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Building Demand Response and Control Methods for Smart

Grids: A Review

Abstract: Demand response (DR) provides a solution to the grid imbalance problems which restrict the use of renewable energy. Since buildings possess high amount of flexible load, they could contribute to smart grid stability and achieve cost savings for buildings and the other participants in the smart grid. However, the research and application of building DR are still at the beginning stage. Majority of the existing DR studies are from the view point of the grid side, rather than the demand side. This paper therefore provides an overview on the studies on building DR from the view point of buildings at the demand side. It mainly consists of two parts: (1) an overview of different types of DR programs, and the status of the DR programs in several countries and regions; (2) a review on the control methods for DR in commercial and residential buildings. This review intends to support the further development of DR methods for future smart grid applications and their implementation in buildings.

Key words: demand response (DR), building demand side management (DSM), optimal control, smart grid, building energy efficiency.

Introduction

Renewable energies (solar power, wind power, etc.) are increasingly used for electricity generation in responding to challenges from the depletion of fossil fuels, the dramatic growth of energy demand and energy security requirement. However, due to the uncertain and intermittent nature of renewable energy, the integration of large amounts of renewable generations would cause significant stress on the balance of electricity grids. Generally, electricity has to be generated as required to maintain strict balances between the supply side and demand side since the electricity can hardly to be stored efficiently and inexpensively at

large scale. Once significant imbalance occurs, the grid may suffer from a series of problems such as low efficiency, surplus energy waste, high pollutant emission, and voltage sags and facilities damages. In worse cases, the whole power systems, including generation, transmission, and consumption equipment, might be shut down, resulting blackouts.

Power balance can be achieved through many efforts. A conventional solution is to interconnect the grid into regional, national, or continent wide networks, so that redundant alternatives are available for routing the power flow. Another conventional solution is to integrate large energy storage systems in the grid. The surplus electricity can be stored when production exceeds consumption. The stored energy is feed back to the power grid during peak demand periods. In this way the construction of power plants does not need to meet the need of peak demand which only happens during a small percentage of their life-cycle (ETSA 2011; Gyamfi et al. 2013). However, the large scale energy storage facilities are either too expensive or highly relies on natural conditions. For instance, pumped hydro energy storage systems can only be built in places where there are reservoirs with significant difference in height levels.

Power balance may also be achieved by reducing the demand through various efforts on demand side. Firstly, the total electricity demand could be reduced by improving the energy efficiency of electricity loads (i.e., electrical users). Secondly, flexible electricity loads are capable of acting as dynamic power management and regulating resources due to the development of advanced information and control technologies. The use of such demand management resources for power balance is also referred as demand response (DR), which has been increasingly attracting attentions from different disciplines in the recent decade (Wang et al. 2014). One of the most recognized definition of DR is given by the U.S. Department of Energy (2006): "Changes in electric usage by end-use customers 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." DR is showing its great potential in enhancing the grid stability and increasing the renewable energy share (Gils 2014).

As one of the major electricity consumers, buildings are capable of playing a significant role in DR by reducing or shifting their electricity demands during peak periods in response to events or price incentives. Buildings consume over 90% of total electricity in high density urban areas like Hong Kong (Electrical and Mechanical Services Department of Hong Kong 2012), and about 40% of total energy used worldwide (Kolokotsa et al. 2011). More importantly, buildings actually have considerable amount of flexible loads. For instance, the electricity load for cooling/heating could be shifted with the use of building thermal mass and other thermal storage facilities.

Currently, the development and application of buildings DR are still at the beginning stage. Particularly, a comprehensive review for providing sufficient knowledge and information to all DR practitioners and from the viewpoint of demand side is keenly needed.

Though a few review papers on demand response can be found in the literature, most of these papers have their special focuses with limited attention on building DR. For instance, Aghaei and Alizadeh (2013) published a review on smart grids involving renewable energy generations. Siano (2014) addressed the enabling technologies for smart grids. Arteconi et al. (2013) and Shariatzadeh et al. (2015) summarized the efforts on DR in UK and US respectively. Haider et al. (2016) presents an overview on residential DR systems and techniques. Wang et al. (2014) reviewed the potential DR technologies for buildings. But the DR control methods and their implementation in buildings under different DR programs or grid pricing policies are not addressed sufficiently.

This paper therefore aims to provide an overview of DR mechanisms and control methods for buildings in smart grid. It mainly consists of two parts. The first part introduces the mechanisms of different types of DR programs, as well as the current status of DR programs in several countries and regions. The second part provides an overview of DR control methods for both commercial and residential buildings. The rest of this paper is organized as follows: Section 2 presents the fundamental concepts of DR, including the definition and categorization. It also provides an overview of DR programs in different countries. Section 3 and 4 provide a review on the control methods for DR in commercial and residential buildings, respectively. Section 5 provides a summary of this review work.

Different types of DR programs

Categories of DR Programs

A commonly accepted categorization of DR program appears in a U.S. DOE report (U.S. Department of Energy 2006; Albadi and El-Saadany 2008), in which DR programs are categorized into two main categories, i.e. the incentive-based and the price-based, as shown in Figure 1. The incentive-based DR programs are also named as event-based, system-led, emergency-based, or stability-based DR programs. The price-based DR programs also have other names, such as time-based rates, market-led and economic-based DR programs.

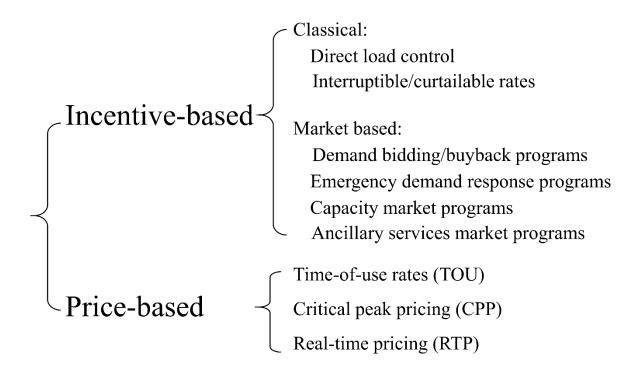


Figure 1. Categorization of DR programs

Incentive-based DR

Incentive-based DR programs provide end-users with incentives for reducing their load when the grid reliability is under threat. These incentive-based DR programs are further classified into two sub-categories based on their incentive mechanisms, i.e. the classical programs and the market-based programs (Albadi and El-Saadany 2008), as summarized in Table 1.

Table 1. Different types of incentive-based DR

Price-based DR

Price-based DR programs are based on dynamic electricity pricing. This category mainly includes time-of-use rates (TOU), critical peak pricing (CPP), and real-time pricing (RTP). These programs aim at flattening the demand curve by offering a high price during peak periods and a low price during off-peak periods. Participants change their usage in response

to varying prices to take advantage of lower-priced periods and avoid higher-priced periods. Different price-based DR types have different rewards, risks and uncertainties as demonstrated in Figure 2 (Hu et al. 2015; Kim and Shcherbakova 2011; FERC 2012). It can be seen that higher rewards often mean higher risks and uncertainties.

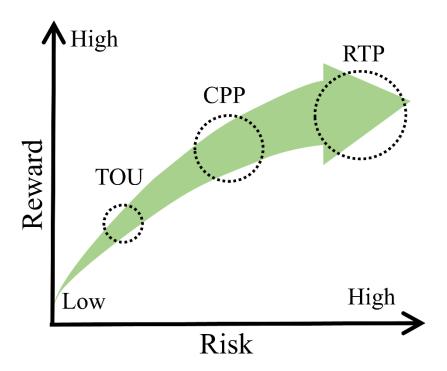


Figure 2. Rewards, risks and uncertainties (indicated by circle size) of price-based DR

TOU employs a static price schedule. Although the electricity prices vary with different time periods, the prices and time periods are normally informed at least one year ahead (Gyamfi et al. 2013). The simplest TOU program consists of two time periods, i.e. the peak period and the off-peak period.

CPP rate is usually used during contingencies, and can be considered as a variant of TOU with less predetermined restrictions (Palensky 2011). It can be superimposed on normal flat rates or TOU rates. The total CPP time in a year is usually limited to days or hours. A special case of CPP is the "extreme day price", in which an extremely high price is effective for a continuous 24 hours of the extreme day which is normally informed only a day ahead.

RTP is the most sophisticated type of price-based DR. End-users are charged with varying prices which is typically informed on a day-ahead or hour-ahead basis. Since the end-users have to provide feedbacks, RTP requires real time and two-way communication. Despite of that, RTP is recognized as the most direct and efficient DR program by many economists (Borenstein 2002).

DR Programs and potentials in different countries and regions

DR programs have been promoted in many countries to improve the utilization and efficiency of power plant and grid capacities. Independent System Operators (ISOs) may offer different DR programs targeting at different customer groups. This section presents a briefing on the available DR programs provided in several countries and regions. DR potentials of those markets are also mentioned.

In United States

The United States has about 10 separated electric power markets (FERC 2015). And the DR market is predicted to grow at a moderate speed in this decade (Shibata and Wyatt 2014).

Walawalkar et al. (2010) conducted a survey on the DR programs in two of the main electricity markets in the US, i.e. NYISO (New York Independent System Operator) and PJM (Pennsylvania-New Jersey-Maryland Interconnection). The NYISO provided five DR programs, including two incentive based programs, a price based program and an ancillary service program. PJM had experienced three generations of DR (PJM 2009). The first generation refers to utility interruptible rates and direct load control. The second generation includes regional transmission operator DR programs. The third generation is the involvement of price responsive demand in both the wholesale (sales and purchases between electric utilities) and the retail market. In 2008, DR programs customers in existing wholesale

and retail markets were estimated to be capable of providing about 38,000 MW of potential peak load reductions (Cappers et al. 2010).

In Europe

In Europe, various forms of load shedding mechanisms were targeting at large industrial customers for reducing peak demands. For instance, in Sweden, a temporary regulation was established to require large industries to reduce their consumptions with the durations between 0.5 and 3 hours per day (Turvey 2003). Finland had carried out interruptible programs for several years. Norway had also launched specific programs aimed to postpone the expansion of grid capacity (Torriti et al. 2010). In the residential sector, European countries mainly focus on the wide application of smart meters.

Although many Europe policy makers often ignore the potential contribution of utility suppliers and end customers in tariff alternatives (Hu et al. 2015; Wolak 2011), some countries are testing or pilot studying the mechanisms of TOU and/or CPP (Ireland Commission for Energy Regulation 2011; Soares et al. 2014; Stromback et al. 2011).

Gils (2014) estimated the theoretical DR potential in Europe. In every hour of a year, the three sectors (industry, tertiary, and residential) combined could provide a minimum load reduction of 61 GW and a minimum load increase of 68 GW.

In China

China is gradually restructuring the power sector to make it more competitive, cost-efficient and market-driven (Wang et al. 2010). Its power generation capacity reached 1,247 GW by the end of 2013, with an annual growth rate of 9.3% (National energy administration 2014). On the other hand, the utilization hours of power generation equipment have continued to drop since 2004 (China Electricity Council 2007). The utilization hours for

equipment with capacity higher than 6 MW dropped to 4286 hours in 2014, with an annual reduction of 235 hours, which is the lowest level since 1978 (National energy administration 2015). The drop mainly happened in thermal power plants.

Although DR programs in China are still in the beginning stage and not widely implemented, significant efforts have been made to promote DR programs. Those programs targeting at major electricity consumers have curtailed significant amount of peak load since 1997 in Beijing, Jiangsu, Guangdong, etc. The dominant residential DR programs in China is the TOU program which is implemented in several cities and provinces, including Beijing, Jiangsu, Guangdong, Zhejiang, etc. (Wang et al. 2010).

In Hong Kong

In Hong Kong, China Light and Power (CLP) has launched three pilot DR programs in 2014 (CLP 2014) including: (1) "myEnergy Pilot Programme" for residential and small-to-medium commercial customers, (2) "Automated DR Programme", and (3) "Bilateral contract DR Programme". Both the second and third programmes are for large commercial and industrial customers.

In the "myEnergy Pilot Programme", smart meters (named as advanced metering infrastructure) are installed. The TOU tariff and "Summer Saver Rebate" are used in this program. About 3,000 domestic customers and 1,400 small-to-medium commercial customers have involved in this 18 months pilot program (CLP 2014).

The "Automated DR programme" is actually a direct load control program. With agreements in advance and free devices installed at customer side, CLP automatically and remotely reduces the electricity consumption of large equipment. In the "Bilateral contract

DR Programme", customers reduce their electricity usage themselves during the periods of potential very high demand which are informed by CLP in advance (CLP 2014).

In other countries

In addition to above countries and regions, many other countries are also developing DR programs, policies, and trials under the umbrella of smart grid, such as Australia (Aghaei and Alizadeh 2013; Fan and Hyndman 2011; Strengers 2010; Charles River Associates 2003; Ericson 2009), India (Harish and Kumar 2014; Filippini and Pachuari 2002), Japan (Asano et al. 2011; Shariatzadeh et al. 2015), Korea (Hu et al. 2015; Jang et al. 2015; Jang et al. 2016), Thailand (Pasom et al. 2015), etc.

Risks and concerns of participating DR programs

Although DR programs provide cost saving opportunities to customers, not all customers are capable of getting such benefits due to some constraints and uncertainties in building demand side control (Kim and Augenbroe 2013; Kim and Shcherbakova 2011; Gyamfi et al. 2013). For instance, customers may either increase or reduce costs by switching from flat pricing to TOU programs. Based on a survey on 43 TOU programs for industrial customers in US, the cost savings ranged from -72.0% to +82.6% depending on different programs and control strategies (Wang and Li 2015). The DR benefits may also be influenced by consumer income and education level (Hu et al. 2015).

The risks and uncertainties may prevent customers from participating DR programs. For instance, some customers tend to prefer not to face penalties for failing to curtail their power demands (Walawalkar et al. 2010). A survey reported that commercial customers have various concerns, though the concerns may be misperceptions (Goldman et al. 2010): (1) Uncertainty exists in DR benefits; (2) The financial benefit is not great enough to justify

participation; (3) DR is "for the utility's benefit", not for customers; (4) The energy services may be reduced below acceptable levels; (5) DR may reduce the funding or labor resources that could be devoted to energy efficiency activities.

The promotion of DR in residential buildings is also not an easy task due to some obstacles. Gyamfi et al. (2013) summarized three main obstacles in residential DR: (1) Unresponsiveness of some residential consumers; (2) Equity issues since low income households may not be capable of avoiding peak prices; (3) High cost of the metering infrastructure, such as smart meters.

DR strategies for commercial buildings

An overview on building DR strategies

Generally, there are four types of strategies could be used for DR: (1) Demand limiting: to flatten the demand curve when the demand is about to exceed a predetermined value; (2) Demand shedding: to limit power demand during grid critical peak periods; (3) Demand shifting: to shift the power demand in peak periods to off-peak periods by utilizing energy flexible equipment; (4) Onsite generation: to use onsite power generation system instead of the grid electricity. The categorization and realization methods of these building DR strategies are shown in Figure 3. Demand shedding and demand limiting share same control methods since they both require buildings to reduce power demand for a period of time. The difference between them is that demand shedding mainly response to grid conditions, while demand limiting mainly response to building electricity load conditions (Sun et al. 2013). In some electricity tariffs, buildings would be charged with a price penalty if their electricity consumptions exceed predetermined peaks. And demand limiting would be useful in such scenario.

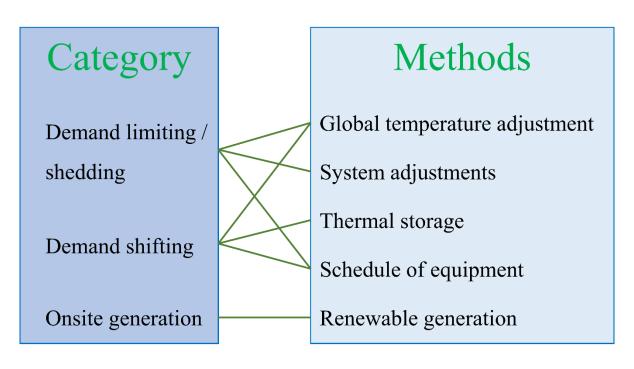


Figure 3. Building DR category and methods

DR strategies are generally developed in associate with different building systems. Various DR strategies can be implemented mainly in HVAC systems, lighting systems, other consumption systems and on site generation systems, etc., as summarized following.

HVAC systems

Classification of DR control strategies for HVAC systems

HVAC systems are excellent DR resources in commercial buildings for several reasons. Firstly, they consume a significant portion (as much as 70% in hot days) of electricity load in buildings (Kueck et al. 2008). Secondly, building structure and envelop may be excellent thermal mass for thermal energy storage, which enables the flexibilities of HVAC systems in adjusting load without immediate impact on indoor thermal environments. Thirdly, most HVAC systems are monitored and controlled by energy management and control systems (EMCS), which provide opportunities for reliable and repeatable DR control. Many DR control strategies are available for HVAC systems. As shown in Figure 4, all the strategies are classified into three categories. (1) The global temperature adjustment (GTA) strategy

achieves flexible building load by adjusting the temperature set-point of air-conditioned spaces. (2) The systemic adjustment (SA) strategies control the systems directly to reduce their power consumptions. (3) The rebound avoidance strategies are used to avoid power rebound at the end of DR periods (Motegi et al. 2006). The three types of strategies may be combined to achieve a high demand reduction. Some of the recent studies on using HVAC system for DR are summarized in Table 2.

DR strategies for HVAC systems

Global temperature adjustment

Load reduction Pre-cooling

Systemic adjustment

Reduce fan power

Limit cooling demand

Reduce chiller demand

Rebound avoidance strategies

Slow recovery strategy

Sequential equipment recovery

Extended DR control period

Figure 4. Classification of DR control strategies for HVAC systems

Table 2 studies on DR of commercial HVAC system

Global temperature adjustment (GTA) strategy

The concept of the GTA strategy is to increase the indoor air temperature set-point in cooling season or decrease the set-point in heating season during the DR period. By this means, the electricity consumption of a HVAC system could be reduced with the reduction of building cooling/heating demand. Although the change in indoor air temperature may

compromise thermal comfort, this strategy is practicably acceptable considering that the DR request commonly happens in hot summer, in which people may still feel comfortable with higher indoor air temperature (Olesen et al. 2004).

The power savings using GTA strategy consists of two parts: the transient savings and the steady-state savings, as illustrated in Figure 5 (Motegi et al. 2006). The transient savings happens at the beginning of DR period. When the space temperatures are reset, HVAC systems automatically tune down their cooling/heating outputs due to the gap between setpoints and measured temperatures. As space temperature increases/decreases, building thermal mass will release the stored thermal energy naturally. After the stored energy is used up and the HVAC systems are stabilized, the load is still lower than the baseline due to the reduction in the temperature difference between indoor and outdoor air. The corresponding savings are named as steady-state savings.

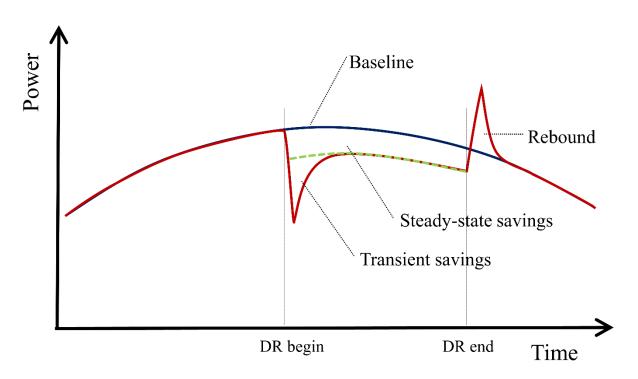


Figure 5. The two types of savings during DR period with GTA strategy applied

As can be noticed from table 2, GTA method appears to be the dominant one in the literature. Some other researches are also helpful for developing GTA methods. For instance, Lee and Braun (2008a, 2008b, 2008c) developed dynamic inverse building model for determining the proper zone temperature set-points in demand limiting controls. It shall be mentioned that GTA could also be used as a pre-cooling method for reducing building peak demand. Pre-cooling refers to precool the zone during unoccupied hours or prior to DR periods, which is the most effective way to get rid of the comfort constrains (Xu 2005; Yin et al. 2015).

Systemic adjustment (SA) strategy

Electricity demand by HVAC systems could also be achieved by systemic adjustment strategy, which is to place limits on certain equipment (Motegi et al. 2006; Watson et al. 2006). Different methods suit different types of HVAC systems. The commonly used systemic adjustment methods are summarized in Figure 6.

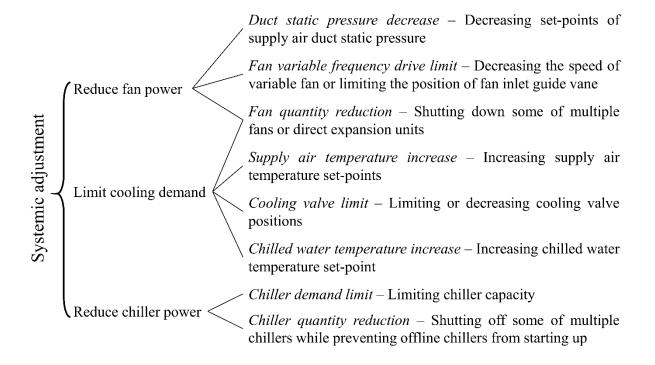


Figure 6. Systemic adjustment strategies

It shall be noticed that the selection of these methods must take the type and characteristics of HVAC systems into account. Otherwise, they may cause disaster to the entire HVAC systems. In addition, some of the methods have to be cooperated with other methods to avoid system imbalance or unstable. For instance, if the chilled water temperature is already optimized, increasing chilled water temperature set-point may result in power increase in chilled water pumps and supply air fans, and finally increase the total power consumption of the entire HVAC systems. This method therefore has to be cooperated with the pump and fan speed limit methods.

Although it is not easy to achieve system rebalance, the use of systemic adjustment method can provide a fast power reduction. For instance, the concept of chiller quantity reduction strategy is to limit chiller power consumption immediately upon request. However, simply shutting down the operating chillers may cause the whole HVAC system unstable, e.g. the imbalance of cooling (chilled water and supply air) distribution to individual zones. When using such fast DR method, the related equipment (such as pumps, AHU fans, valves, dampers) shall be properly controlled. Xue et al. (2015) proposed a chilled water distribution rebalancing scheme. Simulation results show that the imbalance problem could be solved by the water rebalancing scheme coupled with a space air temperature adjustment method.

Rebound avoidance strategies for HVAC system demand shedding

When the HVAC system returns to normal condition at the end of the DR period, there may be a sudden increase in cooling demand. Such increase may cause a spike in the demand curve, which is named as rebound of power demand (Figure 5). The rebound should be avoided since it may have adverse impact on the electricity grid.

Motegi et al. (2006) summarized three methods for avoiding the rebound. A method to avoid rebound is to gradually restore to normal indoor air set-points if GTA strategy is used,

or gradually release restrains on HVAC equipment if systemic adjustment strategies are used. However, for many conventional EMCSs, the implementation of such gradually recovery strategies can be very difficult or may not be possible. An alternative is to extend the DR period to the time when there is significant drop in cooling/heating load. For instance, in office buildings or retail stores, the drop normally happens after working or opening hours.

Lighting systems

Lighting systems may also be excellent DR resource for three reasons. Firstly, it is the second largest power consuming systems just after HVAC systems. Secondly, the demand reduction could be immediately achieved by reducing lighting levels. Thirdly, reducing lighting levels can result in significant reduction in cooling load since lighting produces heat. Sezgen and Koomey (1998) reported that 1 kWh reduction in lighting contributed to 0.48 kWh reduction in cooling system for existing commercial buildings.

The control of lighting for DR in commercial buildings is relatively simpler than the control of HVAC systems. Nearly all of the strategies (Figure 7) are realized by reducing lighting level through dimming (Christantoni et al. 2015) or switching off some lights. All these methods therefore belong to the demand shedding category (Motegi et al. 2006). The switching methods shown in Figure 7 consists of two types, one is to switch off all lights in an entire zone, and the other one is to switch off a portion of luminaires or lamps in luminaires. The dimming methods also have two types depending on the capabilities of lighting systems. The stepped dimming method may be achieved by stepped switching or by installing stepped dimmable ballasts. The continuous dimming method is applicable for lights installed with continuous dimmable ballasts.

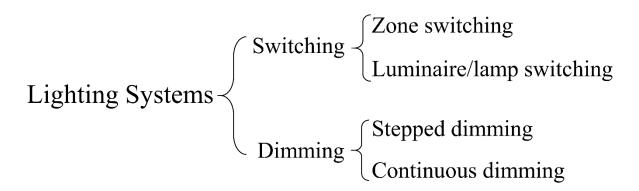


Figure 7. Lighting control methods for DR

Other consuming systems

In addition to HVAC and lighting systems, other electrical equipment could also provide chances for DR in commercial buildings. For instance, Aduda et al. (2014) reported that electrical humidifiers could be used as DR recourse. Their experimental study showed that the adjustable 30.0 kW steam humidifier could shed at least 7.0 kW in power reduction.

Onsite generation systems

Although not all kinds of onsite generation are encouraged for DR, the use of distributed renewable generation integrated with storage systems could be a feasible solution for DR (Lee et al. 2015). Since most of the current commercial buildings are not equipped with renewable generation systems, the use of distributed renewable generation for DR is not surveyed in this work. An overview on the control of connected distribution power generation systems for DR could be found in (Bouzid et al. 2015).

DR strategies for residential buildings

Although DR programs are mainly focused on the commercial and industrial sectors due to the large DR reduction they can offer, residential DR is also gaining the interest of utilities and researchers. As a whole, residential buildings can also provide a considerable amount of flexible load for balancing electricity supply and demand (Gottwalt et al. 2011). Hao et al.

(2015) concluded that residential thermal loads are potentially more cost effective than other energy storage means for providing regulation reserve to the grid. In Texas, residential air conditioning load accounts for 20.1% (6.1 GWh) of grid electricity load on March 31st 2010, and the value went up to 52% (35.3 GWh) on August 3rd 2010 due to hot weather (Wattles 2011). Besides of balancing electricity demand and supply, residential DR is reported to be capable of reducing pollutant emissions during peak electricity demand days (Gilbraith and Powers 2013; Finn et al. 2013). A survey on residential customer response to CPP in California indicates that well equipped participants used 25% and 41% less energy for 5 and 2 hours critical events, respectively (Herter et al. 2007).

Research efforts on residential buildings may be categorized into two types (Tiptipakorn and Lee 2007), i.e. the grid oriented type and the customer oriented type. The grid oriented research mainly focuses on achieving supply and demand balance and stability of electricity grid, while the customer oriented research mainly focuses on achieving minimum electricity cost for consumers. This section provides a brief on customer oriented research. It firstly introduces the classification of home appliances, and then presents a review on the use of different appliances for DR.

Categorization of Home Appliances for DR

The cost savings achieved from residential DR are highly dependent on the control performance of different domestic loads. Researchers divide all domestic loads into six groups based on their functions (Hamidi et al. 2009). When concerning the control method development, however, the categorization of home appliances based on degree of control might be more applicable. The simplest classification consists of two groups, i.e. the controllable groups and the non-controllable groups (Abushnaf et al. 2015). Another more detailed categorization based on degree of control consists of four groups (Soares et al. 2012;

Soares et al. 2014). (1) Non-controllable loads: Loads when reduced may result in discomfort to users or interruption on ongoing activities (lighting, cooking appliances, etc.). (2) Reparameterizable loads: Loads that could be controlled without bringing significant discomfort (refrigerators, air conditioning systems, electric water heaters, etc.). (3) Interruptible loads: Loads that can be interrupted for a short period of time without sacrificing the provided services quality (refrigerators, air conditioning systems and electric water heaters, etc.). (4) Shiftable loads: Loads that can be shifted to other period of time without affecting user comfort (washing machines, clothes dryers, dishwashers, etc.). It should be noted that the non-controllable loads can actually be DR source when sacrificing user comfort is allowed. Also, the reparameterizable loads and interruptible loads may be merged into one group since they show considerable overlaps.

The categorization of DR control methods shown in Figure 3 is also applicable for residential buildings. Different home appliances may use different types of control methods depending on their properties. For instance, the main means of controlling thermal appliances are the load shifting methods and demand limiting methods.

Control of single type of thermal appliance

Refrigerators

Refrigerators can provide considerable power reduction since almost all homes have these loads (Niro et al. 2013). Refrigerators can be shut off for a while without negative impact on the delivered service. Also, the defrosting process in refrigerators has a big saving potential since it is active for a very short time and remains inactive for several hours (Zehir et al. 2012).

The control strategies found in the literature for controlling refrigerators are load shifting methods. To use refrigerators as DR resources, they may be controlled in large scale to achieve considerable amount of demand reduction. Niro et al. (2013) developed three control strategies for large scale control of residential refrigerators to achieve peak demand reduction. The first two strategies directly turn on the refrigerators before peak demand, and turn them off during peak time, unless their inside temperatures reach the high and low limit. The only difference between the two is that the second one turns on the refrigerators group by group before peak demand. The third one, which was tested to be the best, added the refrigerators with two modes to improve the electricity profile while reducing peak demand.

Zehir et al. (2012) analyzed the economic effects on consumers with controlling refrigerators at large scale as a DR resource. Based on different pricing tariffs in Turkey, the simulation results indicate that 37.9% of refrigerators' demand can be shifted to off-peak periods, resulting in 11.4% savings in the annual electricity bills.

Air-conditioners

Similar to HVAC systems in commercial buildings, domestic air-conditioners are ideal DR resources since they are the major electricity loads. The temperature adjustment method used in commercial buildings is also applicable to domestic air-conditioners. Air-conditioners are operated at low boundary temperature during low price periods and at high boundary during high price periods (Tiptipakorn and Lee 2007). A study found that the temperature adjustment method could curtail peak load by 24.7%, and save annual electricity cost up to 10.8% (Yoon et al. 2014).

The programmable communicating thermostats enable air-conditioner better performance for residential DR. Herter et al. (2007) conducted a survey on residential DR to CPP in California. During five hour critical events, participants without using such control

technology used 13% less energy than they did during peak periods, while participants equipped with programmable communicating thermostats used 25% less energy. Newsham et al. (2011) compared four methods to evaluate the effect of a utility program using air-conditioner to shift peak electricity use. In the program, the load is directly controlled by increasing thermostats by 3.6 °F (2 °C) for 4 hours on 5 event days.

The cost savings of using the temperature adjustment method in domestic air-conditioners is highly related to weather conditions. Surles and Henze (2012) found that the control strategies and the electricity tariffs designed for one climate region may have very different effectiveness in another climate region. For instance, it yields much less incremental benefit in Los Angeles than that in Houston when increasing the offset from 3 °F (1.67 °C) to 6 °F (3.33 °C). Research on building energy simulation may be helpful in estimating the cost savings in residential buildings in different climate regions under different electricity tariffs. For instance, El-Ferik et al. (2006) developed physical models to predict load profile of residential air-conditioners.

Heat pumps

Similar to air-conditioners, heat pumps which provide domestic heating or hot water could perform as a DR resource as well. The advantage of using heat pumps for DR is that it can easily be coupled with thermal energy storage systems (Ali et al. 2015). During peak periods, heat pumps could be switched off to curtail electricity demand. A study (Arteconi et al. 2013) in the UK indicates that it is possible to achieve well controlled indoor temperature even if heat pumps are turned off for 3 hours.

Heat pumps could also be coupled with local electricity generation. Schibuola et al. (2015) proposed three dynamic scheduling methods to control such systems. The scheduling of different devices is based on the renewable generation and simultaneous heating load and

electricity prices. The results indicate that up to 30% cost savings could be achieved without compromising thermal comfort too much.

Water heaters

Domestic electric water heaters are suitable for DR since they possess high nominal power and are normally combined with large thermal storages (Kepplinger et al. 2015; Ali et al. 2015). Residential water heaters consume 10% of the household electricity consumption in Norwegian (Larsen and Nesbakken 2005). By controlling load of residential water heaters to reduce peak demand, the average reduction from a household is 0.35-0.58 kWh/h in the morning and 0.18-0.59 kWh/h in the evening (Ericson 2009).

Many control methods are used for controlling water heaters, such as exhaustive search optimal control, model based optimal control, multi-objective optimal control. Du and Lu (2011) proposed an exhaustive search algorithm to balance the energy cost and user comfort level by controlling water heater. The simulation study was based on RTP DR program. By utilizing forecasted price and water usage, the control strategy could achieve balances through varying water temperature within its boundary. Kepplinger et al. (2015) developed a model to predict thermal behavior of water heater. An optimal control is developed based on expected demand and day-ahead price. The simulation study shows the strategy can save approximately 12% cost and 4% energy. Tiptipakorn and Lee (2007) developed a multi objective strategy to minimize the variation of outlet water temperature and the total energy cost simultaneously. Paull et al. (2010) proposed a water heater model for multi-objective DR. The model predicts the temperature of the water in the tank considering the thermal energy losses and the water usage.

Control of several types of appliances together

Many studies on domestic DR focus on the control of several appliances together to achieve higher power reduction during DR periods. The control methods mainly include: (1) moving flexible loads to off-peak times; (2) coordinating the timing of frequent intermittent loads; (3) applying short-term delays to avoid high peaks (Dlamini and Cromieres 2012). The controlled appliances may include domestic loads (consumers), energy storage systems (buffers), and on site generation systems (producers). The studies in existing literature are therefore grouped into three groups according to the involvement of the types of the controlled appliances, as shown in Figure 8.

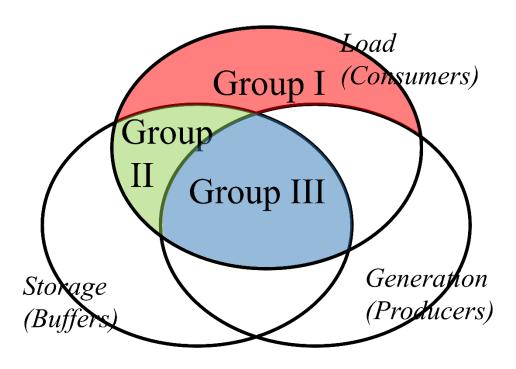


Figure 8. Groups of mixed domestic appliance

Group I: domestic loads only

In Group I, the proposed methods control domestic loads with no energy storage, or without using their energy storage capabilities even if they have. The main task of such methods is to schedule the appliances dynamically according to the electricity price or the incentive offered during peak times.

Chen et al. (2012) developed scenario-based stochastic optimization and robust optimization approaches to control six typical domestic loads (plug-in electric vehicle, dishwasher, cloth washer, electric water heater, air conditioner, and oven) for DR under RTP program. Setlhaolo (2014) proposed a mixed integer nonlinear optimization model to control regular home appliances under TOU tariff. Simulation results indicate that more than 25% of electricity cost could be saved. Abushnaf et al. (2015) proposed a home energy management system to control home appliances, including cooling/heating, dishwasher, water pump, clothes dryer, electrical vehicle, and water heater. Both TOU and RTP programs are considered in the simulation study. The results show significant reduction in both costs and total energy consumption. Fernandes et al. (2014) proposed a dynamic load priority method, which considers users interactions, as well as the technical characteristics of each load, such as time constrains and load priorities. Giorgio and Pimpinella (2012) developed a strategy for smart home controllers. The scheduling of appliances is based on prediction models of four types of loads (plannable, controllable, monitorable, and detectable loads). The strategy was evaluated under TOU tariff based on simulations.

Group II: domestic loads integrated with energy storage systems

In Group II, the DR methods control appliances including energy storage devices or utilize the energy storage capability of some controlled appliances. The energy storage devices could be thermal storages or electricity batteries.

Vanthournout et al. (2015) proposed a strategy to control smart white goods and smart domestic hot water buffers in day-ahead RTP program. A pilot test was conducted in 58 families for a period of about 11 months. It was found that though the white goods outperformed the hot water buffers in terms of relative savings, the absolute savings in hot water buffers were significantly larger.

Besides of thermal buffers, electricity battery is also proposed for residential electricity peak shaving (Leadbetter and Swan 2012). The storage system consists of a rechargeable battery, a bi-directional grid integrated inverter, and a controller. A method for simulation and sizing of such battery is provided in the same study.

Group III: Integrated domestic loads, energy storage and on site generation

In Group III, all the three types of devices (domestic loads, energy storage, and on site generation) are cooperated to achieve cost savings. Due to the comprehensive nature of such systems, advanced control strategies are commonly used for DR control.

Pedrasa et al. (2010) proposed a particle swarm optimization based scheduling method to cooperate distributed energy resources including pool pump, space heater, storage water heater, plug-in hybrid vehicle, and a PV system. The proposed method coordinates the resources so that no PV energy is exported, and the grid electricity use during peak and CPP periods is minimized. Jiang and Fei (2011) proposed to use the PSO algorithm to solve both the nonlinear programming problem of dynamic DR and the linear programming problem of micro CHP. The Q-learning algorithm was also used to solve the problem of battery discharging.

Matallanas (2012) developed a neural network control system to enhance the energy performance of a solar house system which includes PV generation, electricity batteries, automated appliances and a connection to the grid. The method could maximize the use of local PV generation through scheduling the tasks demanded by the user. Kriett and Salani (2012) built a mixed integer linear programming (MILP) model to describe the problem of energy management of a residential micro-grid. The problem is then solved by a MILP solver embedded model predictive control.

Lujano-Rojas et al. (2012) proposed an optimal load management control strategy for residential buildings connected with a smart grid. The strategy optimizes scheduling of different devices by predicting electricity demand, prices, and renewable generation. A case study on controlling several appliances (air-conditioner, computer, wind turbine, EV, etc.) indicated that the cost was reduced by 8% to 20% in a typical summer day. Another method divides the control of residential appliances (fridge, battery, heat store, micro CHP, PV, etc.) into three steps (Molderink et al. 2010): (1) local prediction to predict the energy production and consumption patterns; (2) global planning to reach a global optimal; and (3) local scheduling to decide on/off status of appliances.

Other methods for connecting buildings with smart grid appear in the research field of Zero Energy Buildings (ZEB) (Lu et al. 2015). Beside of the common objective of minimizing electricity cost, the ZEB control methods also aims to reduce the electricity transport by self-consumption and encouraging users to control their energy behavior (Castillo-Cagigal et al. 2011). Though these methods may not be suitable for DR, they could still reduce the grid imbalance stress in the context of increasing the usage of green energy.

Electric Vehicles for DR

With the acceleration of battery technology, electric vehicles are viewed as an alternative to traditional internal combustion engine cars. The batteries in EVs could be utilized as energy storages for DR. Yang et al. (2015) summarized all the scheduling and optimization methods for integrating plug-in electric vehicles onto the grid. The methods are classified into two types, i.e. conventional mathematical methods and meta-heuristic algorithms. The conventional mathematical methods include linear programming, non-linear programming, mixed integer programming, dynamic programming, game theory, queuing theory etc. The

meta-heuristic algorithm approaches include genetic algorithm, particle swarm optimization, etc.

Summary and Conclusions

This paper provides a systematic review on the development and applications of DR programs and particularly DR methods and strategies for commercial and residential buildings.

Based on different incentive mechanisms, DR programs could be divided into two categories: the incentive-based DR and the price-based DR. The status of the DR programs in several countries and regions are reviewed and compared. Among all the reviewed countries and regions, the U.S. and European countries are pioneering in developing and implementing DR programs. Some Asian countries/regions such as China, Hong Kong, India, Japan and Korea are also showing great potentials and efforts in DR, and investing smart grid technologies.

Different DR programs have different rewards, risks and uncertainties. High rewards often mean high risks and uncertainties. Besides of enabling devices, effective DR control methods are essential for achieving rewards while reducing risks and uncertainties.

In commercial buildings, many DR strategies have been developed and implemented in the HVAC systems, lighting systems, and other consumption/generation systems. For the HVAC systems, available DR strategies can be categorized as the global temperature adjustment (GTA), the systemic adjustment strategies and the rebound avoidance strategies. For the lighting systems, DR is realized by reducing lighting level through dimming or switching off some lights.

Residential buildings can also provide a considerable amount of flexible load. Thermal appliances in residential buildings are the major flexible loads. To achieve higher power reduction during DR periods, more than one type of domestic appliances could be controlled in associate with each other. Once energy storage devices and renewable generations are involved, advanced control methods are often needed for optimal scheduling of these devices.

As building DR grows around the world, efforts should be further made to make it becomes practically applicable with minimized disturbance to building system operation/control and minimized sacrifice to the services provided. For example, (1) Solutions should be provided to achieve system rebalance if the direct reduction of chiller plant capacity of centralized air-conditioning systems. (2) Uncertainties in building DR and the methods to reduce their impacts should be further investigated. (3) The impacts of demand rebound after DR period are of interest for more detailed study. (4) The impacts of customer usage pattern, particularly domestic customers need more in-depth investigation. (5) The study on long term practical DR application in large scale buildings is still far from sufficient.

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Tables

Table 1. Different types of incentive-based DR

| Incentive-based DR programs | | Incentive mechanism description | | | |
|-----------------------------|---------------------------|---|--|--|--|
| Classical programs | Direct load control | Usually based on previous agreements, the utilities have | | | |
| | | the ability and authority to remotely shut down the | | | |
| | | specific end-use equipment on a short notice to achieve | | | |
| ll pr | | the desired load reduction. | | | |
| ssica | Interruptible/curtailable | Participants are required to reduce their load to | | | |
| Cla | rates | predefined values. Otherwise, penalties would be | | | |
| | | charged according to agreed terms. | | | |
| Market based programs | Demand bidding/buyback | Participants bid for specific load reductions in the | | | |
| | | electricity wholesale market. In case of failing to curtail | | | |
| | programs | the specified amount of load, the customers have to face | | | |
| | | penalties. | | | |
| | Emergency DR programs | Participants are provided with incentive payments for | | | |
| | | reducing load during DR periods. | | | |
| prog | | Participants typically receive day-ahead notice of events. | | | |
| sed | Capacity market programs | They may receive payments in the programs, or penalties | | | |
| et pa | | for failing to curtail when required to do so. | | | |
| arke | | Participants bid for load reduction in markets. If the bids | | | |
| × | | are accepted, they will receive economic benefits both | | | |
| | Ancillary services market | for being standby and for curtailing load upon needed. | | | |
| | programs | (Note: some researchers consider this type of DR as a | | | |
| | | separate category, rather than an emergency-based DR | | | |
| | | program (Walawalkar et al. 2010).) | | | |

Table 2 Studies on DR of commercial HVAC system

| Methods | Reference | Simulation/Real | |
|--|-----------|-----------------|----------------|
| Briefing | Summary | | test |
| Change thermostat set-point. | GTA | Kundu et al. | simulation |
| | | 2011; | |
| | | Alcazar- | simulation and |
| | | Ortega et al. | real test |
| | | 2011; | |
| Change a global thermostat set-point, and | GTA | Beil et al. | real test |
| then shift all thermostats simultaneously. | | 2015; | |
| Maintain minimum air flows, constrain the | GTA + SA | Goddard et | simulation |
| amount of temperature set-point changes. | | al. 2014; | |
| Adjust global temperature set-point, pre- | GTA + SA | Yin et al. | simulation and |
| cooling, reduce minimum air flow, | | 2015 | real test |
| increase supply air temperature, etc. | | | |
| Zone temperature set-point adjustment, | GTA + SA | Christantoni | simulation; |
| pre-cooling, HVAC components | | et al. 2015 | |
| adjustment, etc. | | | |
| Constrain supply air fan speed. | SA | Hao et al. | simulation |
| | | 2014; | |
| | | Hao et al. | |
| | | 2012; | |
| Constrain Supply air flow to reduce fan | SA | Lin et al. | simulation |
| power and chiller power consumption. | | 2013 | |
| Constrain chiller load by reset operating | SA | Gao et al. | simulation |
| chiller number/capacity. | | 2015; | |
| | | Xue et al. | |
| | | 2015; | |
| Adjust global temperature set-point, | GTA + SA | Watson et al. | real test |
| increase supply air temperature, reduce | | 2006; | |
| duct static pressure, limit fan speed, | | Piette et al. | |
| increase chilled water temperature, | | 2005 | |

| constrain chiller power, shut off fans, limit | | | |
|---|------------|------------|------------|
| cooling valve opening, etc. | | | |
| Pre-cooling. | GTA | Xu et al. | real test |
| | | 2005; | |
| Zone temperature set-point adjustment, on- | GTA + | Lee et al. | simulation |
| site energy storage and generation. | storage + | 2015; | |
| | generation | | |
| Constrain chiller load by resetting | SA | Cui et al. | simulation |
| operating chiller number, on-site energy | | 2015; | |
| storage. | | | |

List of Figure Captions

- Figure 1. Categorization of DR programs
- Figure 2. Rewards, risks and uncertainties (indicated by circle size) of price-based DR
- Figure 3. Building DR category and methods
- Figure 4. Classification of DR control strategies for HVAC systems
- Figure 5. The two types of savings during DR period with GTA strategy applied
- Figure 6. Systemic adjustment strategies
- Figure 7. Lighting control methods for DR
- Figure 8. Groups of mixed domestic appliance