Benefit Models and Optimization Clearing Model for Participants in Cloud Energy Storage

Yanzheng Wu1,*, Junpeng Zhu1 and Yue Yuan1
1College of Energy and Electrical Engineering, Hohai University, Nanjing, China
*673500904@qq.com

Abstract. Energy storage can smooth the fluctuation of renewable energy sources and has the characteristic of flexibility, which makes it an important dispatching resource in distribution network. In order to promote the consumption of renewable energy sources and the reasonable configuration of energy storage resources, this paper expands the basic concept of cloud energy storage and puts forward an operation mechanism involving customers, distributed generation operators and the cloud energy storage operator. According to the commercial mode described, we analyze the benefits of the three parties, establish the opportunity cost model on the consumer side and the benefit models of the three parties. Then we propose the energy storage scheduling strategies, use an optimal scheduling model to solve the pricing and clearing problems of cloud energy storage and solve it with the multi-object searching algorithm based on particle swarm optimization algorithm. At last, the case study shows that the method proposed can effectively improve the overall benefits of cloud energy storage participants on the basis of satisfying the load demand of the customers and ensuring the profitability of distributed generation operators.

1. Introduction
The United Nations Framework Convention on Climate Change has made urgent recommendations to increase the penetration of renewable energy sources (RES) in the electricity market to 20% by 2022. To achieve a universal energy supply by 2030, the International Energy Agency plans to add 470TWh of RES to the grid to replace 368TWh of fossil fuels [1]. As a potential source of flexibility, energy storage can provide various ancillary services to the generation side and the demand side across multiple time scales [2], and help improve the reliability and stability of power supply. In addition, wind speed and light intensity are naturally random and intermittent, which will not only lead to apparent change on real-time electricity price [3], but will also directly lead to the fluctuation of output power of some distributed generation systems. These fluctuations also need to be smoothed by large-scale energy storage systems. This brings economic opportunities for energy storage operators, especially through energy arbitrage [4]. But the cost of energy storage is still high currently, which limits the widespread application of distributed energy storage [5].

In 2015, the Central Committee of the Communist Party and the State Council of China issued document no. 9 on deepening the reform of electric power system, calling for the orderly liberalization of electricity prices in competitive sectors other than power transmission and distribution, the orderly liberalization of power distribution to private capital, and the orderly liberalization of power generation plans other than those for public benefit and regulation. In order to respond to the central government's policies and promote the development of the economic benefits of energy storage, it is
necessary to constantly improve the relevant market mechanisms or find appropriate business models. Literature [5] briefly introduces the operation mechanism and business models of CES, and puts forward the basic research framework from three main lines of operation, object and market. It also proposes the basic models of consumers and the CES operator. Literature [6] introduces the concept of cloud energy storage (CES), that is, centralized energy storage facilities providing distributed storage services for commercial and industrial consumers. It proves the feasibility and economic benefits of CES by using residential load and power data in real life. Literature [7] describes key issues such as how CES should be invested, planned and run, and how CES services should be priced. It summarizes the current research progress of CES and forecasts the future research. Literature [8] studies the annual investment operation cost model of CES participants.

However, the existing operation mechanism involves only consumers, the CES operator, energy storage facilities and power grids, while ignoring a large number of distributed generation operators (DGOs). Most of the established models are in the stage of basic analysis, and optimization models are rare. The potential benefits and opportunity cost of energy storage are not considered in the models of the consumers. Potential benefits of energy storage in electricity markets can be divided into two aspects, the energy capacity and power capacity except for arbitrage through electricity price difference. It can also be arbitrated by time shifts in RES, by reductions in demand and time-of-use charges, by delays in power transmission and distribution upgrades, and by improvements in the resilience of the grid [9].

The contributions of this paper mainly lie in the following aspects:

1) Expanding the range of CES application consumers based on the original concept, and putting forward the CES operation mechanism with the participation of DGOs.

2) The opportunity cost on the consumer side is defined. The potential benefits of DGOs and the benefit sources of the CES operator are described. The benefit analysis models of three parties are established respectively.

3) Energy storage scheduling strategies on the consumer side and the distributed generation side are described, and a CES optimal scheduling model is proposed.

The rest of this article is as follows. Section II describes the operation mechanism. Section III proposes the benefit analysis models of the three parties. Section IV describes the energy storage scheduling strategies and proposes the optimization clearing model. Section V presents the case study based on actual data. Section VI is the summary and outlook.

2. Operation mechanism

There is a large amount of distributed energy storage which is held by dispersed consumers in the distribution network with a high proportion of RES. After the introduction of the concept of cloud energy storage, these dispersed consumers will be orderly organized. Acting as their agents, the CES operator can communicate and trade with the grid at this point. On the one hand, the CES operator can promise to help DGOs consume RES, to reduce wind and solar curtailment. At the same time, it can reduce the benefit loss of overall energy storage and improve the utilization of energy resources. On the other hand, it can provide DGOs and consumers with new trading platforms and trading channels, improve the bargaining power of these retail investors, meet their electricity demand and ensure a certain income.

The CES operation mechanism includes three interest subjects. They are the CES operator, consumers and DGOs. The consumers here include energy storage facilities, ordinary industrial and commercial consumers and residential consumers. During the day-ahead operation, consumers need to provide the CES operator with information about their own load demand, the state of energy storage facilities, as well as energy storage capacity available for lending. DGOs should provide the CES operator with information about the output curves of RES and the amount of energy storage capacity they need to borrow. The CES operator need to obtain real-time electric price from the energy market and forecast energy clearing prices from the ancillary services market. After obtaining such information, the CES operator should generate the energy storage scheduling strategies, then decide
the optimal capacity and unit price to be traded. Decision variables in this paper include the energy capacity that needs to be traded during the day, the unit price of capacity that consumers lend, and the unit price of capacity that the CES operator redistributes to DGOS.

All consumers can directly trade with DGOS through the software interface of CES and do not have to obtain energy through the distribution network. However, before the transaction, DGOS need to sign a long-term strategic cooperation agreement with the power grid. And a part of their profits must be shared with the power grid. The profit sharing of CES will be further discussed in the future. The advantage of the operation mechanism is that it can change the disordered consumers into orderly consumers to form an interaction between buyers and sellers under the guidance of price, meanwhile, promote the consumption of RES and reasonable configuration of energy storage.

3. Participants benefit analysis and modeling

3.1. Consumer-side benefit model

3.1.1. Definition of opportunity cost of energy storage. The consumer-side opportunity cost refers to the difference between the benefits of lending the energy storage and the benefits of not lending the energy storage. This requires exploring what consumers would do with this part of capacity. Their load demand needs to be prioritized when discharging, but not when charging. If the energy capacity does not exceed their load demand, the opportunity cost is equal to the wheeling charges saved by the consumers in obtaining the electricity from the grid. If the energy capacity exceeds their load demand, the opportunity cost will not only include the wheeling charges, but also include the revenue earned from participating in the ancillary services market by using surplus energy capacity in excess of their load demand. This paper only discusses the arbitrage of energy capacity.

3.1.2. The opportunity cost model.

\[
g_{\text{con}} = \begin{cases} 
M(P_{\text{ESS}}) & 0 < X_{\text{ESS}} \leq d, P_{\text{ESS}} > 0 \\
M(P_{\text{ESS}}) + \pi(X_{\text{ESS}} - d) & X_{\text{ESS}} > d, P_{\text{ESS}} > 0 \\
M(P_{\text{ESS}}) + \pi(X_{\text{ESS}}) & P_{\text{ESS}} < 0 
\end{cases}
\]  

(1)

\[
M(P_{\text{ESS}}) = P_{\text{ESS}} \cdot \Delta t \cdot C_{\text{con}}
\]  

(2)

\[
\pi(X_{\text{ESS}} - d) = \pi_{\text{rc}}(X_{\text{ESS}} - d) + \pi_{\text{g}}(X_{\text{ESS}} - d)
\]  

(3)

\[
\pi_{\text{rc}}(X_{\text{ESS}} - d) = (X_{\text{ESS}} - d) \cdot p_{\text{rc}}
\]  

(4)

\[
\pi_{\text{g}}(X_{\text{ESS}} - d) = c\% \cdot (X_{\text{ESS}} - d) \cdot p_{\text{g}}
\]  

(5)

\(P_{\text{ESS}}\) is the output power of the energy storage facility. If \(P_{\text{ESS}}\) is positive, the energy storage facility is discharging. If \(P_{\text{ESS}}\) is negative, the storage facility is charging. \(M\) stands for the wheeling charges. \(g_{\text{con}}\) is the opportunity cost. \(\pi\) stands for the earnings from participation in the ancillary services market. \(X_{\text{ESS}}\) is the energy capacity the consumers would like to lend. \(C_{\text{con}}\) is the unit price of electricity set by the grid for consumers. \(d\) is the customers’ load demand. \(\pi_{\text{rc}}\) refers to the reserve capacity benefits of participating in ancillary services market, and \(p_{\text{rc}}\) is the unit price of the reserve capacity. \(\pi_{\text{g}}\) refers to the earnings of reserve generation, and \(p_{\text{g}}\) is the unit price of the capacity for reserve generation [10]. \(c\%\) is the proportion of generation reserve capacity to reserve capacity.
3.1.3. Benefit model. The customers’ benefit is equal to the service fee that CES operator pays minus the opportunity cost of the energy capacity lent. The benefit model of the customer side is as follows:

\[ B_{\text{con}} = f_{\text{con}} - g_{\text{con}} - h_{\text{con}} \]  

(6)

\[ f_{\text{con}} = X_{\text{ESS}} \cdot C_X \]  

(7)

\[ B_{\text{con}} \] is the benefit of consumers, and \( f_{\text{con}} \) is the rental that customers receive from the CES operator. \( C_X \) is the unit price of the energy capacity traded between customers and the CES operator. \( h_{\text{con}} \) is the money that rewards DGOs. If DGOs return the energy storage within a specified period and our customers find that the energy capacity in the energy storage facility is more than the amount before they lent, our customers should give DGOs some incentives.

\[ h_{\text{con}} = \alpha \cdot (E_0 - E_f) \cdot MCP \]  

(8)

\( E_0 \) refers to the initial energy in energy storage facilities. \( E_f \) refers to the energy left in storage facilities at the end of the lease term. \( \alpha \) is the penalty factor. \( MCP \) is the market clearing price.

3.2. Distributed-generation-side benefit model

3.2.1. Definition of the potential profit. The potential profit of DGOs is the difference between the profits they can make from borrowing the energy capacity and not borrowing the energy capacity. This depends on what they do with the capacity. As mentioned in the above operation mechanism, DGOs can use energy storage to absorb redundant wind and solar energy when the grid restricts generation. So DGOs’ potential profit is what they get when they upload the power to the grid. The model is shown below.

\[ g_{\text{DG}} = X_{\text{ESS}} \cdot C_{\text{DG}} \]  

(9)

\( C_{\text{DG}} \) is the unit price of electricity set by the grid for distributed generation. \( g_{\text{DG}} \) is DGOs’ potential profit.

3.2.2. Benefit model. The benefit of DGOs is equal to their potential profit minus the cost. The benefit model for DGOs is shown below.

\[ B_{\text{DG}} = P_{\text{DA}} \cdot C_{\text{DG}} - X_{\text{ESS}} \cdot C_Y - h_{\text{DG}} \]  

(10)

\[ h_{\text{DG}} = \beta \cdot (E_0 - E_f) \cdot MCP \]  

(11)

\( B_{\text{DG}} \) refers to the benefits of DGOs, and \( C_Y \) is the unit price of the energy capacity traded between DGOs and the CES operator. \( P_{\text{DA}} \) is the output power of day-ahead scheduling by DGOs. \( h_{\text{DG}} \) here is the money that compensates for the customers, and \( \beta \) is the penalty factor. If the customers find that the energy capacity in the energy storage facility is less than the amount before they lent, the DGOs should give our customers some compensation.

3.3. Overall benefit model

The benefits of CES operators is shared from the overall benefits of consumers and DGOs. So, to some extent, it ensures its own operating income. The overall benefit model is as follows.

\[ B_{\text{ALL}} = B_{\text{con}} + B_{\text{DG}} \]  

(12)
$B_{CES} = a\% \cdot B_{ALL}$ \hspace{1cm} (13)

In this paper, the benefits of CES operators discussed are all based on the assumption that $a\% = 1$. We just discuss the profits here, and the problem of how the overall benefit should be split will be taken as a future study.

3.4. Constraint conditions

The constraint conditions include the constraints on the charge and discharge power of energy storage, the constraints on the capacity of energy storage facilities, the constraints on various prices and the constraints on the reward and punishment factors. We can put them as follows.

\[
\begin{align*}
SOC_{\text{min}} & \leq SOC_i \leq SOC_{\text{max}} \\
E_t &= (1 - S)E_{t-1} + \Delta t(\eta^C P_{\text{ESS},t} - \frac{P_{\text{ESS},t}}{\eta^D}) \\
E_{\text{min}} & \leq E_t \leq E_{\text{max}} \\
0 < X_{\text{ESS}} & \leq X_{\text{max}} \\
X_{\text{max}} &= E_{\text{max}} - E_{\text{min}} \\
-P_{\text{max}} & \leq P_{\text{ESS},t} \leq P_{\text{max}} \\
C_{\text{con}} & > C_{\text{DG}} \\
C_X & > C_Y \\
B_{\text{con}} & > 0 \\
B_{\text{DG}} & > 0 \\
1 & \leq \alpha \leq 1.1 \\
0.9 & \leq \beta \leq 1
\end{align*}
\]

(14)

The variable $SOC_i$ is the state of the energy capacity at time $t$. The variable $\eta^C$ is the charging efficiency, and the variable $\eta^D$ is the discharging efficiency. $P_{\text{max}}$ is the maximum charge-discharge power. The $E_{\text{max}}$ is the maximum energy capacity. $X_{\text{max}}$ is the maximum capacity the customers lend. The rest variables were explained earlier.

4. Energy storage scheduling strategies

4.1. Energy storage scheduling strategy on the customer side

When the real-time electricity price $\lambda_i$ is greater than the critical electricity price of discharging $\lambda_D$, if $SOC_{\text{min}} < SOC_i < SOC_{\text{max}}$, lend out all the storage capacity. Set the increase speed of the output power of the energy storage facilities as proportional to the absolute value of the difference between the real-time price and the critical price of discharging. Then cyclically optimize $P_{\text{ESS},t}$ to discharging state, and minimize $SOC_i$ when $\lambda_i$ tends to the maximum.

When $\lambda_i$ is not lower than the critical price of charging $\lambda_C$ and not higher than $\lambda_D$, if $SOC_{\text{min}} < SOC_i < SOC_{\text{max}}$, part of the storage capacity can be lent. If $SOC_i < 5.5$, set the increase speed as proportional to the absolute value of the difference between $\lambda_i$ and $\lambda_C$. Then cyclically optimize $P_{\text{ESS},t}$ to charging state. Otherwise, set the increase speed as proportional to the absolute value of the difference between $\lambda_i$ and $\lambda_D$. Then cyclically optimize $P_{\text{ESS},t}$ to discharging state.
When $\lambda_i$ is lower than $\lambda^c_C$, if $SOC_{min} < SOC_i < SOC_{max}$, the customers can choose not to lend any capacity. Set the increase speed of the output power of the energy storage facilities as proportional to the absolute value of the difference between $\lambda_i$ and $\lambda^c_C$. Then cyclically optimize $P_{ESS,t}$ to charging state, and maximize $SOC_i$ when $\lambda_i$ tends to the minimum.

4.2. Energy storage scheduling strategy on the DGO side

According to the changing trend of real-time electricity price, 24h of a day can be divided into peak period and non-peak period. We can calculate the mean value of real-time electricity price, set the time period when the real-time electricity price is higher than the mean value as the price peak period, and the rest as the non-peak period.

During the non-peak period, according to the real-time electricity price and the output characteristics of RES, DGOs should borrow energy storage from CES operators to absorb the RES, alleviate the wind and light curtailment, and integrate the remaining RES into the grid. The goal is to, in turn, maximize the energy storage capacity during all non-peak periods. During the peak period, due to the high real-time electricity price, DGOs can use energy storage to connect to the grid and discharge to make up for the lack of RES output, while maximizing its own benefits. The calculation method of the output power of day-ahead scheduling is as follows.

$$P_{tot}(t) = \min\{P_{w}(t) + P_{ESS}(t), P_{s}(t) + P_{ESS}(t)\}$$

$$0 \leq P_c(t) \leq \min\{P_{w}(t), P_{s}(t), \frac{E_{max}}{t} - \frac{E_{t-1}}{t}, P_{max}\}$$

$$0 \leq P_d(t) \leq \min\{\frac{E_{t-1}}{t} - \frac{E_{min}}{t}, P_{max}\}$$

The variable $P_{w}(t)$ is the wind power output at time $t$. The variable $P_{s}(t)$ is the solar power output at time $t$. Equation (16) is the charging power constraint. Equation (17) is the discharging power constraint.

4.3. Optimization Clearing Model

In this paper, a two-layer optimal scheduling model is used to solve the day-ahead pricing and clearing problems of cloud energy storage at one time. The outer goal is to maximize the overall benefit. The inner layer has two sub-goals, which are to maximize the benefits of customers and maximize the benefits of DGOs. In order to speed up the overall optimization, we replaced the inner optimization with the above two strategies and turned it into pure computing work.

$$\max_{1} \sum_{i=1}^{m} \sum_{j=1}^{24} (B_{con,i,t} + B_{DG,i,t})$$

The variable $i$ represents the number of customers and DGOs, and $m$ is the total number of transactions. All the constraints are the same as shown in equation (14).

5. Case study

5.1. Basic data setting

In this paper, the scenario with high penetration rate of RES is selected as an example to study. We randomly selected 100 consumers to participate in the CES service. The scenario consists of 52 photovoltaic power stations, 90 wind turbines, 34 thermal units, 9 hydraulic units and 12 energy storage systems. The total installed capacity of the system is 18270MW. Energy storage capacity accounts for 5% of the total installed capacity. The energy limit for each energy storage system is
180MWh. Since there are three typical curves of wind power output, namely inverse peak, positive peak and flat peak, the energy price curves corresponding to these three conditions are also different, this paper will study the overall benefits of cloud energy storage in these three conditions respectively. For specific parameters, please refer to literature [11].

![Load profiles of consumers.](image1)

**Figure 1.** Load profiles of consumers.

![Capacity price of the reserve service.](image2)

**Figure 2.** Capacity price of the reserve service.

The capacity price of the reserve service is selected from the Texas reserve market on April 19, 2014. The technical parameters of load demand come from the actual data of Yangzhou city, Jiangsu province, China. Figure 1 shows the day-ahead load demand information of all customers. Figure 2 shows the capacity price curve of the ancillary services market. Figure 3 and Figure 4 show the wind power and photovoltaic output curves of the distributed generation side respectively. Figure 5 shows the energy price curves corresponding to inverse peaks, positive peaks and flat peaks. The temporal resolution of them is 1h. In figure 3, figure 4 and figure 5, the diamonds represent the inverse peak state, the triangles represent the flat peak state, and the squares represent the positive peak state. We assume that the maximum charge and discharge power of energy storage is 20MW [11].

![Output of wind power.](image3)

**Figure 3.** Output of wind power.
The minimum charged state of the energy storage device is 10%, the initial charged state is 20%, and the efficiency of charging and discharging is 96%. We set $\lambda_c$ for customers to be 5% lower than the 24-hour average price, and set $\lambda_d$ to be 5% higher than the 24-hour average price. In this paper, the exchange rate of USD to RMB is set at 6.9774RMB/USD.

5.2. Results and analysis
The optimal clearing model proposed in this paper has three optimization objectives, which are to maximize the benefits of customers, maximize the benefits of DGOs, and maximize the overall benefits of DGOs. Because the model is to solve a multi-objective optimization problem, and considering its nonlinear characteristics, this paper uses the multi-objective search algorithm based on particle swarm optimization algorithm to solve the problem.

5.2.1. Benefit in the inverse peak state. Figure 6 shows the distribution of the non-inferior solutions in the target space under the inverse peak state. Figure 7 shows the fitness values of the non-inferior solutions, which means the overall benefit. Figure 8 shows the specific values of the three-dimensional non-inferior solutions, that is, the energy capacity to be lent on the day, the capacity unit price to be acquired and sold by the CES operator.
The most important thing in multi-objective problem solving is the non-inferior solutions. As can be seen from figure 6, the optimization result of 100 sets of data after 200 cycles is that there are 57 non-inferior solutions. In the process of solving practical problems, too many non-inferior solutions cannot be directly applied, so we can only choose one solution which is closest to the conditional expected value as our final solution. We use the method of transforming a multi-objective problem into a single-objective problem. Therefore, we have to provide the relative importance between the three goals. The goal of maximizing overall benefit is the first priority.

It can be seen from figure 7 that the 37th non-inferior solution should be selected as the optimal solution. The corresponding value of the non-inferior solution can be found in figure 8. The simulation results show that when the wind output curve is in inverse peak state, all customers lend a total of 1458.68MWh energy capacity in a day. The CES operator is acquired at 16.66$/MWh and resells to the DGOs at 1.44$/MWh. That is when the overall benefit reached its highest point, at 4709,754$. DGOs accounts for 96.21% of the profits. The overall profits are enough to guarantee the economic benefits of cloud energy storage.

5.2.2. Benefit in the flat state. In the same way, the simulation results show that when the wind output curve is in flat state, all customers lend a total of 1166.30MWh energy capacity in a day. The CES operator is acquired at 13.02$/MWh and resells to the DGOs at 1.60$/MWh. That is when the overall benefit reached its highest point, at 4414,106$. DGOs accounts for 97.61% of the profits. So the overall profits are enough to guarantee the economic benefits of cloud energy storage.
5.2.3. Benefit in the positive peak state. In the same way, the simulation results show that when the wind output curve is in positive peak state, all customers lend a total of 1625.24 MWh energy capacity in a day. The CES operator is acquired at 17.52 $/MWh and resells to the DGOs at 2.45 $/MWh. At this point, the overall benefit is the highest at 5686,264$. DGOs accounts for 96.28% of the profits. Therefore, the overall profits are sufficient to ensure the economic benefits of cloud energy storage.

6. Conclusion
Cloud energy storage is a new form of energy storage for future power system. On the basis of expanding the basic concept of cloud energy storage, this paper puts forward an operation mechanism involving customers, DGOs and CES operators. According to the business model described, this paper analyses the benefit sources of the three parties, defines the opportunity cost of energy capacity the customers lend, and establishes the overall benefit model. In this paper, an optimal scheduling model is used to solve the pricing and clearing problems of cloud energy storage. Due to the nonlinearity of the model, we use the multi-objective search algorithm based on particle swarm optimization algorithm to solve it. The final example shows that the method proposed in this paper can improve the overall benefit on the basis of satisfying the customer load demand and ensuring the profitability of DGOs, which means guaranteeing the benefits of the CES operator itself. In addition, the issue of benefit sharing of CES participants will be studied in the future.

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