Study on the Promotion Impact of RTP-based Demand Response on Distributed PV Penetration by using a Non-Cooperative Game Theoretical Analysis

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Abstract

Promoting the penetration of distributed photovolataic systems (PV) at the end-user side is an important contribution to carbon reduction. This study aims to evaluate the promotion impact of the level of smart consumers on the installation of distributed PV using a non-cooperative game theoretical model, which can find the Nash equilibrium of residential smart consumers with different levels of demand control capability in a electricity power market with real-time pricing mechanism under different installed PV capacities and battery capacities. As a case study, 5 levels of smart control, 32 combinations of PV installed capacities and battery capacities were analyzed and inter-compared using the developed model. The results show that: (i) the consumers with higher smart control level are able to accept larger PV capacity because the marginal revenue of new installed PV for smart consumers decreases much more slowly compared to that of a common consumer; (ii) the smarter consumers need less batteries to promote PV economic acceptability; (iii) the smarter consumers can meet the electricity demand in real-time with least expenditure thanks to their advanced demand-response capability, so they get more ultimate benefit from the games.

Key words: Demand response, Distributed PV, Real-time Pricing, Non-cooperative Game, Complementarity Model

Nomenclature

Indices

t	hour series in a day (1–24)
d	representative days (3 typical days)
i, j	user group (1-5)
c	controllable appliances

Parameters

NCL(i,d,t)	non-controllable load (kW)
STA(i,d,c)	earliest start time of one controllable appliance
STO(i,d,c)	latest stop time of one controllable appliance
RP(i,d,c)	rated power of one controllable appliance (kWh)
IRR(d,t)	solar irradiation in terms of output power/rated power (%)
DAYS(d)	amount of days represented by representative day in each year
PV(i)	installed PV capacity (kWh)
BA(i)	installed battery capacity (kWh)
α, β	coefficient of electricity price
NRL(d,t)	non-residential load (kWh)
CHAEFF	battery charge efficiency
DISEFF	battery discharge efficiency

Variables

be(i,d,t)	power bought from grid (kWh)
se(i,d,t)	power sold to grid (kWh)
ca(i,d,c,t)	power consumed by one controllable appliance (kWh)
pr(d,t)	power price established by power retail (RMB per kWh)
brin(i,d,t)	battery charge rate (%)
brout(i,d,t)	battery discharge rate (%)

Abbreviations

PV	photovoltaic
FIT	feed-in tariff
RTP	real-time pricing
TOU	time of use
GAMS	General Algebraic Modeling System
MCP	mixed complementarity problem

1. Introduction

With the dramatic increase of fossil fuel consumption, the reduction of CO_2 emission and the promotion of renewable energy have become urgent tasks for societies. PV, as one of the most important renewable energy technologies, has been commonly used in a distributed configuration, installed very near or at the end user`s location. To promote the application of PV, many kinds of subsidization policies have been proposed [1-3]. For example, in many countries, governments provide a lump-sum grant to consumers who install PV systems or subsidies on the electricity generated by PV. Moreover, utility companies are often obligated to purchase PV power at a price relatively higher than the regular tariff under government-supported feed-in tariffs (FIT). However, in the traditional power grid, PV power is difficult to integrate due to its intermittence and low voltage [4]. Thanks to the recent rapid development of communication and automation technologies using telemetry, remote and automated control have enabled smart grid and demand response, which is expected to help dispatch and utilize PV power in both macro-grids [5, 6] and micro-grids [7, 8].

Apart from policy and subsidies, highly varied electricity prices resulting from the restructuring of the electricity market can also create an incentive to incorporate more PV panels [9]. Practically, energy demand is not constant, but varies from moment to moment depending on end-users patterns of usage. In order to meet the energy demand of consumers, the generation and transmission capacities of the grid need to be designed to satisfy the peak power demand rather than the average power demand, leading to an over-capacity system for much of the time. In the traditional power market, the electricity price is usually fixed. A fixed price cannot reflect the fluctuation of generation cost caused by peak load, unit commitment constraints, congested transmission lines etc., and thus consumers have no motivation to shift consumption during the peak load periods. This results in a redundancy of power generation capacity and transmission infrastructures in the off-peak times, and therefore, the whole system becomes inefficient and cost-ineffective. To solve this problem, economic dispatch based on a real-time pricing (RTP) system and demand-response technologies is proposed, which can motivate consumers to shift their loads from peak times. Various pricing strategies have been proposed to incentivize demand-response in smart grid, and the most efficient one is the RTP [10, 11]. Demand response programs under real-time pricing markets have been widely adopted in practice, and the promotion impacts on market access to distributed energy have been determined in previous studies [12].

There have been several models developed with a focus on the relationship between demand-response and the installation capacity of distributed PV. The existing models can mainly be divided into two types in terms of the mathematical methodology. One type is the optimal model, including static optimization models solving optimal load commitment problems of electric appliances in smart homes with distributed PV installed [13-15], and dynamic optimization models solving optimal expansion planning problems for PV in smart homes [16, 17]. In these optimal models, the power price is usually set as exogenous. The consumers are price-takers rather than players in the market, which means that the consumers' behavior has no impact on the electricity price. The other type of model is the game theoretical model, for example the non-cooperative game models handling games among residential consumers equipped with distributed electricity generators [18-20], Stackelberg game models dealing with games between utility companies and smart end-users (such as residential smart homes) in demand response programs [21], and market equilibrium models focusing on the whole power market [22]. In these game theoretical models, consumers' strategies can affect the power price. Compared with optimal models, game theoretical models have advantages in handling situations where market participants have different or even conflicting objectives, which is more realistic. However, in existing studies, the differences in the smart levels of consumers, especially the difference between smart consumers and non-smart consumers were not yet considered. In addition, the PV installed capacities are usually exogenously given or obtained as optimal results, which do not indicate the detailed impacts of the level of smart control on PV installation capacities.

The purpose of this study is to uncover the impact of the level of smart control on distributed PV installation. In order to analyze the impacts of end users' participation and different smart levels of consumers in an electricity power market, a non-cooperative game theoretical model was developed. In the model, consumers participate in the game in a real-time pricing market and every consumer pursues his/her own minimized expenditure on electricity consumption. Different from existing studies, different levels of smart control (smart levels) have been considered in the proposed model to analyze their impact on the integration of distributed PV. The smart level is measured by the ability to respond to price fluctuation. The development of smart technologies is the foundation of the actualization of consumers' demand-response. Such technologies include smart metering, remote control, and automated control, and so on [10, 23]. Newly built houses are considered to be equipped with the latest commercially-effective advanced smart electric devices and consumers can therefore respond to the price fluctuations quickly and flexibly. One the other hand, old houses are typically not smart enough and thus cannot allocate energy consumption according to price fluctuations. Consumers with different smart levels were then analyzed and compared. The equilibrium results with different installed capacities of PV as well as batteries were obtained. Every consumer's optimal operation pattern and total expense can be clarified. The economical acceptability of PV was then evaluated, and the feasibility of the methodology was demonstrated practically through its application to a case study in China.

2. Methodology

2.1. Model Framework

The model framework is shown in Figure 1. Non-residential consumers, such as commercial and industrial consumers, usually have contracts with power retailers and they are charged a rate based on the time of use (TOU) of their energy. Their electricity price is pre-given, and thus their consumption can be regarded as constant in the real-time pricing market. On the other hand, residential consumers are bidirectionally connected to the retailer. The power retailers gather consumption data and set the real-time price based on the total wholesale hourly power consumption. The residential consumers respond to the hourly price by shifting their power load in the form of submitting new demand bids and the retailer sets a new price again. This procedure will be repeated until equilibrium is achieved.

2.2. Residential micro-grid module

Residential micro-grids consist of controllable and non-controllable electric appliances, distributed photovoltaic panels, batteries, and central control appliances. Controllable appliances refer to appliances which can be operated at any time of the day or within a particular time interval while non-controllable appliances refer to those whose operation time is fixed. For example, a washing machine is controllable, however, an air-conditioner is usually non-controllable. Distributed photovoltaic panels are connected to the power grid, and surplus generated power can be sold to the grid at the price of the feed-in tariff.

Using automated central control technology, residential consumers can gain real-time access to market prices and the operation of controllable electric appliances can be arranged automatically to avoid purchasing power during high price periods. It is important to note that this type of system requires expensive technologies that may not be available to all consumers. Alternative solutions such as online real-time power price access and remote control of smart appliances can substitute to some extent. Due to the potential disparities in control technologies and capabilities, it is reasonable to divide the residential consumers into several types according to their ability to response to price fluctuation, in other words their smart level. In this paper, the smart level is measured by length of the time interval in which energy consumption can be shifted.

In the residential micro-grid, the primary constraint is to make supply and demand meet.

$$IRR(d,t) \times PV(i) + be(i,d,t) - se(i,d,t) = \sum_c ca(i,d,c,t) + NCL(i,d,t) + BA(i) \times CHAEFF \times brin(i,d,t) - BA(i) \times DISEFF \times brout(i,d,t), \quad (\ \lambda_{balance}(i,d,t)) \quad \forall i,d,t$$

(2-1)

Here, *IRR(d,t)* is the solar irradiation in terms of the output power divided by rated power of PV panels at day *d* time slot *t*; *PV(i)* is the installed capacity of PV panels in consumer *i*'s home; *be(i,d,t)* and *se(i,d,t)* are the volume of electricity consumer *i* buys from and sells to the grid at day *d* time slot *t*, respectively; *ca(i,d,c,t)* is the power consumption of consumer *i*'s specific controllable appliance *c* at day *d* time slot *t*. *NCL(i,d,t)* is the total power consumption of consumer *i*'s non-controllable appliances at day *d* time slot *t*; *BA(i)* is the installed capacity of battery in consumer *i*'s home;

brin(i,d,t) and *brout(i,d,t)* are the charge and discharge rate of consumer *i*'s battery at day *d* time slot *t*. *CHAEFF* and *DISEFF* are the charge and discharge efficiency. $\lambda_{balance}$ is the dual variable for balance constraints.

Batteries cannot be charged exceeding its capacity or discharged after empty. All these constraints for the batteries are described in equation (2-2) – (2-6), respectively. Particularly, equation (2-6) means the batteries should not be charged and discharged simultaneously, which is a logical constraint.

$$\sum_{k=1}^{t}[brin(i,d,k) - brout(i,d,t)] \geq 0, \left(\lambda_{BA-lower}(i,d,t)\right), \forall i,d,t \tag{2-2}$$

$$\sum_{k=1}^{t}[brin(i,d,k) - brout(i,d,t)] \leq 1, \left(\lambda_{BA-upper}(i,d,t)\right), \forall i,d,t \tag{2-3}$$

$$0 \leq brin(i,d,t) \leq 1, \forall i,d,t \tag{2-4}$$

$$0 \leq brout(i,d,t) \leq 1, \forall i,d,t \tag{2-5}$$

$$brin(i,d,t) \times brout(i,d,t) = 0, \left(\lambda_{BA-logical}(i,d,t)\right), \forall i,d,t \tag{2-6}$$

Each controllable appliance can only work once for one hour (which is the length of one entire time interval) in the given interval, as shown in equations (2-7) – (2-9).

$$\sum_{t} ca(i,d,c,t) = RP(c), \left(\lambda_{CA-power}(i,d,c,)\right) \ \ , \forall i,d,c$$

(2-7)

$$ca(i,d,c,t) \leq RP(c), \forall STA(i,d,c) \leq t \leq STO(i,d,c) \tag{2-8}$$

$$ca(i,d,c,t) \equiv 0, \forall t < STA(i,d,c) \quad or \quad t > STO(i,d,c) \tag{2-9}$$

Here, *RP(c)* is the rated power of controllable appliance c, $\lambda_{CA-power}(i,d,c,)$ is the dual variable for controllable appliance's power consumption constraint. $STA(i,d,c)$ is the starting time and $STO(i,d,c)$ is the corresponding stop time of the time interval in which the operation time of controllable appliance *c* can be shifted.

Consumers are only allowed to sell electric power generated from the distributed PV to the grid because the chance of arbitrage should be avoided. In detail, the possibility of buying electricity from the grid when the price is low and storing the electricity in the battery, then selling it by discharging when the price is high should be eliminated, which is shown in equation (2-10). On the other hand, logically, the consumers should not purchase electricity power from and sell electricity power to the retailer simultaneously. This is shown in equation (2-11).

$$0 \leq se(i,d,t) \leq IRR(d,t) \times PV(i), \forall i,d \quad (2\text{-}10)$$

$$se(i,d,t) \times be(i,d,t) = 0, \left(\lambda_{CONSUMER-logical}(i,d,t)\right), \forall i,d \quad (2\text{-}11)$$

2.3. Retailer pricing module

The obligation of the retailer is to meet electricity demand from all consumers. Retailers purchase electricity from a variety of sources in a wholesale electricity market, in which the electricity is generated by a variety of technologies and fuels. Each technology has a different marginal cost, which is defined as the incremental cost incurred to produce an additional unit of electric power. Naturally, (unless otherwise compelled) the retailer will purchase electricity from the cheapest source first, leading ultimately to a non-decreasing marginal cost curve. Therefore, if the retailer wants to earn a fixed ratio profit, it is reasonable to approximately assume that the supply-price curve is non-decreasing.

In this paper, an average-cost based pricing scheme is used as shown by equation (2-12). Here, the *NRL(d,t)* is the non-residential electricity power load at day *d* time slot *t*, which is set to be an exogenous constant, and the α and β are coefficients.

$$pr(d,t) = \alpha \frac{\sum_i [be(i,d,t) - se(i,d,t)] + NRL(d,t)}{\frac{[\sum_t \sum_i NCL(i,d,t) + \sum_i \sum_c RP(i,d,c) - \sum_t \sum_i PV(i) \times IRR(d,t) + NRL(d,t)]}{24}} + \beta, (\ \lambda_{price}(d,t)\ ), \forall d,t \tag{2-12}$$

Such a pricing function can ensure the supply-price curve is non-decreasing. Furthermore, the pricing mechanism also encourages users to schedule their energy consumption and batteries in a way that the energy demand is more equally distributed over all time slots. As shown in the equation, α + β is the average price.

2.4. Non-cooperation game theoretical complementarity model

The objective of each residential consumer is to minimize his/her energy expenditure on electricity consumption in a whole year as is shown in formula (2-13). Each consumer decides his/her own load commitment and battery operation pattern. All information is public and there is no collusion between consumers. Therefore this is a typical non-cooperation game.

$$\min_{be,se,bc,pv} \{\sum_d [\sum_t pr(d,t) \times be(i,d,t) - \sum_t FIT \times PV(i) \times IRR(d,t)] \times DAYS(d)\}, \forall i \quad (2\text{-}13)$$

In the objective function (2-13), *FIT* is the feed-in tariff rate and *DAYS(d)* is the amount of the representative day, *d*, in a year. The optimization is subject to constraints (2-1) – (2-12). The Karush–Kuhn–Tucker conditions (also known as KKT or first order conditions) of the non-cooperation game model are established as (2-14) – (2-19). The objective function is quadratic and all the constraints are linear, and thus the KKT conditions are necessary and sufficient for the optimization of the objective function. Since the non-cooperation game model is a simultaneous-move game, solving the KKT conditions simultaneously for expenditure minimizing problems yields a Nash equilibrium solution. [24]

$$pr(d,t) \times DAYS(d) + \lambda_{balance}(i,d,t) + \lambda_{price}(d,t) \times \frac{\alpha \times be(i,d,t)}{[\sum_t \sum_i NCL(i,d,t) + \sum_i \sum_c RP(i,d,c) - \sum_t \sum_i PV(i) \times IRR(d,t) + NRL(d,t)]/24} + \lambda_{CONSUMER-logical}(i,d,t) \times se(i,d,t) \perp be(i,d,t), \forall i,d,t \quad (2\text{-}14)$$

$$-\lambda_{balance}(i,d,t) - \lambda_{price}(d,t) \times \frac{\alpha \times se(i,d,t)}{\frac{[\sum_t \sum_i NCL(i,d,t) + \sum_i \sum_c RP(i,d,c) - \sum_t \sum_i PV(i) \times IRR(d,t) + NRL(d,t)]}{24}} + \lambda_{CONSUMER-logical}(i,d,t) \times be(i,d,t) \perp se(i,d,t), \forall i,d,t \quad (2\text{-}15)$$

$$-\lambda_{balance}(i,d,t) + \lambda_{CA-power}(i,d,c) \perp ca(i,d,c,t), \forall i,d,c,t$$

(2-16)

$$-\lambda_{balance} \times BA(i) \times CHAEFF + \sum_{k=0}^{t} \lambda_{BA-upper}(i,d,t) - \sum_{k=0}^{t} \lambda_{BA-lower}(i,d,t) + \lambda_{BA-logical}(i,d,t) \times brout(i,d,t) \perp brin(i,d,t), \forall i,d,t \tag{2-17}$$

$$-\lambda_{balance} \times BA(i) \times CHAEFF - \sum_{k=0}^{t} \lambda_{BA-upper}(i,d,t) + \sum_{k=0}^{t} \lambda_{BA-lower}(i,d,t) + \lambda_{BA-logical}(i,d,t) \times brin(i,d,t) \perp brout(i,d,t), \forall i,d,t \tag{2-18}$$

$$\sum_{i} be(i,d,t) \times DAYS(d) + \lambda_{price}(d,t) \perp pr(d,t), \forall d,t \tag{2-19}$$

2.5. Tool

The non-cooperation game theoretical complementarity model is developed in the General Algebraic Modeling System (GAMS) [25] as a mixed complementarity problem (MCP). The mathematical properties of existence and uniqueness for the MCP solution can be found in [26, 27]. In the present study, the MCP problem is solved using the PATH solver [28]. It takes 68s to solve this problem on a computer with i7 2.5 GHZ CPU and 4G memory.

GAMS is a platform that uses algebraic language and efficient solvers for analyzing complex and large-scale linear, nonlinear, integer, and complementarity problems. The PATH solver is a Newton-based algorithm for solving complementarity problems.

3. Case study

The developed non-cooperation game theoretical power market complementarity model was applied to a district in China. All the residential consumers participate in the real-time pricing program. To investigate the promotion impact of smart levels of residential consumers on the acceptability of distributed PV power, the economic performance of installed PV power, consumers' expenditure on power consumption and the optimal operation pattern of electric appliances under the non-cooperation game will be analyzed using the proposed model.

3.1. Data

The consumption of electricity has obvious time-dependent characteristics. Residential consumers always arrange their electric appliances' operations according to their life style arbitrarily when demand response is not involved. Seasonal difference is also a factor in determining the load pattern. In summer and winter, the load is relatively higher than that in spring and autumn due to the high electricity demand for cooling and heating. Therefore, three representative days for summer, winter, and mid-seasons respectively are selected, upon which to base the assessment of the whole year.

3.1.1. Non-residential load

Non-residential load data was obtained using a foreign city as reference [6]. In China, non-residential load accounts for 80% of the total load [29]. The non-residential consumers don't respond to real-time price as described in Section 2, therefore their load is constant, as is shown in Figure 2. The peak load appears at noon and the lowest load appears before dawn. The power load in summer and winter is higher than that in a typical mid-seasonal day.

3.1.2. Residential load and variable time zone

Taking reference [30] as reference basis, we conducted a survey on the residential consumers' life style with regards to electricity consumption. Eleven households were sampled, and their electric appliances' daily operation patterns were recorded. According to the survey result, we summarized the residential load data. The residential load consists of two parts. The first part is the non-controllable load, which consists of all the non-controllable appliances as shown in Figure 3. The second part is the controllable load, which consists of all the controllable appliances, and the initial distribution of the controllable load is depicted in Figure 4.

As is mentioned in Section 1, the rapid upgrading of smart house technologies leads to different demand response abilities (smart levels) in houses constructed in different technical eras. In the present study, five types of residential consumers with different abilities to respond to price changes have been taken into consideration. The smart house technologies available to them in order of their houses' age are: (1) automated controller and access to real-time price data; (2) remote controller and access to real-time price data; (3) timing start and access to real-time price data; (4) only access to real-time price; and (5) no access to even real-time price, in reverse order of increased smart level respectively. To quantify their different smart levels, it is assumed that the length of the time interval during which energy consumption can be shifted is 24 hours for consumer 1, 11 hours for the consumer 2, 5 hours for the consumer 3, 3 hours for the consumer 4, and 1 hour for the consumer 5, respectively.

In the present study, we take consumer 3 as an example to illustrate the meaning of the time interval length: if resident 3 is accustomed to using the washing machine at 1:00 pm before going out to work in the afternoon, he can choose to shift the operation within the time interval 11:00 am to 3:00 pm, of which 1:00 pm is the midpoint. In particular, consumer 1 can shift his load to any other hour within the day and consumer 5 cannot shift any load.

Each type of residential consumer includes 1000 households. The 5000 households share the same non-controllable load and initial controllable load.

3.1.3. Solar irradiation

The solar irradiation corresponding to the three representative days is depicted in Figure 5. The amount of PV generation power can be calculated by equation (3-1). [6, 16]

$$P_{PV} = \eta_{PV} \times PV \times I_{PVI} \times \left(1 - 0.005 \times (t_{CR} - 25)\right) \tag{3-1}$$

where, η_{PV} is the conversion efficiency of the solar cell array (14.4%), PV is the rated capacity of PV panels, I_{PVI} is the solar irradiation on an inclined surface (kW/m^2), and t_{CR} is the outside air temperature (° C). The angle of incidence of the solar array panel is 30 degrees. Thus, the irradiation coefficient *IRR* can be calculated by equation (3-2).

$$IRR = {}^{P_{PV}}/_{PV} = \eta_{PV} \times I_{PVI} \times \left(1 - 0.005 \times (t_{CR} - 25)\right) \tag{3-2}$$

3.2. Policy assumptions

In this paper, the subsidy policy for distributed PV panels is assumed to be a fixed subsidy on every kWh power generated by PV panels [1, 31, 32], which means residential consumers cannot be paid via sending excess PV power to the grid, resulting in incentive for consumers to utilize the PV power as much as possible.

3.3. Simulation study

The battery capacities and PV capacities are assumed to be the same for all consumers. The battery capacities vary from 0 to 3 kWh in steps of 1kWh. The PV capacities vary from 0 to 3.5 kW in step of 0.5 kW. Different combinations of PV capacities and battery capacities lead to different optimized operation and economic benefit results. The numerical results will be provided in Section 4.

4. Result

4.1. Electricity expense

The simulations were run for all the combinations of PV capacities and battery capacities. The annual total expenditures of each type of consumers on electricity power consumption have been summarized in Figure 6 in the form of the annual expenses saved comparing to consumer 5, whose smart level is the lowest. The saved money is the value of the “smart level”. As shown in the results, consumers with higher smart levels can save more money. With the PV installed capacity increase, the superiorities become even more significant. When there is a 3.5 kW PV but no battery, a consumer with the highest smart level will spend 36.6% less expenditure than the consumer with the lowest smart level annually. However, when same capacity battery is integrated, the superiorities in saving electricity expenditure of the consumers with higher smart level are attenuated compared to low smart level ones. For example, with 2 kWh battery and 3.5 kW PV, a consumer with the highest smart level can save only 25.2% compared to the lowest smart level consumer. This indicates that the batteries can reduce the economic performance gap between consumers with different smart levels. The reasons for this are investigated as described in section 4.3.

4.2. Marginal revenue of PV power

The cost of PV panels and batteries have not been counted into the expenses in this study, because we only focus on the promotion impacts of the consumers' smart levels on the integration of PV power. Moreover, the cost of PV panels and battery modules are reducing dramatically year by year [33, 34]. Therefore, the marginal revenue was considered a more reasonable index than levelised cost of electricity. Marginal revenue is the increment when capacity increases one unit. In practice, if the capital cost of a certain capacity of PV is less than its marginal revenue, it is economically acceptable.

As shown in Figure 7, the consumers with higher smart levels (consumer 1 and consumer 2) have flatter marginal revenue for new installed PV. On the other hand, the consumers with lower smart levels (consumer 4 and consumer 5) have sharply dropping marginal revenue. For consumer 5, the marginal revenue of each 0.5 kW PV panel decreased from 404 RMB for the first unit PV panel, to 85 RMB for the seventh PV panel. However, for consumer 1, the marginal revenue of each 0.5 kW PV panel only decreased from 399 RMB for the first unit PV panel, to 341 RMB for the seventh unit PV panel. The difference indicates that the higher the smart level of the consumers, the more PV panels can be economically acceptable. Furthermore, batteries can help the consumers with lower smart levels to delay the decrease of PV marginal revenue effectively. Taking consumer 3 as an example, the marginal revenue of PV starts to decrease sharply when PV capacity is 1.5 kW when there is no battery; and the turning point of marginal revenue of PV moves to 2kW PV capacity when there is a 1 kWh battery. Furthermore, the turning point will move to 2.5kW and 3 kW PV capacity respectively when 2kWh and 3kWh batteries are deployed.

On the other hand, according to the numerical result shown in Figure 7, compared to consumers 3, 4 and 5, the battery has no obvious impacts on the marginal revenue of PV for consumer 1 and consumer 2 whose smart level is relatively higher. Therefore, consumers with a high smart level can economically accept a large generating capacity of PV power, and thus the battery contributes little in further promoting distributed PV installation for them.

4.3. Price variance under different situations

The daily price variance can be calculated by equation (4-1).

$$price\ \ varianve = \frac{1}{24-1}\sum_t \left(pr(d,t) - \frac{1}{24}\sum_t pr(d,t)\right)^2 \qquad (4\text{-}1)$$

The price variances under different situations are exhibited in Figure 8. It is depicted that the price variance decreases with the increase of battery capacity. The consumers with high smart levels are able to utilize the price fluctuation to save money by purchasing electricity power during lower price periods. Since the total load is the same for all the consumers, the different smart levels do not cause any difference when the price variances become zero (price is a constant). In other words, smarter consumers can benefit from higher price variance more.

Analyzing the results shown in Figure 7 and Figure 8 together indicates that batteries can help consumers with relatively lower smart levels to promote PV panel installation. When the battery capacities increases from zero to 1 kWh, consumer 1 can save 31 RMB with a 3.5 kW PV panel installed, while consumer 5 can save 281 RMB. The reason is that the battery can reduce price variances effectively, and the consumers with lower smart levels can benefit more when the price variance becomes low.

This, following-on from the previous section has significant implications for policy and the roll-out of PV and its supporting technologies. In the case of relatively smart technologies, batteries are not so crucial, while dealing with less-smart demand-side infrastructure encourages battery installation. However, the capital and maintenance costs of these alternative installations should also be carefully considered with regards to appropriate subsidisation and investment.

4.4. Operation pattern

When the non-cooperative game reaches an equilibrium state, every consumer's appliance operation pattern is considered to be optimal. The equilibrium was obtained from the hour-by-hour simulation and the feasibility was inherent. A typical day in summer with 1kWh battery, 3kW PV was chosen as an example. The operation patterns of consumer 1 and consumer 5 are shown in Figure 9. It is apparent that consumer 1 responds to the real-time price by using more power when the price is lower before dawn and using less power when price is higher in the evening.

5. Conclusion

In the present study, a non-cooperation game theoretical power market complementarity model was developed to study the equilibrium real-time power price for residential consumers considering smart residential micro-grid and distributed PV panels. The model was applied to case studies to uncover the impacts of smart levels on the economic integration of distributed PV power, and the impacts of PV capacities and battery capacities on consumers' power expenses.

Five types of residential consumers with different capabilities of responding to price changes were considered to be playing in the game and 32 different combinations of battery capacities and PV capacities were simulated. The results show that: (a) residential consumers with higher smart levels at higher integration of PV are able to benefit more from the non-cooperative game in form of saving money on electricity expenditure. The preponderances increase with the increase in PV capacity and decrease with the increase of battery capacity. In this study, consumers with the highest smart level can save 36.6% on electricity expenditure compared to the consumers with the lowest smart level at most; (b) the marginal revenue of new installed PV panels decreases for all residential consumers. However, consumers with lower smart level suffer a sharper drop. The difference of the marginal revenue among different users can reach 300% in this study. It can be concluded that consumers with higher smart levels are able to economically integrate a larger PV capacity. (c) Batteries can help consumers with relatively low smart levels to mitigate the decrease of PV marginal revenue, however, they cannot significantly raise the PV marginal revenue for consumers with high smart levels.

The real-time power price was obtained simultaneously. By analyzing the price, it is uncovered that consumers with lower smart levels get more benefit from the increase of battery capacity as a result of the decrease of price variances. When there is no PV, the price variance in a typical summer day as an example decreases by 94.4% with the integrated battery capacity increasing from 0 to 3 kWh and the electricity consumption difference between consumers with highest and lowest smart level decreases by 50%.

Figures

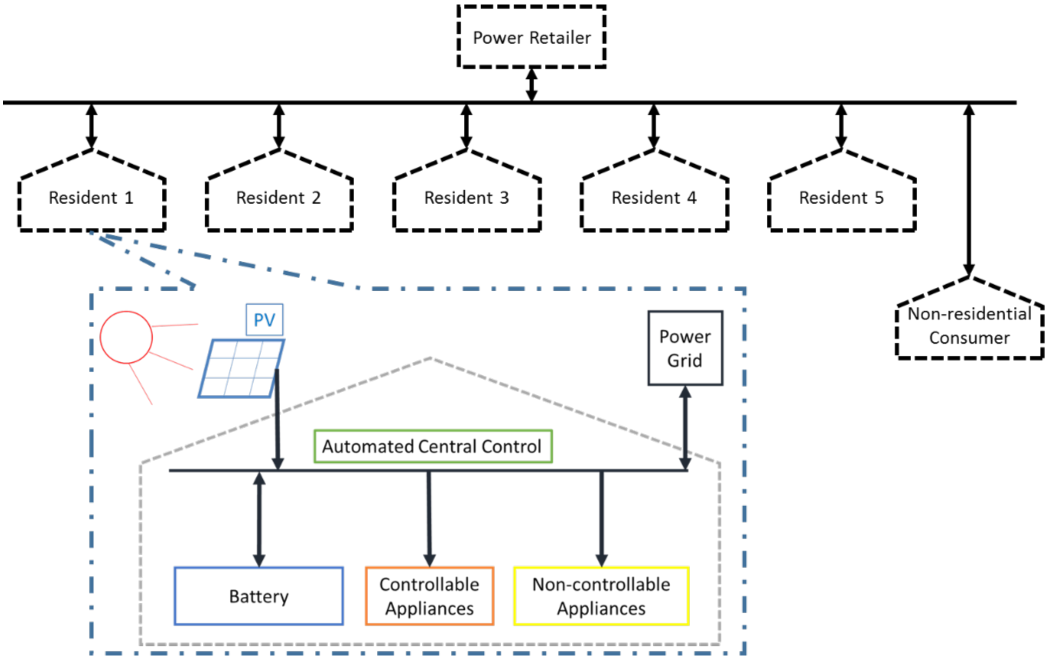

Figure 1 Structure of the target system

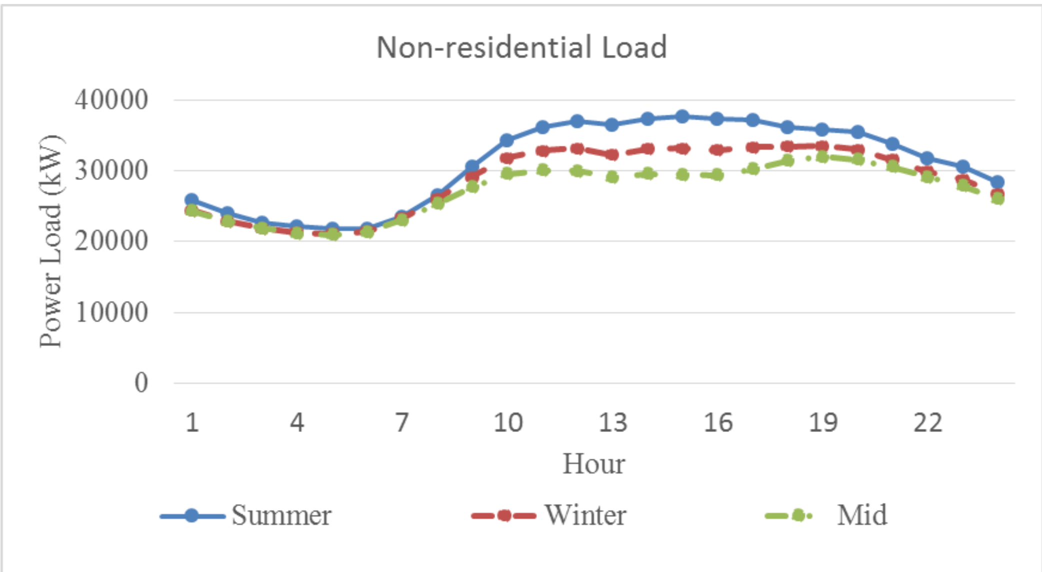

Figure 2 Non-residential electricity load

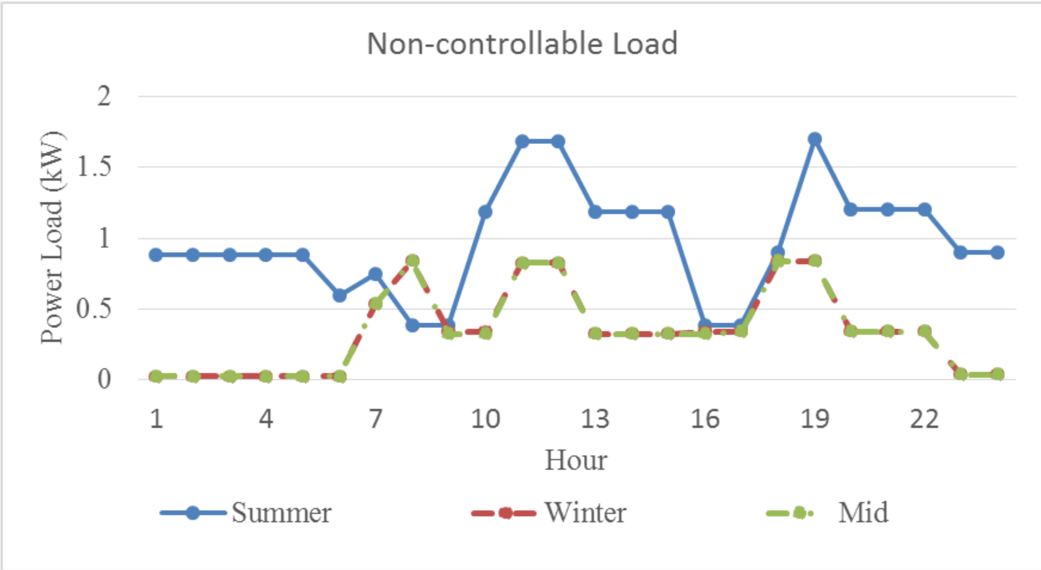

Figure 3 Non-controllable load of one household

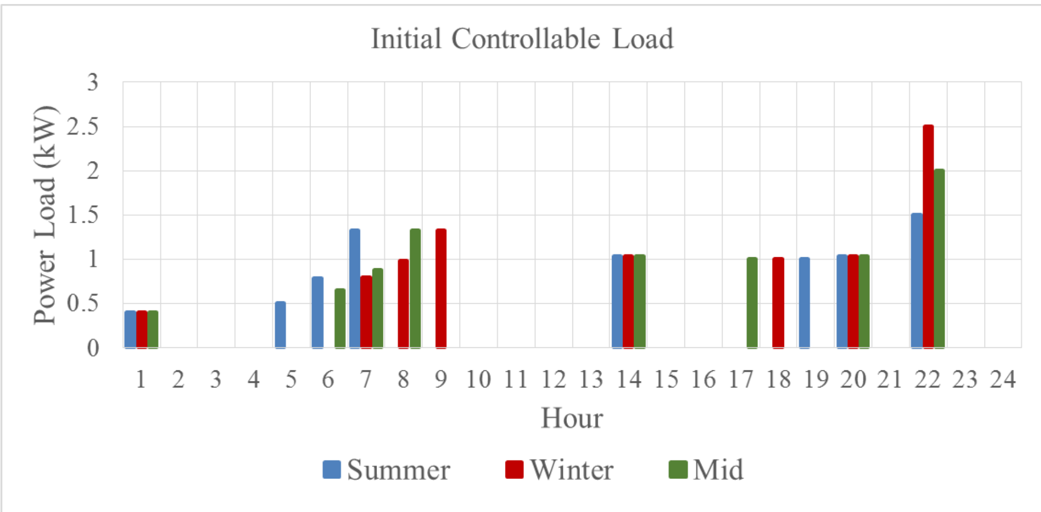

Figure 4 Initial controllable load of one household

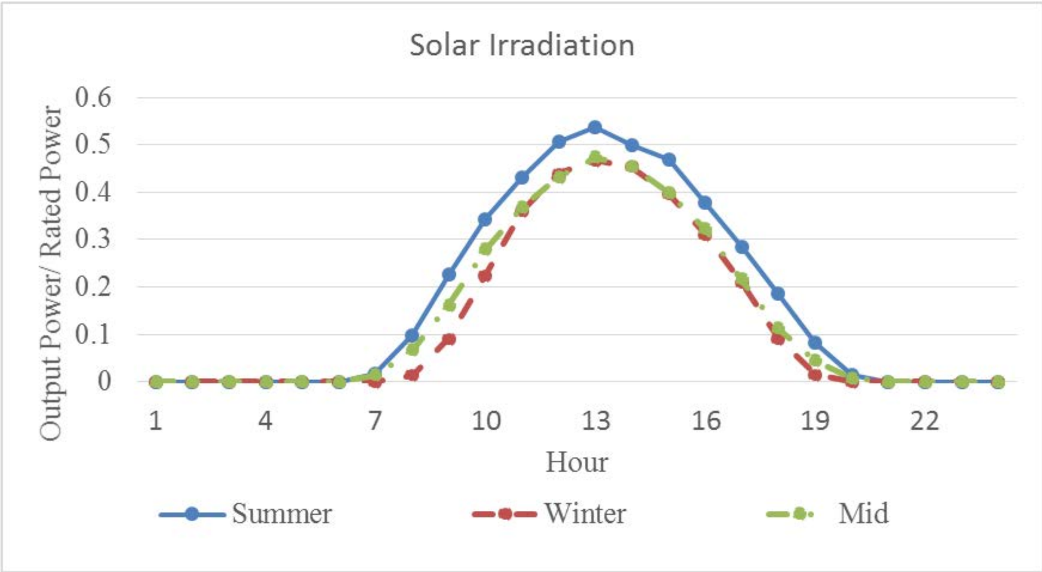

Figure 5 Solar irradiation coefficient in different seasons

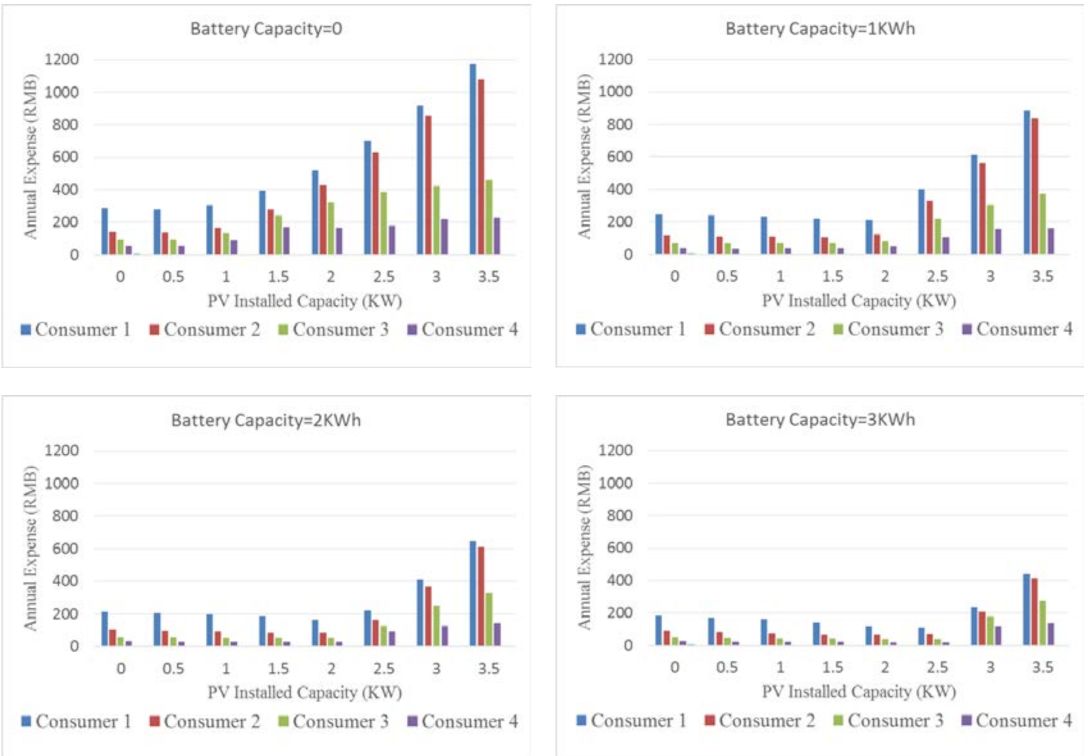

Figure 6 Saved annual electricity power expense of one household comparing to consumer 5 under different PV and battery capacity

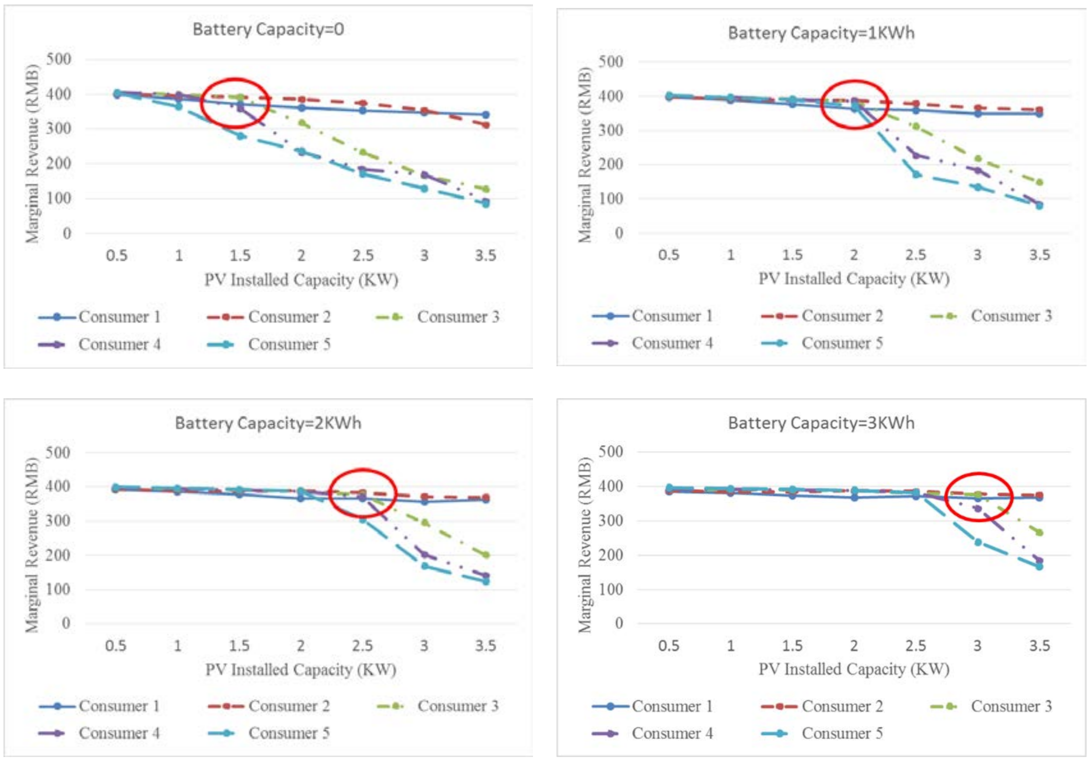

Figure 7 Marginal revenue of new installed PV capacity under different battery capacity

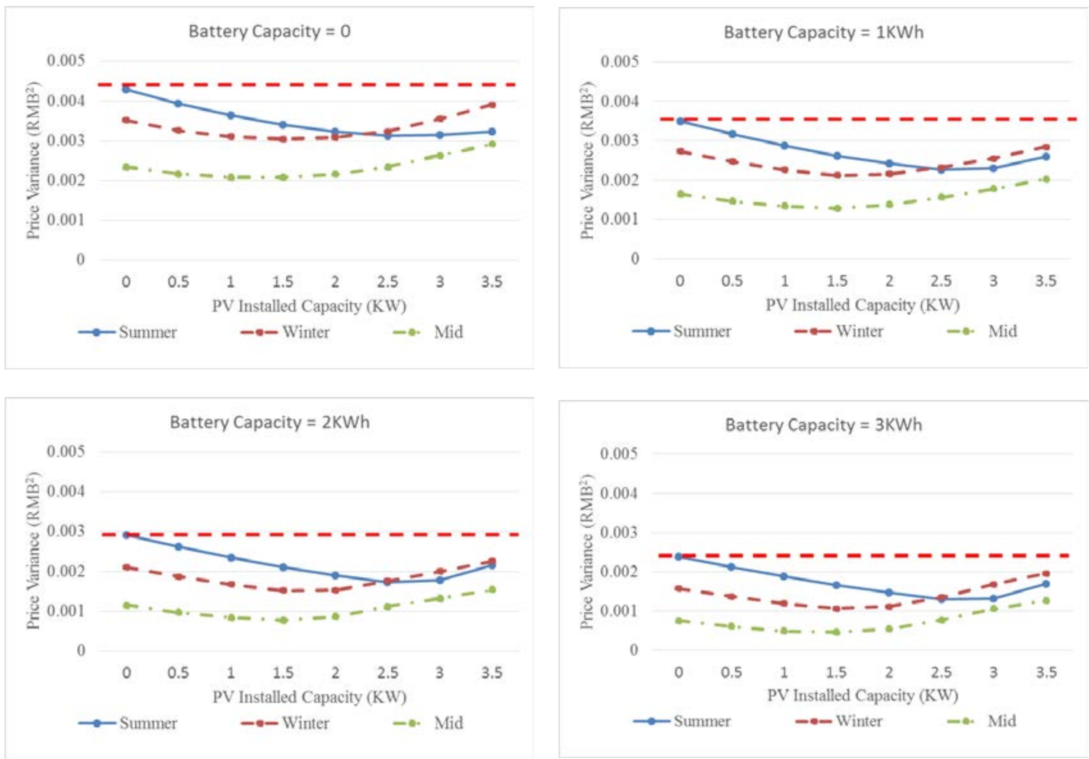

Figure 8 Daily variance of real-time power price under different PV and battery

capacities

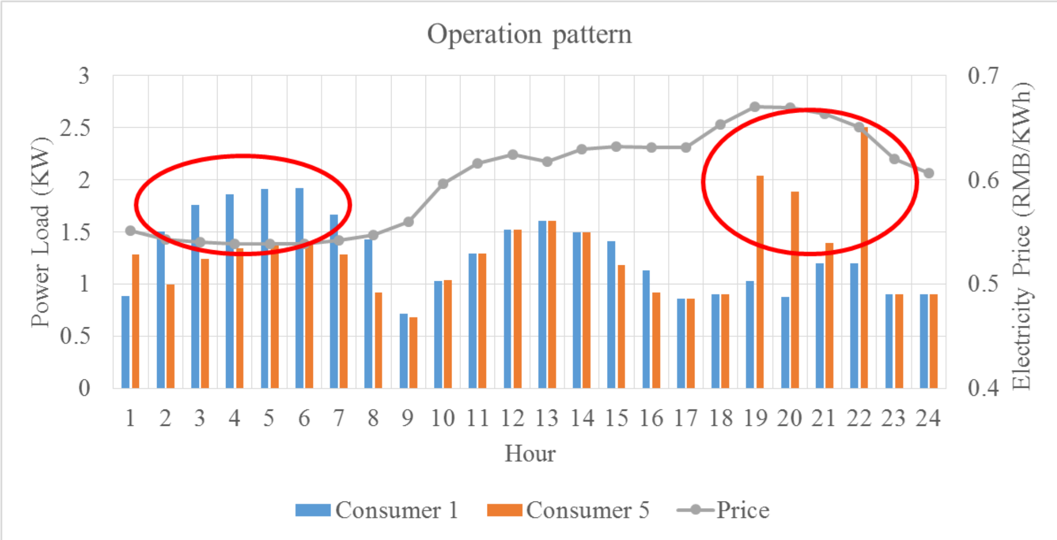

Figure 9 Operation patterns of consumer 1 and consumer 5 in the summer represent day with 1 kWh battery and 3 kW PV

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