# Bidding and Offering Models in Generation-Grid-Load-Storage Transactions Based on Flexible Order Types

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***Abstract*—The increase in the installation of renewable energy generating units brings great challenges to power systems in terms of balancing their intermittence and fluctuation. The concept of the interactive transaction of "Generation-Grid-Load-Storage" is therefore proposed, for exploring the adjustable potential of the decentralized resources, such as the flexible load and energy storage, in China's electricity market reform. To better help these decentralized resources with different characteristics to participate in the electricity market, this paper proposes bidding and offering models based on flexible order types, which are different from those of traditional generating units. First, the hourly curve-based bidding and offering models of wind generating units are developed considering the chronological and stochastic characteristics of their generating capacity and penalty cost. Then, the bidding and offering models of large industrial users and small thermostatically controlled loads are developed based on the utility function and comfort loss, respectively. Moreover, the bidding and offering models of energy storage are developed considering the degradation cost. Finally, numerical examples are performed to validate the proposed models.**

***Keywords—Offering and bidding models, wind generating unit, flexible load, energy storage***

## I. Introduction

With the vision of a low-carbon economy, the world-wide utilization of renewable energies for electricity generation, such as wind and solar, has been greatly promoted. However, the intermittence and fluctuation of renewable energies raise severe challenges for the balance of power systems [1]. In some regions in Jiangsu province, China, owing to the limited balancing resources and capacities of key transmission sections, the spill of wind generation could occur [2]. Therefore, besides the reserve margin of thermal power units, the flexibility and adjustable potential of power systems should be further explored to promote the utilization of renewable energies.

With the development of information and communication technologies and the progressive reform of the electricity market in China, the decentralized demand-side resources both have the will and capability to participate in the electricity market and provide balancing power [3]. Moreover, the development of energy storage technologies and the construction of storage stations can also serve as a new powerful tool. Under this circumstance, the concept of Generation-Grid-Load-Storage (GGLS) has been proposed correspondingly [4]. It aims to intensify the interaction of renewable energy, flexible load, and storage within the transmission capacity of the power grid in a tech-economic way. In Jiangsu province, many demonstration projects on the interaction of GGLS have been carried out, and the adjustable flexible loads reach 2.6 GW till June 2018 [4].

However, there still exists some unneglectable issues in the interactive transaction of GGLS under the current framework of electricity market reform [5]. First, the renewable generations are difficult to predict, and the predicted value in the day-ahead may be far different from that in the ultra-short-term. The generating curve received by the power exchange center is lagged from its updated value, which leaves all the balancing burden on the real-time dispatching. Second, the current trading on the demand-side focuses on the wholesale market and large industrial users. The transaction of decentralized resources and energy storage are far different from generating units and large users, which has a limited duration and capacity. Corresponding offering and bidding mechanisms in the current electricity market in China are still incomplete.

The transaction of GGLS and corresponding bidding and offering of flexible load and storage have been studied recently. A distributed transactive energy trading framework in

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distribution networks was proposed in [6]. The bidding strategy of prosumers was investigated in [7]. Multi-agent-based transactive energy trading methods for microgrids, residential buildings, and energy storage were further developed in [8], [9], and [10], respectively. Optimal offering strategies for wind power in energy and primary reserve markets were proposed in [11]. In these studies, however, the energy seller or buyer only bid in a time-independent manner, such as a fixed cost, or piecewise/polynomial function for a single hour, which cannot reveal the limited and time-dependent adjustable capabilities of flexible load or energy storage.

Nord Pool provides an excellent example for accommodating small volume market participants with flexible order types, such as hourly curve, block order, and exclusive group [12]. The detailed description of different types of orders is referred to the EUPHEMIA Public Description published by Nord Pool[13]. Compared with the regular orders in the wholesale market, the major differences of the flexible orders are that they can contain more detailed information, such as duration, and excicution relations among multiple orders (such as linked, excluded, etc.), so that specific physical characteristics of small volume market participants can be reflected. The day-ahead clearing of the electricity market with adjustable profile blocks with spatial relations considering the network constraints was studied in [12]. The optimal bidding for demand-side with block order was studied in [14] considering the customers' satisfaction. However, these studies focus on the physical characteristics of flexible loads, where the marginal cost of flexible loads is neglected. This is not a straightforward issue, either, because it is multidisciplinary and involves multiple uncertainties.

To tackle this issue, this paper proposes bidding and offering models of renewable generation, flexible load, and storage, considering their different tech-economic characteristics. First, under the uncertainties of wind, the bidding and offering models of wind generating units are developed considering its stochastic power output and corresponding penalty cost. The models are time-independent which can be further fit into hourly curve orders. Then, the offering model of small thermostatically controlled loads (TCL) is developed based on the comfort loss. The thermal dynamics of TCLs are incorporated for evaluating their time-related discomfort cost. Moreover, the bidding and offering models of energy storage are developed considering its degradation cost. Finally, numerical examples are performed to validate the proposed models.

## II. Bidding and Offering Models of Wind Generating Units

The bidding and offering models in the electricity market mainly contain the information of two aspects: volume and price. The volume is constrained by the physical conditions, such as the wind speed, capacity of the energy storage, etc. In a perfectly competitive market, the offering price of the energy producer is close to its marginal cost, and the offering price for an energy consumer is close to its marginal revenue. Consequently, tech-economic assessments of market participants are required for establishing their bidding and offering models.

The offering and bidding models of wind generating units depend on two factors: the available electricity generating capacity and marginal cost. The available electricity generating capacity of the wind generating unit, $GC^{w}$, is a piecewise function depending on the wind speed, denoted as $GC^{w}=f^{w}(v)$ [15].

In the day-ahead market, the wind generating unit submits an electricity generation curve for the next day based on the wind power forecast. Based on the timeframe, the wind forecast in the spot market can be divided into short-term (usually in the day-ahead) and ultra-short-term (in the intraday operation, usually several hours ahead) forecast [16]. The time resolution of the forecast is determined by the time resolution of the transaction and the time resolution in which the wind generating units are assessed, e.g., 30 min. Without losing generality, considering the day-ahead and intraday markets, here we denote the duration of the transaction interval as $\Delta t$. Thus, the number of the period in a day is $24hour/\Delta t=NK$.

Based on the historical data, the wind speed can be clustered into finite states in an ascendant order, $1,...,h,...,NH$. The transition among these states in each transaction period can be modeled as a continuous-time and discrete-state Markov process [17]. Suppose the day-ahead wind forecast is conducted at the beginning of period $k^{DA}$ (set as $t=0$), when the state of wind speed is $h^{DA}$. The probability of wind being in each state in the future, $p_{h}^{DA}(t)$, can be calculated by solving the following set of derivative equations [18]:

$$\begin{cases} \dfrac{dp_{h}^{DA}(t)}{dt}=-p_{h}^{DA}(t)\sum\limits_{h'=1}^{NH,h'\neq h}\lambda_{h,h'}+\sum\limits_{h'=1}^{NH,h'\neq h}p_{h'}^{DA}(t)\lambda_{h',h}, \\ \qquad\qquad\qquad\qquad h=1,2,...,NH \\ p_{1}^{DA}\big|_{t=0}=0,...,p_{h^{DA}}^{DA}\big|_{t=0}=1,...=p_{NH}^{DA}\big|_{t=0}=0 \end{cases} \tag{1}$$

where $\lambda_{h,h'}$ is the state transition rate from state $h$ to $h'$.

Therefore, the electricity generation curve submitted to the power exchange center in the day-ahead for period $k$ in the next day, $P^{w,DA}(k)$, can be calculated as:

$$P^{w,DA}(k)=\sum_{h=1}^{NH}p_{h}((NK-k^{DA}+1+k)\Delta t)f^{w}(\overline{v}^{h}(k)) \tag{2}$$

Suppose the ultra-short-term wind forecast is conducted at the beginning of period $k^{RT}$, $k^{RT}>k^{DA}$, and the wind speed state at that time is $h^{RT}$. The wind speed can be forecast using a similar method, by replacing the boundary condition in (1) by:

$$p_{1}^{RT}\big|_{t=0}=0,...,p_{h^{RT}}^{RT}\big|_{t=0}=1,...=p_{NH}^{RT}\big|_{t=0}=0 \tag{3}$$

where $p_h^{RT}$ is the probability of wind in state $h$ predicted in the ultra-short-term.

The cost of wind generation consists of two major parts: 1) the investment cost, maintaining cost, etc., that are discounted to present value. 2) penalty cost for the inconsistency between the real-time generation and the submitted generation curve in the day-ahead. The first one can be simplified as a fixed cost $C_0^w$ during the operation, while the second one is the main focus of this section.

The penalty cost measured in the ultra-short-term is also a stochastic value because the real-time wind speed is uncertain. The expected available generating capacity forecast in the ultra-short-term $GC^{w,RT}(k)$ can be obtained using (2) with $k^{RT}$ similarly.

When $GC^{w,RT}(k) < P^{w,DA}(k)$, the wind generating unit will purchase electricity from the GGLS market. Otherwise, it will sell electricity to the GGLS market. When the wind generating unit is bidding or offering, the expected penalty cost can be written in a unified form:

$$\begin{aligned}
&c^w(k,\Delta P^{in}(k),\Delta P^{out}(k)) \\
&= \Pr\left\{GC^{w,RT}(k)+\Delta P^{in}(k)-\Delta P^{out}(k)\le P^{w,DA}(k)\right\} \\
&\quad \times\left(P^{w,DA}(k)-GC^{w,RT}(k)-\Delta P^{in}+\Delta P^{out}(k)\right)\mu \\
&\qquad p_h^{RT}(NK-k^{RT}+1+k) \\
&= \sum_{h=1}^{NH} flag\left(P^{w,DA}(k)-\overline{P}_h^w-\Delta P^{in}(k)+\Delta P^{out}(k)\right) \\
&\quad \left(P^{w,DA}(k)-\overline{P}_h^w-\Delta P^{in}(k)+\Delta P^{out}(k)\right)\mu
\end{aligned} \tag{4}$$

where $\Delta P^{in}(k)$ and $\Delta P^{out}(k)$ are the purchased and sold electricity, respectively. $\mu$ is the penalty cost factor. $\overline{P}_h^w = f^w(\overline{v}_h)$ is the electricity generation in state $h$. $flag(x)$ is defined as: $flag(x)=1$ when $x>1$, $flag(x)=0$ when $x\le 0$.

The bidding model of wind generating unit is following its reduced cost when $\Delta P^{in}(k)$ increases:

$$\begin{aligned}
B^w(k,\Delta P^{in}(k)) &= -\frac{\partial c^w(k,\Delta P^{in}(k),\Delta P^{out}(k))}{\partial \Delta P^{in}(k)}\Big|_{\Delta P^{out}(k)=0}-C_0^w, \\
&\qquad 0\le \Delta P^{in}(k)\le P^{w,DA}-\overline{P}_1^w
\end{aligned} \tag{5}$$

where $\overline{P}_1^w = f^w(\overline{v}_1)$.

Similarly, the offering model of the wind generating unit is its increased cost when $\Delta P^{out}(k)$ increases:

$$\begin{aligned}
F^w(k,\Delta P^{out}(k)) &= \frac{\partial c^w(k,\Delta P^{in}(k),\Delta P^{out}(k))}{\partial \Delta P^{out}(k)}\Big|_{\Delta P^{in}(k)=0}+C_0^w, \\
&\qquad 0\le \Delta P^{out}(k)\le \overline{P}_{NH}^w
\end{aligned} \tag{6}$$

where $\overline{P}_{NH}^w = f^w(\overline{v}_{NH})$.

Due to the discontinuity of the wind states, the $B^w$ and $F^w$ is also apparently a piecewise function. Therefore, the optimal strategy of the wind generating unit in the GGLS market is to submit an hourly curve in the form of a piecewise function.

## III. Bidding and Offering Models of Flexible Loads

The offering and bidding models of flexible loads vary from sector to sector. In this paper, we focus on the decentralized TCL of relatively small volumes, where the duration and capacity for them to adjust the energy consumption are very limited.

The marginal cost of TCLs when reducing the electricity consumption is evaluated as the user's comfort loss $c^{TCL}$ [19]:

$$c^{TCL}(T) = \sigma PPD(T) \tag{7}$$

where $T$ is the temperature. $\sigma$ is a constant coefficient that transforms the percentage of dissatisfaction to the comfort loss. $PPD$ is the Predicted Percentage of Dissatisfied (PPD) model, which is often used to describe the percentage of users' comfort loss. The specific formulation can be found in [19].

Assume the temperature is initially set to their most comfortable value $T_{set}$, where $\frac{dPPD(T)}{dT}\Big|_{T=T_{set}}=0$. Then, we only have to consider the offering of TCLs, for the increase in electricity consumption can no longer bring them additional comfort benefit. Also, assume the current season is summer, and the air condition (AC) operates in the cooling mode. If the TCL chooses to sell electricity, the setting temperature will be turned up. In the next tens of minutes, the temperature in the building gradually increases to the ambient temperature. This thermodynamic process can be expressed as [3]:

$$\begin{cases} c_A\rho_A V\dfrac{dT}{dt} = KA(T_{am}-T)-(P_{AC}^{DA}-\Delta P^{out})COP \\ T\big|_{t=0} = T_{set} \end{cases} \tag{8}$$

where $c_A$ and $\rho_A$ are the heat capacity and density of air. $V$ is the volume of the room. $P_{AC}^{DA}$ is the electric power of AC. $COP$ is the coefficient of performance, quantifying the efficiency of the AC to convert electricity to cooling. $K$ is the heat transfer coefficient. $A$ is the surface area of the wall that is exposed to the outside. $T_{am}$ is the ambient temperature.

Substitute the solution of (8) $T(t)$ into (7), then the comfort loss is a function of both $t$ and $\Delta P^{out}$, $c^{TCL}(t,\Delta P^{out})$.

According to the TCL's different requirements for the temperature, two cases are considered.

1) Suppose the TCL has an up limit for the temperature, $T_{\max}$, $T_{\max}\ge T_{am}$, or the TCL does not have any requirement for the temperature.

In this case, the AC can be shut down permanently. Under the current flexible order types in the NordPool, the TCL can bid using linked curve order or block order in an exclusive group with minimum income condition.

Considering the discretized transaction period, in the period $k$, the offering model can be described as:

$$F^{TCL}(\Delta P^{out}) = \frac{d\int_{(k-1)\Delta t}^{k\Delta t} c^{TCL}(\tau, P_{AC}^{DA} - \Delta P^{out}) d\tau}{d\Delta P^{out}}, \quad 0 \le \Delta P^{out} \le P_{AC}^{DA} \tag{9}$$

Regardless of the specific form of (9), it can be approximate into a piecewise linear function or a polynomial function.

2) $T_{\max} \le T_{am}$ . Then, the adjustment of TCL has a time limit $D_{\max}$ , which is the solution of $t$ in:

$$T(t) = T_{\max} \tag{10}$$

The offering model is similar with (9), except that the duration of linked curve order or block order should not exceed $D_{\max}$ , $0 \le D \le D_{\max}$ , where $D$ is the length of the linked curve order or block order.

## IV. Bidding and Offering Models of Energy Storages

The charging and discharging will cause the gradual degradation of energy storage. The lifetime of the lithium-ion battery is relatively short, and thus the battery degradation cost is the major cost for energy storage. When participating in the energy transactions, the irregular charge and discharge will be more frequent, and thereby the degradation cost will be more unneglectable [20]. The degradation of the battery is related to many factors, such as circle depth, average state of charge, current rate, ambient temperature, etc. [21]. Here we focus on the impact of circle depth, for the impacts of other factors can be appropriately managed [9]. Take the discharge process as an example, the increase in cycle depth $\Delta\delta$ can be written as [21]:

$$\Delta\delta = \Delta P^{out} \Delta t / (\eta^{dis} E) \tag{11}$$

where $E$ is the capacity of the energy storage. $\eta^{dis}$ is the discharge efficiency.

The cycle life loss $\Phi$ is a function of $\delta$ [22]:

$$\Phi(\delta) = (5.24 \times 10^{-4})\delta^{2.03} \tag{12}$$

Suppose the cycle depth before the transaction is $\delta_0$ . During a transaction period $\Delta t$ , the energy storage discharges at $\Delta P^{out}$ . Then, the degradation cost from this transaction is:

$$c_{dg} = C_{ES} \frac{\Delta P^{out} \Delta t}{\eta^{dis} E} \frac{\eta^{dis} E \int_{\delta_0}^{\delta_0 + \frac{\Delta P^{out}\Delta t}{\eta^{dis} E}} \Phi(\delta) d\delta}{\Delta P^{out} \Delta t} \tag{13}$$

where $C_{ES}$ is the placement cost of the energy storage.

Besides the replacement cost, the marginal cost in the offering also includes the energy cost. It is assumed as the electricity purchasing cost in the day-ahead market. Then, the total cost in the offering model is:

$$c^{ES} = c^{dg} + \Delta P^{out} \Delta t \rho^{DA} \tag{14}$$

where $\rho^{DA}$ is the electricity price in the day-ahead market.

$\delta_0$ is a constant determined before the transaction. In each transaction period, the offering model is a function of $\Delta P^{out}$ :

$$F^{ES}(\Delta P^{out}) = \frac{dc^{dg}(\Delta P^{out})}{d\Delta P^{out}} + \Delta t \rho^{DA}, \quad 0 \le \Delta P^{out} \le P_{\max}^{out}, 0 \le D \le \frac{E \times SOC_0 \eta^{dis}}{\Delta P^{out}} \tag{15}$$

where $SOC_0$ is the state of charge (SOC) of the energy storage before the transaction.

The charging process is similar. The bidding model can be calculated by replacing the $\Delta P^{out}$ and $\eta^{dis}$ in (13) with $\Delta P^{in}$ and the charging efficiency, $\eta^{ch}$ , respectively:

$$B^{ES}(\Delta P^{in}) = \Delta t \rho^{DA} - \frac{dc^{dg}(\Delta P^{in})}{d\Delta P^{in}}, \quad 0 \le \Delta P^{in} \le P_{\max}^{ch}, 0 \le D \le \frac{E(1 - SOC_0)}{\Delta P^{in} \eta^{ch}} \tag{16}$$

The offering and bidding model can also be fitted into a polynomial or piecewise function. Similarly, under the current flexible order types in the NordPool, the energy storage can bid or offer using linked curve order or block order in an exclusive group with minimum income condition.

## V. Case study

Three cases are studied to validate the proposed bidding and offering models for wind generating units, flexible loads, and energy storage, respectively. The transaction period was set to $\Delta t = 30\,\text{min}$ , and thus the number of transaction period is $NK = 48$ .

### A. Bidding and Offering Models of Wind Generating Units

The wind speed data were acquired from the past ten years' historical data in Texas, the US, from the National Oceanic and Atmospheric Administration (NOAA). The wind speed is clustered into eight states. The wind generating unit consists of 100 Vestas V-80 wind turbines with 2 MW rated power, and the parameters are referred to [23]. The short-term wind forecast is conducted at the opening time at NordPool (8:00). The object of the transaction is the electricity at 12:00 on the next day. The ultra-short-term wind forecast is conducted 1.5 hours before the real-time (10:30). $h^{DA} = 4$ . $\mu = 30$ \$/MWh [24].

After solving the derivative equations in the day-ahead forecast, the expected electricity generation can be obtained, which is 94.66 MW. According to different $h^{RT}$ , the wind generating unit will take different actions. When $h^{RT} \in \{1,2,3,8\}$ , it will purchase electricity from GGLS market. Otherwise, it tends to sell electricity to the GGLS market. This is because, for example, when $h^{RT} = 8$ , the wind speed in real-time is more likely to exceed the cut-out speed, and therefore the wind turbine will have to shut down.

The bidding and offering curve with different $h^{RT}$ is presented in Fig. 1. We can find that with the increase in the transaction volume, the price of the bidding decreases while the price of the offering increases. This is because when the wind generating units are selling the electricity, the more they sell, the more likely they can not meet the generation curve that submitted in the day-ahead. Vice versa for the offerings.

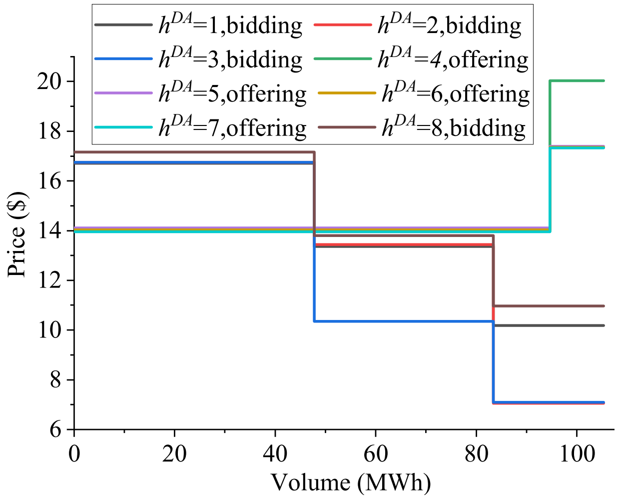


Fig. 1. Bidding and offering of wind generating units.

## B. Bidding and Offering Models of Flexible Loads

The PPD of the TCL is fitted as a quadratic function $PPD(T) = 0.7022T^2 - 33.58T + 406.4$ [19]. $c_A$ =1.005 kJ/℃, $\rho_A$ =1.205 kg/m³, $K$ =7.69 $W/℃\cdot m^2$ , $T_{am} = 30℃$ , $COP = 4$ [3]. $T_{set} = 24℃$ .

For a small residential user, $V = 250m^3$ , $A = 100m^2$ . Then, to keep the balance between the heat gain and loss, $P_{AC}^{DA} = KA(T_{am} - T)/COP$ =1171 W.

The analytical solution of time-varying temperature can be obtained:

$$T(t) = 0.0052\Delta P^{out} - (0.0052\Delta P^{out})e^{0.00254t} + 23.91 \quad (17)$$

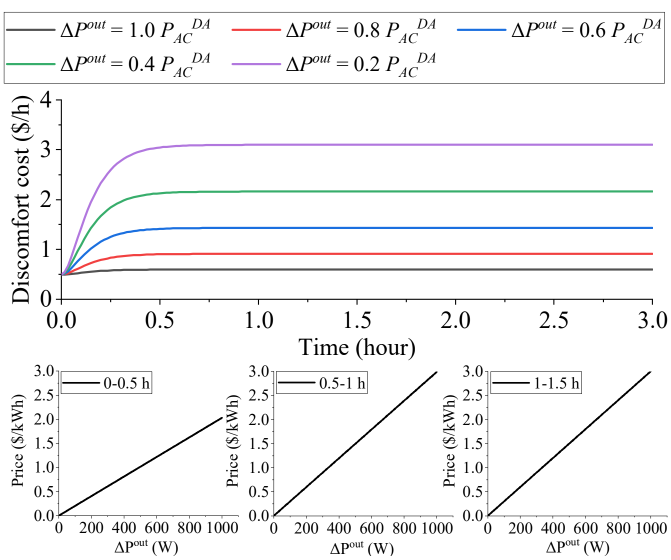


Fig. 2. Offering of TCLs.

The offering curve in each transaction period is shown in Fig. 2. As we can see, the discomfort cost will increase over time. After more than half an hour, the discomfort cost stabilizes. This pattern indicates that the offering price of TCL also increases over time. During 0-0.5 h, the marginal offering price for 1 kW at its maximum capacity is 2.03 $/kWh. While during 1.0-1.5 h, the marginal offering price for 1 kW at its maximum capacity is 3.00 $/kW, increased by 47.78%. Therefore, it can be seen that the small TCLs of residential users are not so cost-efficient when the requirement for capacity is large.

## C. Bidding and Offering Models of Energy Storages

The parameters are the energy storage is listed as follows [20]: 1) rated charging and discharging power is 20 MW; 2) energy capacity is 12.5 MWh; 3) charging and discharging efficiency is 0.95; 4) replacement cost is 300000 $/MWh. 5) the SOC of the battery is 50% before the transaction. The electricity price in the day-ahead market is 40 $/MWh.

The offering and bidding strategies of the energy storage are presented in Fig. 3. We can find that with the increase of time and volume of the transaction, the marginal cost increases significantly. This is because the charging/discharging power and duration will have influences on the cycle depth, and further affect the life cycle loss of the energy storage. Besides, we can find in the bidding curve that only when the cycle depth is strictly controlled (perhaps by the energy management software), the energy storage can benefit from the GGLS market transactions (The negative bidding price mean that the energy storage can benefit).

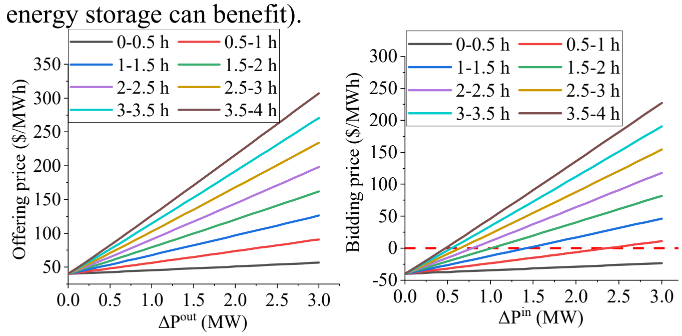


Fig. 3. Offering and bidding of energy storages.

## VI. Conclusions

With the reform of the electricity market in China, decentralized resources, such as flexible loads and energy storage, become more important in balancing the fluctuation of renewable generations. The bidding and offering models of these resources are therefore developed based on flexible order types in this paper, to better explore their adjustable potential and marginal cost. From the numerical studies, we find that the bidding and offering of these decentralized resources are different from traditional large generating units. Considering the stochastic characteristics of wind generating units, the bidding and offering can be regarded as independent for each transaction period, in the form of piecewise linear functions. For TCLs, the discomfort cost increase over time due to the thermal dynamic model, and thus the offering curve for each transaction period should be linked. For energy storage, strict energy management and the control of depth of charge are the prerequisites for profiting. The bidding and offering orders for each transaction period should also be linked.

With the quantitative bidding and offering models developed in this paper, the market participant that owns these decentralized resources can better profit in the spot market. Moreover, the transactions in the GGLS market also benefits the power systems in return.

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