TANG, Rui; WANG, Shengwei; LI, Hangxin. Game theory based interactive demand side management responding to dynamic pricing in price-based demand response of smart grids. Applied Energy, 2019, 250: 118-130.

https://doi.org/10.1016/j.apenergy.2019.04.177

Game Theory Based Interactive Demand Side Management Responding to Dynamic Pricing in Price-based Demand Response of Smart Grids

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Abstract: Bidirectional interaction between power grid and buildings is a key characteristic of smart grids. Achieving a win-win situation for a grid and buildings with such interactions remains a challenge. Game theory is a powerful tool for using strategic analysis to identify the best interactions between multiple players. Stackelberg game can effectively reflect the core status of grid and the auxiliary position of buildings in this interaction (particularly in demand response programs), but no study used this game to establish such interactions while simultaneously considering the multiple requirements of grid and buildings, particularly for the commercial sector. In this study, therefore, basic and enhanced interaction strategies between a grid and buildings are developed using the Stackelberg game based on their identified Nash equilibria. The grid optimizes the price to maximize its net profit and reduce demand fluctuation, and individual building optimizes the hourly power demand to minimize electricity bill and the effects of demand alternation from the baseline. In addition, the effects of building demand baseline uncertainty on the interaction are investigated and the enhanced robust interaction is proposed to deal with such uncertainty. Real site data of buildings on a campus in Hong Kong are used to validate the proposed interaction strategies. The results show that the proposed basic interaction increased net profit by 8% and reduced demand fluctuation by about 40% for the grid, with a savings in electricity bills of 2.5~8.3% for the buildings. Moreover, the proposed robust interaction effectively relieved the negative effects caused by prediction uncertainty.

Keywords: demand response; dynamic pricing; building demand management; load uncertainty; Stackelberg game; smart grid.

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1. Introduction

The rapid growth of power demand and the greater integration of renewable energy generation, which depend heavily on weather conditions, impose enormous stress on the balance of power grids [1]. Facing the challenge of power imbalance, the smart grid is considered as a state-of-the-art technology offering better flexibility, reliability and security in grid operations [2,3]. Demand response (DR) management, a key characteristic of smart grids, is characterized as the end-users changing their power usage in response to changes in electricity prices over time. DR programs can go far beyond simply reducing the electricity bills of end-users and lowering costs of power generation. Such programs can provide reliability and security for the real-time operation of power grids [4-6].

Buildings, which consume 73.6% of overall electricity in the United States [7] and over 90% in Hong Kong [8], should play an important role in DR programs by actively altering their load profiles during peak times. Demand shifting, which aims to take advantage of electricity rate differences via shifting on-peak loads to off-peak hours, is a commonly used means for demand response, particularly for buildings with central air-conditioning systems. The elastic power demand and automation systems in these kinds of buildings can benefit the implementation of demand response strategies [9, 10]. Many studies have been conducted on building demand shifting towards specific electricity tariffs from the viewpoint of the demand side [11-15]. In fact, demand shifting conducted by buildings will lead to an alternation of total power usage on the demand side, which in turn influences the operating conditions and the dynamic pricing of smart grids. (Dynamic pricing, or real-time pricing, acts as an incentive mechanism to encourage buildings conducting power demand management, changing each period of the day and visible to users one day ahead or at least some hours ahead [16].) Hence, the bidirectional interaction between buildings and a smart grid via dynamic pricing has attracted many attentions recently.

Among the studies for the grid-building interaction, game thematic approaches are commonly adopted due to the powerful and effective ability to capture the complex and strategic interactions between multiple players. Game theory is the study of the mathematical models of conflict and cooperation between intelligent and rational decision makers. It is a formal analytical and conceptual framework with a set of mathematical tools enabling the study of complex interactions among independent rational players [17, 18]. Ibars et al. [19] applied a congestion game to control the power demands of residential buildings and achieve energy savings by responding to the prices given by smart grids. Nwulu and Xia [20] optimized the incentives paid out to users over one day by using game theory to reduce fuel costs and power generation emissions. Mohsenian et al. [21] proposed a game-theoretic energy consumption schedule for residential buildings to minimize the electricity bills of end-users. Overall, these interaction strategies between smart grid and buildings are based on static games, that is, the decisions are made simultaneously by the grid and buildings with both sides in an equal position.

By contrast, for the grid-building interaction in a DR event, the primary objective is to improve the flexibility of power grids and hence keep the healthy operation of power grids. The building as a convenient source at the demand side conducts the power demand management to benefit the grid operations, while the grid gives economic incentives to encourage buildings participating in such interactions/DR programs. This process is actually a price-based DR program. In such DR events, the smart grid and buildings are not in an equal position, but the grid is in a core position and the buildings are in an ancillary position. The Stackelberg game is a hierarchical and dynamic game and considered as a good candidate to provide insight into such interaction between a power grid and buildings in a price-based DR program, effectively reflecting the core status of the grid and the ancillary position of the buildings. In the Stackelberg game, the grid acts first and then the buildings make decisions based on certain prices [18], which means that the power grid is the leader and the buildings are the followers whose reactions are based on the power grid's decisions. Maharjan et al. [22] proposed an interaction strategy between the grid and buildings using the Stackelberg game to maximize the profit of the grid. Meng et al. [23] modeled electricity trading between the retailer and customers with the aim of minimizing the customer's daily payments while maximizing the retailer's profit. Yang et al. [24] proposed a game thematic model to optimize the time-of-use price of power grid considering the response of building users. Yu and Hong [25] established the interaction between a utility company and users as a Stackelberg game for optimizing the power generation and the power demands of users. Chai et al. [26] developed an interaction strategy between power grids and residential buildings by using a two-level game and demonstrated the existence of the Nash equilibrium.

In fact, multiple requirements and objectives need to be considered and investigated for the grid (e.g., profit, demand fluctuation, peak load) and buildings (e.g., electricity bill, demand constraint, demand alternation) when establishing the interaction in DR events. Meanwhile, above studies for the interaction between the power grid and buildings are mainly from the viewpoint of supply side of power grids without considering detailed interests and conditions of the buildings, including: power demand constraints of buildings when conducting demand management; quantification of the benefits of demand side when establishing the interaction; baseline prediction uncertainty of building power demand (which may negatively influence the performance of developed interactions) and how to handle the negative effects on the interaction caused by the load prediction uncertainty.

To address these aforementioned problems and challenges, this study therefore develops two interaction strategies between the smart grid and buildings using game thematic method. The main importance of this work is to effectively consider the multiple requirements of both the smart grid and buildings when establishing the grid-building interaction in a price-based DR event, particularly for the interests of demand side. The main contributions of this work include: (1) Building demand shifting interacting with a power grid in a DR event is built as a Stackelberg game and the Nash equilibrium is identified. The established interaction considers multiple aspects for both the power grid and buildings (the grid's net profit and demand fluctuation are taken into account. Simultaneously, the electricity bill, user dissatisfaction and mismatching cost caused by the power demand alternation are considered for the buildings, along with the daily constraints of building power demand); (2) The influence of baseline prediction uncertainty of building power demand on the Nash equilibrium is investigated. And an enhanced interaction strategy is developed for the identification of Nash equilibrium to address the negative effects caused by the uncertainty of baseline prediction of demand side; (3) Real site data of buildings on a university campus in Hong Kong are used to validate the win-win situation of the grid and buildings, and also to quantify the corresponding benefits in the two proposed interaction strategies. The potential benefits for the power grid and buildings in Hong Kong, if the proposed interactions are adopted, are also assessed.

2. Structure and objective of proposed grid-building interaction

2.1 Structure of grid-building interaction

As increasing amount of renewable energy systems are being absorbed into smart grids, and their future mode of operation would be bidirectional to cope with the challenge of imbalance caused by the intermittent and uncontrollable characteristics of renewable energy systems. Meanwhile, future buildings, as a major power consumer on the demand side of a power grid [27], are expected to have '*grid-responsive features*'; that is, they are expected to have features that help the power grid to relieve the pressure of operational problems. Fig. 1 presents the architecture of communication and interaction between the smart grid and grid-responsive buildings. The power grid collects power usage information from buildings and then optimizes electricity prices one day ahead or at least some hours ahead to achieve the expected level of power management, thus maximizing profit. Here, the buildings equipped with intelligent devices (i.e., smart meters), which can inform users as to when and how to consume power, change their usage behavior to obtain economic profits by responding to the price information given by the power grid. For commercial and industrial building sectors, the smart meter can be directly connected with building automation systems to realize their optimized usage of power. As the developments of intelligent devices, Internet communication technologies and renewable energy systems, to create the aforementioned win-win interactions for smart grids and buildings, and make the buildings grid-responsive will be the inevitable developing direction in the future.

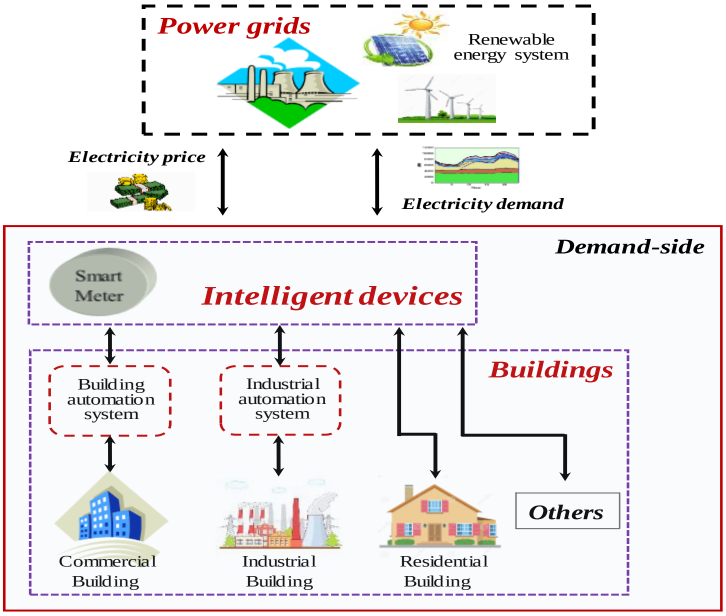

Fig. 1 Structure of interaction strategy between the smart grid and grid-responsive buildings

2.2 Interests of smart grid and buildings in the interaction

Multiple requests and objectives for both the power grid and buildings are considered in the proposed interaction. The power grid aims at maximizing its net profit and simultaneously minimizing demand fluctuation by setting electricity prices (i.e., price-based demand response programs). Simultaneously, individual buildings engage in demand shifting in response to price information to minimize their electricity bills, while also lowering the level of sacrifices and the mismatching cost caused by their deviations from the original power usage profiles. The detailed requests and objectives considered for the power grid and buildings for the proposed interaction are as follows.

<u>Interests of power grid</u>

Profit refers to the net profit of the power grid obtained by selling the electricity to the buildings after removing the corresponding cost of power generation. At time slot k, the net profit of the power grid is determined by the electricity sold and its corresponding generation cost, as calculated by Eq. (1).

$$Profit^k = Pr^k \cdot X_d^k - f(X_d^k) \tag{1}$$

$$f(X_d^k) = a \cdot (X_d^k)^2 + b \cdot (X_d^k) + c \quad a > 0 \quad b, c \geq 0 \tag{2}$$

where $Profit^k$ is the net profit of the power grid at time slot k; Pr^k is the dynamic electricity price at time slot k; X_d^k is the total electricity purchased by buildings at time slot k; $f(X_d^k)$ is the function to calculate the generation cost of X_d^k without considering the loss, as shown in Eq. (2) [28]; and a, b, c are the constant coefficients.

Electricity demand fluctuation (D_f) is defined to describe the deviation between the periodic electricity demand (X_d^k) and the average ($X_{d,average}$) of the entire considered horizon, as shown in Eq. (3). This item indicates a cost that is borne by the power grid and is best maintained as low as possible to achieve a relatively flat pattern of electricity demand. Also, this can reduce the pressure of peak demand on power grid operations. Here, N is the total number of equal size time slots in a day and is set to be 24, that is, a day is divided into 24 time slots and the interaction strategy is conducted every 1 hour accordingly in this study,

$$D_f = \frac{1}{N}\sum_{k=1}^{N}\sqrt{(X_d^k - X_{d,average})^2} \tag{3}$$

$$X_{d,average} = \frac{1}{N}\sum_{k=1}^{N} X_d^k \tag{4}$$

<u>Interests of buildings</u>

User dissatisfaction is an index that represents the user's dissatisfaction, or lack thereof, when the power demand is limited to a level deviating from the normal demand, using the mathematical expression when buying x^k power at time slot k. A quadratic function is selected in this study, as shown in Eq. (5) [21, 29]. The value will increase as the power use deviating from the baseline. When the power demand is equal to the baseline, the dissatisfaction will reach to the minimum.

$$S_i^k(x_i^k) = -\alpha_i \cdot w_i^k \cdot x_i^k + \frac{\alpha_i}{2} \cdot (x_i^k)^2 \tag{5}$$

where w_i^k is the original power demand (i.e., baseline) of building i at time slot k. α_i is a positive pre-determined constant representing the preference of building i to shift the power demand. The user's dissatisfaction decreases as power demand approaches to the baseline.

Mismatching cost is an index to represent the losses or costs (such as losses of energy storage) associated with demand shifting when facing the economic incentives given by the smart grid. Generally, this index (M_i^k) of building i is related to the deviation between the actual power consumption (x_i^k) and the original power demand (w_i^k) at k time slot, as shown in Eq. (6). Where ρ_i is a pre-determined positive factor describing the cost level of building i to conduct the demand shifting. Generally, the increasing power demand alternation results in more mismatching costs for the building.

$$M_i^k = \rho_i \cdot (x_i^k - w_i^k)^2 \tag{6}$$

Electricity bill is the payment when the building buys a certain amount of electricity, as illustrated by Eq. (7), where B_i^k is the payment of building i for consuming x_i^k amount of power at time slot k when the electricity price is Pr^k:

$$B_i^k = Pr^k \cdot x_i^k \tag{7}$$

3. Game theory based interaction for smart grid and buildings

In this section, the Stackelberg game, which belongs to the field of game theory, is adopted to develop a win-win interaction strategy between the smart grid and grid-responsive buildings.

3.1 Establishment of grid-building interaction using Stackelberg game

In this study, *1* power grid and *n* buildings are included in the proposed interaction strategy. In a game, each player (i.e., *1* power grid and *n* users) may partially or totally conflict with one another. They all want to maximize their own welfare by setting their strategies, that is, the grid changes its price while the buildings adjust their individual power demands. A game *G* consists of three components, that is, $G = \{\sigma, S, U\}$. Each player $i \in \sigma$ selects its strategy $s_i \in S$ to maximize its utility/welfare $u_i \in U$. The solution of this game is Nash equilibrium, as defined in Eq. (8) [30]. The Nash equilibrium is a strategy profile s^* such that no player *i* can gain more profit by unilaterally deviating from their strategy s_i^*, assuming every other player $j \in \sigma$ follows their strategy s_{-i}^*. When the Nash equilibrium is reached, the power grid and individual buildings will not change their decisions because their individual benefits are the maximum.

<u>*Definition*</u>: A strategy vector $s^* = \{s_i^*, s_{-i}^*\}$ is a Nash equilibrium if and only if $\forall i \in \sigma$ and $\forall s_i \in S_i$,

$$U(s^*) \geq U(s_i, s_{-i}^*) \tag{8}$$

where s_i is the player *i*'s strategy and s_{-i} represents all of the other players' strategies.

The three components of the proposed game for the grid-building interaction are presented as follows: the players are the power grid and the concerned buildings; the strategies conducted by the power grid and buildings are the dynamic electricity pricing and the building demand management respectively; the utility values of power grid and buildings are related to their corresponding concerned interests (as shown in Eq.(11-a) and Eq.(17-a) respectively). In the DR events, the grid sets the electricity price per unit and announces the price information to the buildings. Then the buildings respond to the given price information by changing their power demands (i.e., conducting demand management) to maximize their benefits. As the grid acts first and then the buildings make decisions based on the given prices, the nature of such an interaction in DR events fits into the Stackelberg game, which provides a paradigm for modeling such a scenario. In the Stackelberg game, the power grid is the leader and the buildings are the followers because their reactions are based on the decision of the power grid. The Nash equilibrium of the proposed game is the best selection set for the power grid and buildings (Pr^*, X^*); this satisfies Eqs. (9-a) and (9-b), where U_{grid} and $U_{building}$ are the objective functions of the power grid and buildings, described in the next sections; Pr^* is the optimal dynamic price of the day, that is, $\{Pr^k\}_{k=1}^N$; X^* is the optimal power demand of buildings, that is, $\{x_1^k, \ldots, x_i^k, \ldots, x_n^k\}_{k=1}^N$; and P, $\emptyset$ are the feasible zones of the dynamic price and power demand, respectively.

$$\forall Pr \in \mathrm{P}, Pr \neq Pr^* \quad : \quad U_{grid}(Pr^*, X) \geq U_{grid}(Pr, X^*) \tag{9-a}$$

$$\forall X \in \emptyset, X \neq X^* \;\; : \;\; U_{building}(Pr, X^*) \geq U_{building}(Pr^*, X) \tag{9-b}$$

The principle of *backward induction* is adopted to solve the proposed Stackelberg game in order to identify the optimal price of power grid and the optimal power demand of each building in a day, as illustrated in Eqs. (10-a) and (10-b). First, $U_{building}$ is maximized and X^* is obtained responding to the price given by the power grid. Second, the determined optimal building power demand is plugged back into the U_{grid} to obtain the optimal dynamic price, that is, Pr^*.

$$(Pr^*, X^*) = arg\ max_{(Pr)}\ \ U_{grid} \tag{10-a}$$

$$X^* = arg\ max_{(X)}\ \ U_{building} \tag{10-b}$$

3.2 Basic scheme for identification of Nash equilibrium

<u>Nash equilibrium of followers – Optimization of building demand management</u>

Each building, facing the given dynamic price, expects to reduce the utility sacrifice by adjusting the power demand at each time slot in a day. Three parts determine the utility sacrifice of a building, including the electricity bill, mismatching cost and user dissatisfaction. *Note that* the utility sacrifices of buildings are considered in the proposed interactions and hence the optimization problem of buildings are converted into minimization problems. Therefore, the utility sacrifice of a building *i*, which is minimized by optimizing the power demand $\{x_i^k\}_{k=1}^N$, is the sum of the electricity bill, mismatching cost and dissatisfaction, as shown in Eqs. (11-a) and (11-b). Where β_i^k is a weighting factor representing the sensitivity of building *i* to the electricity bill at *k* time slot. In this study, it is assumed that buildings can change the patterns of power demands in a day in response to the dynamic price, yet their total daily power demands are kept unchanged and equal to their original values, that is, Eq. (11-c), where ϑ is the set including *n* buildings. *Note that* the daily building power demand constraint is solved by introducing a Lagrange's multiplier to illustrate the process how to cope with the constraints of buildings when establishing the interaction between the power grid and buildings.

$$U_{building,i} = \sum_{k=1}^N (M_i^k + S_i^k) + \beta_i^k \cdot B_i^k \tag{11-a}$$

$$\{x_i^k\}_{k=1}^N = \arg min\ U_{building,i} \tag{11-b}$$

$$\text{s.t. } \sum_{k=1}^N x_i^k = \sum_{k=1}^N w_i^k \qquad \forall\ i \in \vartheta \tag{11-c}$$

Lagrange's multiplier λ_i is used for dealing with the constraint of building *i*, and the optimization problem of building *i* with constraint is converted into Eq. (12) by substituting the related indices of the building into the objective function (11-a).

$$\begin{aligned} L_{building,i} = {} & \sum_{k=1}^N (\rho_i \cdot (x_i^k - w_i^k)^2 - (\alpha_i \cdot w_i^k \cdot x_i^k - \tfrac{\alpha_i}{2} \cdot (x_i^k)^2)) \\ & + \beta_i^k \cdot Pr^k \cdot x_i^k + \lambda_i \cdot (\textstyle\sum_{k=1}^N x_i^k - \sum_{k=1}^N w_i^k) \end{aligned} \tag{12}$$

To obtain the optimal power demand of building *i* for demand shifting, the electricity price

($\{Pr^k\}_{k=1}^N$) is assumed to be known first based on the principle of *backward induction* for solving the Stackelberg game. Hence, the first-order optimality condition for the above minimization problem of the building in the proposed interaction strategy is $\nabla L_{building} = 0$, where $L_{building} = \{L_{building,i}, \forall i \in \vartheta\}$, as calculated as Eq. (13). Here, τ represents the set including all of the time slots concerned in a day.

$$\begin{cases} \frac{\partial L_{building,i}}{\partial x_i^k} = 0 \\ \frac{\partial L_{building,i}}{\partial \lambda_i} = 0 \end{cases} \quad \forall\, k \in \tau, i \in \vartheta \tag{13}$$

$$\begin{cases} \frac{\partial L_{building,i}}{\partial x_i^k} = (2\rho_i + \alpha_i) \cdot x_i^k - (2\rho_i + \alpha_i) \cdot w_i^k + \beta_i^k \cdot Pr^k + \lambda_i = 0 \\ \frac{\partial L_{building,i}}{\partial \lambda i} = \sum_{k=1}^N x_i^k - \sum_{k=1}^N w_i^k = 0 \end{cases} \quad \forall\, k \in \tau, i \in \vartheta \tag{14}$$

The problem of Eq. (13) can be solved by Eq. (14), and the solutions of Eq. (14) are the values of $\{x_i^k\}_{k=1}^N$ and λ_i, as expressed by Eqs. (15-a) and (15-b).

$\forall\, k \in \tau,\ \ i \in \vartheta$

$$x_i^k = w_i^k - \frac{1}{2\rho_i + \alpha_i} \cdot \beta_i^k \cdot Pr^k + \frac{1}{N \cdot (2\rho_i + \alpha_i)} \sum_{k=1}^N \beta_i^k \cdot Pr^k \tag{15-a}$$

$$\lambda_i = -\frac{1}{N} \sum_{k=1}^N \beta_i^k \cdot Pr^k \tag{15-b}$$

The secondary-order derivative of $U_{building,i}$ is calculated to obtain the *Hessian matrix* to demonstrate the existence of Nash equilibrium for the proposed game. In Eq. (16), the diagonal elements of the *Hessian matrix* are all positive (ρ_i, α_i are two positive factors) and the off-diagonal elements are all zero. As such, the *Hessian matrix* is positive definite, meaning that the optimal power demand ($\{x_i^k\}_{k=1}^N, \forall i \in \vartheta$) is the Nash equilibrium (X*) and can minimize the utility sacrifice of buildings effectively in the proposed interaction strategy. It means that the existence and uniqueness of Nash equilibrium of followers (i.e., buildings) are validated.

$$\frac{\partial^2 U_{building,i}}{\partial x_i^k \, \partial x_i^j} = \begin{cases} 2\rho_i + \alpha_i & when\ k = j \\ 0 & when\ k \neq j \end{cases} \quad \forall k, j \in \tau,\ \ i \in \vartheta \tag{16}$$

<u>Nash equilibrium of leader – Optimization of grid dynamic pricing</u>

The power grid aims to maximize its net profit while simultaneously minimizing electricity demand fluctuation by using the proposed interaction strategy through optimizing the dynamic price $\{Pr^k\}_{k=1}^N$. Therefore, the total utility of the power grid is described as Eq. (17-a), and Eq. (17-b) is then attained after substituting the related indices of the power grid into its objective function. Here, δ is a weighting factor. $X_{d,min}^k$ and $X_{d,max}^k$ are the minimum and maximum capacities of power generation at k time slot, respectively. These two values are set to be ±30% compared with the corresponding original total power demands.

$$U_{grid} = \sum_{k=1}^{N} Profit^k - \delta \cdot D_f \tag{17-a}$$

$$U_{grid} = \sum_{k=1}^{N}\{Pr^k \cdot X_d^k - [a \cdot (X_d^k)^2 + b \cdot (X_d^k) + c]\} - \delta \cdot \frac{1}{N}\sum_{k=1}^{N}\sqrt{(X_d^k - X_{d,average})^2} \tag{17-b}$$

$$X_d^k = \sum_{i\in\vartheta} x_i^k \tag{17-c}$$

$$\{Pr^k\}_{k=1}^{N} = \arg max\, U_{grid} \quad Pr \in \mathrm{P} \tag{17-d}$$

$$\text{s.t.} \quad X_{d,min}^k \leq X_d^k \leq X_{d,max}^k \tag{17-e}$$

According to the principle of *backward induction*, the dynamic price ($\{Pr^k\}_{k=1}^{N}$) of a day optimized for the power grid is based on the optimal power demands of all of the buildings (i.e., $X^* = \{\{x_i^k\}_{k=1}^{N}, \forall i \in \vartheta\}$). Therefore, substituting the X^* into Eq. (17-c) can obtain the total power demand of all of the buildings at every time slot (i.e., $\{X_d^k\}_{k=1}^{N}$). After substituting the set of these values into the utility function of the power grid, it can be found that the value of *Pr* is the only variable to be optimized, instead of the two variables (*Pr* and *X*), as shown in Eq. (18-a). Furthermore, the constraint (Eq. (17-e)) can be rewritten as Eq. (18-b). Eventually, such an optimization problem is converted into a single-objective optimization, subject to its constraint (closed interval), and the solution of *Pr* is the best decision for the power grid (i.e., *Pr**). Hence, the existence of Nash equilibrium of the leader (i.e., power grid) is validated. The uniqueness of Nash equilibrium is not the key point for the power grid because the power grid can adopt one alternative set of optimized result (i.e., electricity price) in the interaction, which can maximize the benefit of power grid and meanwhile satisfy the corresponding constraints.

$$U_{grid} = \sum_{k=1}^{N}\{Pr^k \cdot X_d^k(Pr^k) - \{a \cdot [X_d^k(Pr^k)]^2 + b \cdot [X_d^k(Pr^k)] + c]\}$$
$$-\delta \cdot \frac{1}{N}\sum_{k=1}^{N}\sqrt{(X_d^k(Pr^k) - X_{d,average}(Pr^k))^2} \tag{18-a}$$

$$\text{s.t.} \quad X_{d,min}^k(Pr^k) \leq X_d^k \leq X_{d,max}^k(Pr^k) \tag{18-b}$$

3.3 Enhanced scheme for identification of Nash equilibrium considering demand baseline prediction uncertainty

In the proposed interaction strategy illustrated in Section 3.1, the original power demands of buildings (i.e., baselines) affect the optimized dynamic electricity price and the optimized building power demands. In real cases, however, such baselines are predicted one day ahead, and this prediction cannot be truly accurate due to the various uncertainties or unexpected factors. The prediction errors result in the solutions of the proposed game deviating from the Nash equilibrium, leading to poor performance of the proposed interaction strategy. Therefore, an enhanced scheme, that is, a robust interaction strategy, is proposed that considers the uncertainty in the baseline prediction of building demand. Many advanced technologies and methods are available for the baseline prediction of building power demand and for the quantification of uncertainty (error). In this study, the baseline prediction uncertainty of building power demand is assumed to follow a normal distribution to test the modification of the enhanced interaction strategy. The prediction uncertainty is represented by Eq. (19-a). The expectation of the baseline prediction uncertainty is used as the modification term to improve the robustness of the proposed interaction strategy, as shown in Eq. (19-b). It is worthy of note that such modification only changes the parameter values in the identification of Nash equilibrium without influencing the existence characteristic of Nash equilibrium. After revising the solutions of the Stackelberg game, the optimized power demands of buildings and dynamic price determined by the enhanced interaction strategy are shown in Eqs. (19-c) and (19-d), respectively, where subscribe *rev* denotes the cases after revision:

$$\Delta w_i^k = \frac{w_{i,act}^k - w_{i,pre}^k}{w_{i,pre}^k} \qquad \Delta w_i^k \sim N(\mu, \sigma^2). \tag{19-a}$$

$$w_{i,rev}^k = E\left(\left(1 + \Delta w_i^k\right) \cdot w_{i,pre}^k\right) = w_{i,pre}^k \cdot (1 + E(\Delta w_i^k)) \tag{19-b}$$

$\forall\, k \in \tau\,,\;\; i \in \vartheta$

$$x_{i,rev}^k = w_{i,rev}^k - \frac{1}{2\rho_i + \alpha_i} \cdot \beta_i^k \cdot Pr^k + \frac{1}{N \cdot (2\rho_i + \alpha_i)} \sum_{k=1}^{N} \beta_i^k \cdot Pr^k \tag{19-c}$$

$$\{Pr_{rev}^k\}_{k=1}^N = \arg max\, U_{grid}(X_{d,rev}^k, Pr) \tag{19-d}$$

$$X_{d,rev}^k = \sum_{i \in \vartheta} x_{i,rev}^k \tag{19-e}$$

4. Validation test arrangement

The proposed basic and enhanced interaction strategies are tested and validated by using the on-site data of buildings on a university campus in Hong Kong, and the benefits for the power grid and buildings are estimated. Hong Kong is a modern city with high power demand density and a heavy use of air-conditioning systems. The main campus of The Hong Kong Polytechnic University, located in the center area of Kowloon with a total site area of 94,600 m^2, is the district used in this study to interact with the power grid. The buildings on the campus are equipped with central air-conditioning systems as typical non-residential buildings. The layout of this campus is shown in Fig. 2. Twelve buildings, named ‘Phase 1’, ‘Phase 2’, etc., with different functions, such as classrooms, laboratories, offices and a library, are involved. Table 1 presents the floor areas and main functions of all of the buildings in this district. To support the routine university activities, the power demand is considerably high all year long due to the cooling requirements. The electricity bill of the university, as charged by the power grid, is divided into four accounts, and the buildings in each account are also presented in Table 1. These four accounts are regarded as four ‘followers’ interacting with the power grid in the Stackelberg game for this study. The data of July 3, 2017 (Monday) are selected to validate the basic interaction strategy and assess the resulting benefits of the grid and buildings. The data of 10 weekdays in two weeks (i.e., July 3~7, 2017 and July 10~14, 2017) are used to validate the enhanced interaction strategy and assess the corresponding benefits.

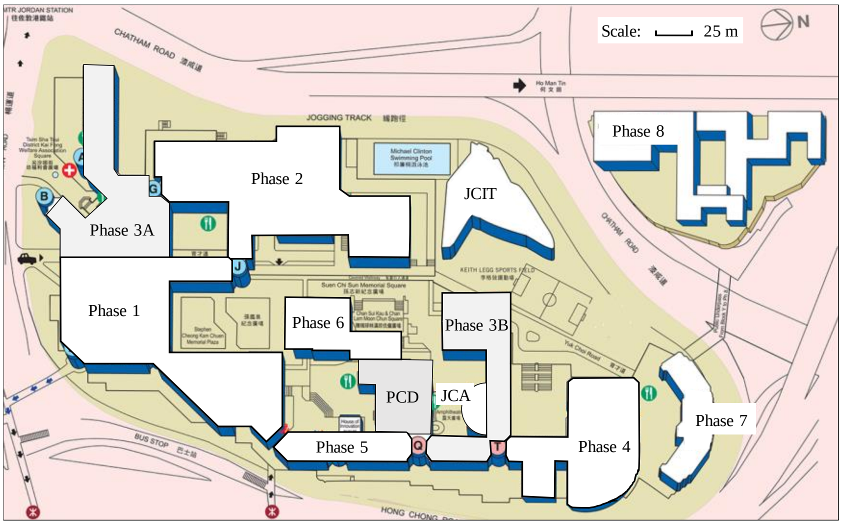

Fig. 2 Campus map of The Hong Kong Polytechnic University

Table 1 Floor areas and functions of buildings on the campus

	Building	Area (m^2)	Functions
Account 1	Phase 1	55,251	Classroom, office, library, laboratory, canteen, stadium
	Phase 2	24,419	Classroom, office, dental clinic
	Phase 3A	16,782	Clinic, lecture hall, office
	Phase 3B	23,400	Classroom, office, canteen, stadium
	Phase 4	19,330	Classroom, office, lecture hall, laboratory
	Phase 5	10,078	Classroom, office, laboratory
Account 2	Phase 6	12,307	Meeting room, classroom, office
	JCA	4,800	Auditorium
	PCD	10,196	Classroom, office
Account 3	Phase 7	25,000	Classroom, office, laboratory, lecture hall
Account 4	Phase 8	44,000	Classroom, office, laboratory, lecture hall, canteen
	JCIT	15,318	Classroom, office, activity room, lecture hall

In this study, dynamic price is determined one day ahead based on the proposed game theory-based interactions. One day is divided into 24 equal size time slots, that is, one hour per time slot. The coefficients a, b, c for power generation cost are set to be 50, 10, and 0 *yuan*/MWh, respectively. The mean value and standard deviation of the baseline prediction uncertainty of building power demand are set to be 0.0019 and 0.1234, respectively [31]. To avoid the monopoly phenomenon caused by a single power grid selling the electricity to the buildings, the time-of-use (TOU) electricity price implemented in Guandong province, China, which is the nearest province to Hong Kong, is referenced as the constraints of the optimized dynamic electricity price. The detailed information of the TOU price in Guandong province is presented in Table 2. At each time slot, +50% and -30% of the corresponding values in the TOU price (in Guandong province) are used as the upper and lower boundaries of the optimized dynamic price.

Table 2 Time-of-use price implemented in Guandong province, China

	On-peak	Mid-peak	Off-peak
Time	14:00~17:00 19:00~22:00	8:00~14:00 17:00~19:00 22:00~24:00	0:00~8:00
Price (*yuan/kWh*)	1.518	0.92	0.46

5. Results and discussion

5.1 Basic grid-building interaction

This section presents the validation and test results of the proposed basic grid-building interaction strategy using the real data of a day, including the corresponding benefits of the power grid and buildings. The baseline prediction of building power demand in the basic grid-building interaction are assumed to be known and without uncertainties. The Nash equilibrium is identified by the basic scheme (the optimized power demand of buildings is determined by Eq.(15-a) and the optimized dynamic pricing of power grid is determined by Eq.(17-d)).

Optimized pricing of power grid

Fig. 3 shows the optimized dynamic electricity price on the test day using the basic grid-building interaction strategy. Here, the price at each time slot is at the Nash equilibrium of the proposed game theory-based strategy. The power grid stimulated the buildings to shift their power demand from on-peak periods to mid-/off-peak periods by setting the price every hour. Compared with the TOU price in Guangdong province, the optimized price fluctuated within the reasonable range (i.e., pre-determined upper/lower limit) fully considering the situations of both power grid and buildings. It is worthy of notice that in the proposed interaction, the power grid improves its net profit by optimizing the electricity price, not by blindly trying to increase the electricity price. Fig. 4 presents the optimized grid power generation for the campus on the test day using the basic interaction strategy, which is equal to the total power demand of the four campus buildings. Compared with the baseline of aggregated power demand of the campus, the peak power demand in the daytime was effectively reduced from 19.53 MW to 16.26 MW, resulting from the higher electricity prices in the on-peak period. A part of the power demand was shifted to the periods of the early morning and evening when the price was only about half that of the peak time (i.e., around 0.65 *yuan*/kWh).

Table 3 summarizes the benefits of the power grid on the test day using the basic grid-building interaction strategy. For the perspective of the power grid, six aspects of improvements (i.e., electricity bill, generation cost, net profit, demand fluctuation, peak load and total utility) were considered and presented after using the proposed interaction strategy. Using the basic grid-building interaction strategy, the net profit of the power grid increased from 78,565 to 85,325 *yuan*, a nearly 8% increase. The net profit increase of the grid was benefited by the reduction of generation cost. But the electricity bills collected from the buildings were reduced and hence used as economic incentives to stimulate the buildings to establish the proposed interaction to achieve a win-win situation to benefit both the power grid and buildings. Meanwhile, the demand fluctuation index improved (i.e., decreased) by approximately 40% and the peak load was also reduced by 16.7%. Overall, the utility of the power grid achieved an obvious improvement of 10.6%. Here, the reference price was the TOU price used in Guangdong province, and the baseline power demands were the actual measurements of building power demands on the campus without any TOU price adopted [32].

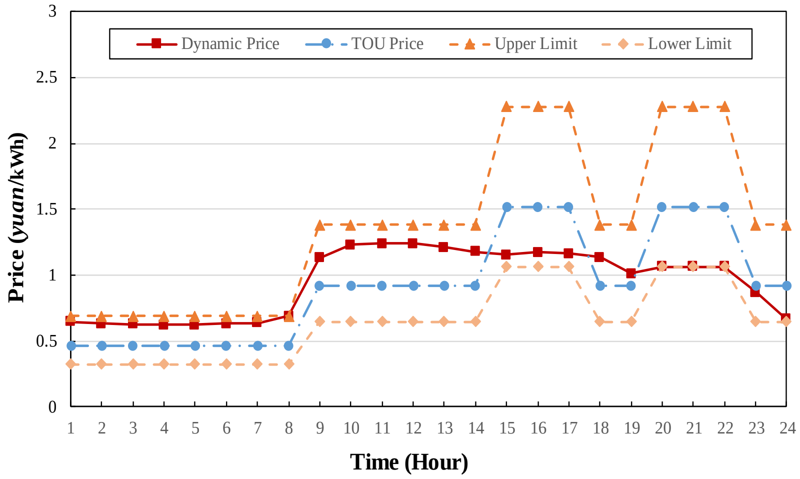

Fig. 3 Optimized dynamic electricity price on the test day using the basic interaction strategy

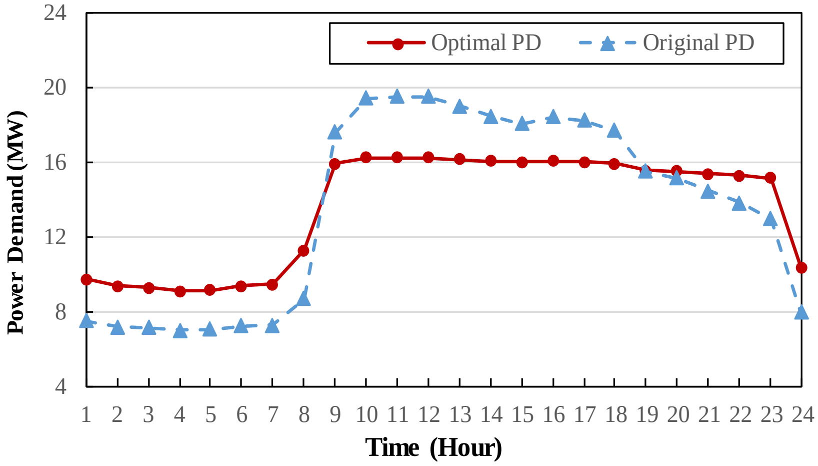

Fig. 4 Baseline and optimized grid power generation for the campus on the test day using the basic

interaction strategy

Table 3 Benefits of the power grid on the test day using the basic interaction strategy

		Electricity bill	*Reduction*		Generation cost	*Reduction*		Net Profit	*Improvement*	
		(*Yuan*)	(*Yuan*)	(%)	(*Yuan*)	(*Yuan*)	(%)	(*Yuan*)	(*Yuan*)	(%)
Grid	Baseline	332,058			253,493			78,565		
	Basic GT	319,578	12,480	3.8%	234,253	19,240	7.6%	85,325	6,760	7.9%
		Demand fluctuation	*Reduction*		Peak Load	*Reduction*		Total utility	*Improvement*	
		--	(%)		(MW)	(MW)	(%)	--	(%)	
	Baseline	5.02			19.53			73,545		
	Basic GT	3.03	39.6%		16.26	3.27	16.7%	82,295	10.6%	

**Basic GT refers to the game theory based interaction strategy with the basic scheme for identification of Nash equilibrium.*

Optimized demand management of buildings

Fig. 5 shows the optimized power demands of four campus accounts on the test day using the basic interaction strategy. The power demand of each building at each hour was at the Nash equilibrium in the proposed game theory-based approach. In general, the building power demand was inversely proportional to the dynamic price given by the power grid. The buildings shifted their demands from the higher to lower price periods to reduce their electricity bills. Fig. 6 presents the electricity bills of the four campus accounts with and without the use of the basic interaction strategy. When the basic interaction strategy was used, the bills during the higher price periods were clearly reduced, while there were slight increases during the lower price periods as more power was consumed. As a result, the daily bills of the test day were reduced when demand shifting was conducted in the buildings.

Table 4 presents the benefits of four campus accounts on the test day when the basic interaction strategy was used. After optimizing the power demands of buildings responding to the given dynamic price, the daily electricity bills of the four accounts were reduced by 2.5%, 8.3%, 3.4% and 5.4%, respectively. Moreover, the overall utility sacrifices of the four accounts, including user dissatisfaction, mismatching cost and electricity cost, were reduced by 1.2%, 5.7%, 1.8% and 2.5%, respectively.

According to the comprehensive results of the power grid and the buildings, it is worthy of notice that the proposed interaction strategy benefits to both the supply and demand sides of a power grid. Adopting this interaction, the more benefit achieved at one player is not built at the expense of the losses of the other players. Therefore, the proposed grid-building interaction strategy is a win-win strategy benefiting every player involved (i.e., grid and buildings).

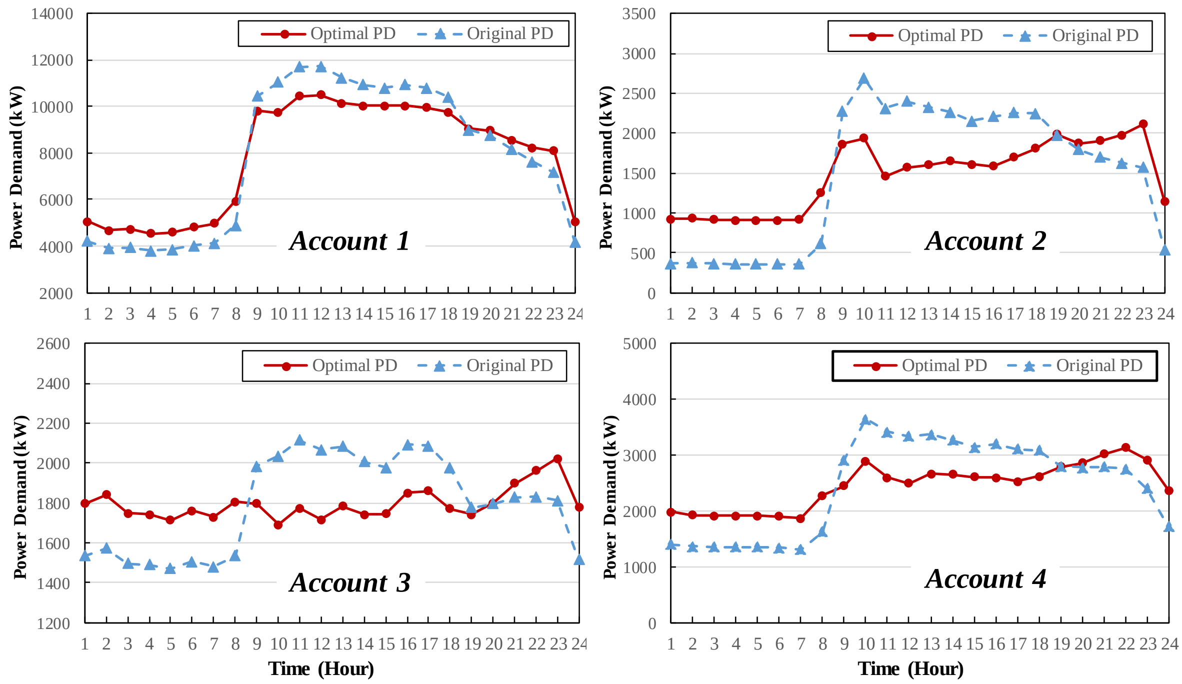

Fig. 5 Optimized demand profiles of four campus accounts on the test day using the basic interaction strategy

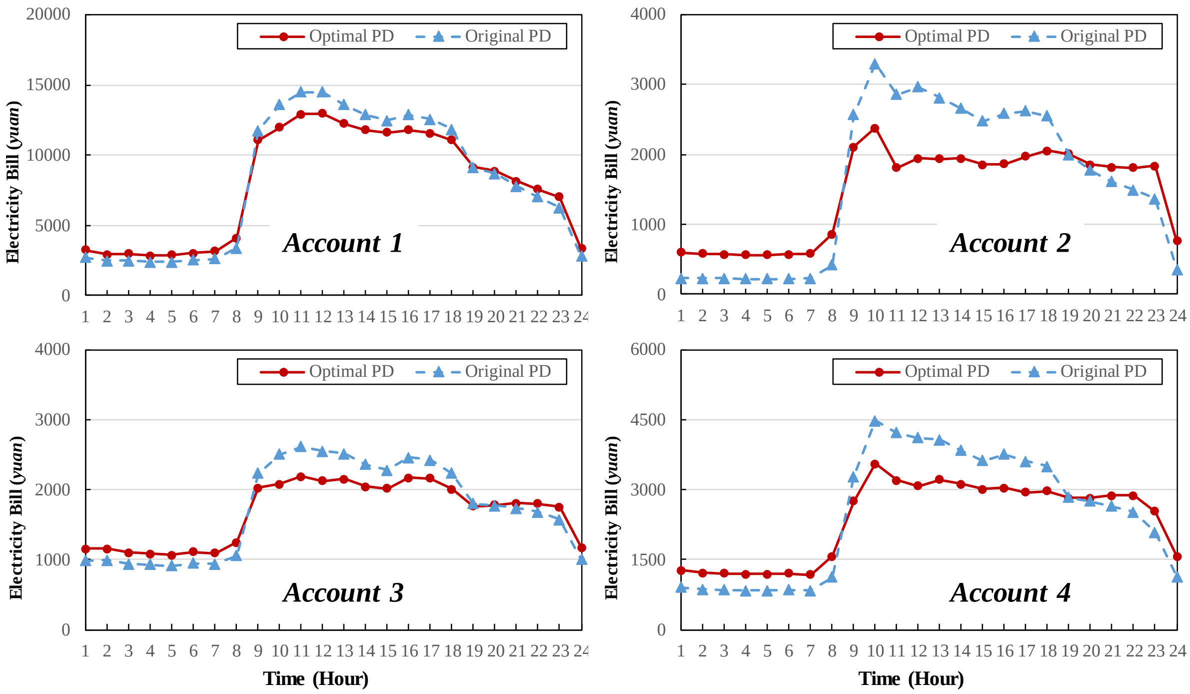

Fig. 6 Optimized electricity bills of four campus accounts on the test day using the basic interaction strategy

Table 4 Benefits of four campus accounts on the test day using the basic interaction strategy

		Utility sacrifice	Saving percentage	Electricity bill (*Yuan*)	Saving (*Yuan*)	Saving percentage
Account 1	Baseline	97,184		192,928		
	Basic GT	96,024	1.2%	188,217	4,711	2.5%
Account 2	Baseline	9,325		38,012		
	Basic GT	9,096	5.7%	34,842	3,170	8.3%
Account 3	Baseline	4,366		41,482		
	Basic GT	4,286	1.8%	40,089	1,393	3.4%
Account 4	Baseline	15,203		59,636		
	Basic GT	14,822	2.5%	56,430	3,206	5.4%

5.2 Enhanced grid-building interaction

In this section, the data of 10 workdays in two weeks were selected to analyze the enhanced interaction strategy when the building power demand baseline prediction was not completely accurate due to the uncertainty. The effect of building power demand baseline uncertainty on the proposed basic interaction strategy was investigated and the robust interaction strategy was tested and validated. The Nash equilibrium is identified by the enhanced scheme (the optimized power demand of buildings is determined by Eq.(19-c) and the optimized dynamic pricing of power grid is determined by Eq.(19-d)).

Optimized pricing of power grid

Fig. 7 presents the dynamic electricity prices on the 10 workdays using the basic and enhanced interaction strategies under uncertainty. The dynamic price at each time slot in different interaction strategies were at the individual Nash equilibrium of the proposed game theory-based approaches. The prediction uncertainty of building demand baseline led to the optimized dynamic electricity price deviating from the Nash equilibrium. Undoubtedly, this may be seen as having diminished the effectiveness of the proposed basic interaction strategy and hence having significantly reduced the benefits of the power grid and buildings, if such uncertainty had not been properly considered and addressed. Fig. 8 shows the optimized total power demand of the campus responding to the dynamic price using different interaction strategies. Although the aggregated power demand could still be shifted from on-peak periods to mid-/off-peak periods using the two proposed interaction strategies, in comparison with the baseline, the enhanced interaction strategy could achieve a notably higher performance for both the power grid and buildings (as shown in Table 5 and Table 6).

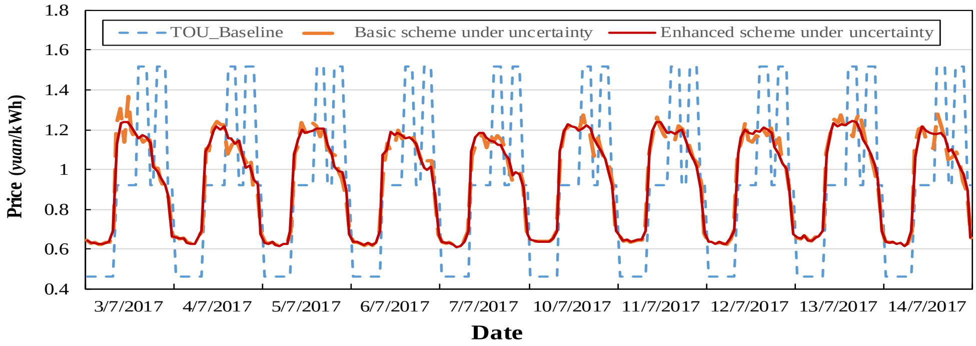

Fig. 7 Optimized dynamic electricity price under uncertainty using different interaction strategies

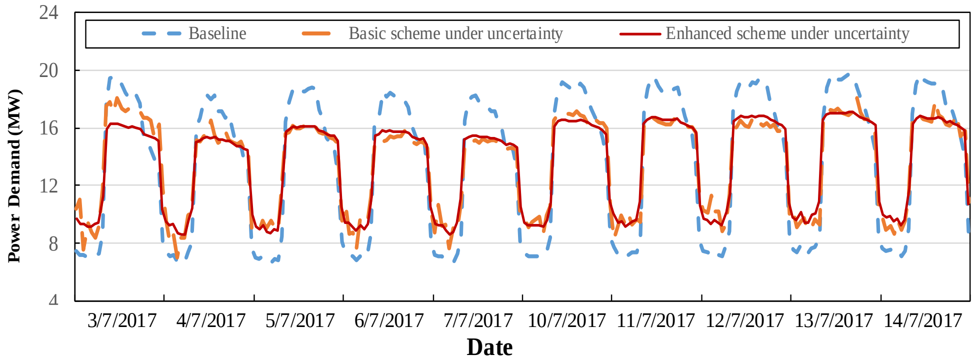

Fig. 8 Baseline and optimized grid power generation for the campus under uncertainty using different interaction strategies

Table 5 presents the averaged benefits per day of the power grid on the ten test days using different interaction strategies. Six aspects of the benefits of the power grid (i.e., electricity bill, generation cost, net profit, demand fluctuation, peak load and total utility) were presented and compared using different interaction strategies. Overall, the benefits of the power grid increased if the interaction was established and dynamic price was implemented, although the uncertainty and inaccuracy were not addressed. The baseline uncertainty of building power demand led to a reduction in the net profit improvement of the power grid from 7,091 *yuan* to 4,503 *yuan*, more than a 3% decrease, when the interaction was established. Moreover, the uncertainty resulted in a significant fluctuation of aggregated power demand and hence the peak load increased obviously. Under the enhanced robust interaction strategy, all the six aspects of the benefits considered for the power grid were improved notably (e.g., net profit was further improved by about 2%) under the uncertainty condition, compared with the results using the basic interaction scheme. But the benefits were still reduced compared with the case without any uncertainty (i.e., basic GT (no uncertainty) shown in Table 5 and Table 6) because the uncertainty existed on the demand side of the power grid would lead to the optimized results deviating from the real Nash equilibrium.

Table 5 Averaged benefits of the grid on the ten test days using different interaction strategies

	Electricity	*Reduction*	Generation	*Reduction*	Net	*Improvement*

		bill			cost			Profit		
		(*Yuan*)	(*Yuan*)	(%)	(*Yuan*)	(*Yuan*)	(%)	(*Yuan*)	(*Yuan*)	(%)
	Baseline	336,495			256,170			80,325		
	Basic GT (no uncertainty)	323,156	13,339	4.0%	235,740	20,430	8.0%	87,416	7,091	8.8%
	Basic GT (uncertainty)	328,051	8,444	2.5%	243,223	12,947	5.1%	84,828	4,503	5.6%
	Enhanced GT	325,380	11,115	3.3%	238,790	17,380	6.8%	86,590	6,265	7.8%
Grid		Demand fluctuation	*Reduction*		Peak Load	*Reduction*		Total utility	*Improvement*	
		--	(%)		(MW)	(MW)	(%)	--	(%)	
	Baseline	4.97			19.09			75,355		
	Basic GT (no uncertainty)	3.09	37.8%		16.01	3.08	16.1%	84,326	11.9%	
	Basic GT (uncertainty)	3.47	30.2%		17.51	1.58	8.3%	81,358	7.9%	
	Enhanced GT	3.23	35.1%		16.61	2.48	13.0%	83,360	10.6%	

**Enhanced GT refers to the game theory based interaction strategy with the enhanced scheme for identification of Nash equilibrium; no uncertainty refers to the condition with completely accurate baseline prediction of building demand; uncertainty refers to the condition that baseline prediction of building demand is not completely accurate and with uncertainty.*

Optimized demand management of buildings

Fig. 9 shows the optimized power demand profiles associated with the four campus accounts on the 10 test days with and without using the enhanced robust interaction strategy. The power demand of each building at every hour corresponded to the Nash equilibrium of the proposed strategy, which was based on game theory. In general, demand shifting could be conducted when the dynamic price was given by the power grid, but the prediction uncertainty of the baseline would lead to the building optimal power demand deviating from the real Nash equilibrium. The enhanced robust interaction strategy could revise/modify the building optimal power demand to effectively cope with the uncertainty, and a notable difference was observed compared with the results which did not properly address such uncertainty. As a result, the power demands of the four accounts, optimized by different interaction strategies, resulted in different electricity bills, as shown in Fig. 10.

A detailed comparison of the averaged benefits per day of the four campus accounts on the ten test days using different interaction strategies is shown in Table 6. Undoubtedly, the best results were achieved when the baseline was accurate and no uncertainty existed. When the building power demand baseline was uncertain, the savings of the electricity bill and the improvement of utility sacrifice were both obviously reduced but still better than those in the baseline case of no interaction established between the power grid and buildings. To some extent, the robust interaction strategy compensated for the losses resulting from uncertainty because of the adjustments and modifications considered in the enhanced interaction strategy.

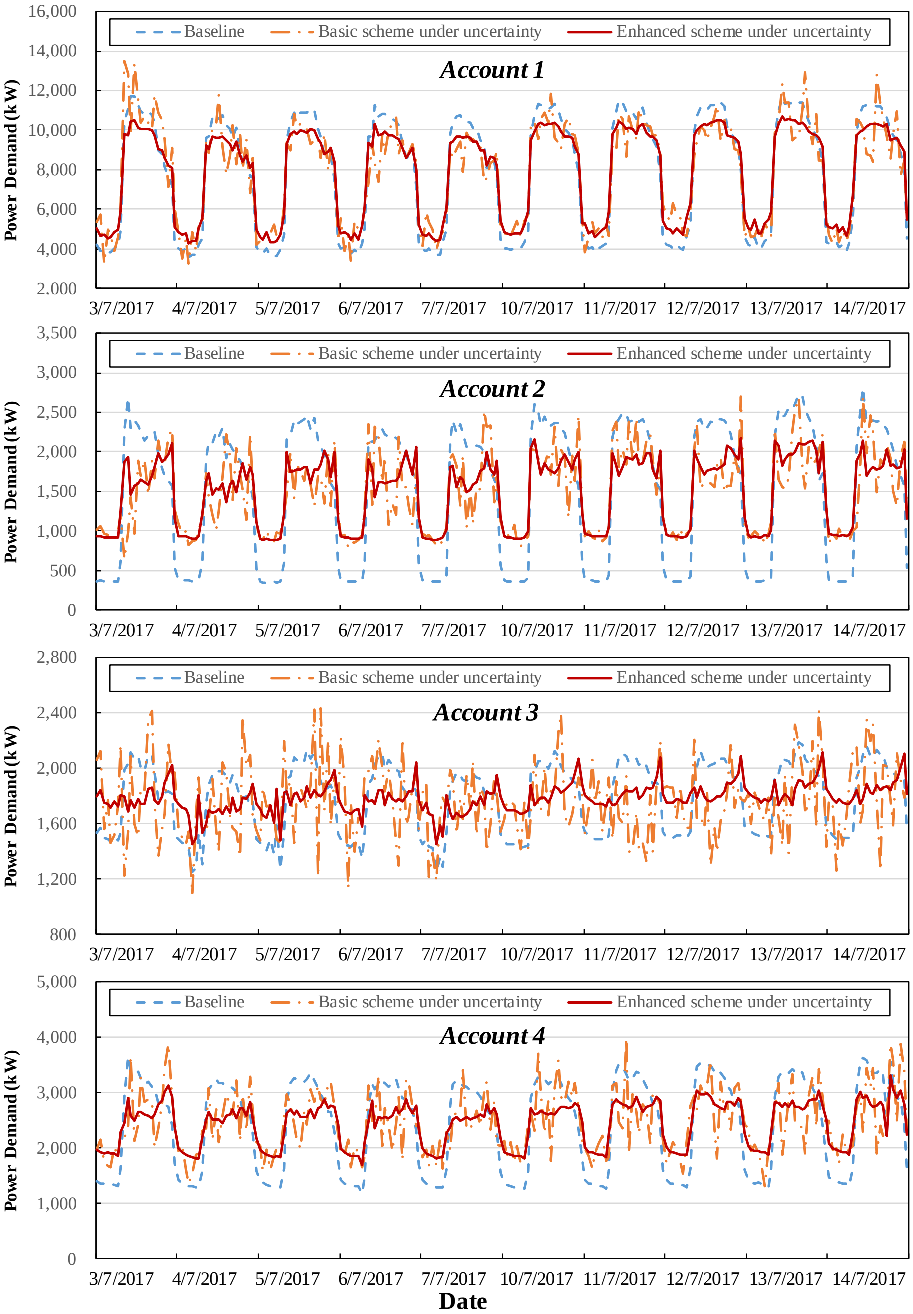

Fig. 9 Optimized demand profiles of four campus accounts under uncertainty using different interaction strategies

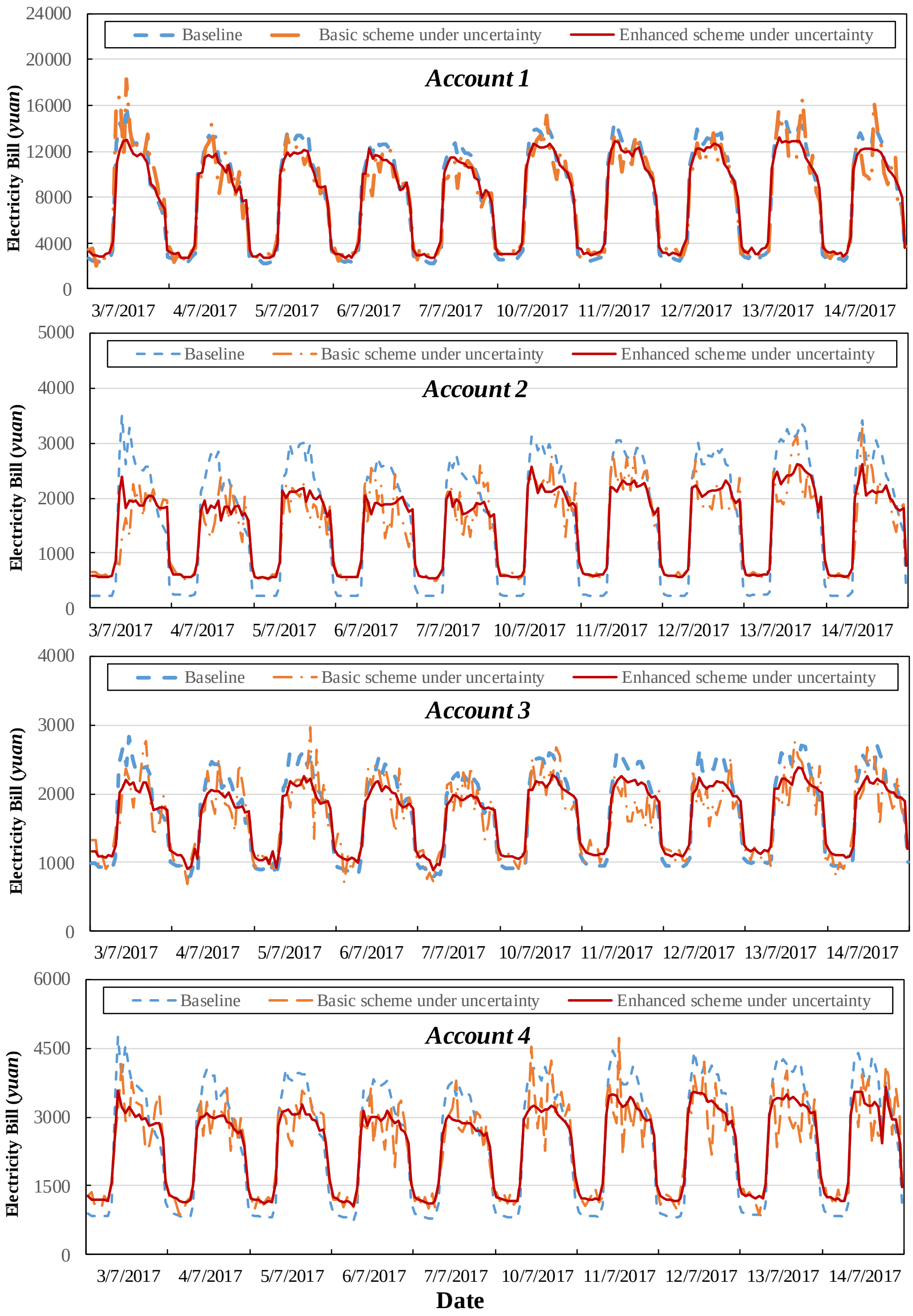

Fig. 10 Optimized electricity bills of four campus accounts under uncertainty using different interaction strategies

Table 6 Averaged benefits of four campus accounts on the ten test days using different interaction strategies

		Utility sacrifice (*Unit*)	Saving percentage	Electricity bill (*Yuan*)	Saving (*Yuan*)	Saving percentage
Account 1	Baseline	98,347		195,750		
	Basic GT (no uncertainty)	97,023	1.3%	190,493	5,257	2.7%
	Basic GT (uncertainty)	97,843	0.5%	192,587	3,163	1.6%
	Enhanced GT	97,409	1.0%	191,631	4,119	2.1%
Account 2	Baseline	9,518		38,900		
	Basic GT (no uncertainty)	9,078	4.6%	35,548	3,352	8.6%
	Basic GT (uncertainty)	9,342	1.8%	36,841	2,059	5.3%
	Enhanced GT	9,156	3.8%	36,117	2,783	7.1%
Account 3	Baseline	4,381		41,782		
	Basic GT (no uncertainty)	4,288	2.1%	40,136	1,646	3.9%
	Basic GT (uncertainty)	4,338	1.0%	40,545	1,237	3.0%
	Enhanced GT	4,319	1.4%	40,343	1,439	3.4%
Account 4	Baseline	15,268		60,063		
	Basic GT (no uncertainty)	14,778	3.2%	56,979	3,084	5.1%
	Basic GT (uncertainty)	15,129	0.9%	58,078	1,985	3.3%
	Enhanced GT	14,980	1.9%	57,289	2,774	4.6%

6. Conclusions

This paper presents two game theory based interaction strategies to build a win-win interaction between the power grid and buildings. The interaction is built as a Stackelberg game, which reflects the core position of the power grid and the auxiliary position of buildings in the demand response (DR) programs, considering the multiple requirements of both smart grid and buildings. The experience and results of this study show that the proposed basic game theory based interaction strategy can effectively improve six aspects on the supply side (i.e., power grid), such as net profit, demand fluctuation, peak load, etc., by optimizing the dynamic price. Simultaneously, the utility sacrifice of individual buildings (including dissatisfaction, the cost of demand mismatching and electricity bills) can be reduced by conducting demand shifting in response to the optimized dynamic price. Moreover, the enhanced game theory based interaction strategy can further effectively relieve the negative effects of the demand baseline prediction uncertainty in the operation of the interaction strategy. The performances of the proposed basic and enhanced interaction strategies were tested and validated based on the real site data of buildings on a university campus in Hong Kong. More detailed conclusions on the performance of the strategies can be drawn as follows.

- According to the results of case study, for the supply side (i.e., power grid), the basic game theory-based strategy achieved an 8% net profit increase (i.e., from 78,565 to 85,325 *yuan*). The power demand fluctuation was also effectively reduced by nearly 40% and the peak demand was also decreased by 16%.
- For the demand side, the basic game theory-based strategy achieved 2.5%, 8.3%, 3.4% and 5.4% of savings for the electricity bills of the four campus accounts, respectively, while it achieved utility sacrifice reductions of 1.2%, 5.7%, 1.8% and 2.5% for the buildings associated with those four accounts, respectively.
- The uncertainty in the baseline prediction of building demand would significantly reduce the benefits of both the power grid and buildings given by the proposed basic interaction strategy. The total utility of the power grid was reduced from 11.9% to 7.9%, while the improvements of building utility sacrifices were reduced from 1.3%, 4.6%, 2.1% and 3.2% to 0.5%, 1.8%, 1.0% and 0.9% for the buildings associated with the four accounts, respectively.
- The proposed enhanced interaction strategy could effectively reduce the negative effects of the uncertainty existing in the demand baseline prediction and therefore improve the benefits of the power grid and buildings. The total utility of the power grid was increased from 7.9% to 10.6%, while the improvements of building utility sacrifices were increased from 0.5%, 1.8%, 1.0% and 0.9%, to 1.0%, 3.8%, 1.4% and 1.9% for buildings associated to the four accounts, respectively.

This work establishes the grid-building interaction using the game theoretic method. In the future work, the adaptive control strategy (e.g., model predictive control) can cooperate with the proposed interaction strategy to achieve the real-time optimization of dynamic pricing and building power demand management rather than a day-ahead optimization to improve the interaction strategy flexibility and robustness. Meanwhile, for the interests of demand side, on-site survey (e.g., questionnaire) would be conducted to investigate the interests of users at the demand side and also to determine the accurate utility profiles of power use.

7. Acknowledgements

The research presented in this paper is financially supported by a grant (152152/15E) of the Research Grant Council (RGC) of the Hong Kong SAR and a grant under the Strategic Focus Area

(SFA) Scheme of the Research Institute for Sustainable Urban Development (RISUD) in The Hong Kong Polytechnic University.

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