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Optimal demand response strategy of a portfolio of multiple commercial buildings: Methods and a case study

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Commercial building demand response control is an effective way to reduce summer electrical peak demand in cities. However, a portfolio of a large number of buildings has different demand response control strategies than individual buildings. In this article, an optimization method is proposed for scheduling demand response strategies for multiple commercial buildings that can be recognized as a multi-building portfolio during demand response. Through this optimal scheduling, decision makers can determine which buildings should participate in the demand response program that controls the strategies that should be used as well as the corresponding optimum starting/ending time. In this article, the optimal scheduling problem is converted into a time series 0-1 programming problem and is solved by the Branch and Bound method, with three optimization objectives of smooth reduction, maximum reduction, and maximum economic benefits. As a pilot demand response case test, the measured data for 18 large commercial buildings (as a multi-building portfolio) in a recent large-scale demand response experiment were used to evaluate the effectiveness of the optimal scheduling method. The results demonstrated that the optimal scheduling scheme can significantly improve the demand response effectiveness of a large number of buildings together.

Introduction

Demand response (DR) is an effective method to regulate the unbalance between supply and demand in the electricity market. DR refers to a type of short-term behavior through which users adjust their inherent pattern of electricity utilization to respond to the notification of pre-signals, which can decrease or shift the demand peak load, contribute to the stability of the power grid, and suppress price increases (U.S. Department of Energy 2006). The traditional power DR mainly occurs in the industrial sector. However, after 2010, an increasing number of commercial and residential buildings have participate in the DR program (Cappers et al. 2010; Torriti et al. 2010). In Europe, DR has begun to acquire momentum in both commercial and residential buildings (Torriti et al. 2010), and in the United States, the DR market has begun to mature gradually (Cappers et al. 2010). In China, demand side management (DSM) traditionally focuses on energy savings in the industrial sector only. However, several DR pilot programs for commercial buildings have been established around the country. In all of these countries, aggregators who are normally responsible for the DR control a large number of buildings and play an important role. Normally, aggregators have up to 10 to 100 buildings participating in a DR event as a group. Therefore, how to distribute the total reduction objective to each building, i.e., how to schedule each building optimally, becomes an essential problem in multi-building portfolio DR events.

In the area of DR of commercial buildings, many researchers have focused on the optimal control strategy of individual buildings and the impact of DR on comfort and economic savings. Morris et al. (1994) researched a building precooling strategy that would contribute to minimum energy demand and fees by a simulation method and validated the method through an experiment. Braun and Lee (2006) optimized air conditioning system control by adjusting the set points for indoor air temperatures, which could create an approximately 30% peak load reduction compared with the night setup control strategy. Then, Lee and Braun (2008) proposed a method for adjusting the indoor air temperature set point, which made the air conditioning load reduction meet the objective during the DR period. Ma et al. (2012) proposed and verified a model predictive control (MPC) technique to achieve the objective of energy cost reduction for a building air conditioning system. Keeney et al. (1997) studied and tested a control strategy on an office building that maintained the indoor air temperature in the comfort range and reduced the air conditioning peak cooling load to 75% by using the building thermal mass when one of four chillers was lost. Song et al. (2003) conducted several surveys on large office, commercial, and hospital buildings and found no effect on most of the occupants and indoor air comfort with a 20~30 min interruption of air conditioning. Xue et al. (2015) noted that conventional DRs are usually subject to significant delay and proposed a fast chiller power DR control strategy for commercial buildings, which solved the disordered chilled water

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flow distribution and uneven indoor thermal comfort degradation caused by simply shutting down some chillers. They concluded that no matter which strategy was used, such as indoor air temperature set point adjustment, shutting down part of the chillers or halting the chiller periodically, the electricity loads can be reduced to a certain degree. The effects of these DR control strategies on a single building can be predicted by building energy simulation software (Madison 1990; Pan et al. 2004) or by the models for the studies mentioned previously.

In general, conventional DR controls for commercial buildings focus on an individual building (Gao and Sun 2015). However, the response buildings are normally connected by the same power grid (Pavlak et al. 2015). For the grid or decision makers, it is more important to realize a total demand reduction to satisfy the current power gap. In the case of affecting the normal operation of a single commercial building, the amount and duration of electricity load reduction are not important to the decision makers. The amount of reduction of the entire portfolio is the key concern of grid managers and DR aggregators.

Some studies noted that integrating multiple buildings as a portfolio will improve the multi-building performance. Gao and Sun (2015) proposed a coordinated DR control that targeted minimizing the building-group-level peak demand based on a genetic algorithm (GA), and they concluded that the control improved the building-group-level performance compared with the conventional one. Farzan et al. (2015) proposed an operation optimization framework for a multi-building portfolio that demonstrated that plans under the proposed pricing schemes resulted in a 5–10% peak reduction. Pavlak et al. (2015) studied the synergistic effect of a multi-building portfolio and DR optimal control and showed that optimizing buildings as a portfolio achieved up to seven additional percentage points of cost savings over individually optimized cases.

The advantage of integrating multiple buildings as a group is obvious (Reddy et al. 2004). The optimal scheduling becomes a problem that needs to be solved when multiple buildings participate in DR as a portfolio.

Abundant previous research on the optimal scheduling of buildings has focused on residential buildings (Du and Lu 2011; Mohsenian-Rad and Leon-Garcia 2010; Yi et al. 2013; Zhao et al. 2013). These investigators studied the optimal startup and shutdown times in accordance with the equipment schedules and the DR price mechanism (i.e., time of use [TOU]). The optimization problem for residential buildings is similar to the optimal scheduling for a commercial multi-building portfolio DR event. However, the problem is more complicated for commercial multi-building portfolios because for each response, a building could have several control strategies, in addition to determining the beginning and ending time of each building.

For the optimal scheduling problems of multiple commercial buildings, several researchers performed relevant studies. Berkeley researchers at the Lawrence Berkeley National Laboratory (Department of Energy 2004) developed and tested a multi-building internet DR control system that used the price signal to influence the behavior of different buildings. Xing (2004) studied the control strategy of how to combine the preset through a smart enumeration and GA. Oh et al. (2014) developed a power scheduling algorithm with the minimum objective of reducing multi-building portfolio electricity fees, and they summarized the problem as a convex optimization that was solved by the Lagrangian relaxation method. Pavlak et al. (2015) optimized a portfolio based on MPC for a single building and considered optimizing a portfolio as a generalization of the single building problem. Richard et al. (2009) proposed a multi-building coordinator that can control the energy use of individual buildings. An energy company can use the coordinator to control these buildings to accomplish DR.

Therefore, optimal scheduling is an important issue for the DR of a multi-building portfolio, especially for decision makers, such as aggregators, and the curtailment of service providers (CSPs). This article aims to propose a new optimal scheduling method for a commercial multi-building portfolio. The method can be used from the perspective of multi-building portfolio decision makers to determine which buildings should respond, as well as their corresponding control strategies and responding time when multiple buildings participate in DR as a portfolio. A detailed description of current problems arising from the multi-building portfolio DR process is presented in Section 2, and the mathematical solution is provided in Section 3. A case study follows in Section 4 that evaluates a portfolio DR strategy for 18 commercial buildings in Shanghai. The conclusion and future work are described in Section 5.

Multi-building DR framework

A multi-building portfolio is defined as a cluster of several buildings. Not all buildings necessarily participate in a DR event, and each building has a number of DR control schemes to select. A DR scheme includes a chilling plant shutting down or cycling, global temperature reset, and so on. DR aggregators or utility decision makers determine which building to use to achieve the desired response, control strategies, and starting–ending time according to the overall portfolio DR objective.

The optimal scheduling framework for multi-buildings in DR is shown in Figure 1. One multi-building portfolio includes N buildings (capital letter denotes building). Taking building A as an example, n_A ($n_A \geq 1$, lowercase letters) is the number of DR strategies for each building. Each control strategy (use "ST" for short) has its corresponding load reduction curves. The problem studied can be described as how to choose these curves and optimize them to match the DR event objective (corresponding to the task of "optimal scheduling" solver in Figure 1).

During a DR event, the electricity grid operators determine the size of the gap between supply and demand for the grid and when the gap appears and ends. Two indices (Xu and Haves 2006) can be proposed to evaluate the effectiveness of a DR: the cumulative load reduction (ΔQ [kWh]) and the load reduction (ΔP [kW]). The DR reduction is calculated by a comparison to a given baseline. The methods to determine the baseline have been discussed in many literature studies (Coughlin et al. 2008). Because the article focuses on an optimal scheduling method that is independent of the baseline

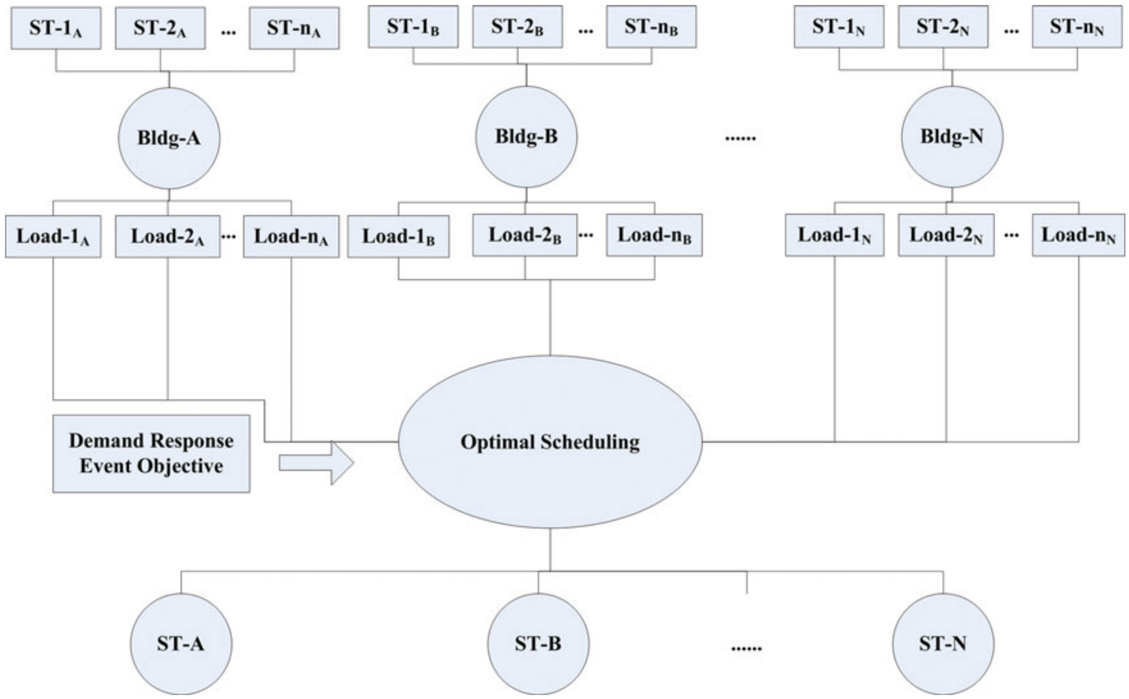

Fig. 1. Optimal scheduling framework for multi-buildings in DR.

method, a similar day of the DR days is chosen as the baseline day. The date of the similar day should be close to the DR day to eliminate the influence of building activity, the type (weekday or weekend) should be the same as the DR day and the ambient temperature should be similar to the temperature of the DR day. In this way, the baseline can easily be determined by comparing these parameters between the 2 days.

The optimal scheduling is then converted into an integer programming problem in this article. In a DR event, the status of a given strategy should be either on or off, which can be described as 0-1 programming. The Branch and Bound method, which can be accomplished by the "bintprog" function in the MATLAB toolbox, is used to solve the problem. The time when a building DR status transfers from 0 to 1 is the response starting time.

The DR objectives are varied in depth (ΔP kW) and width (ΔQ kWh). A short-sharp reduction strategy is correct when the gap is large but the duration is short. Long–smooth reduction is required when the gap is small but the duration is long. Different control strategies for both long–smooth and short–sharp reduction are required by the power grid on different occasions.

The optimal scheduling strategy for a multi-building portfolio presented in this article can run optimal scheduling with three distinct objectives:

Obj. 1: Smooth reduction. Keep the integral reduction to meet the required quantity and, at the same time, keep the reduction smooth during the response period.

Obj. 2: Maximum reduction. Maximize the total reduction during the response period.

Obj. 3: Maximum economic benefit. Maximize the economic interest of electric charge savings or subsidy in the response event.

The mathematical description

Programming and branch and bound

As stated in section 2, the optimal scheduling problem is solved as 0-1 programming. The typical description of 0-1 programming is formed as follows.

$$\min f(x) \tag{1}$$

Subject to:

$$a \cdot x \leq bor - ax \geq -b \tag{2}$$

$$aeq \cdot x = beq \tag{3}$$

The value of x is limited to 0 or 1 in the above equations.

The Branch and Bound method is a common method that is used to solve the integer programming problem. A search tree is formed by adding constraints to the problem, called branching. In each step of branching, the noninteger variable xj is branched into two branches by constraining $xj = 0$ and $xj = 1$. The entire process is described as a binary tree network in Figure 2. In each node, the algorithm solves a slack problem of linear programming, the result of which determines whether to branch or shift to another node.

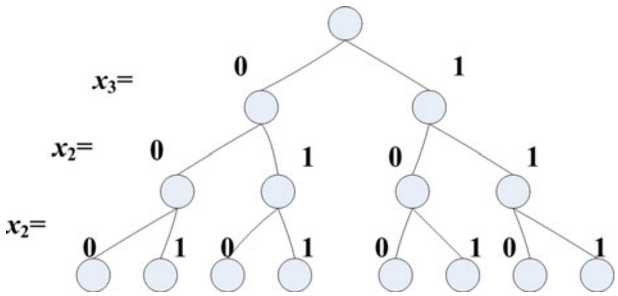

Fig. 2. Tree network with three variables.

The solution of the LP slack problem is always regarded as the lower limit of binary integer programming. Once the problem is a binary vector, the solution is the upper limit. With the increase in search tree nodes, the upper and lower limits of the objective function are updated during the bounding process. The bound on the objective value serves as the threshold to cut off unnecessary branches. Detailed introduction of the Brand and Bound method can be can be found in *Introduction to Mathematical Programming* (Walker, 1999).

The mathematical description of Obj. 1: Smooth reduction

As defined in Section 2, this objective requires the multi-building portfolio to keep the reduction smooth during the response period. To simplify the optimal problem, the response duration is divided into a number of time steps. The objective is to limit the reduction during every time step within a certain range. The scheduling problem for each time step belongs in 0-1 programming. Time steps are dependent upon each other, in that the status of each time step is influenced by the status of the previous time step and influences the status of the next time step. For example, once the response control strategy is determined, the corresponding building must retain this strategy until the implementation of the strategy is finished. In all of the above cases, including no more than one strategy could be chosen for one building, which constitutes the constraints of the optimal process.

First, it is assumed that a multi-building portfolio is composed of N buildings, with n_N types of DR control strategies corresponding to each building. The response time is t, time step is Δt, and total number of time steps is m_t.

$$m_t = \frac{t}{\Delta t} \tag{4}$$

The objective (cumulative and mean) reduction of each time step is $\Delta Q_{m,goal}$ kWh or $\Delta P_{m,goal}$kW, while the actual (cumulative and mean) reduction is $\Delta Q_{m,real}$ and $\Delta P_{m,real}$ kW, respectively ($m = 1,2,\ldots, m_t$). No matter which $\Delta Q_{m,goal}$ kWh or $\Delta P_{m,goal}$kW is used for evaluation, the optimal scheduling method has the same form. Therefore, the cumulative reduction (ΔQ_m) of each time step is determined as the variable studied hereafter. Even if the objective variable is the average loadΔP_m, substitute ΔQ_m with ΔP_m.

During the optimization process, the certain status of the previous time step can possibly constrain the status of the next time step, while the first time step constraint is slightly different from later ones.

Assuming the load curve n_N of the building N has a reduction of $\Delta Q_{m,n_N}$kWh during time step m, the multi-building portfolio reduction is described as:

$$Q_{m,total} = \sum_{i_A=1}^{n_A} x_{m,i_A} \cdot \Delta Q_{m,i_A} + \sum_{i_B=1}^{n_B} x_{m,i_B} \cdot \Delta Q_{m,i_B} + \cdots + \sum_{i_N=1}^{n_N} x_{m,i_N} \cdot \Delta Q_{m,i_N} \tag{5}$$

where$x_{m,i_A}, x_{m,i_B}, \ldots, x_{m,i_N}$ are the strategy curve coefficients, the value of which is limited to 0 and 1. The value of 0 denotes that the corresponding strategy has not been chosen, and vice versa. Because the reduction is not required to be less than a given percentage of the goal reduction in an actual DR event (for example, $\geq 90\%$ $Q_{m,goal}$) and the surplus part would not obtain the allowance (for example, $\leq 110\%$ $Q_{m,goal}$), the decision makers intend to make the reduction exceed the lower limit and approach the goal.

The optimization problem of the first time step in Obj. 1

Combining Equations 2 and 3, the optimization problem for the first time step can be converted into a 0-1 programming problem.

$$\min f_1(x) = \sum_{i_A=1}^{n_A} x_{1,i_A} \cdot \Delta Q_{1,i_A} + \sum_{i_B=1}^{n_B} x_{1,i_B} \cdot \Delta Q_{1,i_B} + \cdots + \sum_{i_N=1}^{n_N} x_{1,i_N} \cdot \Delta Q_{1,i_N} \tag{6}$$

Subject to:

$$\left(\sum_{i_A=1}^{n_A} x_{1,i_A} \cdot \Delta Q_{1,i_A} + \sum_{i_B=1}^{n_B} x_{1,i_B} \cdot \Delta Q_{1,i_B} + \cdots + \sum_{i_N=1}^{n_N} x_{1,i_N} \cdot \Delta Q_{1,i_N}\right) \geq 90\% \cdot \Delta Q_{1,goal} \tag{7}$$

$$\left(\sum_{i_A=1}^{n_A} x_{1,i_A} \cdot \Delta Q_{1,i_A} + \sum_{i_B=1}^{n_B} x_{1,i_B} \cdot \Delta Q_{1,i_B} + \cdots + \sum_{i_N=1}^{n_N} x_{1,i_N} \cdot \Delta Q_{1,i_N}\right) \leq 110\% \cdot \Delta Q_{1,goal} \tag{8}$$

$$\sum_{i_A=1}^{n_A} x_{1,i_A}, \sum_{i_B=1}^{n_B} x_{1,i_B}, \ldots, and \sum_{i_N=1}^{n_N} x_{1,i_N} \leq 1 \tag{9}$$

The constraint Equations 7, 8, and 9 denote that the total reduction of the multi-building portfolio must be no less than 90% but must be no more than 110% of the goal reduction and that no more than one control strategy can be chosen for one building.

The optimization problem of the mth (m > 1) time step in Obj. 1

When scheduling continues to the next time step, the previous time step status is a constraint for the next time step. Here, the buildings involved in the response must keep the response control strategy until the end.

$$\text{If}\, x_{m-1,i_N} = 1,\, x_{m,i_N} 1 \tag{10}$$

Assuming that the DR ends when$m = m_{0,i_N}$, the reduction $Q_{m,,i_N} = 0$, and the value of $x_{m,i_N} = 0 \text{or} 1$ have no impact on the optimization results. Therefore, the optimal scheduling objectives and constraints between the second and last time step can be expressed as follows:

$$\min f_m(x) = \sum_{i_A=1}^{n_A} x_{m,i_A} \cdot \Delta Q_{m,i_A} + \sum_{i_B=1}^{n_B} x_{m,i_B} \cdot \Delta Q_{m,i_B} + \cdots + \sum_{i_N=1}^{n_N} x_{m,i_N} \cdot \Delta Q_{m,i_N} \tag{11}$$

Subject to:

$$\left(\sum_{i_A=1}^{n_A} x_{m,i_A} \cdot \Delta Q_{m,i_A} + \sum_{i_B=1}^{n_B} x_{m,i_B} \cdot \Delta Q_{m,i_B} + \cdots + \sum_{i_N=1}^{n_N} x_{m,i_N} \cdot \Delta Q_{m,i_N} \right) \geq 90\% \cdot \Delta Q_{m,goal} \tag{12}$$

$$\left(\sum_{i_A=1}^{n_A} x_{m,i_A} \cdot \Delta Q_{m,i_A} + \sum_{i_B=1}^{n_B} x_{m,i_B} \cdot \Delta Q_{m,i_B} + \cdots + \sum_{i_N=1}^{n_N} x_{m,i_N} \cdot \Delta Q_{m,i_N} \right) \leq 110\% \cdot \Delta Q_{m,goal} \tag{13}$$

$$\sum_{i_A=1}^{n_A} x_{m,i_A}, \sum_{i_B=1}^{n_B} x_{m,i_B}, \ldots, and \sum_{i_N=1}^{n_N} x_{m,i_N} \leq 1 \tag{14}$$

$$x'_{m-1} \cdot x_m = \text{length}\,(x_{m-1}\,(x_{m-1} = 1)) \tag{15}$$

Where

$$x_m = \left[x_{m,1_A}, x_{m,2_A}, \ldots, x_{m,n_A}, x_{m,1_B}, x_{m,2_B}, \ldots, x_{m,n_B}, \ldots x_{m,1_N}, x_{m,2_N}, \ldots, x_{m,n_N} \right] \tag{16}$$

Constraints for Equations 12, 13, and 14 have the same form as Equations 7, 8, and 9, denoting that the total reduction of the multi-building portfolio must be no less than 90% but should be no more than 110% of the goal reduction and that no more than one control strategy can be chosen for one building.

Constraint in Equation 15 denoted that the control strategy involved in the previous time step must be implemented in this step. Analysis follows:

The product of the two parameters equals 1 only if both x_{m-1} and x_m are equal 1 at the same time step, and the length $(x_{m-1}\,(x_{m-1} = 1))$ isindicated for the number of value 1 in x_{m-1}. Therefore, Equation 15 constrains the number with a value of 1 in the product results between x_{m-1} and x_m to be equal to that in x_{m-1}, which implies that if the variable is 1 in the previous time step, it must be 1 in this time step. Conversely, if the previous time step value is 0, the value of this time step can be 0 or 1. These constraints have the limit that if the control strategy is conducted in a previous time step, it must be conducted in this time step, while if the control strategy is not conducted in last time step, it could be conducted or not at this time step.

Equations 6–9 and Equations 11–15 express the mathematical formulation of Obj. 1. Each problem at every time step is a 0-1 programming problem that can be solved with the Branch and Bound method.

The mathematical description of Obj. 2: Maximum reduction

The maximum reduction objective can also be reached by 0-1 programming, the objective of which is the cumulative reduction Q_{total} kWh in response duration. Assuming that the strategy n_N for building N contributes to cumulative reduction Q_{n_N} kWh, then the total reduction of the whole multi-building portfolio is:

$$\Delta Q_{total} = \sum_{i_A=1}^{n_A} x_{i_A} \cdot \Delta Q_{i_A} + \sum_{i_B=1}^{n_B} x_{i_B} \cdot \Delta Q_{i_B} + \cdots + \sum_{i_N=1}^{n_N} x_{i_N} \cdot \Delta Q_{i_N} \tag{17}$$

In this total reduction, $x_{m,i_A}, x_{m,i_B}, \ldots, x_{m,i_N}$ are the strategy curve coefficients, the value of which is limited to 0 and 1. The value 0 denotes that the corresponding strategy has not been chosen, and vice versa.

$\Delta Q_{i_A}, \Delta Q_{i_B}, \ldots, \Delta Q_{i_N}$ are the total reductions for the corresponding control strategy conducted during the response duration, that is, $\Delta Q_{i_N} = \sum_{m=1}^{m_t} \Delta Q_{m,i_N}$. The optimization objective can be expressed as:

$$\max \Delta Q_{total} = \sum_{i_A=1}^{n_A} x_{i_A} \cdot \Delta Q_{i_A} + \sum_{i_B=1}^{n_B} x_{i_B} \cdot \Delta Q_{i_B} + \cdots + \sum_{i_N=1}^{n_N} x_{i_N} \cdot \Delta Q_{i_N} \tag{18}$$

Transform Equation 18 as 0-1 programming to obtain the following equations:

$$\min f(x) = -\Delta Q_{total} = -\left(\sum_{i_A=1}^{n_A} x_{i_A} \cdot \Delta Q_{i_A} + \sum_{i_B=1}^{n_B} x_{i_B} \cdot \Delta Q_{i_B} + \cdots + \sum_{i_N=1}^{n_N} x_{i_N} \cdot \Delta Q_{i_N}\right) \tag{19}$$

Subject to:

$$\sum_{i_A=1}^{n_A} x_{i_A}, \sum_{i_B=1}^{n_B} x_{i_B}, \ldots, and \sum_{i_N=1}^{n_N} x_{i_N} \leq 1 \tag{20}$$

Equations 19 and 20 are the mathematical descriptions of Obj. 2. Equation 20 limits each building to choose no more than one control strategy.

The mathematical description of Obj. 3: Maximum economic benefits

In DR events, aggregators and individual building owners are concerned about the economic Benefits more than grid operators. Therefore, in some DR events, decision makers consider not only the reduction objective but also the economic index. Thus, the price mechanism or subsidy policy would directly influence the scheduling results.

According to the method of definition and category from the U.S. Department of Energy (2006), DR can be categorized into two classes: one class is the incentive-based program (IBP) and the other class is the price-based program (PBP). This article considers PBP as an example to analyze the optimal scheduling for Obj. 3.

Assume the response duration, time step and total number of time steps are t, Δt, and m_t, respectively, as referred to in Equation 4. The corresponding subsidy is A_m ($m = 1,2,\ldots m_t$) for each time step, then the total multi-building portfolio subsidy can be expressed as:

$$A_{m,total} = \Delta Q_{m,total} \cdot A_m \tag{21}$$

Obj. 3 can be described as:

$$\max A_{total} = \sum_{m=1}^{m_t}\left[\left(\sum_{i_A=1}^{n_A} x_{m,i_A} \cdot \Delta Q_{m,i_A} + \sum_{i_B=1}^{n_B} x_{m,i_B} \cdot \Delta Q_{m,i_B} + \cdots + \sum_{i_N=1}^{n_N} x_{m,i_N} \cdot \Delta Q_{m,i_N} =\right) \cdot A_m\right] \tag{22}$$

Transform Obj. 3 into 0-1 programming as:

$$\min f(x) = -A_{total} \tag{23}$$

Table 1. Response time for each response building before optimization.

Building no.	A	B	C	D	E	F	G	H	I
Staring time	13:00	13:00	13:00	13:00	13:00	13:00	13:00	13:00	13:00
Building no.	**J**	**K**	**L**	**M**	**N**	**O**	**P**	**Q**	**R**
Staring time	13:00	14:00	14:00	14:00	14:15	14:15	14:00	14:00	14:00

Subject to:

$$\sum_{i_A=1}^{n_A} x_{i_A}, \sum_{i_B=1}^{n_B} x_{i_B}, \ldots, and \sum_{i_N=1}^{n_N} x_{i_N} \leq 1 \tag{24}$$

Equations 23 and 24 are the mathematical description of Obj. 3. Equation 24 limits each building to choose no more than one control strategy.

Equation 22 can be written as the following when the subsidy is constant with time.

$$\begin{aligned}\max A_{total} &= \left(\sum_{i_A=1}^{n_A} x_{i_A} \cdot \Delta Q_{i_A} + \sum_{i_B=1}^{n_B} x_{i_B} \cdot \Delta Q_{i_B} + \cdots + \sum_{i_N=1}^{n_N} x_{i_N} \cdot \Delta Q_{i_N}\right) \cdot A_m \\ &= A_m \cdot \Delta Q_{total}\end{aligned} \tag{25}$$

Transform Equation 25 into the 0-1 programming form of Equation 23. Obviously, A_{total} reaches the maximum when obtaining the maximum reductionΔQ_{total}, which equals Obj. 2. Therefore, the Obj. 2 and Obj. 3 share the same solution when the subsidy is a constant value.

Case study

Simple scheduling strategy

A pilot project was conducted during the summer in Shanghai in 2014. A total of 29 buildings were involved in this experiment. In this article, 18 buildings were selected as a multi-building portfolio, and all of them were office buildings, the basic information for which is listed in Table 1. The DR time was for 13:00–16:00. In the test in 2014, the control strategy and response starting time for each building was determined by each building operator. There is no overall portfolio scheduling.

As mentioned previously, the load curve of the previous DR day was selected as the baseline to calculate the reduction. The time step was set as 15 min, and the evaluating index was the whole building energy consumption accumulated during

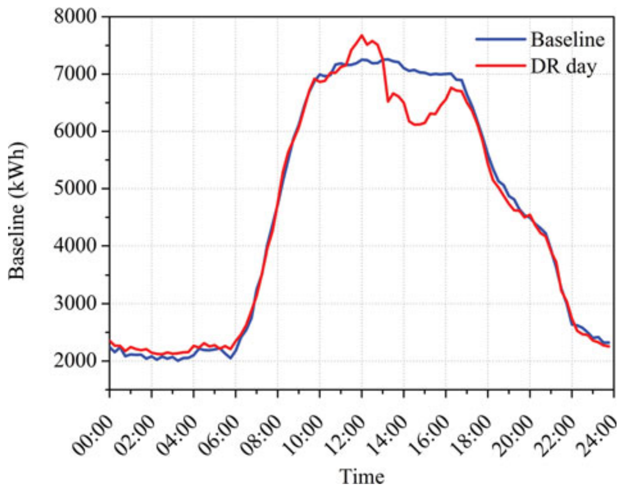

Fig. 3. Daily energy consumption curve of baseline and demand response day.

every 15 min, which can be acquired directly from the interval meters for each building. The total energy reduction of the entire multi-building portfolio can be seen in Figure 3. In the 2 hours before response time, the actual energy consumption was markedly increased because some buildings used precooling strategies. The energy consumption curve matches well with the baseline, except for the precooling and response periods, validating the rationality of the baseline curve. The load reduction during the response period in the afternoon was obvious.

However, in this experiment, a large fluctuation exists during the response period because of the lack of an overall scheduling strategy. The load reduction maximized at 14:00, but after 15:00, the load bounced back. The total reduction of the whole multi-building portfolio can also be increased because some buildings did not participate in the DR in the beginning (shown in Table 1).

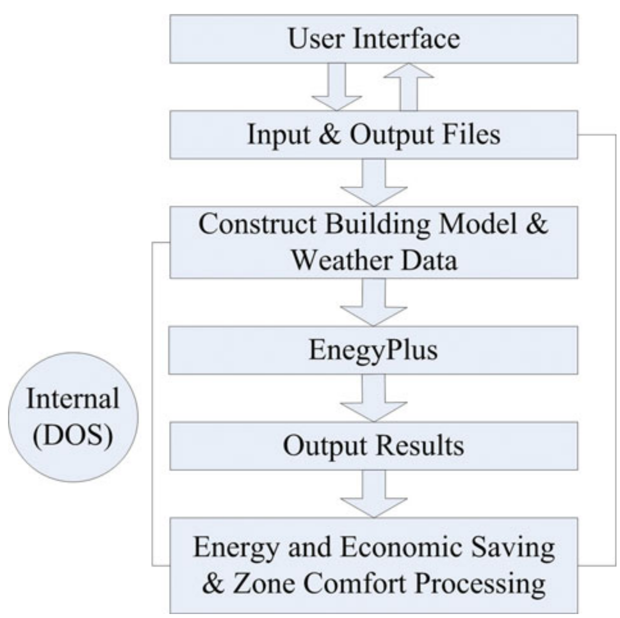

Fig. 4. Structure of DRE.

The effects of various DR controls in each individual building were analyzed with the experimental results. The strategy used in this experiment is labeled as Strategy 1, and the measured data are the corresponding reduction result. The DR effects of the other two strategies (Strategy 2 and Strategy 3) were estimated through a software DR estimator (DRE), which is a tool that is used to quickly estimate the performance of DR strategies for commercial building and is based on EnergyPlus. The basic structure of DRE, date transmission and the relationship between each part are shown in Figure 4 (Li and Xu 2016).

Table 2 shows that the most popular strategies are chiller cycling and an indoor air temperature reset. The indoor air temperature reset consisted of setting the temperature to the lower comfort limit at 22°C before DR and then setting the temperature back to the upper limit of comfort at 28°C during the DR. Therefore, "turning off all chillers" is set as Strategy 2 and "precooling with temperature reset" is set as Strategy 3. The cumulative load reductions for each time step for the 3 strategies are shown in Figure 5.

Obj. 1: Smooth reduction

In the previous discussion, the goal of the portfolio decision makers is to meet the overall DR objective. In the experiment, the average cumulative reduction in one time step is 708 kWh, so the objective of the smooth reduction is set at 708 kWh per time step from 13:00–16:00.

From Figure 3, the energy consumption of the whole multi-building portfolio is stable from 13:00–16:00 on one baseline day, which indicated that the independent variable is almost the same, thus determining that the load reduction curves are not affected by actual response starting time. Three corresponding curves are listed in Figure 5. The control strategies and response starting time are determined with this optimal scheduling method by decision makers.

The objective can be described as

The 1st time step refers to Eq. (6) $\sim$ (9), and the time steps from 2 to 12 refer to Eq. (11) $\sim$ (16). The parameters of these equations have the following values: $N = R, n_A = n_B = \ldots = n_R = 3$, $Q_{1,goal} = 708$kWh, and $m = 12$.By the Brand and Bound method, the response buildings and corresponding starting times are listed in Table 3.

After optimal scheduling, the entire load reduction, simple scheduling load reduction and objective load reduction are compared in Figure 6. It can be concluded that the optimal scheduling method accomplishes the objective well because the optimal reduction is much closer to the objective with $\pm 10\%$ bias.

Obj. 2: Maximum reduction

The second optimization objective that we investigated was maximum cumulative reduction during the response period. The selection of the optimization strategy is dependent on the financial incentive of the decision maker and the

Table 2. Basic information for the objective multi-building portfolio.

No.	Building area	AC system profile	Control strategy
A	33,000	Fan coil with four air-cooled heat pumps of 678 kW	Precooling, then one air-cooling heat pump turned off
B	95,000	Fan coil with four chillers of 337 kW	One chiller turnoff
C	35,000	Fan coil with eight chillers of 337 kW	Four chiller turnoff
D	39,000	Fan coil with three chillers (one of 210 kW and two of 175 kW)	One chiller of 210 kW turnoff
E	190,000	Fan coil with eight chillers (five of 681 kW and three of 322 kW)	Precooling with three chillers of 681 kW turnoff
F	50,000	Two VRV of 260 kW	Adjust indoor air temperature to upper limit (28°C)
G	32,000	Fan coil with four chillers of 742 kW	One chiller turnoff
H	20,000	All-air system with two chillers of 170 kW	Adjust indoor air temperature to upper limit (28°C)
I	58,000	All-air system with two air-cooled heat pumps of 280 kW	One air-cooled heat pump turnoff
J	82,000	All-air system with four chillers of 740 kW	Two chillers turnoff
K	50,000	All-air system with three air-cooled heat pumps of 200 kW	Precooling, then two air-cooled heat pumps turnoff
L	85,000	Fan coil with eight air-cooled heat pumps of 217 kW	Precooling, then three air-cooled heat pumps turnoff
M	31,0000	All-air system with three air-cooled heat pumps of 100 kW	Two air-cooled heat pumps turnoff
N	50,000	Fan Coil with 3 Chillers (1 of 228 kW and 2 of 337 kW)	One chiller turnoff
O	18,000	Fan coil with two chillers of 170 kW	One chiller turnoff
P	27,000	Fan coil with four chillers of 187 kW	One chiller turnoff
Q	16,000	Fan coil with six air-cooled heat pumps of 111 kW	Three air-cooled heat pumps turnoff
R	30,000	Fan coil with two chillers of 238 kW	Precooling with one chiller turnoff

situation on the grid. If the response duration is short, buildings are required to respond quickly and achieve a large reduction as quickly as possible. In this case study, the objective reduction is defined as the maximum cumulative reduction during 13:00–15:00. The optimal equations are same as Equation 19∼20, where $N = R$ and $n_A = n_B = \ldots = n_R = 3$.

DR strategies for buildings are determined by the Branch and Bound method. With the assumption that each DR building starts responding at 13:00, the results indicate that the objective reduction reaches 9368.2 kWh with the optimal scheduling of Strategy 1 employed on buildings D, E, I, N, O, and Q and Strategy 2 on the remaining buildings. By contrast, the reduction under the simple response scheduling strategy is 6123.3 kWh. Therefore, it can be concluded that the optimal scheduling method achieves the objective and, in the meantime, increases the flexibility in scheduling DR for buildings.

Obj. 3: Maximum economic benefits

The decision makers are sometimes more concerned about the economic benefits than the shape and depth of the load reduction. In this case, the decision makers need to determine the optimal scheduling strategy considering the subsidy policy. In this case study, the total economic benefits were considered for 18 buildings and the optimization objective was set as the maximum economic benefits. For this situation, the optimal equations are the same as in Equations 22∼24, where $\mathrm{N} = R$, $n_A = n_B = \ldots = n_R = 3$, and $m_t = 8$.

In this experiment, the incentive policy is 2RMB/kWh in Shanghai, i.e., $\mathrm{A_m} \equiv 2\mathrm{RMB/kWh}$ and the optimization equation is written as Equation 25.

Equation 40 has a common solution, where Strategy 1 is used for buildings D, E, I, N, O, and Q and Strategy 2 is used for the others with Equations 36 and 37 because $\mathrm{A_m}$ is constant. The total economic benefits increase by 52%, when the scheduling strategy changes from no optimization to a reduction of 6123.3 kWh for the maximum benefit strategy (reduction of 9368.2 kWh).

Conclusions and further work

This research discusses an optimal scheduling scheme for a portfolio of buildings during DR events. In the present research, optimal scheduling is converted into a time series 0-1 programming problem and solved by the Branch and Bound method. Three commonly used optimization objectives are investigated: smooth reduction, maximum reduction, and maximum economic benefit. Measured data for 18 commer-

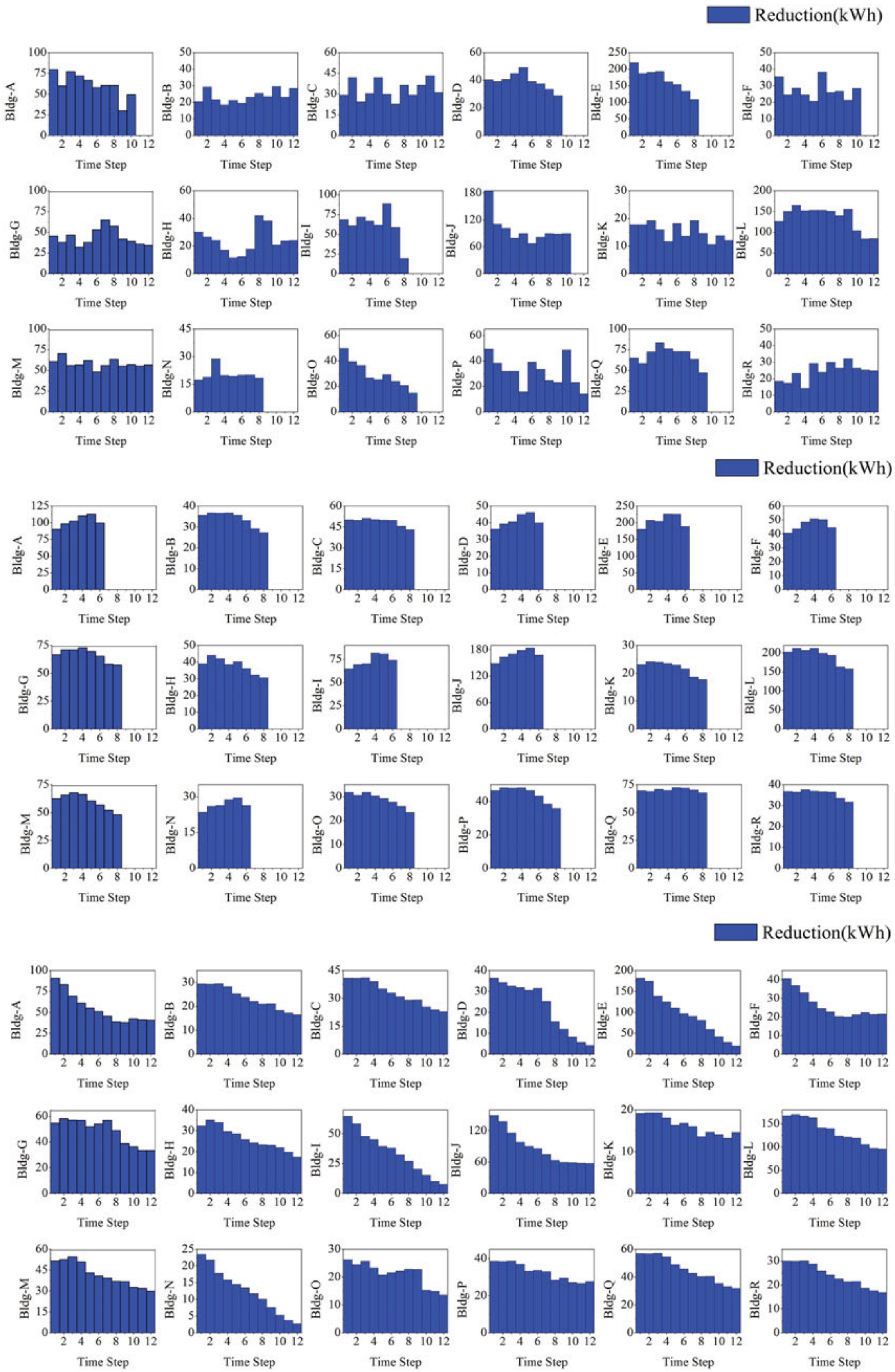

Fig. 5. Load reduction curve from building A to R.

Table 3. Response time for each response building after optimization.

Building no.	A	B	C	D	E	F	G	H	I
Strategy no.	3	1	1	3	2	3	3	1	1
Staring time	13:00	13:00	14:30	14:30	13:00	13:00	14:15	13:00	14:45
Building no.	**J**	**K**	**L**	**M**	**N**	**O**	**P**	**Q**	**R**
Strategy no.	3	3	1	1	1	3	3	2	1
Staring time	13:00	13:00	13:00	14:30	13:30	13:45	13:00	14:30	14:00

cial buildings during a large scale DR test in Shanghai are used as the baseline for a case study to test the optimization scheme. The control strategy implemented in the actual DR experiment is defined as Strategy 1. The performance of Strategy 2 (all chillers off) and Strategy 3 (precooling and temperature reset) is based on data obtained by simulation. Optimal scheduling is used to determine which buildings should use which strategy and the starting and ending time of each strategy. The following conclusions were drawn from this experiment and the optimization study.

- The three optimization objectives of smooth reduction, maximum reduction, and maximum economic benefit are all achievable. As long as a goal is set, the optimization scheme can meet the goal.
- Under the objective of smooth reduction, the multi-building profile keeps the electricity load within a ±10% bias of the objective value.
- The goal of the maximum reduction and maximum economic benefits can be reached with this optimal scheduling method. By simulated calculation, the optimal cumulative reduction increases by 3.2 MWh compared to no overall optimization.
- Decision makers can use the results of the optimal scheduling to determine which buildings should participate, which corresponding strategies to use, and the DR starting and end time.

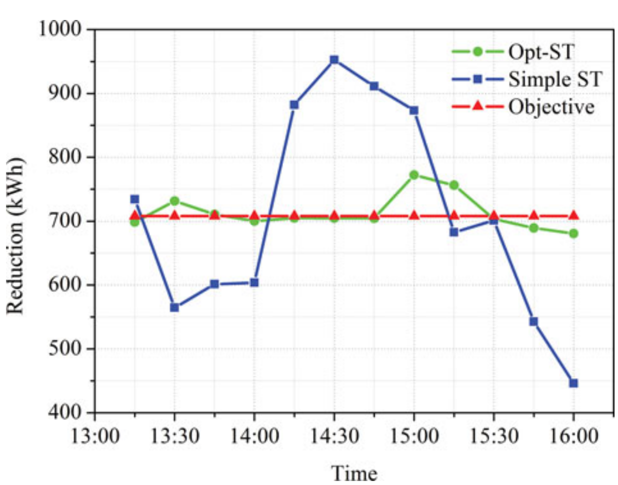

Fig. 6. Comparison between the optimal and simple scheduling strategy.

This study is a first step in optimal scheduling for multiple buildings during a DR event. In the future, the effectiveness of the scheme should be verified further. In addition, only three objectives are proposed for the use of the 0-1 programming to solve the optimal scheduling problem in a multi-building portfolio. Grid operators and aggregators sometimes have a specific load curve to match. In that case, the mathematical description must be further investigated beyond 0-1 programming.

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