R., O. Badran, and E. Abdulhadi. 2009. A fuzzy inference model for short-term load forecasting. Energy Policy 37(4):1239-1248.

Marijic, Z., Z. Ilic, and A. Bazant. 2010. Fixed-data-rate power minimization algorithm for OFDM-based power-line communication networks. IEEE Transactions on Power Delivery 25(1):141-149.

Márquez, J.L., M.G. Molina, and J.M. Pacas. 2010. Dynamic modeling, simulation and control design of an advanced micro-hydro power plant for distributed generation applications. International Journal of Hydrogen Energy 35(11):5772-5777.

Massie, D.D., J.F. Kreider, and P.S. Curtiss. 2004. Neural Network Optimal Controller for Commercial Ice Thermal Storage Systems. ASHRAE Transactions 110(2):361-369.

Matallanas, E., M. Castillo-Cagigal, A. Gutiérrez, F. Monasterio-Huelin, E. Caamaño-Martín, D. Masa, and J. Jiménez-Leube. 2012. Neural network controller for Active Demand-Side Management with PV energy in the residential sector. Applied Energy 91(1):90-97.

MATLAB. 2006. http://www.mathworks.com/products/matlab/

Ma Zhenjun. 2008. Online Supervisory and Optimal Control of Complex Building Central Chilling Systems. PhD Thesis. Pao Yue-kong Library, Hong Kong Polytechnic University.

http://repository.lib.polyu.edu.hk/jspui/bitstream/10397/3415/2/b2239753x_ir.pdf

Medina, J., N. Muller, and I. Roytelman. 2010. Demand Response and Distribution Grid Operations: Opportunities and Challenges. IEEE Transactions on Smart Grid 1(2):193-198.

Meliopoulos, A.P.S., G. Cokkinides, R. Huang, E. Farantatos, S.Y. Choi, Y.H. Lee, and X.B. Yu. 2011. Smart Grid Technologies for Autonomous Operation and Control. IEEE Transactions on Smart Grid 2(1):1-10.

Meliopoulos, A.P.S., G.J. Cokkinides, F. Galvan, B. Fardanesh, and P. Myrda. 2007. Delivering accurate and timely data to all. IEEE Power Energy Magazine 5(3):74-86.

Mellit, A., M. Benghanem, and S.A. Kalogirou. 2006. An adaptive wavelet-network model for forecasting daily total solar-radiation. Applied Energy 83(7):705-722.

Metke, A.R., and R.L. Ekl. 2010. Security Technology for Smart Grid Networks. IEEE Transactions on Smart Grid 1(1):99-107.

Middelberg, A., J.F. Zhang, and X.H. Xia. 2009. An optimal control model for load shifting - With application in the energy management of a colliery. Applied Energy 86(7-8):1266-1273.

Mitchell, K., M. Nagrial, and J. Rizk. 2005. Simulation and optimisation of renewable energy systems. International Journal of Electrical Power & Energy Systems 27(3):177-188.

Mitra, S., L. Sun, and I.E. Grossmann. 2013. Optimal scheduling of industrial combined heat and power plants under time-sensitive electricity prices. Energy 54(1):194-211.

Moghaddam, M.P., A. Abdollahi, and M. Rashidinejad. 2011. Flexible demand response programs modeling in competitive electricity markets. Applied Energy 88(9):3257-3269.

Moghaddam, M.P., A. Abdollahi, and M. Rashidinejad. 2011. Flexible demand response programs modeling in competitive electricity markets. Applied Energy 88(9):3257-3269.

Molderink, A., V. Bakker, M.G.C. Bosman, J.L. Hurink, and G.J.M. Smit. 2010. Management and Control of Domestic Smart Grid Technology. IEEE Transactions on Smart Grid 1(2):109-119.

Moon, J.W., and J.J. Kim. 2010. ANN-based thermal control models for residential buildings. Building and Environment 45(7):1612-1625.

Morais, H., P. Kádár, P. Faria, Z.A. Vale, and H.M. Khodr. 2010. Optimal scheduling of a renewable micro-grid in an isolated load area using mixed-integer linear programming. Renewable Energy 35(1):151-156.

Morgan, S., and M. Krarti. 2010. Field testing of optimal controls of passive and active thermal storage. ASHRAE Transactions 116:134-146.

Mukoyama, S., M. Yagi, T. Masuda, N. Amemiya, A. Ishiyama, N. Kashima, S. Nagaya, Y. Aoki, M. Yoshizumi, Y. Yamada, T. Izumi, and Y. Shiohara. 2009. Development of (RE)BCO cables for HTS power transmission lines. Physica C: Superconductivity 469(15-20):1688-1692.

Nair, N.K.C., and N. Garimella. 2010. Battery energy storage systems: Assessment for small-scale renewable energy integration. Energy and Buildings 42(11):2124-2130.

Nayeripour, M., M.R. Narimani, T. Niknam, and S. Jam. 2011. Design of sliding mode controller for UPFC to improve power oscillation damping. Applied Soft Computing 11(8):4766-4772.

Nazih, A.S., and E. Fawwaz. 2011. Medium-term electric load forecasting using singular value decomposition. Energy 36(7):4259-4271.

Newsham, G.R., A.D. Galasiu, M.M. Armstrong, I. Beausoleil-Morrison, F. Szadkowski, J.M. Sager, A.J. Pietila, and I.H. Rowlands. 2013. The zero-peak house: Full-scale experiments and demonstration. Energy and Buildings 64:483-492.

Newsham, G.R., B.J. Birt, and I.H. Rowlands. 2011. A comparison of four methods to evaluate the effect of a utility residential air-conditioner load control program on peak electricity use. Energy Policy 39(10):6376-6389.

Nghiem, T.X., G.J. Pappas, and R. Mangharam. 2013. Event-based Green scheduling of radiant systems in buildings. American Control Conference (ACC), 17-19 June 2013. page:455-460.

Nghiem, T.X., M. Behl, R. Mangharam, and G.J.Pappas. 2011. Green scheduling of control systems for peak demand reduction. Decision and Control and European Control Conference (CDC-ECC). page:5131-5136.

Niro, G., D. Salles, M.V.P. Alcântara, and L.C.P. da Silva. 2013. Large-scale control of domestic refrigerators for demand peak reduction in distribution systems. Electric Power Systems Research 100:34-42.

NIST. 2012. NIST Framework and Roadmap for Smart Grid Interoperability Standards, Release 2.0. NIST Special Publication 1108R2. http://www.nist.gov/smartgrid/upload/NIST_Framework_Release_2-0_corr.pdf.

Niu, D.X., J.C. Li, J.Y. Li, and D. Liu. 2009. Middle-long power load forecasting based on particle swarm optimization. Computers & Mathematics with Applications 57(11-12):1883-1889.

Nolde, K., and M. Morari. 2010. Electrical load tracking scheduling of a steel plant. Computers & Chemical Engineering 34(11):1899-1903.

Notton, G., L. Stoyanov, M. Ezzat, V. Lararov, S. Diaf, and C. Cristofari. 2011. Integration Limit of Renewable Energy Systems in Small Electrical Grid. Energy Procedia 6:651-665.

Obara, S.Y. 2007. Analysis of a fuel cell micro-grid with a small-scale wind turbine generator. International Journal of Hydrogen Energy 32(3):323-336.

Oliveira, L.W., S. Carneiro, E.J. Oliveira, J.L.R. Pereira, I.C. Silva, and J.S. Costa.

2010. Optimal reconfiguration and capacitor allocation in radial distribution systems for energy losses minimization. International Journal of Electrical Power & Energy Systems 32(8):840-848.

Olmos, L., S. Ruester, S.J. Liong, and J.M. Glachant. 2011. Energy efficiency actions related to the rollout of smart meters for small consumers, application to the Austrian system. Energy 36(7):4396-4409.

Omer, A.M. 2008. Energy, environment and sustainable development. Renewable and Sustainable Energy Reviews 12(9):2265-2300.

Orecchini, F. 2006. The era of energy vectors. International Journal of Hydrogen Energy 31:1951-1954.

Orecchini, F., and A. Santiangeli. 2011. Beyond smart grids - The need of intelligent energy networks for a higher global efficiency through energy vectors integration. International Journal of Hydrogen Energy 36(13):8126-8133.

Oshiro, M., K. Tanaka, A. Uehara, T. Senjyu, Y. Miyazato, A. Yona, and T. Funabashi. 2010. Optimal voltage control in distribution systems with coordination of distribution installations. International Journal of Electrical Power & Energy Systems 32(10):1125-1134.

Pacheco, R., J. Ordóñez, and G. Martínez. 2012. Energy efficient design of building: A review. Renewable and Sustainable Energy Reviews 16(6):3559-3573.

Padmakumari, K., K.P. Mohandas, and S. Thiruvengadam. 1999. Long term distribution demand forecasting using neuro fuzzy computations. International Journal of Electrical Power & Energy Systems 21(5):315-322.

Parameshwaran, R., S. Kalaiselvam, S. Harikrishnan, and A. Elayaperumal. 2012.

Sustainable thermal energy storage technologies for buildings: A review. Renewable and Sustainable Energy Reviews 16(5):2394-2433.

Paull, L., H. Li, and L.C. Chang. 2010. A novel domestic electric water heater model for a multi-objective demand side management program. Electric Power Systems Research 80(12):1446-1451.

Peacock, A.D., and M. Newborough. 2007. Controlling micro-CHP systems to modulate electrical load profiles. Energy 32(7):1093-1103.

Pearson, I.L.G. 2011. Smart grid cyber security for Europe. Energy Policy 39(9):5211-5218.

Pedrasa, M.A.A., T.D. Spooner, and I.F. MacGill. 2010. Coordinated Scheduling of Residential Distributed Energy Resources to Optimize Smart Home Energy Services. IEEE Transactions on Smart Grid 1(2):134-143.

Pedregal, D.J., and J.R. Trapero. 2010. Mid-term hourly electricity forecasting based on a multi-rate approach. Energy Conversion and Management 51(1):105-111.

Pelzer, R., E.H. Mathews, D.F. le Roux, and M. Kleingeld. 2008. A new approach to ensure successful implementation of sustainable demand side management (DSM) in South African mines. Energy 33(8):1254-1263.

Perfumo, C., E. Kofman, J.H. Braslavsky, and J.K. Ward. 2012. Load management: Model-based control of aggregate power for populations of thermostatically controlled loads. Energy Conversion and Management 55:36-48.

Pietila, A., I. Beausoleil-Morrison, and G.R. Newsham. 2012. Zero peak housing: Exploring the possibility of eliminating electrical draws from houses during periods of high demand on the electrical grid. Building and Environment

58:103-113.

Poel, B., G. van Cruchten, and C.A. Balaras. 2007. Energy performance assessment of existing dwellings. Energy and Buildings 39(4):393-403.

Popovic, D.S., L.R. Glamocic, and M.D. Nimrihter. 2011. The optimal automation level of medium voltage distribution networks. International Journal of Electrical Power & Energy Systems 33(3):430-438.

Qi, R.H., L. Lu, and H.X. Yang. 2012. Investigation on air-conditioning load profile and energy consumption of desiccant cooling system for commercial buildings in Hong Kong. Energy and Buildings 49:509-518.

Qureshi, W.A., N.C. Nair, and M.M. Farid. 2011. Impact of energy storage in buildings on electricity demand side management. Energy Conversion and Management 52(5):2110-2120.

Rahim, A.H.M.A. 2004. A minimum-time based fuzzy logic dynamic braking resistor control for sub-synchronous resonance. International Journal of Electrical Power & Energy Systems 26(3):191-198.

Rahimi, F., and A. Ipakchi. 2010. Demand Response as a Market Resource Under the Smart Grid Paradigm. IEEE Transactions on Smart Grid 1(1):82-88.

Rankin, R., and P.G. Rousseau. 2008. Demand side management in South Africa at industrial residence water heating systems using in line water heating methodology. Energy Conversion and Management 49(1):62-74.

Ren, P., Z. Xiang, and Z.L. Qiu. 2013. Intelligent domestic electricity management system based on analog-distributed hierarchy. International Journal of Electrical Power & Energy Systems 46:400-404.

Reynders, G., T. Nuytten, and D. Saelens. 2013. Potential of structural thermal mass for demand-side management in dwellings. Building and Environment 64:187-199.

Rijksen, D.O., C.J. Wisse, and A.W.M. van Schijndel. 2010. Reducing peak requirements for cooling by using thermally activated building systems. Energy and Buildings 42(3):298-304.

Rismanchi, B., et al. "Energy, exergy and environmental analysis of cold thermal energy storage (CTES) systems." Renewable and Sustainable Energy Reviews 16.8 (2012): 5741-5746.

Rochester Gas and Electric Corporation' New York State Electric and Gas Company. 2007. Advanced Metering Infrastructure Overview and Plan. www.dps.state.ny.us/NYSEG_RGE_AMI_Filing.pdf.

Roels, S. 2011. "Reliable building energy performance characterization based on full scale dynamic measurements". IEA ECBCS Annex 58, Final proposal.

Røpke, I., T.H. Christensen, and J.O. Jensen. 2010. Information and communication technologies - A new round of household electrification. Energy Policy 38(4):1764-1773.

Rújula, A.A.B. 2009. Future development of the electricity systems with distributed generation. Energy 34(3):377-383.

Sadineni, S.B., S. Madala, and R.F. Boehm. 2011. Passive building energy savings: A review of building envelope components. Renewable and Sustainable Energy Reviews 15(8):3617-3631.

Sadinezhad, I., and V.G. Agelidis. 2011. Slow sampling on-line harmonics/interharmonics estimation technique for smart meters. Electric Power Systems Research 81(8):1643-1653.

Saele, H., and O.S. Grande. 2011. Demand Response From Household Customers: Experiences From a Pilot Study in Norway. IEEE Transactions on Smart Grid 2(1):102-109.

Sarwar, A., and M.S.J. Asghar. 2011. Simulation and Analysis of a Multilevel Converter Topology for Solar PV Based Grid Connected Inverter. Smart Grid and Renewable Energy 2:56-62.

Schweppe, F.C., M.C. Caramanis, R.D. Tabors, and R.E. 1988. Bohn. Spot Pricing of Electricity. Boston, Dordrecht, London: Kluwer Academic Publishers.

Seethalekshmi, K., S.N. Singh, and S.C. Srivastava. 2011. A Synchrophasor Assisted Frequency and Voltage Stability Based Load Shedding Scheme for Self-Healing of Power System. IEEE Transactions on Smart Grid 2(2):221-230.

Sehar, F., S. Rahman, and M. Pipattanasomporn. 2012. Impacts of ice storage on electrical energy consumptions in office buildings. Energy and Buildings 51:255-262.

Sezgen, O., C.A. Goldman, and P. Krishnarao. 2007. Option value of electricity demand response. Energy 32(2):108-119.

Siler-Evans, K., M.G. Morgan, and I.L. Azevedo. 2012. Distributed cogeneration for commercial buildings: Can we make the economics work? Energy Policy 42:580-590.

Silva, C.G.D. 2010. Renewable energies: Choosing the best options. Energy 35(8):3179-3193.

Siwek, K., S. Osowski, and R. Szupiluk. 2009. Ensemble neural network approach for accurate load forecasting in a power system. International Journal of Applied Mathematics and Computer Science 19(2):303-315.

Smith, A.D., P.J. Mago, and N. Fumo. 2013. Benefits of thermal energy storage option combined with CHP system for different commercial building types. Sustainable Energy Technologies and Assessments 1:3-12.

Soares, L.J., and M.C. Medeiros. 2008. Modeling and forecasting short-term electricity load: A comparison of methods with an application to Brazilian data. International Journal of Forecasting 24(4):630-644.

Sood, V.K., D. Fischer, J.M. Eklund, and T. Brown. 2009. Developing a communication infrastructure for the smart grid. IEEE Electrical Power & Energy Conference (EPEC). 22-23 October 2009. Montreal, QC, Canada. DOI: 10.1109/PES.2007.386013. pages:1-7.

Stadler, I. 2008. Power grid balancing of energy systems with high renewable energy penetration by demand response. Utilities Policy 16(2):90-98.

Stetiu, C. 1999. Energy and peak power savings potential of radiant cooling systems in US commercial buildings. Energy and Buildings 30(2):127-138.

Su, C.L., C.N. Lu, and M.C. Lin. 2000. Wide area network performance study of a distribution management system. International Journal of Electrical Power & Energy Systems 22(1):9-14.

Sun, L.L., and H.X. Yang. 2010. Impacts of the shading-type building-integrated photovoltaic claddings on electricity generation and cooling load component through shaded windows. Energy and Buildings 42(4):455-460.

Sun, Y.J., S.W. Wang and G.S. Huang. 2010. A demand limiting strategy for maximizing monthly cost savings of commercial buildings. Energy and Buildings 42(11):2219-2230.

Sun, Y.J., S.W. Wang, and G.S. Huang. 2009. Chiller sequencing control with enhanced robustness for energy efficient operation. Energy and Buildings 41(11):1246-1255.

Sun, Y.J., S.W. Wang, and G.S. Huang. 2010. Model-based optimal start control strategy for multi-chiller plants in commercial buildings. Building Services Engineering Research & Technology 31(2):113-129.

Sun, Y.J., S.W. Wang, F. Xiao, and D.C. Gao. 2013. Peak load shifting control using different cold thermal energy storage facilities in commercial buildings: A review. Energy Conversion and Management 71:101-114.

Sun, Y.J., S.W. Wang, F. Xiao, and G.S. Huang. 2012. A study of pre-cooling impacts on peak demand limiting in commercial buildings. HVAC&R Research 18(6):1098-1111.

Surles, W., and G.P. Henze. 2012. Evaluation of automatic priced based thermostat control for peak energy reduction under residential time-of-use utility tariffs. Energy and Buildings 49:99-108.

Suvire, G.O., and P.E. Mercado. 2010. DSTATCOM with Flywheel Energy Storage System for wind energy applications: Control design and simulation. Electric Power Systems Research 80(3):345-353.

Synnefa, A., M. Santamouris, and H. Akbari. 2007. Estimating the effect of using cool coatings on energy loads and thermal comfort in residential buildings in various climatic conditions. Energy and Buildings 39(11):1167-1174.

Tanrioven, M. 2005. Reliability and cost-benefits of adding alternate power sources to an independent micro-grid community. Journal of Power Sources 150:136-149.

Tatsidjodoung, P., N. Le Pierrès, and L. Luo. 2013. A review of potential materials for thermal energy storage in building applications. Renewable and Sustainable Energy Reviews 18:327-349.

Thananunsophon, K., B. Mangalabruks, Y. Fujii, and P.P. Yupapin. 2011. Community Monitoring and Security using an Intelligent Camera in EAT Smart Grids. Procedia Engineering 8:332-336.

Thukaram, D., H.M.W. Banda, and J. Jerome. 1999. A robust three phase power flow algorithm for radial distribution systems. Electric Power Systems Research 50(3):227-236.

Tiptipakorn, S., and W.J. Lee. 2007. A Residential Consumer-Centered Load Control Strategy in Real-Time Electricity Pricing Environment. Power Symposium, 2007. NAPS '07. 39th North American, Sept. 30 2007-Oct. 2 2007. page:505-510.

Toledo, O.M., D.O. Filho, A. Sônia, and A.C. Diniz. 2010. Distributed photovoltaic generation and energy storage systems: A review. Renewable and Sustainable Energy Reviews 14(1):506-511.

Toronto Hydro Electric System. 2010. Peaksaver. http://www.torontohydro.com/peaksaver.

Torriti, J., M.G. Hassan, and M. Leach. 2010. Demand response experience in Europe: Policies, programmes and implementation. Energy 35(4):1575-1583.

Trifunovic, J., J. Mikulovic, Z. Djurisic, and M. Kostic. 2011. Reductions in electricity losses in the distribution power system in case of the mass use of compact fluorescent lamps. Electric Power Systems Research 81(2):465-477.

Trifunovic, J., J. Mikulovic, Z. Djurisic, M. Djuric, and M. Kostic. 2009. Reductions in electricity consumption and power demand in case of the mass use of compact fluorescent lamps. Energy 34(9):1355-1363.

TRNSYS. 2004. TRNSYS 16 documentation. http://sel.me.wisc.edu/trnsys.

Tuite, D. 2010. For Power Design Opportunities, Try the Smart Grid. Electronic Design 58:108-110.

United States Department of Energy. 2003. "Grid 2030" - A national vision for electricity's second 100 years. www.energy.gov/sites/prod/files/oeprod/DocumentsandMedia/Electric_Vision_Document.pdf.

US Department of Energy. 2006. Benefits of demand response in electricity markets and recommendations for achieving them. http://eetd.lbl.gov/EA/EMS/reports/congress-1252d.pdf.

Vachirasricirikul, S., I. Ngamroo, and S. Kaitwanidvilai. 2010. Coordinated SVC and AVR for robust voltage control in a hybrid wind-diesel system. Energy Conversion and Management 51(12):2383-2393.

Vazquez, S., S.M. Lukic, E. Galvan, L.G. Franquelo, and J.M. Carrasco. 2010. Energy Storage Systems for Transport and Grid Applications. IEEE Transactions on Industrial Electronics 57(12):3881-95.

Venkatesan, N., J. Solanki, and S.K. Solanki. 2012. Residential Demand Response model and impact on voltage profile and losses of an electric distribution network.

Applied Energy 96:84-91.

Virulkar, V., M. Aware, and M. Kolhe. 2011. Integrated battery controller for distributed energy system. Energy 36(5):2392-2398.

Vokas, G., N. Christandonis, and F. Skittides. 2006. Hybrid photovoltaic-thermal systems for domestic heating and cooling-A theoretical approach. Solar Energy 80(5):607-615.

Walsh, B.P., S.N. Murray, and D.T.J. O'Sullivan. 2013. Free-cooling thermal energy storage using phase change materials in an evaporative cooling system. Applied Thermal Engineering 59(1-2):618-626.

Wang, B., N.L. Tai, H.Q. Zhai, J. Ye, J.D. Zhu, and L.B. Qi. 2008. A new ARMAX model based on evolutionary algorithm and particle swarm optimization for short-term load forecasting. Electric Power Systems Research 78(10):1679-1685.

Wang, D., S. Parkinson, W. Miao, H. Jia, C. Crawford, and N. Djilali. 2012. Online voltage security assessment considering comfort-constrained demand response control of distributed heat pump systems. Applied Energy 96:104-114.

Wang, J.H., C. Liu, D. Ton, Y. Zhou, J.H. Kim, and A. Vyas. 2011. Impact of plug-in hybrid electric vehicles on power systems with demand response and wind power. Energy Policy 39(7):4016-4021.

Wang, J.H., C.N. Bloyd, Z.G. Hu, and Z.F. Tan. 2010. Demand response in China. Energy 35(4):1592-1597.

Wang, J.J., Y.Y. Jing, C.F. Zhang, and Z.Q. Zhai. 2011. Performance comparison of combined cooling heating and power system in different operation modes. Applied Energy 88(12):4621-4631.

Wang, J.X., X.F. Wang, and Y. Wu. 2005. Operating Reserve Model in the Power Market. IEEE Transactions on Power Systems 20(1):223-229.

Wang, N., J.F. Zhang, and X.H. Xia. 2013. Energy consumption of air conditioners at different temperature set points. Energy and Buildings 65:412-418.

Wang, P., H. Zareipour, and W.D. Rosehart. 2011. Characteristics of the prices of operating reserves and regulation services in competitive electricity markets. Energy Policy 39(6):3210-3221.

Wang, S.W. 1998. Dynamic simulation of a building central chilling system and evaluation of EMCS on-line control strategies. Building and Environment 33(1):1-20.

Wang, S.W., and X.H Xu. 2006. Simplified building model for transient thermal performance estimation using GA-based parameter identification. International Journal of Thermal Sciences 45(4):419-432.

Wang, S.W., and X.H. Xu. 2006. Parameter estimation of internal thermal mass of building dynamic models using genetic algorithm. Energy Conversion and Management 47(13-14):1927-1941.

Wang, S.W., and Z.J. Ma. 2008. Supervisory and Optimal Control of Building HVAC Systems: A Review. HVAC&R Research 14(1):3-32.

Wang, S.W., and Z.J. Ma. 2008. Supervisory and Optimal Control of Building HVAC Systems: A Review. HVAC&R Research 14(1):3-32.

Wang, W.Y., Y. Xu, and M. Khanna. 2011. A survey on the communication architectures in smart grid. Computer Networks 55(15):3604-3629.

Wang, X.C., P. Guo, and X.B. Huang. 2011. A Review of Wind Power Forecasting

Models. Energy Procedia 12:770-778.

Waqas, A., and Z.U. Din. 2013. Phase change material (PCM) storage for free cooling of buildings-A review. Renewable and Sustainable Energy Reviews 18:607-625.

Watson, D.S., S. Kiliccote, N. Motegi, and M.A. Piette. 2006. Strategies for Demand Response in Commercial Buildings. ACEEE Summer Study on Energy Efficiency in Buildings, Pacific Grove, CA (2006). http://drrc.lbl.gov/publications/strategies-demand-response-commercial-buildings.

Williams, T., D. Wang, C. Crawford, and N. Djilali. 2013. Integrating renewable energy using a smart distribution system: Potential of self-regulating demand response. Renewable Energy 52:46-56.

Wissner, M. 2011. The Smart Grid - A saucerful of secrets?. Applied Energy 88(7):2509-2518.

Wong, P.W., Y. Shimoda, M. Nonaka, M. Inoue, and M. Mizuno. 2008. Semi-transparent PV: Thermal performance, power generation, daylight modelling and energy saving potential in a residential application. Renewable Energy 33(5):1024-1036.

Woo, C.K., R. Li, A. Shiu, and I. Horowitz. 2013. Residential winter kW h responsiveness under optional time-varying pricing in British Columbia. Applied Energy 108:288-297.

Xia, C.H., J. Wang, and K. McMenemy. 2010. Short, medium and long term load forecasting model and virtual load forecaster based on radial basis function neural networks. International Journal of Electrical Power & Energy Systems

32(7):743-750.

Xie, D., J.Y. Yu, and J.L. Yu. 2000. The physical series algorithm of mid-long term load forecasting of power systems. Electric Power Systems Research 53(1):31-37.

Xu, P., and L. Zagreus. 2006. Demand shifting with thermal mass in light and heavy mass commercial buildings. Berkeley: Lawrence Berkeley National Laboratory. LBNL-61172.

Xu, P., P. Haves, J.E. Braun, and L.T. Hope. 2004. Peak demand reduction from pre-cooling with zone temperature reset in an office building. In: Proceedings of 2004 ACEEE summer study of energy efficiency in buildings, Pacific Grove, CA.

Xu, P., P. Haves, M.A. Piette, and L. Zagreus. 2005. Demand shifting with thermal mass in large commercial buildings: field tests, simulations and audits. Berkeley: Lawrence Berkeley National Laboratory. LBNL-58815.

Xu, S.L., D.H. Feng, Z. Yan, L. Zhang, N.H Li, L. Jing, and J.H. Wang. 2013. Ant-Based Swarm Algorithm for Charging Coordination of Electric Vehicles. International Journal of Distributed Sensor Networks 2013(2013) Article ID 268942, 13 pages. http://dx.doi.org/10.1155/2013/268942.

Xue, X., S.W. Wang, Y.J. Sun, and F. Xiao. 2014. An interactive building power demand management strategy for facilitating smart grid optimization. Applied Energy 116:297-310.

Yagi, M., S. Mukoyama, N. Amemiya, S. Nagaya, N. Kashima, and Y. Shiohara. 2008. Development of YBCO HTS cable with low AC loss. Physica C: Superconductivity 468(15-20):2037-2040.

Yamaha, M., and S. Misaki. 2006. The Evaluation of Peak Shaving by a Thermal Storage System Using Phase-Change Materials in Air Distribution Systems. HVAC&R Research 12(3):861-869.

Yan, C.C., S.W. Wang and F. Xiao. 2012. A simplified energy performance assessment method for existing buildings based on energy bill disaggregation. Energy and Buildings 55:563-574.

Yang, H., L. Lu, and W. Zhou. 2007. A novel optimization sizing model for hybrid solar-wind power generation system. Solar Energy 81(1):76-84.

Yang, L.N., and Y.G. Li. 2008. Cooling load reduction by using thermal mass and night ventilation. Energy and Buildings 40(11):2052-2058.

Yao, Y., Z.W. Lian, S.Q. Liu, and Z.J. Hou. 2004. Hourly cooling load prediction by a combined forecasting model based on Analytic Hierarchy Process. International Journal of Thermal Sciences 43(11):1107-1118.

Yau, Y. H., and B. Rismanchi. 2012. A review on cool thermal storage technologies and operating strategies. Renewable and Sustainable Energy Reviews 16(1):787-797.

Yin, R.X., P. Xu, M.A. Piette, and S. Kiliccote. 2010. Study on Auto-DR and pre-cooling of commercial buildings with thermal mass in California. Energy and Buildings 42(7):967-975.

Yogev, R., and A. Kribus. 2013. Operation strategies and performance of solar thermal power plants operating from PCM storage. Solar Energy 95:170-180.

Yousefi, S., M.P. Moghaddam, and V.J. Majd. 2011. Optimal real time pricing in an agent-based retail market using a comprehensive demand response model.

Energy 36(9):5716-5727.

Yuan, J.H., and Z.G. Hu. 2011. Low carbon electricity development in China - an IRSP perspective based on super smart grid. Renewable and Sustainable Energy Reviews 15(6):2707-2713.

Zarnikau, J., G. Landreth, I. Hallett, and S.C. Kumbhakar. 2007. Industrial customer response to wholesale prices in the restructured Texas electricity market. Energy 32(9):1715-1723.

Zeng, Z., H. Yang, R.X. Zhao, and C. Cheng. 2013. Topologies and control strategies of multi-functional grid-connected inverters for power quality enhancement: A comprehensive review. Renewable and Sustainable Energy Reviews 24:223-270.

Zhang, D., N. Shah, and L.G. Papageorgiou. 2013. Efficient energy consumption and operation management in a smart building with microgrid. Energy Conversion and Management 74:209-222.

Zhang, H., A. Davigny, F. Colas, Y. Poste, and B. Robyns. 2012. Fuzzy logic based energy management strategy for commercial buildings integrating photovoltaic and storage systems. Energy and Buildings 54:196-206.

Zhang, J., and J. Meng. 2010. Robust narrowband interference rejection for power-line communication systems Using IS-OFDM. IEEE Transactions on Power Delivery 25(2):680-692.

Zhang, P., F.X. Li, and N. Bhatt. 2010. Next-Generation Monitoring, Analysis, and Control for the Future Smart Control Center. IEEE Transactions on Smart Grid 1(2):186-192.

Zhang, Y.P., G.B. Zhou, K.P. Lin, Q.L. Zhang, and H.F. Di. 2007. Application of latent heat thermal energy storage in buildings: State-of-the-art and outlook. Building and Environment 42(6):2197-2209.

Zhao, C., J. Wang, J.P. Watson, and Y. Guan. 2013. Multi-Stage Robust Unit Commitment Considering Wind and Demand Response Uncertainties. IEEE Transactions on Power Systems 28(3):2708-2717.

Zhao, F., J.H. Wang, V. Koritarov, and G. Augenbroe. 2010. Agent-based modeling of interaction between commercial building stocks and power grid. IEEE Conference on Innovative Technologies for an Efficient and Reliable Electricity Supply (CITRES) page:225-232.

Zhao, J.Y., S. Kucuksari, E. Mazhari, and Y.J. Son. 2013. Integrated analysis of high-penetration PV and PHEV with energy storage and demand response. Applied Energy 112:35-51.

Zhao, X., J. Ostergaard, and M. Togeby. 2011. Demand as Frequency Controlled Reserve. IEEE Transactions on Power Systems 26(3):1062-1071.

Zhou, G., G.P. Henze, and M. Krarti. 2005. Parametric Analysis of Active and Passive Building Thermal Storage Utilization. Journal of Solar Energy Engineering 127(1):37-46.

Zhou, K.L., S.L. Yang, and C. Shen, 2013. A review of electric load classification in smart grid environment. Renewable and Sustainable Energy Reviews 24:103-110.

Zhou, W., H. Yang, and L. Lu. 2010. Current status of research on optimum sizing of stand-alone hybrid solar-wind power generation system. Applied Energy 87(2):380-389.

Zhu, N., S.W. Wang, X.H. Xu, and Z.J. Ma. 2010. A simplified dynamic model of building structures integrated with shaped-stabilized phase change materials. International Journal of Thermal Sciences 49(9):1722-1731.

Zhu, N., Z.J. Ma, and S.W. Wang. 2009. Dynamic characteristics and energy performance of buildings using phase change materials: A review. Energy Conversion and Management 50(12):3169-3181.

Zio, E., and T. Aven. 2011. Uncertainties in smart grids behavior and modeling: What are the risks and vulnerabilities? How to analyze them? Energy Policy 39(10): 6308-6320.