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A robust demand response control of commercial buildings for smart grid under load prediction uncertainty

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ABSTRACT

Various demand response control strategies have been developed for grid power balance and user cost saving. Few studies have systematically considered the impacts of load prediction uncertainty which can cause the strategies fail to achieve their objectives. This study, therefore, develops a robust demand response control of commercial buildings for smart grid under load prediction uncertainty. Based on the initial control signals from the conventional genetic algorithm method, the optimal control signals with improved robustness are obtained using the Monte Carlo method. Under dynamic pricing of smart grid, the study results show the impacts of load prediction uncertainty reduce the daily electricity cost saving from 8.5% to 4.1%. Such a significant cost saving reduction implies the necessity of taking account of the load prediction uncertainty in the development of a demand response control. Moreover, under the load prediction uncertainty, the proposed demand response control can still achieve 7.3% daily electricity cost saving, which demonstrates its robustness and effectiveness. The improved robustness of the proposed control has also been demonstrated by the statistics analysis results from the Monte Carlo studies. The proposed robust control is useful for commercial buildings to achieve significant cost savings in practice particularly as uncertainty exists.

1. Introduction

With the increasing population and the improving living standards, electrical energy use keeps rapidly increasing in the last several decades. The rapid increase of electricity demand has imposed great stress on electricity grid especially for maintaining grid power balance [1,2]. The power supply and demand of a grid must always balance and such real time balance is a critical system requirement. Any power imbalance/mismatch will cause severe consequences in the reliability and quality of power supply (e.g. power outages, voltage fluctuations) [3,4]. In order to maintain the real time power balance, great efforts have been made from power demand side (e.g. demand response control) [5,6].

Among different users on demand side, building plays a significant role in maintaining grid power balance since it consumes over 40% of overall energy [7]. Building demand response control has been widely recognized as an effective solution to grid power balance [6]. Demand response refers to changes in electric usage by end-users from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized [8]. Demand response includes all intentional electricity consumption pattern modifications by end-use customers that are intended to alter the timing, level of instantaneous demand, or total electricity consumption [9]. With regards to the mathematical models and approaches in demand response for smart grid, a comprehensive survey was conducted in Ref. [10]. Based on the survey, the potential challenges and future research directions in the context of demand response for smart grid were outlined. In residential buildings, most of demand response control can be eventually generalized into optimal scheduling problem [11,12]. In contrast, demand response control in commercial buildings involves more complicated load profile alteration management and it draws more attentions.

Load shedding and load shifting are two main means in the load profile alteration management in commercial buildings. Load shedding control reduces peak electric load in a building via

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turning off non-essential electrical load [13]. Different approaches including priority based load shedding [14], statistics based load shedding [15] have been developed and used in practice. Compared with load shedding control, load shifting control is a more commonly used method for peak demand limiting. Load shifting aims at taking advantages of electricity rate difference between different periods via shifting on-peak load to off-peak hour. Since HVAC (heating, ventilation and air conditioning) systems in commercial buildings consume a major part of energy, many studies focus on the load shifting control of HVAC systems [16,17].

The development of a load shifting control in a HVAC system consists of three essential parts including load prediction, thermal energy charging control and discharging control [17]. Charging control is used to store required amount of thermal energy (e.g. cooling) in off-peak period for reducing on-peak load to an optimized level. Discharging control is used to release stored thermal energy in an expected way to offset a part of on-peak load. Different charging and discharging control strategies have been developed as different storage facilities are used. Four different facilities have been widely used in existing load shifting controls and they are building thermal mass (BTM) [18–20], thermal energy storage system (TES) [21,22], combined use of BTM and TES [23,24] and phase change material (PCM) [25,26].

In addition to charging and discharging control, load prediction is another essential element to the development of demand response control in commercial buildings. Load prediction uncertainty is inevitable in practice and it has significant impacts on the performance of the developed demand response control. The uncertainty of load prediction can largely compromise the final cost saving even the charging and discharging control strategies are perfect. In fact, it is one common reason that causes the existing demand response controls fail to achieve their objectives in practice [27]. In order to ensure a satisfying performance, demand response control needs to consider the impacts of load prediction uncertainty.

Although price uncertainty has been considered in the load scheduling [28], few existing studies have systematically considered the load prediction uncertainty impacts in the development of demand response control. Therefore, this study proposed a robust demand response control of commercial buildings under load prediction uncertainty. Since smart grid can efficiently deliver sustainable, economic and secure electricity supplies, it represents the future grid development trend. Considering the wide applications of smart grids in future, the demand response control in the study is developed under dynamic pricing which is commonly used in smart grids.

The study results demonstrate the significant impacts of load prediction uncertainty on demand response control. With recognition of such significant impacts, researchers will take careful considerations of the load prediction uncertainties in the associated demand response control developments. Moreover, a robust demand response control has been developed in this study which is able to achieve 7.3% cost saving under the load prediction uncertainty. The developed robust control is useful for commercial buildings to achieve significant cost savings in practice particularly as uncertainty exists.

The structure of the paper is arranged as follows. In Section 2, the basic idea of the robust demand response control is introduced. In Section 3, the central air-conditioning system with a thermal storage system is described and the component modellings are given. Meanwhile, the local control strategies used in the constructed platform are illustrated. In Section 4, case studies are conducted and the study results are analyzed. The conclusion part is given in Section 5.

2. Methodology

2.1. Basic idea of the robust demand response control

The basic idea of the proposed demand response control under load prediction uncertainty is as shown in Fig. 1. It consists of four main parts. The first part is to predict the hourly cooling load using the three-step method developed in Ref. [29]. The second part is to identify the distribution of the load prediction uncertainty. One means for identifying uncertainty distribution is to compare the prediction results with the actual measurements [18]. Using the predicted cooling load, the third part is to obtain the hourly initial control signals using the genetic algorithm (GA) method. The hourly control signal refers to the hourly cooling charging and discharging rates of the building thermal storage system. If the predicted cooling load is perfectly accurate, the initial control signals can achieve the optimal result, i.e. minimizing the daily electricity cost at a given dynamic pricing. Since load prediction uncertainty is inevitable, the initial control signals cannot achieve the objective of cost minimization and they need to be further optimized. Under load prediction uncertainty, the fourth part is to obtain the hourly optimal control signals through optimizing the initial control signals using Monte Carlo method. Note that the first part (i.e. load prediction part) is the previous work of the authors while the third part and the fourth part are the main original work of the study.

2.2. Load prediction and its uncertainty distribution

The load prediction method consists of three steps Step one is the original load prediction according to a selected reference day. The reference day is selected based on occupancy similarity principle. The load of the reference day is taken as the original load prediction result of the targeted day. Step two is the calibration of the original load prediction result using the weather forecast data which are most correlated to cooling load. Step three is to further improve the accuracy of the calibrated load prediction using the load prediction errors. More details can be referred to [29].

With regard to the uncertainty distribution, the cooling load actual measurements and the associated prediction results are compared, as shown in Eqn. (1). The comparison results are used for the uncertainty distribution identification.

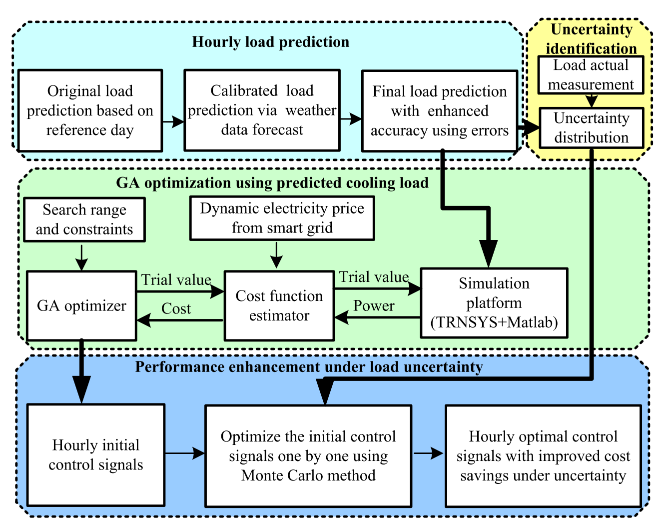

Fig. 1. Framework of the robust demand response control under load prediction uncertainty.