A hybrid demand response mechanism based on real-time incentive and real-time pricing

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Abstract

This paper proposes a hybrid demand response mechanism considering three types of participants: power grid operator (PGO), retailers and end users. Different from the traditional price-based or incentive-based methods, this hybrid mechanism combines real-time pricing and real-time incentive together to implement demand response programs dispatched by PGO, i.e., the PGO provides incentives to retailers and the retailers set optimal real-time prices to users every 5 minutes. This hybrid DR mechanism can better motivate retailers to participate by providing them with monetary incentives from PGO for load shifting. We use a three-level Stackelberg game to model the proposed mechanism. The PGO first determines the optimal incentive rate to minimize its cost, then the retailers decide the optimal electricity price to maximize their profits, and the users finally choose the optimal power demand to maximize their welfare. The analytical solutions of the optimal decisions for every participant are given. We also propose a distributed algorithm to implement this mechanism in a practical application by considering information asymmetry. The simulation results verify its advantages over traditional demand response mechanisms.

Keywords: Demand response; Real-time pricing; Real-time incentive; Stackelberg game; Smart grid

1. Introduction

Traditional power grid is undergoing a significant change to overcome the challenges of increasing supply-demand imbalance [1, 2]. The smart grid, which integrates state-of-the-art communication, metering and control technologies, is envisaged as a promising candidate to cope with power imbalance and the instability of power grid [3, 4]. As one of the key characteristics of smart grid, demand response (DR) is described as an effective way to induce power consumers to alter their power demand from peak hours to off-peak hours within a day [5-7]. By adjusting the shiftable load, DR programs can reduce the peak-to-average ratio (PAR) to maintain the stability of the power grid [8] and avoid the cost of backup generators [9]. Therefore, it is of vital importance for power grid operators to establish an effective DR mechanism to enhance the flexibility of the power system [10].

In the current research, DR is mainly implemented in two ways: price-based DR and incentive-based DR [11]. **Price-based DR (PBDR)** refers to mechanisms where retailers or utility companies set time-varying electricity prices to induce users to transfer their power usage from peak to off-peak hours [12]. To change the power demand of users, they usually set higher prices during peak hours and lower prices during off-peak hours. There have been many studies on the design and modeling of PBDR. Tang et al. [13], for example, developed a Stackelberg game-based interactive strategy between a utility company and several smart buildings to promote the revenue of the grid and reduce the cost caused by load fluctuation. However, since this method considers only one utility company in the market, it is usually not applicable if the retail market is not monopolized. Yu and Hong [14] proposed a real-time price-based DRM algorithm, which realizes the optimal load control of continuous and discrete devices through a virtual power transaction process once an hour. Studies [15-17] have developed models that extend price-based DR to the scenario of multiple retailers competing to sell power to users in a power retail market. Alipour et al. [18] firstly applies the real-time pricing (RTP) to the demand response management of heat and power consumers. On the premise of meeting the total demand of consumers, the procurement cost of electricity and heat was minimized. Monfared et al. [19] proposed an interesting PBDR method, which adopted time-of-use pricing scheme in off-peak and mid-peak hours while real-time pricing method in peak-hours. **Incentive-based DR (IBDR)** refers to mechanisms where retailers or utility companies encourage users to participate in load reduction projects of power systems based on the signed agreement. If users reduce power usage in peak hours, they will receive monetary compensation [20]. The existence of incentive mechanism promotes the participation of power users. The aim of such IBDR is to avoid the high capacity penalties from the power grid operator (PGO) if the power usage exceeds maximum capacity [21], or to avoid the financial risk like price fluctuations in the wholesale market [22-24]. Similar to PBDR, this mechanism was originally designed to maximize the expected profit of demand side mediators, such as retailers and utility companies. Since retailers take the capacity penalty of PGO into account when making decisions, these traditional DR mechanisms may reduce PAR indirectly.

However, there is still room for improvement in traditional mechanisms: (1) Most previous studies focused on the interactions between retailers and end users [25]. However, since retailers are not responsible for the stability of the entire power grid [26], the potential of DR in load shifting cannot be fully exploited without the efforts of PGO to coordinate the collective actions of all retailers [27-29]. (2) Most previous mechanisms only focus on incentives for users, but fail to consider incentives for retailers. Since peak load reduction does not always improve the profit of retailers, it is inevitable that retailers are usually not fully motivated to participate in DR programs [30], and the effect of DR is therefore weakened. (3) The system scheduling frequency of the traditional mechanisms is usually once an hour, i.e., one hour RTP or TOU. However, the intermittence and uncertainty of renewable power on the generation side requires timely feedback of supply-demand relationship and price signals to the demand side [31].

To overcome the weakness of traditional PBDR and IBDR, we propose a hybrid DR mechanism combining both real-time pricing and real-time incentive. There are three types of participants in this mechanism: PGO, retailers and power users. First, PGO provides monetary incentives to retailers with optimal incentive rate that can minimize its cost to motivate their participation in DR. A retailer gets monetary incentive if its customers change their power demand according to the requirements of PGO. Second, to maximize their profits, retailers induce their customers to change power demand by setting optimal real time price (RTP) every 5 minutes. Finally, users decide the optimal power consumption in this period to maximize their welfare. This three level DR mechanism can better motivate retailers to participate since they receive monetary incentives from PGO for load shifting. Therefore, compared with PBDR or IBDR, the effect of our proposed DR can be significantly enhanced.

The contributions of this study can be concluded as follows: (1) We propose a three-level hybrid DR mechanism that combines RTP and RTI with the participation of PGO, retailers and users. Compared with traditional PBDR and IBDR, this mechanism can reduce peak load and stabilize load fluctuation more effectively; (2) We formulate a three-level Stackelberg game to model the proposed DR mechanism and prove the existence and uniqueness of Stackelberg equilibrium (SE); (3) We propose a distributed algorithm to implement the proposed DR mechanism considering that PGO's inability to obtain the user's preference and retailer's cost parameters in the practical application. This distributed algorithm can help obtain the approximate solution of the optimal strategies of DR participants.

The following part of this paper is organized as follows: In Section 2, the proposed DR mechanism are modeled. In Section 3, a three-level Stackelberg game is formulated and the analytical solution of the tripartite optimal strategy is given. In section 4, the distributed algorithm is proposed. In Section 5, the numerical simulation is carried out. In Section 6, the DR mechanism of this paper is summarized and the future work is prospected.

2. Modeling of the proposed demand response mechanism

2.1. Assumptions

(1) Each user chooses only one retailer to purchase power and related service during the studied period.

(2) Each user is equipped with an energy management system (EMS)[1] to support the real-time two-way interactions between the user and retailer.

2.2. Framework

As shown in Fig.1, our proposed DR mechanism considers a demand-side system consisted of a power grid operator (PGO), multiple retailers and multiple end-users (users). Let $\mathrm{J} = \{1, 2, \cdots, J\}$ and $\mathrm{I} = \{1, 2, \cdots, I\}$ denote the set of retailers and users respectively and J and I be the number of retailers and users. Let I_j denotes the set of users who purchase power from the retailer $j \in \mathrm{J}$ .The period (usually one day) studied can be divided into multiple time slots and the set of time slots is represented as $\mathrm{H} = \{1, 2, \cdots, H\}$ and the number of time slots is H. In this paper, the demand side system is scheduled every 5 minutes, i.e., the incentive rate, electricity price and power demand change every 5 minutes. Therefore, we have $H = 288$ in the proposed mechanism.

Our proposed DR mechanism has three levels. First, PGO at the upper level provides conditional incentive to retailers in order to transfer peak load to non-peak period. The amount of the incentive is positively related to the reduction(increase) of the electricity demand in peak(off-peak) hours. Second, retailers at middle level set optimal RTP to maximize their profits, with incentive income, electricity charges and power supply cost considered. Finally, users at the lowest level respond to the RTP by determining the optimal power demand to maximize their welfare, which consists of utility, electricity bills and the dissatisfaction cost caused by DR.

[1] EMS mainly consists of smart grid infrastructure like smart meters, smart interactive terminals, intellectual sockets [32]. It integrates the functions of real-time collection and analysis of power consumption data, equipment monitoring, optimal dispatching of power usage, two-way communication with power grid and power retailers, etc. [33].

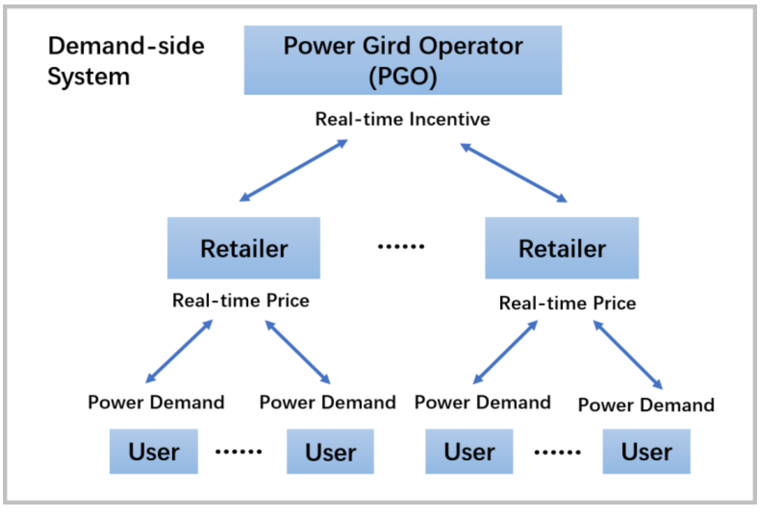

Fig.1 An illustration of the hybrid DR mechanism

2.3. The welfare of users

The welfare of users is composed of utility $U_i^h\left(d_{i,j}^h\right)$, electricity bills $P_i^h\left(d_{i,j}^h\right)$ and dissatisfaction cost $S_i^h\left(d_{i,j}^h\right)$ [13, 15]. User $i \in \mathrm{I}$ taking part in DR will receive electricity prices from a selected retailer $j \in \mathrm{J}$ before the start of each period. Then each user decides the optimal power demand $d_{i,j}^h$ to maximize his/her welfare.

$$\max \sum_{h \in \mathrm{H}} W_i\left(d_{i,j}^h\right) = \max \sum_{h \in \mathrm{H}} \left[U_i^h\left(d_{i,j}^h\right) - P_i^h\left(d_{i,j}^h\right) - S_i^h\left(d_{i,j}^h\right)\right] \tag{1}$$

Utility function $U_i^h\left(d_{i,j}^h\right)$ quantifies the utility a user gain from the amount of power consumption $d_{i,j}^h$, which is a differentiable function with diminishing marginal utility [34], i.e., with the increase of electricity consumption, the comfort obtained by the user from the last kilowatt-hour of electricity will be decreasing [20]. Mathematically, the second derivative of utility with respect to electricity consumption is negative. Without the loss of generality, we adopt a quadratic function [15] as follows:

$$U_i^h\left(d_{i,j}^h\right) = \omega_i^h d_{i,j}^h - \frac{\omega_i^h}{2\beta_i^h}\left(d_{i,j}^h\right)^2 \tag{2}$$

where ω_i^h reflects a user's utility preference. β_i^h denotes the maximum of power demand in time slot h.

Electricity bill $P_i^h\left(d_{i,j}^h\right)$ refers to a user's payment to the selected retailer when consuming $d_{i,j}^h$ amount of electricity under the RTP $d_{i,j}^h$ during time slot h :

$$P_i^h\left(d_{i,j}^h\right) = p_j^h d_{i,j}^h \tag{3}$$

Dissatisfaction cost $S_i^h\left(d_{i,j}^h\right)$ captures the unwillingness of users to shift their power demand [35]. Since price-based DR induces users to deviate from the original level of power consumption and may lead to dissatisfaction or monetary loss of users (such as energy storage loss, cost of changing production plan, etc.) [13]. Dissatisfaction cost can be modeled as a quadratic function associated with the amount of power shifting $\left(d_{i,j}^h - m_i^h\right)$:

$$S_i^h\left(d_{i,j}^h\right) = \alpha_i^h\left(d_{i,j}^h - m_i^h\right)^2, \alpha_i^h \geq 0 \tag{4}$$

where $m_{i,j}^h$ refers to the original electricity demand of user i before participating in DR, which can be obtained from historical data of power consumption; α_i^h is a non-negative parameter. The larger the α_i^h of user i, the more resistant the user will be towards load shifting. In particular, $\alpha_i^h = 0$ indicates that user i is fully in favor of participating in DR and does not have to bear any additional dissatisfaction cost.

2.4. The profits of retailers

Under the proposed DR mechanism, retailers not only supply power to users, but also act as aggregators. A single low-load user (e.g., a resident user) cannot directly negotiate with PGO [36], while retailers can gather a large number of contracted users to meet the minimum load reduction requirement of PGO.

The goal of a profit-seeking retailer is to maximize profits R_j, which consists of electricity charges P_j^h, incentive income I_j^h and electricity supply cost C_j^h.

$$\max \sum_{h \in \mathrm{H}} R_j\left(p_j^h\right) = \max \sum_{h \in \mathrm{H}} \left[P_j^h + I_j^h - C_j^h \right] \tag{5}$$

Electricity charges P_j^h is an index referring to the income that a retailer gains from its users when selling $D_{i,j}^h$ amount of power., which is the sum of all users' electricity bill.

$$P_j^h = p_j^h D_j^h = p_j^h \sum_{i \in \mathrm{I}_j} d_{i,j}^h \tag{6}$$

$$p_j^h = y_j^h + \rho_j \tag{7}$$

where $D_j^h = \sum_{i \in \mathrm{I}_j} d_{i,j}^h$; p_j^h is the real-time price in the h time slot; ρ_j is the flat price before the application of DR [37] and y_j^h is the change of price after DR in the h time slot.

Incentive income I_j^h refers to the amount of monetary costs that a PGO pays for a retailer when power demand D_j^h reduces (or increases) during peak (or off-peak) hours according to the requirement of PGO. Numerically, it equals to the product of the incentive rate λ^h and the change in power consumption in time slot h.

$$I_j^h = \lambda^h \left(D_j^h - M_j^h \right) \tag{8}$$

where the original power consumption M_j^h can be expressed as $M_j^h = \sum_{i \in \mathrm{I}_j} m_i^h$.

Electricity supply cost C_j^h refers to the cost of a retailer to supply power during time slot h. This cost occurs when a retailer purchases electricity from the wholesale market and operates the power sales business. We assume that this cost increases with the growth of power demand D_j^h and use a quadratic function to model this cost [38]:

$$C_j^h = a_j^h \left(D_j^h \right)^2 + b_j^h D_j^h + c_j^h \tag{9}$$

where a_j^h, b_j^h, c_j^h are non-negative parameters of retailer j at time slot h.

2.5. The cost of power grid operator (PGO)

A PGO is responsible for operating the transmission and distribution grids in the region under a certain degree of supervision. Whether the income of PGO is related to the amount of electricity transmitted depends on local energy policies [30,39]. In order to simplify the problem, we assume that the revenue of PGO is fixed and therefore transform the profit maximization problem into the cost minimization problem. The cost of PGO includes the incentive cost I_g^h and load fluctuation cost F_g^h.

$$\min \sum_{h\in \mathrm{H}} C_g\left(\lambda^h\right)=\min \sum_{h\in \mathrm{H}}\left(F_g^h+I_g^h\right) \tag{10}$$

Incentive cost demonstrated in (11) refers to a PGO's payment to retailers if they increase or reduce the amount of power demand $\left(D^h-M^h\right)$ as required.

$$I^h=\lambda^h\left(D^h-M^h\right) \tag{11}$$

where $M^h=\sum_{j\in \mathrm{J}} M_j^h$ and $D^h=\sum_{j\in \mathrm{J}} D_j^h$.

Load fluctuation cost refers to the operational cost of PGO when the power demand deviates from the average level. We calculate load fluctuation cost by using the sum of squares of the deviation between the power demand D^h in each time slot and the average demand $\bar{D}=\frac{1}{H}\sum_{h\in \mathrm{H}} D^h$, multiplied by the cost parameter σ [37]. By flattening the load curve, the peak load can be reduced, thereby avoiding the use of costly backup generators and reducing the operating pressure of the grid. In addition, minimizing load fluctuation in (12) is approximately equivalent to maximizing load factor [35, 40], which is an index to measure the efficiency of power usage [41]. Load fluctuation cost F_g^h can be expressed as follows:

$$F_g^h=\frac{\sigma}{H}\left(D^h-\bar{D}\right)^2 \tag{12}$$

3. A three-level Stackelberg Game based Analysis of Hybrid DR Mechanism

3.1. Formulation of a Three-level Stackelberg Game

To analyze the effect of the hybrid DR mechanism, this paper adopts a special Stackelberg Game approach with a three-level structure to model the interactions among PGO, retailers and users. The three-level Stackelberg game has a hierarchical structure, where its participants include PGO, retailers and users and their status and decision-making order are different in the game. A PGO plays a leading role because it provides incentives to retailers. It makes the first decision and decides the optimal incentive rate on the basis of considering the responses of retailers and users. After receiving the incentive signal, each retailer optimizes its profit function and sets the optimal RTP with the response of the users considered. Finally, after receiving the price signal, each user optimizes its welfare function to determine the optimal power demand. It is worth noting that the role of retailers is multiple. They are followers of the power grid and leaders of end users. For such a hierarchical Stackelberg game, the strategy set $\left(\lambda^*,\mathbf{p}^*,\mathbf{D}^*\right)$ constitutes Stackelberg Equilibrium (SE) in time slot h only if the following conditions are satisfied (for simplicity, the superscript of the time slot is omitted):

$$C_g\left(\lambda^*,\mathbf{p}^*,\mathbf{D}^*\right)\le C_g\left(\lambda,\mathbf{p}^*,\mathbf{D}^*\right) \tag{13}$$

$$U_j\left(p_j^*,\lambda^*,\mathbf{D}_j^*\right)\ge U_j\left(p_j,\lambda^*,\mathbf{D}_j^*\right) \tag{14}$$

$$W_{i,j}\left(d_{i,j}^*,\mathbf{D}_{-i,j}^*,p_j^*\right)\ge W_{i,k}\left(d_{i,j}^h,\mathbf{D}_{-i,j}^*,p_j^*\right) \tag{15}$$

where $\mathbf{p}^*=\left[\left(p_1^h\right)^*,\left(p_2^h\right)^*,\cdots,\left(p_j^h\right)^*\right]$ represents the set of optimal prices of retailers in the time slot h. $\mathbf{D}_j^*=\left[\left(d_{1,j}^h\right)^*,\left(d_{2,j}^h\right)^*,\cdots,\left(d_{i,j}^h\right)^*\right]$ denotes the set of optimal power demand of users who purchase power from retailer j, while $\mathbf{D}_{-i,j}^*$ denotes users who purchase power from retailers except j. $\mathbf{D}^*=\left[\mathbf{D}_1^*,\mathbf{D}_2^*,\cdots,\mathbf{D}_j^*\right]$ denotes the set of optimal power demand of all users.

3.2. The Existence and Uniqueness of SE

Theorem: There is a unique SE $\left(\lambda^*, \mathbf{p}^*, \mathbf{D}^*\right)$ in the proposed three-level Stackelberg game. Considering the different decision-making order in a Stackelberg game, we apply *backward induction* [42] to prove the proposed **Theorem** in 3.2.1, 3.2.2 and 3.2.3.

3.2.1. The optimal power demand of users in response to retailers' RTP

Given the price p_j^h announced by retailer, the best response of users can be obtained from the first-order condition of welfare function:

$$\frac{\partial W_i}{\partial d_{i,j}^h} = \omega_i^h - \frac{\omega_i^h}{\beta_i^h} d_{i,j}^h - p_j^h - 2\alpha_i^h d_{i,j}^h + 2\alpha_i^h m_i^h \tag{16}$$

Let $\frac{\partial W_i}{\partial d_{i,j}^h} = 0$ and the optimal power demand that maximizes the welfare of users can be solved as follows:

$$\left(d_{i,j}^h\right)^* = \frac{\beta_i^h\left(\omega_i^h - p_j^h + 2\alpha_i^h m_i^h\right)}{\omega_i^h + 2\alpha_i^h \beta_i^h} \tag{17}$$

Then, we prove the existence and uniqueness of optimal power demand by calculating Hessian matrix of the welfare function of the user.

$$\frac{\partial^2 W_i}{\partial d_{i,j}^h \partial d_{i,j}^t} = \begin{cases} -\frac{\omega_i^h}{\beta_i^h} - 2\alpha_i^h, h = t \\ 0, h \neq t \end{cases} \tag{18}$$

Since $\omega_i^h > 0$, $\beta_i^h > 0$ and $\alpha_i^h \geq 0$, the value of formula (18) is constantly non-positive, the elements on the diagonal of the Hessian matrix are negative and all other elements are zero, i.e. the matrix is negative definite. Hence, every user can find a unique value of power demand $\left(d_{i,j}^h\right)^*$ that maximizes its welfare.

3.2.2. The optimal RTP of retailers in response to PGO's incentives rate

Given the incentive rate λ^h and the sum of best response of users $\left(D_j^h\right)^*$ obtained from (17), the optimal price of a retailer in time slot h can be solved via the first-order condition of profit function.

Firstly, the optimal $\left(D_j^h\right)^*$ of users can be solved as follow:

$$\begin{aligned} \left(D_j^h\right)^* &= \sum_{i\in\mathrm{I}}\left(d_i^h\right)^* = \sum_{i\in\mathrm{I}} \frac{\beta_i^h\left(\omega_i^h - p_j^h + 2\alpha_i^h m_i^h\right)}{\omega_i^h + 2\alpha_i^h \beta_i^h} \\ &= \sum_{i\in\mathrm{I}} \frac{\beta_i^h\left(\omega_i^h - y_j^h - \rho_j + 2\alpha_i^h m_i^h\right)}{\omega_i^h + 2\alpha_i^h \beta_i^h} \\ &= \sum_{i\in\mathrm{I}} \frac{\beta_i^h\left(\omega_i^h - \rho_j + 2\alpha_i^h m_i^h\right)}{\omega_i^h + 2\alpha_i^h \beta_i^h} - y_j^h \sum_{i\in\mathrm{I}} \frac{\beta_i^h}{\omega_i^h + 2\alpha_i^h \beta_i^h} \end{aligned} \tag{19}$$

For simplicity, we abbreviate the constant parts of formula (19) as follows:

$$E_j^h = \sum_{i\in\mathrm{I}} \frac{\beta_i^h\left(\omega_i^h - \rho_j + 2\alpha_i^h m_i^h\right)}{\omega_i^h + 2\alpha_i^h \beta_i^h} \tag{20a}$$

$$B_j^h = \sum_{i\in I} \frac{\beta_i^h}{\omega_i^h + 2\alpha_i^h \beta_i^h} \tag{20b}$$

Secondly, Formula (19) can be rewritten accordingly as:

$$\left(D_j^h\right)^* = E_j^h - B_j^h y_j^h \tag{21}$$

Thirdly, by substituting $\left(D_j^h\right)^*$ into the profit function (5a) of the retailer, the response of the retailer can be obtained:

$$\begin{aligned}
&R_j^h\left(\rho_j^h, \pi^h, D_j^h\right) = p_j^h\left(D_j^h\right)^* + \lambda^h\left[\left(D_j^h\right)^* - M_j^h\right] - a_j^h\left[\left(D_j^h\right)^*\right]^2 - b_j^h\left(D_j^h\right)^* - c_j^h \\
&= \left(\rho_j + y_j^h\right)\left(E_j^h - B_j^h y_j^h\right) + \lambda^h\left(E_j^h - B_j^h y_j^h - M_j^h\right) \\
&-a_j^h\left(E_j^h - B_j^h y_j^h\right)^2 - b_j^h\left(E_j^h - B_j^h y_j^h\right) - c_j^h \\
&= -\left[B_j^h + a_j^h\left(B_j^h\right)^2\right]\left(y_j^h\right)^2 + \left(E_j^h + b_j^h B_j^h + 2a_j^h E_j^h B_j^h - \rho_j B_j^h - \lambda^h B_j^h\right) y_j^h \\
&+\left[\rho_j E_j^h + \lambda^h E_j^h - \lambda^h M_j^h - a_j^h\left(E_j^h\right)^2 - b_j^h E_j^h - c_j^h\right]
\end{aligned} \tag{22}$$

Finally, the optimal price can be obtained via the first-order partial derivative of formula (5)

$$\frac{\partial R_j^h}{\partial y_j^h} = -2\left[B_j^h + a_j^h\left(B_j^h\right)^2\right] y_j^h + \left(E_j^h + b_j^h B_j^h + 2a_j^h E_j^h B_j^h - \rho_j B_j^h - \lambda^h B_j^h\right) \tag{23}$$

Let $\frac{\partial R_j^h}{\partial y_j^h} = 0$ and we get the optimal real-time price of retailer j:

$$\left(y_j^h\right)^* = \frac{E_j^h + b_j^h B_j^h + 2a_j^h E_j^h B_j^h - \rho_j B_j^h - \lambda^h B_j^h}{2B_j^h\left(a_j^h B_j^h + 1\right)} \tag{24}$$

$$\left(p_j^h\right)^* = \left(y_j^h\right)^* + \rho_j = \frac{E_j^h + b_j^h B_j^h + 2a_j^h E_j^h B_j^h + \rho_j B_j^h + 2a_j^h \rho_j\left(B_j^h\right)^2 - \lambda^h B_j^h}{2B_j^h\left(a_j^h B_j^h + 1\right)} \tag{25}$$

In addition, the second-order condition is solved as follows to verify the uniqueness of $\left(p_j^h\right)^*$:

$$\frac{\partial^2 R_j^h}{\partial y_j^h \partial y_j^t} = \begin{cases} -2\left[B_j^h + a_j^h\left(B_j^h\right)^2\right], h = t \\ 0, h \neq t \end{cases} \tag{26}$$

Since B_j^h and a_j^h are non-negative, the elements on the diagonal of the Hessian matrix are negative while other elements are zero, i.e., the matrix is negative definite. Therefore, every retailer can find a unique price $\left(p_j^h\right)^*$ shown in (25) that maximize their profit.

3.2.3. The optimal incentives rate of PGO

After getting the optimal response of users and retailers, we obtain the optimal incentive rate of the PGO. Firstly, we solve the optimal power demand variance of users:

$$\begin{aligned}
\left(D^h\right)^* &= \sum_{j\in J}\left(D_j^h\right)^* = \sum_{j\in J}\left[E_j^h - B_j^h\left(y_j^h\right)^*\right] \\
&= \sum_{j\in J} E_j^h - \sum_{j\in J} \frac{E_j^h + b_j^h B_j^h + 2a_j^h E_j^h B_j^h - \rho_j B_j^h - \lambda^h B_j^h}{2a_j^h B_j^h + 2} \\
&= \lambda^h \sum_{j\in J} \frac{B_j^h}{2a_j^h B_j^h + 2} + \sum_{j\in J} \frac{E_j^h + \rho_j B_j^h - b_j^h B_j^h}{2a_j^h B_j^h + 2}
\end{aligned} \tag{27}$$

Note that the components in the formula (27) are all constants except for the incentive rate, and therefore (27) can be simplified as follows:

$$\mu^h = \sum_{j \in J} \frac{B_j^h}{2a_j^h B_j^h + 2} \tag{28a}$$

$$\theta^h = \sum_{j \in J} \frac{E_j^h + \rho_j B_j^h - b_j^h B_j^h}{2a_j^h B_j^h + 2} \tag{28b}$$

Then, Formula (27) can be rewritten as:

$$\left(D^h\right)^* = \mu^h \lambda^h + \theta^h \tag{29}$$

In Formula (27), we can find that the total optimal power demand of users is only related to the incentive rate λ^h and constant parameters, suggesting that PGO can change users' power demand and reduce PAR by setting proper incentive rate λ^h. Here, constant μ^h refers to incentive elasticity, i.e., the change in consumption of power by users in relation to a change in the incentive rate.

By substituting $\left(D^h\right)^*$ into the cost function of the PGO, the best response of a retailer can be obtained:

$$\begin{aligned}
C_g^h &= \frac{\sigma}{H}\left[\left(D^h\right)^* - \bar{D}\right]^2 + \lambda^h\left[\left(D^h\right)^* - M^h\right] \\
&= \frac{\sigma}{H}\left(\mu^h\lambda^h + \theta^h - \bar{D}\right)^2 + \lambda^h\left(\mu^h\lambda^h + \theta^h - M^h\right) \\
&= \left[\frac{\sigma}{H}\left(\mu^h\right)^2 + \mu^h\right]\left(\lambda^h\right)^2 + \left(\frac{2\sigma\mu^h\theta^h}{H} + \theta^h - \frac{2\sigma\mu^h\bar{D}}{H} - M^h\right)\lambda^h \\
&\quad + \frac{\sigma}{H}\left(\theta^h\right)^2 + \frac{\sigma}{H}\bar{D}^2 - \frac{2\sigma\theta^h\bar{D}}{H}
\end{aligned} \tag{30}$$

Under the real-time DR mechanism, when the PGO intends to optimize the incentive rate λ^h in the h time slot, it does not know the power demand of users in $h+1$ to H time slots. Consequently, the average power demand $\bar{D}$ cannot be directly obtained. To handle this problem, short-term load forecasting technologies [43-45] can be applied to predict the hourly average power demand $\bar{D}$ to define the baseline of load fluctuation. In this model, we assume that $\bar{D}$ is a known prediction result.

By solving the first-order condition of (10a) on incentive rate, we have

$$\frac{\partial C_g^h}{\partial \lambda^h} = 2\left[\frac{\sigma}{H}\left(\mu^h\right)^2 + \mu^h\right]\lambda^h + \left(\frac{2\sigma\mu^h\theta^h}{H} + \theta^h - \frac{2\sigma\mu^h\bar{D}}{H} - M^h\right) \tag{31}$$

Let $\frac{\partial C_g^h}{\partial \lambda^h} = 0$ and we obtain the optimal incentive rate of the PGO:

$$\left(\lambda^h\right)^* = \frac{2\sigma\mu^h\bar{D} - 2\sigma\mu^h\theta^h + M^h H - \theta^h H}{2\mu^h\left(\sigma\mu^h + H\right)} \tag{32}$$

To verify the uniqueness of $\left(\lambda^h\right)^*$, we continue to solve the second-order condition of (10a)

$$\frac{\partial^2 C_g^h}{\partial \lambda^h \partial \lambda^t} = \begin{cases} 2\left[\frac{\sigma}{H}\left(\mu^h\right)^2 + \mu^h\right], h = t \\ 0, h \neq t \end{cases} \tag{33}$$

Since σ and μ^h are non-negative, the elements on the diagonal of the Hessian matrix are positive while other elements are zero, i.e., the matrix is positive definite and the cost function of PGO is strictly convex with respect to λ^h in its feasible region. Therefore, the optimal incentive rate $\left(\lambda^h\right)^*$ in Formula (32) is unique.

In conclusion, the unique optimal set of strategies $\left(\lambda^*, \mathbf{p}^*, \mathbf{D}^*\right)$ of users, retailers and PGO can be obtained respectively from (17) (25) (32). The **Theorem** proposed in 3.2 is proved. Assuming that each participant in the market has complete information about others, the analytic solutions of the optimal strategies of PGO, retailers and users can be obtained.

4. A distributed algorithm for implementing the hybrid DR mechanism

In Section 4, the analytical solution of the optimal strategies assumes that PGO, retailer and user are rational and have complete information about others. For example, under the complete information assumption, a PGO needs to know retailers' cost functions and users' welfare functions in order to decide optimal incentive rate, which, however, is usually unrealistic in reality due to market competition and privacy protection [25]. Therefore, it is not applicable for participants to make optimal decisions by directly applying theoretical conclusions presented in Section 4.

In light of this, we propose a distributed algorithm to obtain the approximate solution of optimal strategies of all the DR participants to realize our proposed hybrid DR mechanism. The distributed algorithm iteratively searches for the unique optimal set of strategies through conditional information exchange between the three types of participants. In this algorithm, we assume that each retailer only knows the preference its own users. Retailers and PGO only exchange decisions instead of other private information.

The specific process of this algorithm is as follows: First, PGO sends a set of incentive rates to the demand side. In specific, PGO enumerate the incentive rates from $\lambda_{\min}^h$ to $\lambda_{\max}^h$ according to a certain step size $\Delta\lambda$. Second, according to the decisions of retailers and users in previous rounds, PGO compares the costs of different incentive rates and adopts the one that minimizes its cost. Under each incentive rate, following steps are repeated: (1) retailers calculate the optimal price in response to the incentive rate, (2) users' EMS automatically calculate the optimal power demand in response to the price and return it to the retailer and (3) the retailer returns to PGO the sum of the power demand of all enrolled users at the current price. Finally, PGO compares the overall incentive costs under each incentive rate and choose the optimal incentive rate that minimizes its costs. The pseudocode of this algorithm is as follows:

Table 1: Pseudocode

1: **for** each time slot h **, do:**

2: Initialize $\lambda^h = \lambda_{\min}^h$ and $\left(C_g^h\right)^* = C_g^h\left(\lambda_{\min}^h\right)$, then set the step size $\Delta\lambda^h$

3: **repeat:**

4: PGO sends λ^h to retailers

5: Each retailer $j \in \mathrm{J}$ calculates the optimal price $\left(p_j^h\right)^*$ according to (25)

6: Each retailer j send $\left(p_j^h\right)^*$ to each of their enrolled users $i \in \mathrm{I}_j$:

Each user i selects the optimal power demand $\left(d_{i,j}^h\right)^*$ in response using (17)

Each user i sends $\left(d_{i,j}^h\right)^*$ back to the retailer j

7: Each retailer j sends the total power demand $\left(D_j^h\right)^*$ to PGO.

8: PGO calculates the total cost C_g^h , if $C_g^h < \left(C_g^h\right)^*$, let $\left(\lambda^h\right)^* = \lambda^h$

9: $\lambda^h = \lambda^h + \Delta\lambda^h$

10: **Until** $\lambda^h \geq \lambda_{\max}^h$ is satisfied.

11: $\left(\lambda^*, \mathbf{p}^*, \mathbf{D}^*\right)$ is the set of optimal strategies in h time slot.

12: **end for**

It is worth noting that since the cost function C_g^h of PGO is strictly convex with regard to incentive rate λ^h, it will eventually lead to the unique incentive rate $\left(\lambda^h\right)^*$ that minimize the cost of PGO by enumerating λ^h from $\lambda_{\min}^h$ to $\lambda_{\max}^h$ [25]. There are only three kinds of possible results for the convergence value of $\left(\lambda^h\right)^*$: lower bound $\lambda_{\min}^h$, upper bound $\lambda_{\max}^h$ or the approximate value of λ^h in formula (32) when SE is reached.

5. Simulation

5.1. Simulation design

This section applies a numerical analysis to verify the reliability and advantages of our proposed model and distributed algorithm. We divide a day into 288 time slots and each time slot represents 5 minutes. We assume that there are two retailers in a regional retail market and each retailer has contracted with three power users respectively. Both retailers purchase electricity from the wholesale market at similar prices and their cost parameters are equal.

The values of common parameters in the simulation comes from previous literatures. For the unique parameters in this paper, sensitivity analysis is also carried out to ensure the reliability of the results. For PGO, its cost parameter of load fluctuation is $\sigma = 1$ [37]. We set the retailer's cost parameters to $a_j^h = 0.01$, $b_j^h = 0.02$ and $c_j^h = 0$ [12]. The flat price before DR is set to $\rho_j = 8$, which is similar to [37]**.** In this case study, the original power demand for six users is shown in Fig.3. We also set the user's preference parameter to $w_i^h = 12.5$ [15] and the dissatisfaction parameters $\alpha_i^h = 0.01$.

We use two typical load profiles (A and B) to evaluate our proposed hybrid DR mechanism (see Fig.2 and 3). The data was provided by a power grid company from China. The original power demand can be determined according to the average power consumption of users in the past few days, or by the agreement among the PGO, retailers and users. In these two cases, the original electricity demand reflects the average electricity consumption of users in the past week. The peak of original load profile in case A is at around 3:00 PM and 7:00 PM respectively, while the peak of load profile in case B is at around 11:00 AM. In both cases, the off-peak load period was in the early morning.

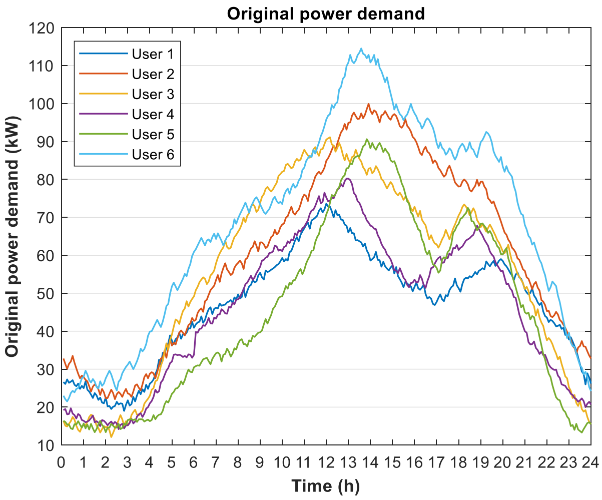

Fig. 2: Original power demand of users in case A

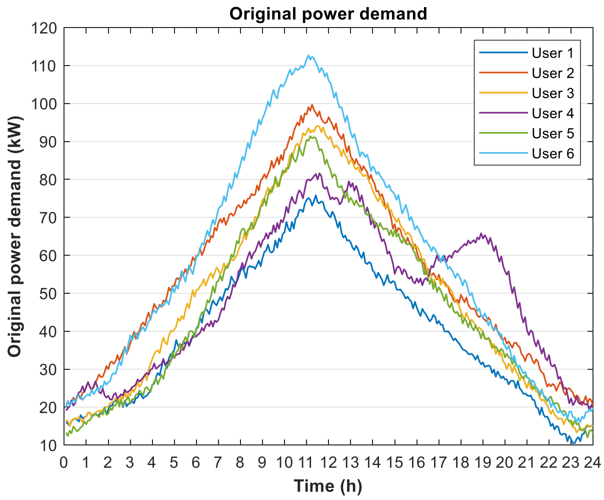

Fig. 3: Original power demand of users in case B

In order to verify the advantages of our proposed DR mechanism, we compare the performance of this mechanism with four other models, which are **(1) Hybrid DR:** PGO provides monetary incentives to retailers, then retailers set real-time electricity prices, i.e., the DR method proposed in this paper. **(2)** ***Price-based DR:*** Retailers set real-time electricity prices while PGO doesn't take part in DR. This is the method adopted by most recent DR studies [13-18]. **(3) Incentive-based DR:** Retailers provides monetary incentives to users if they change their power demand as retailers' requirement [21-25]. (4) **Non-DR:** Retailers set a flat electricity price and PGO doesn't take part in this process. This represents the situation where no DR approaches are adopted. The performance of the models is evaluated from the following two perspectives: the extent of load shifting and the improvement of DR participants' benefits.

5.2. Optimal incentive, RTP and power demand

Fig. 4 and Fig. 5 show the optimal incentive rate of PGO in the two cases. The incentive rate is negative in peak hours, encouraging the retailers to raise the prices so as to reduce the power demand of users. On the contrary, the incentive rate is positive in off-peak hours to encourage the retailers to lower the electricity price so as to make users consume more power.

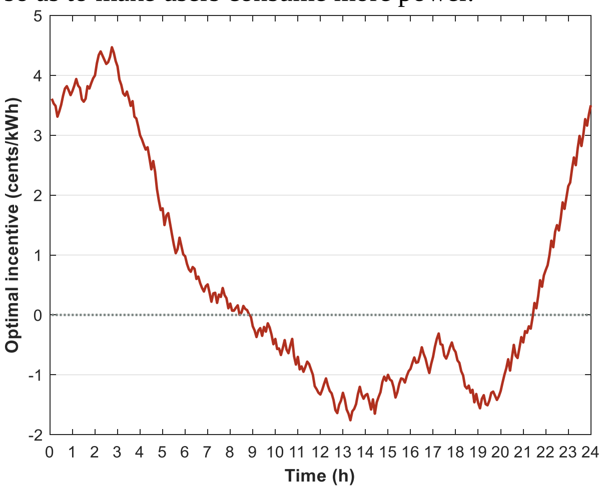

Fig. 4 Optimal incentive rate set by PGO in case A

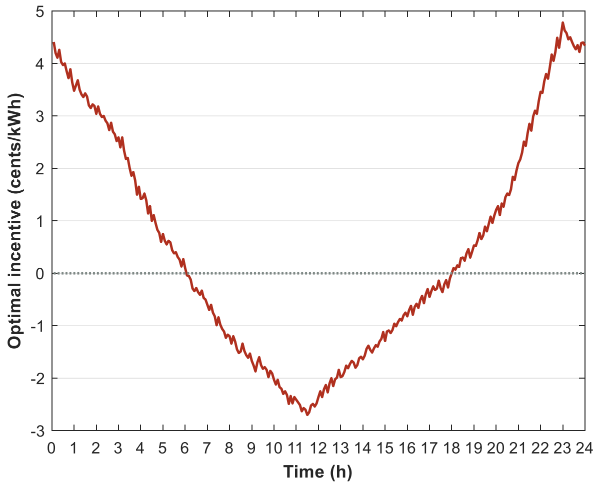

Fig. 5 Optimal incentive rate set by PGO in case B

As shown in Fig. 6-Fig. 9, for the two retailers in the case A and B, the peak-valley difference and variation range of the real-time electricity prices in hybrid DR is much larger than that in price-based DR, suggesting that the existence of incentives motivates retailers to actively change RTP. In contrast, without incentives of PGO, electricity prices change less and retailers are not motivated enough to set RTP.

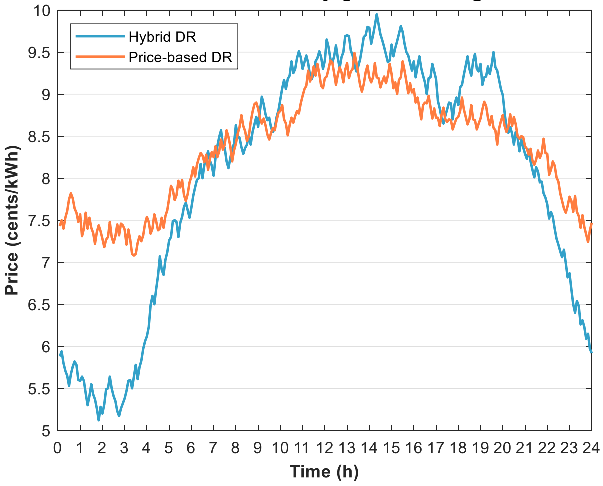

Fig. 6 Optimal RTP set by retailer 1 in case A

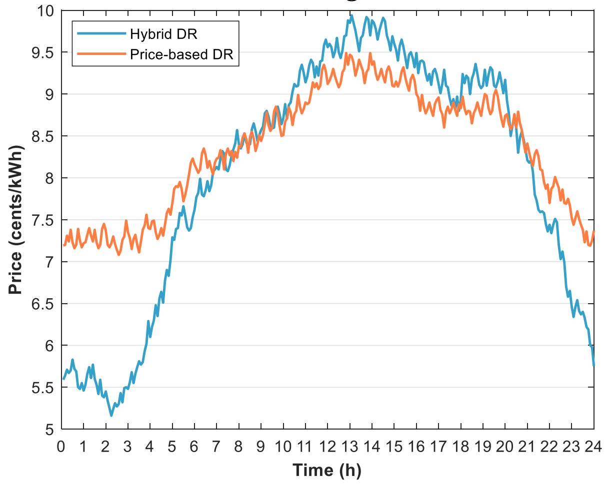

Fig. 7 Optimal RTP set by retailer 2 in case A

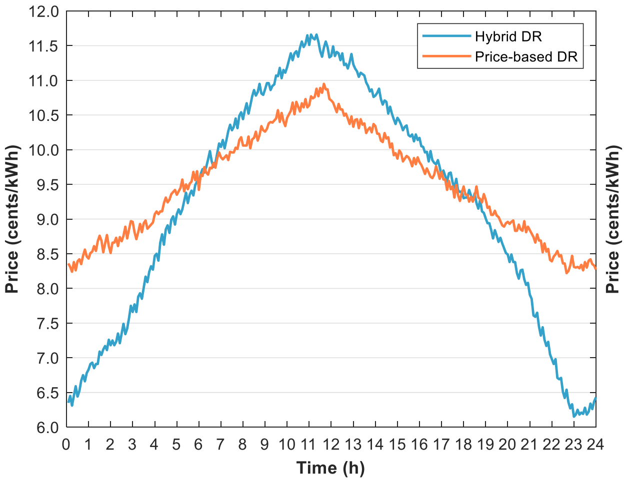

Fig. 8 Optimal RTP set by retailer 1 in case B

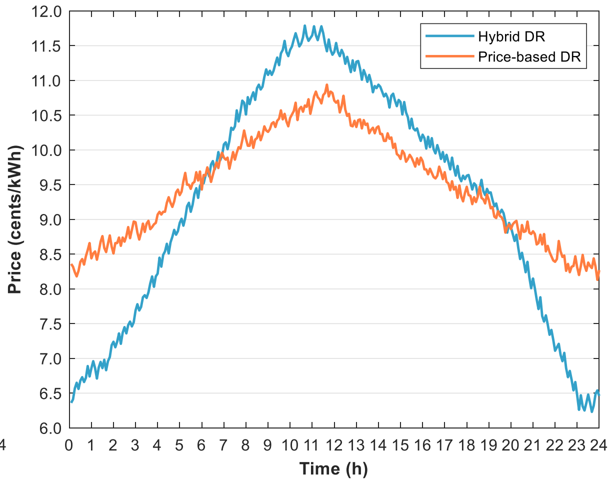

Fig. 9 Optimal RTP set by retailer 2 in case B

In Fig.10, the optimal power demand of users in the case A is demonstrated. It can be seen intuitively that, compared with a non-DR scenario, both hybrid DR, price-based DR and incentive-based DR show a reduction of peak load around 3pm and 19pm and an increase of off-peak power demand at 00AM-07AM and 10PM-00PM. However, the hybrid DR, which reduce 26.44% of the peak load at 3PM, obviously outperforms PBDR and IBDR with 18.44% and 18.25% peak load reduction, respectively.

Fig.11 shows the optimal power demand of users in the case B. At 11 AM, the hybrid DR can reduce the peak load by 24.14%. However, PBDR and IBDR can only reduce the load by 10.16% and 15.97% respectively. In off-peak hours in the morning, the hybrid DR significantly increases the power consumption, and load transfer is therefore realized.

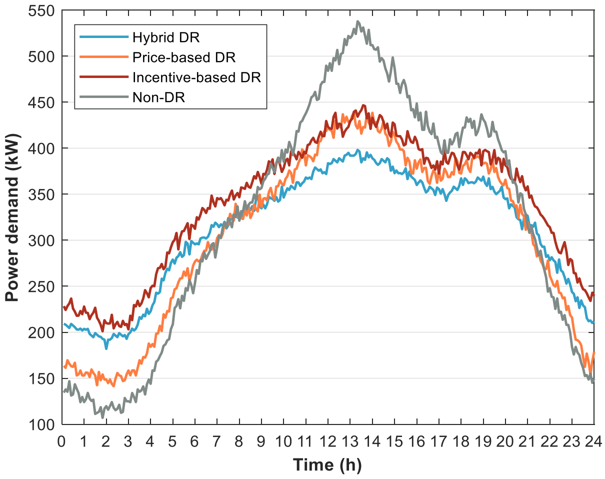

Fig. 10 Optimal power demand of users in case A

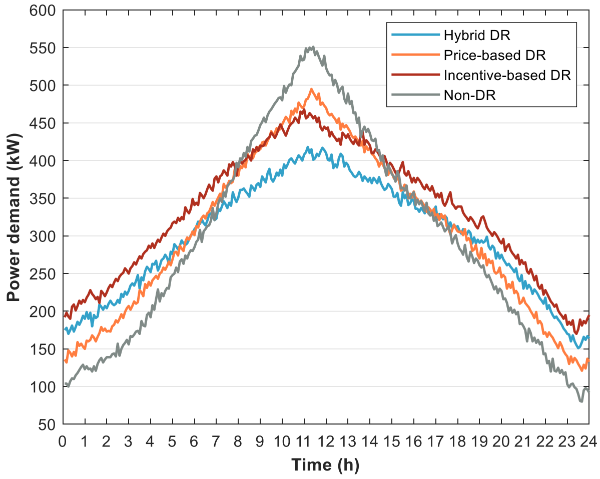

Fig. 11 Optimal power demand of users in case B

5.3. Model comparison

According to previous studies [7, 12], we use the following 6 indexes to evaluate the performance of the models. As shown in Table 2 and 3, our proposed hybrid DR model outperforms other classical DR models from every perspective in both cases.

Table 2: Model comparison in case A

Model	Peak load reduction	Peak-to-average ratio	Cost of PGO (cents)	Profit of Retailer 1 (cents)	Profit of Retailer 2 (cents)	Electricity bill of users (cents)
Hybrid DR	**26.44%**	**1.225**	**6956**	**26480**	**26171**	**62338**
Price-based DR	18.44%	1.386	9233	25542	25193	63325
Incentive-based DR	18.25%	1.294	7329	21124	20278	65511
Non-DR	0	1.619	37550	20992	20521	62140

Table 3: Model comparison in case B

Model	Peak load reduction	Peak-to-average ratio	Cost of PGO (cents)	Profit of Retailer 1 (cents)	Profit of Retailer 2 (cents)	Electricity bill of users (cents)
Hybrid DR	**24.14%**	**1.368**	**9153**	**29869**	**31590**	**69504**
Price-based DR	10.16%	1.578	12138	26292	27039	71433
Incentive-based DR	15.97%	1.373	9171	19291	22834	71574
Non-DR	0	1.842	38578	20143	23766	69741

From the perspective of load shifting, the percent of peak load reduction of hybrid DR is significantly larger than that of PBDR and IBDR. Moreover, peak-to-average ratio (PAR) of hybrid DR is lower than that of other singe-type DR mechanisms, indicating that the load shifting effect of DR mechanism proposed in this paper is more effective.

From the perspective of DR participants' benefits, our hybrid DR also performs better. In case A, the cost of PGO in hybrid DR decreases significantly, equivalent to 75.3% of that in price-based DR, 94.9% of that in incentive-based DR and only 18.5% of the case where no DR approach is adopted. Compared with non-DR scenario, the profits of Retailer 1 and Retailer 2 in hybrid DR increase by 26.1% and 27.5% respectively. Meanwhile, the profit of Retailer 1 and Retailer 2 in hybrid DR is 3.7% and 3.9% more than that in PBDR. On the contrary, IBDR reduces the profit of retailers and weakens their motivation to participate in DR. Similar results are also observed in case B.

In addition, for both A and B, the electricity bills of users in hybrid DR are lower than those in price-based DR and incentive-based DR. Therefore, we conclude that the performance of our proposed DR mechanism, which includes both incentive and RTP, is better than that of PBDR and IBDR in these cases.

6. Conclusion

In this paper, **first**, we design a novel hybrid DR mechanism by incorporating PGO, retailers and users as participants, where PGO provide monetary incentives to retailers and retailers set real time prices to users. **Second**, we analyze the effects of this mechanism by using a three-level Stackelberg game approach. The existence and uniqueness the optimal equilibrium strategies of different participants is also proved in this research. **Third**, we propose a distributed algorithm to implement the proposed hybrid DR in practice, which solves the problem of the lack of complete information of DR participants.

We also performed numerical simulations to validate the conclusions. The simulation result shows that, in case study A, hybrid DR achieved 26.44% peak load reduction, which is much higher than 10.16% and 15.97% of PBDR and IBDR, respectively. The profits of the two retailers increased by 26.1% and 25.7% respectively. In case study B, hybrid DR reduced 24.14% of peak load and increased profits of two retailers by 48.3% and 32.9% respectively.

Both theoretical analysis and numerical simulations show that this hybrid DR mechanism outperforms other traditional DR methods from the perspective of load shifting and benefits improving. Moreover, the proposed 5-min scheduling time horizon contributes to the consumption of renewable energy, since the uncertainty feature of renewable power supply requires timely adjustment of power demand. This research may shed lights on future studies on demand response management in smart grids.

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