Coupon-Based Demand Response for Consumers Facing Flat-Rate Retail Pricing

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***Abstract*—Even though smart meters have been widely used in power systems around the world, many consumers are still hard to participate in demand response (DR) due to the flat-rate retail pricing policy. To address this issue, this paper proposes a coupon-based demand response (CDR) scheme to achieve the equivalent dynamic retail prices to inspire consumers' inherent elasticity. Firstly, a security-constrained unit commitment optimization model is developed in the day-ahead market to obtain coupon rewards, which are then broadcasted to consumers to motivate them to reschedule their power consumption behaviors. To evaluate the adjustment value of consumers' power consumption, a collective utility function is proposed to formulate the relationship between power quantity and coupon rewards. On this basis, the security-constrained economic dispatch model is developed in the intra-day market to reschedule generating units' output power according to real-time load demands and fluctuating renewable energies. After the operation interval, a settlement method is developed to quantify consumers' electricity fees and coupon benefits on monthly basis. The proposed CDR scheme avoids the real-time iterative bidding process and effectively decreases the difficulty of massive small consumers participating in DR. The proposed CDR is implemented in a realistic DR project in China to verify that consumers' energy cost and renewables' curtailment can both be decreased.**

***Index Terms*—Demand response, flat-rate retail pricing, small consumers, coupons, renewable energies.**

NOMENCLATURE

A. Acronyms

CBL	Consumer baseline of load
CDR	Coupon-based demand response
CUF	Collective utility function
DR	Demand response
DSR	Demand side resource
LSE	Load serving entity
PCDR	Price-based CDR
PV	Photovoltaic
PVP	Peak-valley pricing
RTP	Real-time pricing
SCED	Security-constrained economic dispatch
SCUC	Security-constrained unit commitment
TG	Thermal generator

B. Indexes

i , I	Index and total number of traditional generators
j , J	Index and total number of consumers
k , K	Index and total number of wind generators
l , L	Index and total number of PVs
r	Index of the date
s	Index of the season
t_s	Start time of the dispatching period
t_e	End time of the dispatching period
t , T	Index and total number of time intervals

C. Parameters

b_d	Intercept parameter of the demand curve
β	Exponential smoothing constant
$c_{0,gi}$	Constant term of the i-th TG's generation cost
$c_{1,gi}$	Linear term of the i-th TG's generation cost
$c_{2,gi}$	Quadratic term of the i-th TG's generation cost
c_{wk}	Linear term of the k-th wind generator's cost
c_{vl}	Linear term of the l-th PV's cost
D_{gi}	Minimum duration time for shutting down
O_{gi}	Minimum duration time for starting up
π_{pvp}	Peak-valley price
π_{tds}	Transmission, distribution and service fees
π_{gov}	Government funds and special charges
λ	Transformation rate of coupons and prices
m_d	Slope parameter of the demand curve
$P_{gi}^{\min}$	Minimum output power of the i-th generator
$P_{gi}^{\max}$	Maximum output power of the i-th generator

D. Variables

α_{gi}	Operating state of the i-th generator
B_{dj}	Benefits of the j-th consumer
B_d	Total utility function of all the consumers
BON_{dj}	Monthly bonus of the j-th consumer
C_{gi}	Cost of the i-th traditional generator
C_{wk}	Cost of the k-th wind generator
C_{vl}	Cost of the l-th PV
EF_{dj}	Monthly electricity fee of the j-th consumer

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π_c Coupon values
π_d Clearing price in the day-ahead market
π_e Equivalent price considering coupon values
P_{dj} Demand power of the *j*-th consumer
$P_{CBL,d}^D$ Day-ahead forecasted CBL
P_{wk}^D Day-ahead forecasted power of the *k*-th wind
P_{vl}^D Day-ahead forecasted power of the *l*-th PV
P_{gi}^D Day-ahead dispatch power of the *i*-th generator
P_d^D Clearing demand in the day-ahead market
P_{gi} Intra-day power output of the *i*-th generator
P_{wk} Intra-day power output of the *k*-th wind
P_{vl} Intra-day power output of the *l*-th PV
SU_{gi} Start-up cost of the *i*-th generator
SF Smoothing function value

I. INTRODUCTION

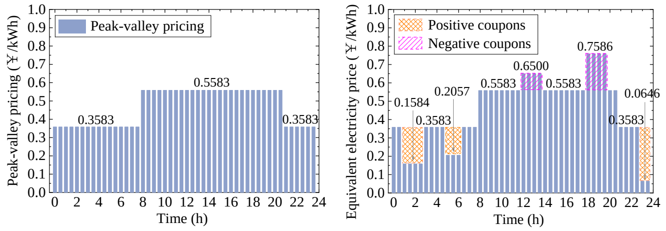
THE progressed information and communication technologies make it possible for the remote control of massive demand side resources (DSRs) [1]. Small consumers in the power system have more opportunities to participate in demand response (DR) [2], i.e., adjusting their power consumption along with the dynamic electricity prices or incentive policies [3]. For example, an electricity market is designed in [4] to enable small residential consumers to provide regulation services. By analyzing a tremendous number of smart meters' data, home appliances are proved to have large regulation flexibility [5]-[6]. Air conditionings [7], thermostatic loads [8]-[9], electric vehicles [10], and energy storage batteries [11] can be aggregated as important regulation resources to decrease the power system's load peak-valley differences and increase the utilization rate of fluctuating renewable energies [12]. During this regulation process, consumers can obtain benefits [13], and the social welfare of the power system can also be increased at the same time [14].

Many demonstration projects on DR have been carried out in recent years. For example, in America, EnerNOC develops Network Operating Centre to directly control DSRs for responding to system regulation signals [15]. In Norway, the SEMIAH project is carried out to control large-scale load appliances for effectively participating in electricity market [16]. In Bornholm, the EcoGrid EU project is implemented to enable small-scale DSRs and small consumers to actively participate in the real-time electricity market [17]. Besides, Austria has enabled DR in the balancing markets. Belgium has allowed DR to participate in the primary and tertiary reserves. Spain implements hourly spot prices for residential consumers and interruptible load programs for industrial consumers. The activated DR potential in Europe is expected to 160GW in 2030 [18]. Generally, the above DR projects can be divided into two categories: the price-based DR and incentive-based DR. The price-based DR generally includes time-of-use rates, critical peak pricing and real-time pricing, which put emphasis on the economic or the market [19]. By contrast, the incentive-based DR includes direct load control, interruptible/curtailable rates, emergency demand response programs, capacity market programs and demand bidding programs, which are mainly about the system emergency or stability [20].

However, the above studies mainly focus on DR methods or policies in the competitive electricity market by releasing dynamic electricity prices or motivated payments to consumers. The DR methods and policies in the flat-rate retail pricing market have not been fully studied. Nevertheless, it does not mean that DR in flat-rate pricing markets does not need to be studied. For example, in China, the penetration of renewable energies in power generation is increasing rapidly and brings more fluctuations to the power system, which raises the requirement on regulation capacities [21]. With the gradual elimination of traditional generators due to high carbon emissions, DR has been widely considered as an effective way to absorb high-penetration renewable energies [22].

However, it is not easy to implement DR in power systems with flat-rate retail pricing market, where the generation prices and consumer electricity prices are generally decided by the government [23]. That is to say, in supply-side, the generation companies have no right to fix the generation prices. In demand-side, consumers have to accept the prescribed electricity prices from the price catalogue, which depends on the consumers' professions and voltage levels [24]. Therefore, most of implemented DR projects in the flat-rate pricing markets are based on administrative means, which do not consider consumers' demand and may be unfair to consumers. In recent years, even though electricity companies pay some compensations to the consumers after load shedding, these compensations are generally set as a fixed value. It cannot reflect the real-time varying energy cost [25]. To sum up, due to the immutable electricity policies set up by the government, the electricity companies cannot directly carry out price-based DR or incentive-based DR as that in open electricity markets.

Inspired from widely used coupons in industries (e.g., coupons in airline industries, vouchers in retail sectors, and points of credit cards), the coupon-based demand response (CDR) is explored to provide coupon incentives for consumers in DR projects with flat-rate retail pricing market [26]-[35]. For example, the residential consumers in Cypress, Texas, USA, can participate in lotteries with $35 gift cards if they respond to the 30-minute-length DR [26], [27]. By developing lottery-like rebates in [28], the demand loads can be shifted to off-peak time. Besides, the CDR can be optimized with fluctuating wind power outputs to increase the utilization of renewable energies [29] and decrease the carbon emissions [30]. Previous results have verified that CDR can be achieved in realistic systems with more flexibilities [31], [32]. However, most previous CDR methods are based on the iterative bidding framework [33], i.e., the load serving entity (LSE) offers coupon values to consumers, and each consumer submits their demand reduction [34], [35]. After collecting all consumers' demand reduction, the LSE adjusts the coupon values with the objective to maximize its profits. Then the updated coupons are broadcasted again, and each consumer has to submit their demand reduction capacities again. This iterative process will end until the LSE's profit does not increase. In realistic power system, small end consumers (e.g., small commercial and residential consumers) probably have no ability, time or the professional knowledge to quote the



(a) PVP (b) PCDR

Fig. 1. The peak-valley pricing and proposed coupon-based demand response.

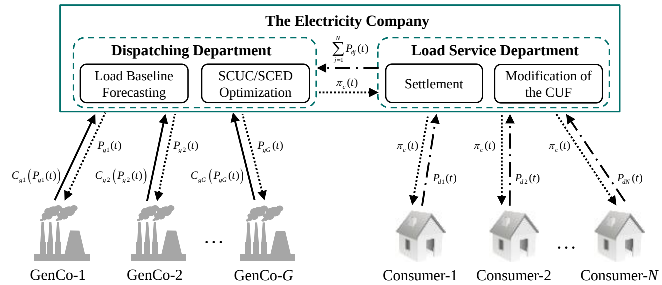


Fig. 2. The framework of the proposed PCDR.

demand reduction capacities. In fact, most of residential consumers do not even know the power consumption of their appliances at different time of a day, and surely cannot submit demand reduction capacities to the LSE.

To address this issue, this paper proposes a novel price-based CDR (PCDR) scheme to decrease the difficulty of small consumers participating in DR in the power system with flat-rate retail pricing market. The proposed PCDR fully considers the feasibility of electric company's staffs and massive small consumers, so as to realize the implementation in practical power systems. The main contributions of this paper can be summarized as follows:

1) A novel PCDR scheme is proposed for consumers facing the flat-rate retail pricing policy, which avoids real-time iterative bidding process and decreases the difficulty of small consumers participating in DR.
2) A coupon calculation algorithm is developed based on the security-constrained unit commitment optimization model in the day-ahead market, where a collective utility function (CUF) is developed to evaluate the adjustment value of consumers' power consumption facing coupons.
3) Considering the high-penetration fluctuating renewables and dynamic real-time load demands, a security-constrained economic dispatch optimization model is developed in the intra-day market to reschedule generating units' output power. The consumers' energy cost can be decreased, while renewables' utilization rate is increased.

The remainder of this paper is organized as follows. Section II presents the framework of the PCDR. The modelling methodology of the PCDR is formulated in Section III. Numerical studies are presented in Section IV. Finally, Section V and Section VI are conclusions and discussions, respectively.

II. Framework of the Proposed PCDR

A. Existing Flat-Rate Retail Pricing Policy

The existing flat-rate retail pricing policy faced by residential consumers in China is taken as an example. As shown in Fig. 1(a), there are two prices, i.e., the peak price (0.5583￥/kWh) on the daytime (8:00am-21:00pm) and the valley price (0.3583 ￥/kWh) at night (0:00am-8:00am, 21:00pm-24:00pm). This electricity price policy is named as peak-valley pricing (PVP), which is similar with the time-of-use rates in open competitive electricity markets, such as PJM and ERCOT [19].

However, PVP has threefold disadvantages and significantly decreases the DR effectiveness. The first disadvantage is the long time-scale of the flat price. The PVP keeps constant value for 13 hours and 11 hours during peak and valley periods, respectively. It cannot motivate the consumers to adjust the power consumption during the flat price periods. Only few energy-storing appliances (e.g., batteries and water heaters) can store energy on daily basis and may be regulated from daytime to the evening. Most household appliances (e.g., air conditioner, lights and microwave) cannot decrease or transfer their power consumption so long time. The second disadvantage is that the price difference of the PVP is only 0.2￥/kWh, which is small and hard to motivate consumers to adjust their original power consumption behaviors. The third disadvantage is that the PVP keeps unchanged for four seasons and has been going on for several years (actually more than 10 years in many provinces in China). The peak and valley periods of loads are obviously variable in four seasons and different years. This causes the PVP cannot reflect the real energy cost of the power system.

B. Design of the PCDR

Faced with PVP's disadvantages, the main purpose of the proposed PCDR is increasing the electricity price fluctuations in a day by coupons. As shown in Fig. 1(b), the PCDR is carried out by broadcasting coupon values with 15min time interval to consumers. Coupons contain both positive and negative values. The consumers can obtain more coupons, when they use electricity during positive coupon periods. By contrast, consumers' coupons will be cut down, when they consume electricity during negative coupon periods.

Generally, positive coupon values appear during the valley load periods or high renewable generation periods, so as to motivate consumers to increase their power consumption. Negative coupon values generally exist in the peak load periods or high system operation cost periods, so as to encourage consumers to cut down their electricity consumption. Based on the original PVP and coupon values, consumers can be regarded as facing a more dynamic pricing policy, which is called equivalent electricity prices in this paper and calculated as:

$$\pi_e(t) = \pi_{pvp}(t) - \lambda \cdot \pi_c(t), \ \forall t \in \mathcal{T}, \tag{1}$$

where $\pi_e(t)$, $\pi_{pvp}(t)$ and $\pi_c(t)$ are the equivalent price, the PVP and coupon values, respectively. Symbol λ is the transformation rate between the coupon values and the electricity prices, which is a fixed value and equal to 0.01￥/coupon in the DR project in China. Hence, positive coupons can be regarded as decreasing electricity prices, while negative coupons are increasing electricity prices. Note that the value of λ keeps constant as a parameter during the whole DR project implementation process. Because the coupon values π_c are dynamic with time to decide the incentive degree to consumers, while the transformation rate λ need not be dynamically optimized. The

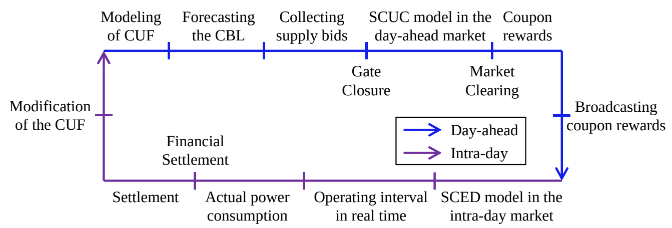


Fig. 3. The implementation timeline of the proposed PCDR.

algorithm for optimizing coupon values π_c in each time interval will be described in detail in Section III.

After the operation interval, coupons and electricity fees will be settled at the end of each month. Because of the existence of negative coupon values, the total coupon values of one specific consumer may be less than zero. It means that this consumer has to pay more money compared with PVP. In order to avoid the worries on increasing payment, the total coupons of one specific consumer will be reset to zero if the obtained coupons are negative at the end of each month. Therefore, the *j*-th consumer's benefits from the PCDR project can be calculated as:

$$B_{dj}(t_s,t_e)=\max\{0,\ \lambda\int_{t_s}^{t_e}P_{dj}(t)\pi_c(t)dt\},\forall t\in\mathcal{T},\forall j\in\mathcal{J},\quad (2)$$

where B_{dj} is the obtained benefits from time t_s to t_e; $P_{dj}(t)$ is the demand power of the *j*-th consumer.

C. *Framework of the PCDR*

The framework of the proposed PCDR is shown in Fig. 2, which mainly includes three participants: the electricity company, generation companies, and consumers. The electricity company undertakes both the role of the system operator (i.e., the dispatching department) and the role of LSE (i.e., the load service department). The dispatching department calculates coupon values based on generation companies' bidding data and forecasted load demands in the day-ahead market. The load service department gets the calculated coupon values from the dispatching department and broadcast to consumers. Besides, the load service department also monitors consumers' power consumption data in the intra-day market and provides to the dispatching department for the next interval's optimization.

The implementation timeline of the PCDR is shown in detail in Fig. 3, which can be divided into five steps in the day-ahead and intra-day markets, respectively. Firstly, in the day-ahead market, a collective utility function (CUF) is developed to formulate the adjustment values of consumers' power consumption as a result of coupons. Then, the consumer baseline of loads (CBL) (i.e., the original demand before implementing PCDR) is forecasted by the system operator. The CBL can be forecasted based on historical load data by utilizing many off-the-shelf methods, for example, the artificial neural networks [36], the auto regressive moving average method [37], the synchronous pattern matching method [38], and the 10-day average method [39]. Next, power generation and corresponding bidding data are provided by generation companies. Based on this, the system operator clears the market using the security-constrained unit commitment (SCUC) optimization model with the objective of maximizing the social welfare [40]. During this process, the coupon values $\pi_c(t)$ in each time interval can also be obtained and broadcasted to consumers who participate in PCDR.

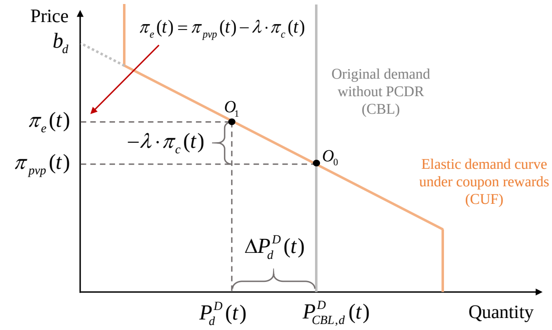


Fig. 4. The demand power curve under the equivalent electriciy price.

In the intra-day market, consumers' demand power and renewables' generation power will not be the same with the forecasted values in the day-ahead market. To address this issue, a security-constrained economic dispatch (SCED) optimization model is developed in the pre-operating interval (15min earlier) to reschedule generation units according to the updated values of power supplies and demands. The objective is to minimize the generation costs. Note that coupon values will no longer change in the intra-day market, because the advanced notification time is too short for small end consumers to change their power consumption behaviors, which can greatly increase the difficulty of massive small consumers participating in DR. After the operating interval, the financial settlement will be carried out based on the actual consumed energy. Finally, the CUF is modified based on the actual operation data to prepare for the next round optimization. In accordance with the above PCDR scheme, consumers do not need to bid iteratively in real time, so as to increase the feasibility in practical power systems.

III. Optimization Models and Methodology

A. *Security-Constrained Unit Commitment Model in the Day-ahead Market*

The objective of the SCUC optimization model in the day-ahead market is to maximize the social welfare, as follows:

$$\begin{aligned}\min\Bigg\{&\sum_{t=1}^{T}\sum_{i=1}^{I}\Big[C_{gi}(P_{gi}^D(t))+SU_{gi}(t)\Big]+\sum_{t=1}^{T}\sum_{k=1}^{K}C_{wk}(\Delta P_{wk}^D(t))\\&+\sum_{t=1}^{T}\sum_{l=1}^{L}C_{vl}(\Delta P_{vl}^D(t))-\sum_{t=1}^{T}B_d(P_{CBL,d}^D(t)-\Delta P_d^D(t))\Bigg\},\quad (3)\\&\forall t\in\mathcal{T},\forall i\in\mathcal{I},\forall k\in\mathcal{K},\forall l\in\mathcal{L},\end{aligned}$$

where P_{gi}^D, C_{gi} and SU_{gi} are the day-ahead scheduling power, the energy cost and the start-up cost of the *i*-th generator, respectively; ΔP_{wk}^D and C_{wk} are the forecasted power curtailment and corresponding cost of the *k*-th wind generator, respectively; ΔP_{vl}^D and C_{vl} are the forecasted power curtailment and corresponding cost of the *l*-th photovoltaic (PV), respectively; $P_{CBL,d}^D$, ΔP_d^D and B_d are the CBL, the demand adjustment value due to coupons, and the utility function of consumers, respectively; I, K and L are the total number of traditional generators, wind generators and PVs, respectively. The start-up cost SU_{gi} of the *i*-th generator in Eq. (3) can be calculated as:

$$SU_{gi}(t)=S_{gi}\cdot\alpha_{gi}(t)\cdot(1-\alpha_{gi}(t-1)),\ \forall t\in\mathcal{T},\forall i\in\mathcal{I},\quad (4)$$

where S_{gi} and α_{gi} are the start-up cost and operating state of the *i*-th generator, respectively; α_{gi} equals to 1 if the generator is in the ON-state, while it is 0 in the OFF-state.

The objective in Eq. (3) is subject to:

$$\sum_{i=1}^{I}P_{gi}^{D}(t)+\sum_{k=1}^{K}(P_{wk}^{D}(t)-\Delta P_{wk}^{D}(t))+\sum_{l=1}^{L}(P_{vl}^{D}(t)-\Delta P_{vl}^{D}(t)) \\ =P_{CBL,d}^{D}(t)-\Delta P_{d}^{D}(t),\qquad \forall t\in\mathcal{T},\forall i\in\mathcal{I},\forall k\in\mathcal{K},\forall l\in\mathcal{L}, \tag{5}$$

$$(\alpha_{gi}(t)-\alpha_{gi}(t-1))+(\alpha_{gi}(t+\upsilon_{gi}^{on}-1)-\alpha_{gi}(t+\upsilon_{gi}^{on}))\le 1, \\ \forall i\in\mathcal{I},\forall\upsilon_{gi}^{on}\in\left[1,2,...,O_{gi}-1\right], \tag{6}$$

$$(\alpha_{gi}(t-1)-\alpha_{gi}(t))+(\alpha_{gi}(t+\upsilon_{gi}^{off})-\alpha_{gi}(t+\upsilon_{gi}^{off}-1))\le 1, \\ \forall i\in\mathcal{I},\forall\upsilon_{gi}^{off}\in\left[1,2,...,D_{gi}-1\right], \tag{7}$$

$$P_{gi}^{\min}\cdot\alpha_{gi}(t)\le P_{gi}^{D}(t)\le P_{gi}^{\max}\cdot\alpha_{gi}(t),\ \forall t\in\mathcal{T},\forall i\in\mathcal{I}, \tag{8}$$

$$0\le\Delta P_{wk}^{D}(t)\le P_{wk}^{D}(t),\ \forall t\in\mathcal{T},\forall k\in\mathcal{K}, \tag{9}$$

$$0\le\Delta P_{vl}^{D}(t)\le P_{vl}^{D}(t),\ \forall t\in\mathcal{T},\forall l\in\mathcal{L}, \tag{10}$$

where P_{wk}^{D} and P_{vl}^{D} are the day-ahead forecasted output power of the k-th wind generator and the l-th PV, respectively; O_{gi} and D_{gi} are the minimum duration time for starting up and shutting down the i-th generator, respectively; υ_{gi}^{on} and υ_{gi}^{off} are the temporary variables for O_{gi} and D_{gi}, respectively; $P_{gi}^{\min}$ and $P_{gi}^{\max}$ are the minimum and maximum output power of the i-th generator, respectively. Eq. (5) shows the power balance. Eqs. (6) and (7) are the minimum ON and OFF periods of generators, respectively. Eqs. (8)-(10) are the generating limits of the i-th generator, the k-th wind generator and the l-th PV, respectively.

The SCUC optimization model in Eqs. (3)-(10) is a typical mixed-integer nonlinear programming (MINLP). Specifically, the objective of this SCUC optimization model in Eq. (3) includes the generation costs and consumers' benefits, which are quadratic functions. The quadratic functions can be linearized by the piecewise linearization method [41], [42]. Then, the SCUC optimization model changes from the MINLP to a mixed-integer linear programming (MILP). The MILP has been widely studied and can be efficiently solved by many methods (e.g., Branch-and-Bound algorithm [43] and Cutting-Plane algorithm [44]) and off-the-shelf solvers (e.g., GUROBI [45], CPLEX [46], and MOSEK [47]).

B. CUF and Coupon Values

Consumers are assumed to be rational participants, whose objective is to maximum their surplus [48]. Therefore, faced with coupons, some consumers probably change their power consumption to get benefits, expressed as:

$$\pi_{d}(t)=m_{d}\cdot P_{d}^{D}(t)+b_{d},\ \forall t\in\mathcal{T}, \tag{11}$$

where P_{d}^{D} and π_{d} are the clearing demand and electricity price in the day-ahead market; b_{d} and m_{d} are the intercept and slope parameters of the demand curve, respectively. The reservation price b_{d} is a positive value in ￥/MWh. The slop m_{d} is a negative value in ￥/MW^{2}h.

The relationship of the consumed power and electricity price is shown in Fig. 4. The CBL is the original demand without coupons. As shown in the intersection point O_0, the electricity price is $\pi_{pvp}(t)$ and the corresponding power consumption is $P_{CBL,d}^{D}(t)$. Based on the Eq. (11), the elastic demand curve considering coupons is also shown in Fig. 4. It illustrates that the power consumption will be adjusted to $P_{d}^{D}(t)$ if coupons are provided to consumers, i.e., the intersection point O_1 with the equivalent price $\pi_{e}(t)$. Therefore, the CUF of consumers can be calculated as:

$$B_{d}(P_{CBL,d}^{D}(t)-\Delta P_{d}^{D}(t)) \\ =B_{d}(P_{d}^{D}(t))=\frac{1}{2}m_{d}\cdot P_{d}^{D}(t)^{2}+b_{d}\cdot P_{d}^{D}(t),\ \forall t\in\mathcal{T}. \tag{12}$$

The day-ahead clearing price π_{d} can be calculated by the SCUC optimization model in Eqs. (3)-(12). Note that this clearing price π_{d} is only for the generation cost, while it does not include the transmission, distribution, service and other additional charges. In this paper's case – China, the electricity company is in charge of all the operation work except the generation (i.e., the transmission, distribution and service fees π_{tds} are collected by the electricity company). Moreover, the government charges some additional fees for the investment fund of electricity utility. Therefore, the final day-ahead electricity price is expressed as:

$$\pi_{e}(t)=\pi_{d}+\pi_{tds}(t)+\pi_{gov}(t),\ \forall t\in\mathcal{T}, \tag{13}$$

where π_{d} is the day-ahead clearing price for generation cost; π_{tds} indicates the transmission, distribution and service fees; π_{gov} is the additional government's investment fund. Based on Eq. (1), the coupon values in each time slot can be obtained as:

$$\pi_{c}(t)=(\pi_{pvp}(t)-\pi_{e}(t))/\lambda,\ \forall t\in\mathcal{T}, \tag{14}$$

Then the coupon values are broadcasted to consumers in the day-ahead market, so that consumers have enough time to reschedule the next day's electricity plan.

C. Security-Constrained Economic Dispatch Model in the Intra-day Market

In the intra-day market, the consumers' loads and the power generation, especially from the renewable energies, will probably not be the same with the forecasted values in the day-ahead market. Therefore, according to the updated power supplies and demands in the pre-operating interval (15min earlier), the SCED model can be developed. The objective is to minimize the generation costs and expressed as:

$$\min\left\{\sum_{t=1}^{T}\sum_{i=1}^{I}C_{gi}(P_{gi}(t))+\sum_{t=1}^{T}\sum_{k=1}^{K}C_{wk}(\Delta P_{wk}(t)) \\ +\sum_{t=1}^{T}\sum_{l=1}^{L}C_{vl}(\Delta P_{vl}(t))\right\},\ \forall t\in\mathcal{T},\forall i\in\mathcal{I},\forall k\in\mathcal{K},\forall l\in\mathcal{L}, \tag{15}$$

subject to:

$$\sum_{i=1}^{I}P_{gi}(t)+\sum_{k=1}^{K}(P_{wk}(t)-\Delta P_{wk}(t))+\sum_{l=1}^{L}(P_{vl}(t)-\Delta P_{vl}(t)) \\ =\sum_{j=1}^{N}P_{dj}(t),\ \forall t\in\mathcal{T},\forall i\in\mathcal{I},\forall k\in\mathcal{K},\forall l\in\mathcal{L}, \tag{16}$$

$$\underline{P_{gi}}\le P_{gi}(t)\le\overline{P_{gi}},\ \forall t\in\mathcal{T},\forall i\in\mathcal{I}, \tag{17}$$

$$0\le\Delta P_{wk}(t)\le P_{wk}(t),\ \forall t\in\mathcal{T},\forall k\in\mathcal{K}, \tag{18}$$

$$0\le\Delta P_{vl}(t)\le P_{vl}(t),\ \forall t\in\mathcal{T},\forall l\in\mathcal{L}, \tag{19}$$

where P_{gi}, P_{wk} and P_{vl} are the power outputs of the i-th generator, the k-th wind generator and the l-th PV, respectively; P_{dj} is the actual power of the j-th consumer. Eq. (16) shows the

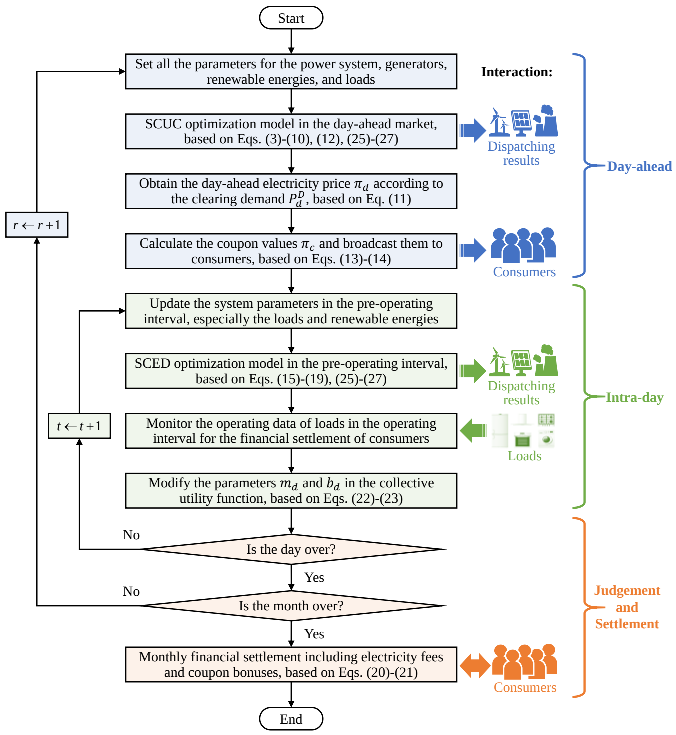


Fig. 5. The flowchart of the proposed algorithm.

power balance. Eqs. (17)-(19) show the generating unit limits.

D. Financial Settlement of the Consumers

The financial settlement of consumers includes two parts, the electricity fees based on the existing PVP and the bonuses based on coupon values. Both the electricity fees and coupon values are updated in each time interval, so that consumers can check their expenditures and profits at any time. However, the final statement is generated on monthly basis. In order to dispel the consumers' worries about the increase of the electricity cost after participating in the PCDR project, the coupon values will be reset to zero when it is negative at the end of each month. Therefore, the monthly electricity fee EF_{dj} and the bonus BON_{dj} of the *j*-th consumer can be expressed as:

$$EF_{dj} = \sum_{t=1}^{T} P_{dj}(t) \cdot \pi_{pvp}(t),\ \forall t \in \mathcal{T}, \forall j \in \mathcal{J}, \tag{20}$$

$$BON_{dj} = \max\left\{0,\ \sum_{t=1}^{T} \lambda \pi_c(t) P_{dj}(t)\right\},\ \forall t \in \mathcal{T}, \forall j \in \mathcal{J}. \tag{21}$$

E. Modification of the CUF

In previous studies [40], [48], each consumer's utility function is assumed to be known. The utility parameters are assumed to be provided by the consumers themselves. However, in fact, most of the consumers, especially the small end consumers, have no the ability to set the parameters in the utility function. To avoid this problem, the CUF is developed in this paper to formulate the total power consumption adjustment of consumers facing coupons, as shown in Eqs. (11)-(12). In this way, the consumers do not need to set their utility functions or bid iteratively in real time, which can decrease the difficulty for small consumers to participate in the PCDR. In order to improve the evaluation accuracy of the power consumption adjustment of consumers under the PCDR in the day-ahead market,

(a) Area 1 (b) Area 2

Fig. 6. The PCDR demonstration area with 110,000 houses in China.

the CUF parameters (i.e., m_d and b_d) will be modified iteratively on the basis of the actual consumed energy after each operating interval. Similar with the elastic demand curve in Fig. 4, the slope and intercept of the actual demand curve with PCDR can be calculated as:

$$\begin{cases} \hat{m}_d = \left[\sum_{j=1}^{J} P_{dj}(t) - P_{CBL,d}^{D}(t) \right] \Big/ \left(\pi_e(t) - \pi_{pvp}(t) \right), \\ \hat{b}_d = \left[\pi_e(t) \cdot P_{CBL,d}^{D}(t) - \pi_{pvp}(t) \cdot \sum_{j=1}^{N} P_{dj}(t) \right] \Big/ \left(\pi_e(t) - \pi_{pvp}(t) \right), \\ \forall t \in \mathcal{T},\ \forall j \in \mathcal{J}. \end{cases} \tag{22}$$

Considering that the CUF model is related to the date (working day or non-working day), the seasons, and the time of a day, the parameters m_d and b_d are designed to be calculated based on different dates and seasons. It likes the load forecasting studies by finding the most similar days [39]. Based on the original parameters m_d and b_d in Eq. (11) and the new parameters $\hat{m}_d$ and $\hat{b}_d$ in Eq. (22), the slope and intercept values in CUF model can be modified by the exponential moving average method, expressed as follows:

$$\begin{cases} \tilde{m}_d(r,s,t) = m_d(r,s,t) + \beta \cdot (\hat{m}_d(r,s,t) - m_d(r,s,t)) \\ \tilde{b}_d(r,s,t) = b_d(r,s,t) + \beta \cdot (\hat{b}_d(r,s,t) - b_d(r,s,t)) \\ \forall r \in \mathcal{R},\ \forall s \in \mathcal{S}, \forall t \in \mathcal{T}, \end{cases} \tag{23}$$

where β is the exponential smoothing constant; r and s are the date and season, respectively. Then, in the next round of dispatch, m_d and b_d will be replaced by $\tilde{m}_d$ and $\tilde{b}_d$, respectively. This in turn prompts the increase of forecasting accuracy on consumers' power adjustment value as a result of the PCDR coupons.

Fig. 5 summarizes the proposed algorithm in Section III by a flowchart. Firstly, set all the parameters for the power system, generators, renewable energies, and loads. Then, implement the day-ahead SCUC optimization model based on Eqs. (3)-(10), (12), (25)-(27). According to the clearing demand P_d^D in the SCUC optimization model, obtain the day-ahead electricity price π_d based on Eq. (11). The coupon values π_c can be calculated and broadcasted to consumers based on Eqs. (13)-(14). The above steps belong to the day-ahead market for obtaining the dispatching results of generators and the coupon values of consumers in all time intervals of the next day. In the intra-day, the power system parameters (especially loads and renewable energies) are updated in the pre-operating interval (15 min earlier). Then, implement the SCED optimization model based on Eqs. (15)-(19), (25)-(27). During the operating interval, monitor the operating data of loads for the financial settlement. After the operating interval, modify the parameters in the CUF

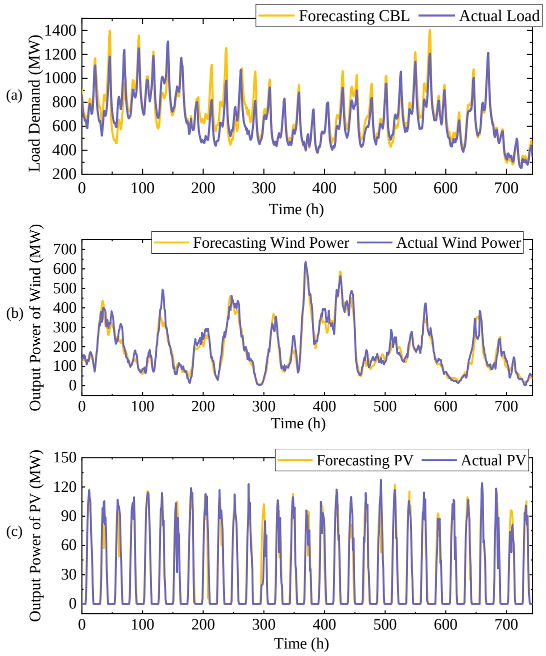


Fig. 7. The test system data: (a) The forecasted CBL and actual load. (b) The forecasted and actual wind power. (c) The forecasted and actual PV power.

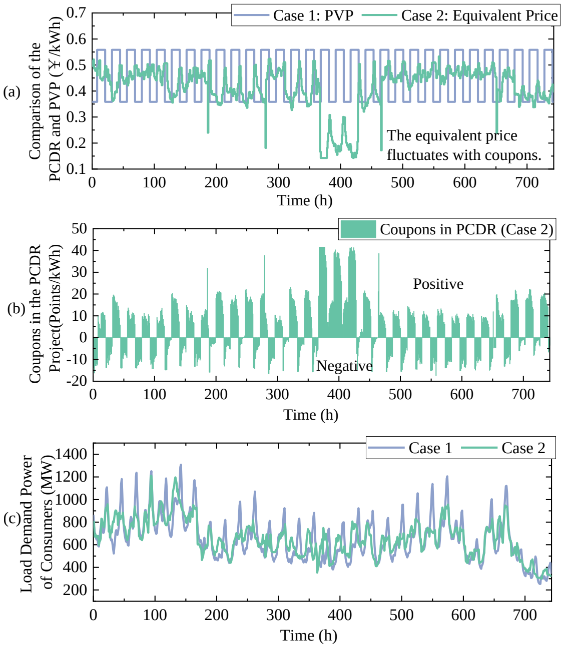


Fig. 8. The electricity prices and loads in Case 1 and Case 2. (a) The comparison of PVP in Case 1 and equivalent price of PCDR in Case 2. (b) The coupon values of PCDR in Case 2. (c) Load curves in Case 1 and Case 2.

based on Eqs. (22)-(23). The intra-day and day-ahead optimization loops will end until the day and the month are over, respectively. Finally, the monthly financial settlement is implemented based on Eqs. (20)-(21).

IV. Case Studies

A. The Test System

The effectiveness of the proposed PCDR is verified based on a large-scale DR project in China "Friendly Interactive System of Urban Consumers Between Supply-side and Demand-side" [49]. This project is implemented in Suzhou and Changzhou cities, Jiangsu Province, as shown in Fig. 6. It aims to provide a low-carbon cost-effective solution towards future power systems, such as lower peak-valley difference of loads and less energy consumption of consumers. Around 110,000 houses are installed with smart devices to achieve the remote communication and monitor of the power consumption in real time. However, compared with the construction of hardware devices, the development of the market mechanism on DR is more difficult in China. Because the electricity price is decided by the government, and electricity companies cannot offer dynamic prices or incentive schemes to consumers. To break down this policy barrier, the proposed PCDR scheme is implemented in this project.

Moreover, considering the power system will be with high-penetration renewable energies in the near future, wind generations and PVs are integrated into the test system based on the realistic data from Ireland [50] and NREL [51]. The loads, wind power outputs, and PV power outputs are shown in Fig. 7(a), (b) and (c), respectively. Apart from the renewable energies, the test system has six traditional thermal generators (TGs), whose parameters are shown in the Appendix. Three different electricity pricing policies are compared in this paper, including the existing PVP in Case 1, the proposed PCDR in Case 2, and the real-time pricing (RTP) in Case 3.

Case 1: The PVP is the present price policy, which includes the peak and valley prices. Considering the electricity retail prices are decided by the government and immutable, the consumers are assumed to have no desire to change their power consumption behaviors. Therefore, the objectives of the SCUC model in Section III-A and SCED model in Section III-C are both to minimize the system generation cost.

Case 2: The consumers can get coupons in the PCDR, whose objective is to maximum their benefits. Therefore, the objective of the SCUC model in the day-ahead market is to maximize the social welfare, including minimizing the system generation cost and maximizing consumers' benefits. The objective of the SCED model in intra-day market is to minimize the system generation cost, because the coupons cannot be changed in real time. The time slot of the market is 15min. The transformation rate λ is 0.01￥/coupon.

Case 3: The consumers are assumed to get RTP in an open electricity market with the objective of maximizing their benefits. Therefore, both objectives of SCUC model in the day-ahead market and SCED model in the intra-day market are maximizing the social welfare in Case 3. The time slot of RTP market is also set as 15min.

All the models and methods are formulated in MATLAB R2019b, and solved by GUROBI 8.1.0 [45] on a laptop with Intel(R) Core(TM) i7-5500U processors, clocking at 2.40GHz and 8GB RAM.

B. Comparison of PVP and PCDR

This subsection compares the results of PVP in Case 1 and the proposed PCDR in Case 2. As shown in Fig. 8(a), the equivalent electricity prices in Case 2 are more dynamic in a day compared with the original PVP. Fig. 8(b) shows the broadcasted coupons in PCDR in Case 2. The positive coupons mean that consumers can earn benefits if they consume power during this process. Hence, positive coupons are equivalent to decreasing electricity prices and motivate consumers to increase their power consumption. By contrast, negative coupons in Fig. 8(b) mean that consumers' benefits are decreased if they consume power during this process. Hence, negative coupons are equivalent to increasing electricity prices to reduce the power consumption. Fig. 8(c) shows the impact of coupons on consumers' power consumption. It can be seen that compared with Case 1, some power in peak periods are shifted to valley periods in Case 2. In most of days, peak loads are decreased while valley loads are increased. As shown in Table I, the minimum and maximum load demand of this month are 253MW and 1,308MW in Case 1, respectively. However, the minimum value is increased to 299MW and the maximum value is decreased to 1,209MW in Case 2, respectively. Therefore, we can conclude that coupons can motivate consumers to change their electricity consumption behaviors and decrease the peak-valley difference of loads.

Fig. 9 shows the influence of coupons on the supply-side. In Figs. 9(a) and (b), it can be seen that lots of output power from wind generators and PVs are curtailed in Case 1. By contrast, in Case 2, more output power from wind generators and PVs are utilized under the PCDR. As shown in Table I, around 12,397MWh wind power and 4,764MWh PV power are curtailed in Case 1, while only about 790MWh wind power and 174MWh PV power are curtailed in Case 2. The curtailment rate of wind is decreased from 8.52% to 0.54%. The curtailment rate of PV is decreased from 20.79% to 0.76%. Therefore, the proposed PCDR contributes to the utilization of renewable energies, which is important for the near future power systems with high-penetration renewable energies.

As shown in Table I, the generation cost is reduced from around 107 million in Case 1 to 95 million in Case 2. There are mainly two reasons. The first one is that due to the decrease of renewable energies' curtailment in Case 2, more energies are utilized from renewable energies while less energies are generated from TGs. The energy share from renewable energies increases from 30.79% in Case 1 to 34.13% in Case 2, while the energy share from thermal generators decreases from 69.21% in Case 1 to 66.24% in Case 2. The second reason is that the regulation frequencies and amplitudes of traditional TGs are both reduced in Case 2, as shown in Fig. 9(c). Here we define one smoothing function to evaluate the up and down regulation amplitudes of TGs [52], as follows:

$$SF = \sum_{t=1}^{T}\sum_{i=1}^{I}\left|P_{gi}(t+1) - P_{gi}(t)\right| \Big/ T,\ \forall t \in \mathcal{T}, \forall i \in \mathcal{I}, \quad (24)$$

where the smoothing function value SF will be smaller if TGs are regulated less. In other words, the smoothing function can reflect the cost during ramping process. It can be seen from Table I that the SF decreases from 43.43MW in Case 1 to 13.93MW in Case 2. This contributes to decreasing the generation cost for up and down regulations. The above two reasons decrease the energy cost.

The consumers' total power consumption in Case 1 and Case 2 are 491,176MWh and 490,653MWh, respectively. These two values are similar and prove that most of loads are transferred

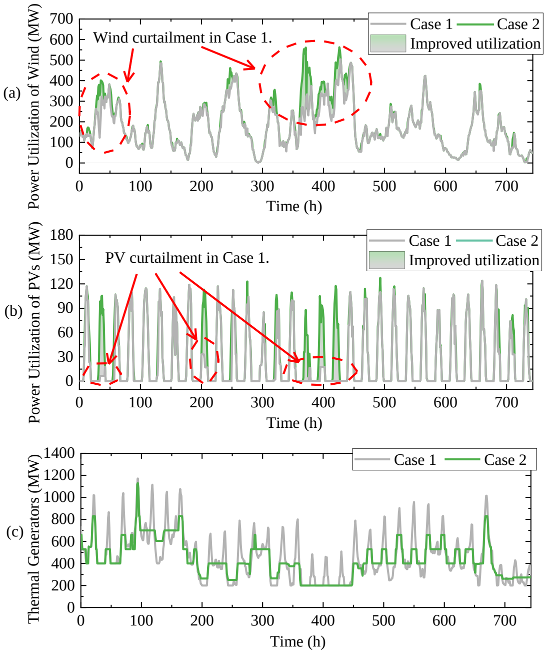


Fig. 9. The influence of coupons on the supply-side in Case 1 and Case 2. (a) The output power utilization of wind generators. (b) The output power utilization of PVs. (c) The generation power of thermal generators.

TABLE I
THE RESULTS OF THREE CASES.

Indexes	Case 1	Case 2	Case 3
Minimum demand (MW)	253	299	287
Maximum demand (MW)	1,308	1,209	1,215
Load consumption (MWh)	491,176	490,653	491,285
Wind utilization (MWh)	133,101	144,708	145,483
PV utilization (MWh)	18,151	22,741	22,874
Energy share from renewable	30.79%	34.13%	34.27%
Wind curtailment (MWh)	12,397	790	15
Curtailment rate of wind	8.52%	0.54%	0.01%
PV curtailment (MWh)	4,764	174	41
Curtailment rate of PVs	20.79%	0.76%	0.18%
Generation of TGs (MWh)	339,924	325,005	326,678
Energy share from TGs	69.21%	66.24%	66.49%
Smoothing function (MW)	43.43	13.93	20.54
Generation cost (￥)	107,042,126	95,487,314	97,554,081
Electricity fee (￥)	155,583,331	149,739,500	143,668,242
Coupon bonus (Points)	N/A	809,854,456	N/A
Expenses of consumers (￥)	155,583,331	141,640,955	143,668,242

while not reduced. In this perspective, the total energy demand of consumers will not be influenced significantly by the proposed PCDR. The electricity fees of this month are shown in Table I, which are around 155.58 million in Case 1 and 149.73 million in Case 2, respectively. Besides, consumers can get around 810 million coupon rewards in Case 2. Therefore, the equivalent expenses on electricity consumption in Case 2 are only around 141.64 million, which is smaller than the original expenses using PVP in Case 1.

C. Comparison of PCDR and RTP

Fig. 10(a) compares the equivalent price in PCDR and the RTP in the open electricity market. Both of them are more dynamic compared with the PVP in Case 1. The main difference

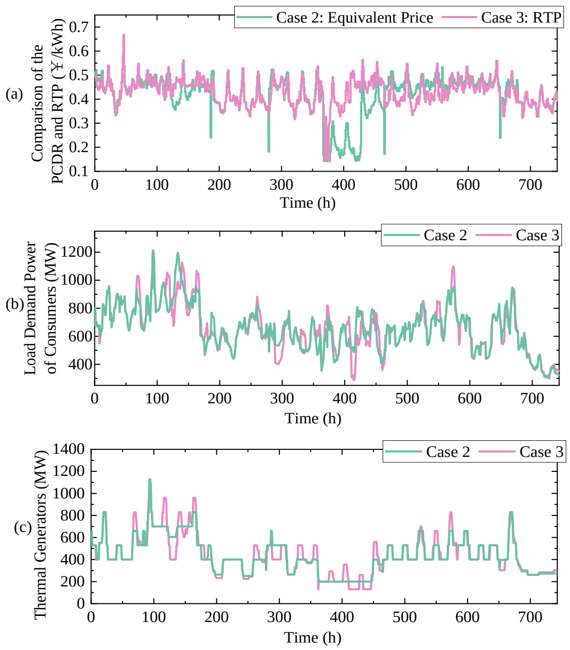


Fig. 10. The electricity prices and loads in Case 2 and Case 3. (a) The comparison of equivalent price of PCDR in Case 2 and RTP in Case 3. (b) Load curves in Case 2 and Case 3. (c) The generation power of thermal generators.

is that RTP in Case 3 is broadcasted to consumers before execution in the intra-day market, while PCDR in Case 2 is broadcasted to consumers in the day-ahead market. Therefore, RTP has more opportunities to change the electricity prices based on the latest intra-day information, e.g., the real-time power generation of renewable energies. By contrast, PCDR is calculated in the day-ahead market based on the forecasting output power of wind generators and PVs. In the intra-day market, it can optimize the power generation of TGs while cannot update coupon rewards to adjust incentives for consumers. Hence more output power of wind generators and PVs can be utilized in RTP in Case 3, as shown in Fig. 11. The curtailment capacity of wind generators decreases from 8.52% in Case 1 to 0.54% in Case 2, and further decreases to 0.01% in Case 3. The curtailment capacity of PVs decreases from 20.79% in Case 1 to 0.76% in Case 2, and further decreases to 0.18% in Case 3.

However, we have to consider that residential consumers are small end-consumers. Most of them have no ability or time to pay attention to the temporarily changed electricity prices or coupons to reschedule their power consumption within 15min. In this perspective, the PCDR sets aside more time for small consumers to arrange their power consumption plan. Besides, RTP probably needs instant communication infrastructure to broadcast prices to massive small consumers in real time, while PCDR can use lots of ready-made methods, e.g., the text message and internet. In this perspective, the PCDR can be implemented more easily in practical power systems.

Fig. 10(b) shows the load curves in Case 2 and Case 3. Compared with the original load curve in Case 1, the peak-valley difference of loads can be reduced by both the PCDR and the RTP. As shown in Table I, the minimum and maximum load demand are 299MW and 1,209MW in Case 2, respectively, which become 287MW and 1,215MW in Case 3, respectively.

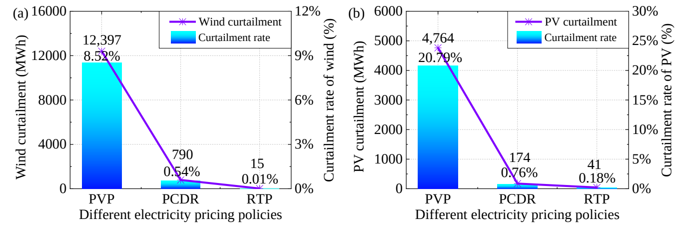


Fig. 11. The curtailment of renewable energies in three cases. (a) Curtailment of wind generators' output power. (b) Curtailment of PVs' output power.

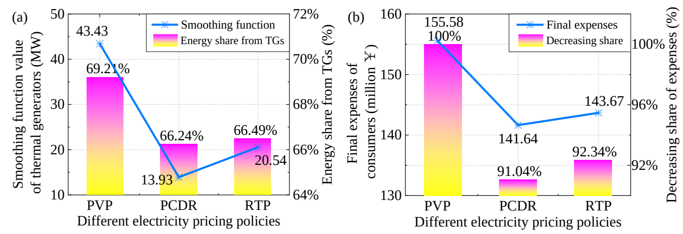


Fig. 12. Thermal generators' operation results and consumers' expenses in three cases. (a) Energy shares and smoothing function values of thermal generators. (b) Final expenses of consumers.

The results surprisingly illustrate that PCDR even has a slightly better effectiveness on peak shaving and valley filling than the RTP. It also verifies that PCDR sets aside more time for small consumers to arrange their power consumption plan better. The different load demand curves in Case 2 and Case 3 further impact the power generation of TGs, as shown in Fig. 10(c). The total generation energy is around 327GWh in Case 3, which is smaller than 340GWh in Case 1 while larger than 325GWh in Case 2. The smoothing function value SF is 20.54MW in Case 3, which is smaller than 43.43MW in Case 1 while larger than 13.93MW in Case 2, as shown Fig. 12(a). These two indexes (i.e., generation energy and SF of TGs) illustrate that the proposed PCDR in Case 2 has a slightly better effectiveness on dispatching TGs, compared with the RTP in Case 3.

Table I and Fig.12 (b) compare the expenses of consumers in three cases, which is the highest in Case 1 (i.e., around 155.58 million). The expense decreases to 141.64 million in Case 2 and 143.67 million in Case 3, respectively. The expense in Case 3 is a little larger than that in Case 2, because the total generation energy and regulation amplitudes of TGs are more in Case 3, as shown in Fig. 10(c). But in general, the expenses in Case 2 and Case 3 are similar, and both of them are smaller than the expense in Case 1. To sum up, the proposed PCDR can achieve similar beneficial effects as the RTP to decrease the peak-valley difference of loads, increase the utilization of renewable energies, and cut down the expenses of consumers.

V. Conclusions

The DR in power systems has been widely considered as an effective alternative of traditional generators to provide regulation services. However, even though many consumers are installed with smart meters, power systems with flat-rate retail pricing policies are difficult to carry out DR projects. Faced with this challenge, this paper proposes a novel PCDR scheme to realize the equivalent dynamic retail prices, which considers the lack of experience and knowledge of small consumers on the electricity market and is designed to decrease the difficulty of massive small consumers participating in DR. The effectiveness of the proposed methods is verified based on a realistic large-scale DR project in in China. By analyzing the generation costs, the utilization rate of renewable energies, the peak-valley difference of loads, and the electricity fees of consumers, the proposed PCDR is illustrated to be a beneficial component of the existing flat-rate retail pricing system. It can inspire the inherent elasticity of consumers to increase the system economy. This research contributes to providing references for the countries or regions which have no mature open competitive electricity market yet.

VI. Discussions

Compared with the present PVP policy, the proposed PCDR can generate more dynamic electricity prices. Hence, the PCDR can inspire the inherent elasticity of consumers to decrease their energy cost, which also contributes to decreasing the peak-valley difference of loads and increasing the consumption of fluctuating renewable energies. However, the PCDR is calculated based on the forecasted data (e.g., loads and power outputs of renewable energies) in the day-ahead, which bring some uncertainties and may cause sub-optimal coupon results. This is a compromise because current small end consumers may have no ability or time to pay attention to the temporarily changed coupons to reschedule their power consumption in 15min. In the future, smart devices can be developed to realize the automatic control of consumers' loads. Then the proposed PCDR can be calculated in a shorter time horizon to further increase the positive effect on power systems.

Actually, the electricity market reform is carrying out in China and the RTP may be implemented in the near future. First, the proposed PCDR is a valuable retail pricing policy before the electricity market opening. It is similar with the day-ahead dynamic prices in power systems with mature electricity markets. Hence, the PCDR can improve consumers' recognitions on the electricity market and engage more consumers to participate in the market. Second, the PCDR can be calculated in a shorter time horizon, i.e., the PCDR is equivalent to the RTP if coupons were calculated and broadcasted in the intra-day market. It means the PCDR can be transformed to the RTP by changing the release manner from coupons to prices.

Appendix

The practical generation costs of TGs are generally approximated by quadratic functions with regard to the power outputs [53], which can be expressed as:

$$C_{gi}(P_{gi}(t)) = c_{2,gi} \cdot P_{gi}(t)^2 + c_{1,gi} \cdot P_{gi}(t) + c_{0,gi} \tag{25}$$

where $c_{2,gi}$, $c_{1,gi}$ and $c_{0,gi}$ are quadratic function's parameters of the *i*-th TG. The six TGs' parameters are shown in Table II. Moreover, the curtailment costs of renewable energies are positively correlated with the curtailment energies, which can be expressed as:

$$C_{wk}(\Delta P_{wk}(t)) = c_{wk} \cdot \Delta P_{wk}(t) \tag{26}$$

$$C_{vl}(\Delta P_{vl}(t)) = c_{vl} \cdot \Delta P_{vl}(t) \tag{27}$$

where c_{wk} and c_{vl} are parameters of the linear functions for wind generators and PVs, respectively. These two parameters are both set as 500￥/MWh in the case study.

TABLE II
THE PARAMETERS OF THERMAL GENERATORS.

TGs	$\overline{P}_{gi}$ (MW)	$\underline{P}_{gi}$ (MW)	O_{gi} (h)	D_{gi} (h)
1	55	20	1	1
2	130	30	2	2
3	130	30	2	2
4	150	50	3	3
5	320	120	5	5
6	445	150	5	5
TGs	SU_{gi} (10^3￥)	$c_{2,gi}$ (￥/MW^{2}h)	$c_{1,gi}$ (￥/MWh)	$c_{0,gi}$ (10^3￥/h)
1	1.260	0.0612	384.13	9.781
2	1.497	0.0313	244.53	10.078
3	1.497	0.0313	244.53	10.078
4	1.689	0.0299	246.01	10.374
5	3.364	0.0046	255.94	14.375
6	3.956	0.0071	239.94	14.820

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