Economic evaluation of pumped storage power station based on multi-scenario stochastic Commitment Model

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Abstract. Pumped storage power stations have excellent characteristics such as fast start and stop speed, rapid load increase and decrease, and low forced outage rate. They can undertake tasks such as peak shaving, frequency modulation, phase modulation, spinning reserve, accident reserve, and black start of the power system, which improves the safety and economy of the power grid. This paper proposes a method for economic analysis of pumped storage based on a multi-scenario random unit combination model. In this paper, we build a scenario tree model based on the statistical characteristics of wind power and load forecast errors, and use a scenario modeling method based on associated nodes to build a stochastic unit combination model; Based on the results of system analysis, the economic efficiency of pumped storage power station is calculated, and the feasibility of the model is verified by example analysis, and the difference between calculation results of different models is also analyzed.

1. Introduction
Pumped storage power stations have excellent characteristics such as fast start and stop speed, rapid load increase and decrease, and low forced outage rate. They can undertake tasks such as peak shaving, frequency modulation, phase modulation, spinning reserve, accident reserve, and black start of the power system, which improves the safety and economy of the power grid. At present, the economic evaluation of pumped storage power stations still adopts the "Interim Measures for the Economic Evaluation of Pumped Storage Power Stations" (State Power Corporation [1998] No. 289) promulgated in 1998 and the "Interim Economic Evaluation of Pumped Storage Power Stations by the State Power Corporation" in 1999. Rules for the Implementation of the Measures (State Power Corporation [1999] No. 47) [1]. However, the large-scale grid connection of renewable energy brings changes to the power supply structure and challenges to the operation of the grid, which have put forward new requirements for the development of pumped storage power stations and have also made their economic evaluation problems more complex. In this case, the original economic evaluation method is still used, which can no longer fully reflect the economic status of pumped-storage power stations and reflect the economic benefits of pumped-storage power stations.

For the reasons mentioned above, this paper considers using unit combination model to study the operation of pumped storage units, and on this basis, analyzes the economics of pumped storage. Stochastic unit combination model is a commonly used method to solve the problem of power system optimal dispatch in uncertain environment. The modeling methods of stochastic programming can be divided into three categories: (1) Scene method. In this method, people use simulation tools to simulate
the random variables, describe the original objective function and constraint conditions with the expected value of the random variable in each scenario, and make the probability expectation of the objective function reach the optimal. To reduce the solution scale, scene reduction is usually performed based on the original scene tree [2] ~ [8]; (2) Chance constraint programming method. It was proposed by Charnes and Cooper, which is mainly aimed at the situation where the random variable is observed before the decision is made and the random variable is included in the constraints. It is usually allowed to make a decision that does not satisfy the constraint condition to a certain extent, but the probability of the decision making the constraint condition is not less than a certain confidence level [9]~[11]; (3) Related chance programming method. This method makes the chance function of the event best in uncertain environment. In view of the problem that Method (1) and (2) two modeling methods adopt a certain feasible set, which may lead to the optimal solution being unable to be executed in practice, the relevant opportunity planning uses an uncertain environment to describe the feasible set. Although definite solutions are also given, the solution is only needed to be implemented as far as possible in actual problems. Method (1) is the most widely used when dealing with the unit commitment problem of the power system.

This paper studies the economics of pumped storage from a system perspective, comprehensively considers wind power and load forecast deviations, and constructs a multi-scene random unit combination model based on associated nodes to comprehensively describe the uncertainty of system operation. On this basis, the operation state of pumped storage power station in power system was analyzed, and the benefit of pumped storage energy is calculated. The feasibility of the model was verified by an example, and the difference between the calculation results of the random unit combination model and the traditional deterministic model is analyzed.

2. Scene tree construction considering wind power and load uncertainty

2.1. Wind power forecast error modeling

This paper considers that the forecast error of wind power output obeys a normal distribution. Consider the forecast error of wind power output in time period t as a random variable that obeys a normal distribution with a mean value of 0 and a variance of \( \sigma_w^2 \) [12], as shown below:

\[
\begin{align*}
\varepsilon'_w &= W'_a - W'_f \\
\varepsilon'_w &\sim N \left(0, \sigma_w^2 \right)
\end{align*}
\]

(1)

Where \( W'_a \) is the actual output of the wind power station, \( W'_f \) is the predicted output of the wind power station.

The standard deviation \( \sigma'_w \) can be calculated by the following formula [12]:

\[
\sigma'_w = \frac{1}{5} W'_f + \frac{1}{50} W'_i
\]

(2)

Where \( W'_f \) is the total installed capacity of the wind power station.

2.2. Load forecast error modeling

With reference to related literature, this paper considers the load forecast error of time period t as a random variable with a normal distribution with a mean value of 0 and a variance of \( \sigma_d^2 \) [2], as shown below [12]:

\[
\begin{align*}
\varepsilon'_d &= D'_a - D'_f \\
\varepsilon'_d &\sim N \left(0, \sigma_d^2 \right)
\end{align*}
\]

(3)

The standard deviation \( \sigma'_d \) can be calculated by the following formula [12]:

\[
\sigma'_d = k D'_f / 100
\]

(4)
Where the value of $k$ is 1.

2.3. Scene tree generation based on wind power and load forecast errors

In the actual operation of the power system, the load curve after deducting the predicted output of wind power is usually used as the basis for making power generation plans for other units. Since the net load curve contains both wind power and load forecast information, the uncertainty of wind power and load forecast can be linked accordingly.

Referring to the literature [12], this paper defines the net load $L_a$ as:

$$L_a = D'_a - W'_a$$

$$= D'_a - W'_a + \varepsilon'_a = L'_a + \varepsilon'_a$$

(5)

Where $L'_a$ is the net load forecast value, $L_a$ is the actual net load value, and $\varepsilon'_a$ is the net load forecast deviation.

In this paper, we assume that the load forecast deviation and the wind power output forecast deviation are uncorrelated random variables, then the net load forecast deviation is a normal distributed random variable that obeys $N(0, \sigma^2_a)$ [12]. Among them, the standard deviation $\sigma_a$ satisfies:

$$\sigma_a = \sqrt{(\sigma_{d}^2) + (\sigma_{w}^2)}$$

(6)

The net load value includes the forecast value of wind power output and load. The normal distribution of net load forecast deviation includes both wind power output and load forecast information. Therefore, through $L_a$ and $\varepsilon'_a$, the uncertainty of wind power and load forecast can be comprehensively described.

Based on completing the net load modeling, Latin hypercube sampling is used to generate the net load forecasting scene tree. The net load forecast value of each period can be expressed in a time series. A complete time series forms a scene. Therefore, through pulling the net load scenario, it can be expressed as $P^s_{nt} = \{P^s_{nt,1}, P^s_{nt,2}, ..., P^s_{nt,T}\}, t \in \{1,2,\cdots, T\}, s \in \{1,2,\cdots, S\}$. Among them, $t$ is the period number, and $s$ is the scene number.

2.4. Reduction of the scene tree

If there are too many scenes, it will increase the difficulty to obtain the solution, while too few scenes will lead to calculation accuracy reduced. To balance the difficulty of the solution and the accuracy of the calculation, it is necessary to perform scene reduction based on the original scene tree. This paper uses the synchronous back-generation reduction method to reduce the original scene tree. The basic idea of this method is to minimize the probability distance between the scene set before the reduction and the scene subset that is finally retained [14].

3. Multi-scene stochastic unit combination model based on associated nodes

3.1. Variable setting and incidence matrix construction

This paper adopts the multi-scenario unit combination modeling method based on associated nodes, by constructing node-period and node-node correlation matrices, and setting optimization variables for each node, instead of traditional scenario-period optimization variables. Under the premise of ensuring the quality of the solution, this method can significantly reduce the number of constraints and variables and increase the calculation speed. The method of variable setting and incidence matrix construction can be found in literature [15].

3.2. Objective function

The decision goal of multi-scenario unit commitment is to minimize the sum of the expected value of system operating cost and unit start-up and shutdown costs, as shown in the following formula:
min\[\sum_{t}^{T}(\sum_{\mu}(C_{\mu,t} + C_{\mu,t}^{d}) + \sum_{j}\pi_{n} \cdot (\sum_{\mu}C_{j,n}^{f} + \sum_{\mu}C_{j,c,t}^{f}))\]

Where \(jt\), \(jc\), \(jh\) and \(js\) are the numbers of thermal power, CCGT, hydropower and pumped storage units respectively; \(T\) and \(N\) are the total number of periods and the total number of nodes respectively; \(\pi_{n}\) is the probability of each node; \(C_{jt,t}^{u}, C_{jh,t}^{u}\), and \(C_{js,t}^{u}\) are the start-up cost of the unit in period \(t\); \(C_{jt,t}^{d}\), \(C_{jh,t}^{d}\) and \(C_{js,t}^{d}\) is the stop costs of units in period \(t\); \(C_{jt,t}^{trans}\) are the mode conversion costs of the CCGT unit (including start-stop costs); \(C_{jt,n}^{f}\), \(C_{j,c,t}^{f}\) are the unit's operating costs at node \(n\).

3.3. Unit operation constraints
In stochastic unit commitment models, optimization variables are divided into two kinds:

(1) The first stage optimization variable, this type of variable is only related to the time period, not the scene, that is, the optimization result of the variable under each scene or node in the same time period is the same. Only the variables that represent the start and stop status of various units belong to the first stage optimization variables, so this type of variable is mainly for the start and stop problems of the unit.

(2) The second stage optimization variables, which are related to the period and scene at the same time, usually get different optimization results at different time periods, different scenes, or nodes. The output of various units is the second stage optimization variable, and this type of variable involves other constraints besides the start and stop of the unit.

For the constraints containing the second-stage optimization variables, they can be divided into two categories: constraints containing only current period variables and constraints containing two period variables at the same time:

(1) For constraints that only contain variables for the current period, after shifting items, they can be expressed in the following form:

\[a_{j} \cdot \xi_{j,t}^{f} + b_{j} \cdot \psi_{j,t} + c_{j} \geq 0\] (8)

In the formula, \(\psi_{j,t}\) and \(\xi_{j,t}\) respectively represent the optimization variables of the first stage and the second stage, and \(a_{j}\), \(b_{j}\) and \(c_{j}\) are the relevant parameters of the constraint conditions. When the first stage variable is not included in the constraint, the value of \(b_{j}\) is 0.

Equation (8) can also express equality constraints. In this case, the equality constraint is equivalent to the working inequality constraint. Constraints conforming to this type of form include power-cost segmentation function, power-flow segmentation function, unit capacity constraint, storage capacity constraint, and unit upper and lower reserve capacity constraints.

In the stochastic model, the corresponding relationship between nodes and time periods needs to be considered when forming this type of constraint. Therefore, formula (8) needs to be modified as follows: node-based optimization variables replace the original time-based optimization variables; the left side of the inequality is expressed Multiply the element \(\alpha_{n,t}\) in the node-period association matrix by the formula.

(2) For constraints having two period variables, based on the linearization model in Chapter 2, the terms can be expressed in the following form after shifting the terms:

\[d_{j} \cdot \phi_{j,t} + e_{j} \cdot \phi_{j,t-1} + f_{j} \geq 0\] (9)

In the formula, \(\phi_{j,t}\) and \(\phi_{j,t-1}\) represent the second stage optimization variables of the current period and the previous period respectively; \(d_{j}\), \(e_{j}\) and \(f_{j}\) are the relevant parameters of the constraint conditions.

Such constraints usually do not contain equality constraints and first-stage optimization variables. Constraints that conform to this type of form include the upper and lower climbing rate constraints and the storage capacity balance constraints. When forming this type of constraint conditions, the
correspondence between nodes and time periods and the association relationship between before and after nodes need to be considered, so the following modifications are required: Replace the original time-based optimization variables with node-based optimization variables; the optimization variable is left multiplied by the element \( \alpha_{nt} \) in the node-period correlation matrix; the left side expression of the inequality is left multiplied by the element \( \beta_{nt} \) of the node-node correlation matrix.

The optimization variables and constraints of various units can be summarized into the above forms, so the above methods can be referred to, based on the chapter deterministic model, and the constraints applicable to the stochastic model can be formed.

Taking the thermal power unit as an example, the constraints of the thermal power unit in the random model formed by the above method are listed below. Other unit modeling methods are the same as this kind, so this paper will not repeat them here.

(1) Operating cost of the unit:

\[
\begin{align*}
\alpha_{nt} \cdot (p_{jt,n} - \sum_{i} \rho_{jt,i,n} - p_{jt,0}) & = 0 \\
c_{jt,n} - C_{jt,0} v_{jt,n} - \sum_{i} \mu_{jt,i} p_{jt,n} & = 0 \\
0 & \leq p_{jt,n} \leq p_{jt,max}
\end{align*}
\]  

(10)

Where \( \alpha_{nt} \) represents the element in the \( n \)-th row and \( t \)-th column of the node-node association matrix \( \alpha \), when the node \( n \) is related to the time period \( t \), it is 1, otherwise it is 0; \( p_{jt,n} \) is the output of the unit in the \( n \)-th node; \( v_{jt,n} \) is the start and stop status of the unit; \( \rho_{jt,i,n} \) is the power variable of the \( i \)-th segment of the operating cost segmentation function of unit \( j \) at node \( n \); \( C_{jt,0} \) is the minimum output and minimum operating cost of the unit; \( \mu_{jt,i} \) is the slope and maximum power of the \( i \)-th segment of the unit operating cost segment function.

(2) Start-up cost and shutdown cost of the unit:

\[
\begin{align*}
c_{jt,t}^u & \geq C_{jt,k}^u (v_{jt,t} - \sum_{k} v_{jt,t-k}) \\
c_{jt,t}^d & \geq 0 \\
c_{jt,t}^d & \geq C_{jt}^{down} (v_{jt,t-1} - v_{jt,t}) \\
c_{jt,t}^d & \geq 0
\end{align*}
\]  

(11)

(12)

Where \( k \) is the number of time intervals of start-up cost; \( C_{jt,k}^u \) is the start-up cost constant of unit \( jt \) during the time interval \( k-1 \) to \( k \); \( C_{jt}^{down} \) is the shutdown cost of unit \( jt \).

(3) Unit capacity constraints:

\[
\begin{align*}
\alpha_{nt} \cdot (p_{jt,n} v_{jt,t} - p_{jt,\min}) & \geq 0 \\
\alpha_{nt} \cdot (v_{jt,t} p_{jt,max} - p_{jt,n}) & \geq 0
\end{align*}
\]  

(13)

Where \( p_{jt,\min} \) and \( p_{jt,max} \) are the maximum and minimum output of the unit \( jt \) respectively.

(4) Up/down climbing rate constraint:

\[
\begin{align*}
\beta_{nt} \left( \alpha_{nt} p_{jt,n} - \alpha_{nt-1} p_{jt,n} \right) & \leq RAMP_{jt}^{up} \\
\beta_{nt} \left( \alpha_{nt-1} p_{jt,n} - \alpha_{nt} p_{jt,n} \right) & \leq RAMP_{jt}^{down}
\end{align*}
\]  

(14)
Where $\beta_{n,n'}$ represents the element in the $n$-th row and $n'$-th column of the node-node association matrix $\beta$, which is 1 when the nodes $n$ and $n'$ are related to each other, otherwise it is 0; $\text{RAMP}_{\text{up}}$, $\text{RAMP}_{\text{down}}$ are the upper and lower climbing rate limit of the unit.

(5) Upper/lower reserve capacity constraints:

$$\begin{align*}
\alpha_{n,t} (p_{j,n} + p_{j,n}^{\text{r,n}} - p_{j,\text{max}} \cdot v_{j,t}) \leq 0, & \quad p_{j,n} \leq \text{RAMP}_{\text{down}} \\
\alpha_{n,t} (p_{j,n} - p_{j,n}^{\text{r,n}} - p_{j,\text{max}} \cdot v_{j,t}) \geq 0, & \quad p_{j,n} \leq \text{RAMP}_{\text{up}}
\end{align*}$$

Where: $p_{j,n}^{\text{r,n}}$, $p_{j,n}^{\text{d,n}}$ are the available upper and lower spare capacity variables of unit $j$ at node $n$.

(6) The minimum operating time constraints of the unit:

$$\begin{align*}
\sum_{t=1}^{T_{\text{on}, \text{ini}}} (1 - v_{j,t}) = 0 \\
\sum_{t=T_{\text{on}, \text{ini}} + 1}^{T_{\text{on}, \text{ini}} + 1} v_{j,t} (n) \geq T_{\text{on}, \text{ini}} (v_{j,t} - v_{j,t-1}), & \quad \forall t = T_{\text{on}, \text{ini}} + 1, \cdots, T - T_{\text{on}, \text{ini}} + 1 \\
\sum_{t=T_{\text{on}, \text{ini}} + 2}^{T} \left[ v_{j,t} - (v_{j,t} - v_{j,t-1}) \right] \geq 0, & \quad \forall t = T - T_{\text{on}, \text{ini}} + 2, \cdots, T
\end{align*}$$

Where $T_{\text{on}, \text{ini}}$ is the minimum operating time of the unit; $T_{\text{on}, \text{ini}}$ is the minimum length of time the unit needs to maintain the operating state at the initial moment.

(7) The minimum downtime constraints of the unit:

$$\begin{align*}
\sum_{t=1}^{T_{\text{off}, \text{ini}}} v_{j,t} = 0 & \quad \forall i \in G \\
\sum_{t=T_{\text{off}, \text{ini}} + 1}^{T_{\text{off}, \text{ini}} + 1} (1 - v_{j,t}) \geq T_{\text{off}, \text{ini}} (v_{j,t-1} - v_{j,t}), & \quad \forall t = T_{\text{off}, \text{ini}} + 1, \cdots, T - T_{\text{off}, \text{ini}} + 1 \\
\sum_{t=T_{\text{off}, \text{ini}} + 2}^{T} \left[ 1 - v_{j,t} - (v_{j,t-1} - v_{j,t}) \right] \geq 0, & \quad \forall t = T - T_{\text{off}, \text{ini}} + 2, \cdots, T
\end{align*}$$

Where $T_{\text{off}, \text{ini}}$ is the minimum shutdown time of the unit; $T_{\text{off}, \text{ini}}$ is the minimum time the unit needs to maintain the shutdown state at the initial moment.

3.4. System coupling constraints

(1) System load balance

$$\begin{align*}
\sum_j p_{j,n} = P_n^{\text{load}} - \sum_{j \neq n} \sum_{n'} p_{jw,n'} \\
\alpha_{n,t} \cdot P_n^{\text{load}} = P_t^{\text{load}}
\end{align*}$$

Where $p_{j,n}$ represents the output of various units including thermal power, hydropower, CCGT, nuclear power and pumped storage units; $p_{jw,n'}$ is the predicted output of wind turbines; $P_t^{\text{load}}$, $P_n^{\text{load}}$ represents the system load of time period $t$ and node $n$ respectively.

(2) System reserve capacity constraints


\[
\begin{align*}
\sum_{j} p_{j,a}^{ru} &= P_{n}^{u} \\
\sum_{j} p_{j,a}^{rd} &= P_{n}^{l}
\end{align*}
\]  

Where \( P_{n}^{ru} \) and \( P_{n}^{rd} \) respectively represent the system's upper and lower spare capacity requirements under node \( n \).

3.5. Benefit calculation of pumped storage

(1) Through calculating the operating cost \( C_{\text{no,PS}} \) of the system without pumped-storage power station and \( C_{\text{with,PS}} \) when the pumped-storage power station is included, we obtained the system operating cost saved by the pumped-storage power station \( \Delta C_{\text{system}} = C_{\text{no,PS}} - C_{\text{with,PS}} \);

(2) The net income \( P_{\text{net}} \) of pumped storage is equal to the difference between the operating cost \( \Delta C_{\text{system}} \) saved by the system and the fixed cost of pumped storage. The variable cost of pumped storage (mainly power loss) is reflected in the unit portfolio model and has therefore been deducted from \( \Delta C_{\text{system}} \);

(3) Calculate the present value \( P \) of the revenue per unit capacity of the pumped storage during the lifetime and compare it with the investment cost of unit capacity \( C_{\text{invest}} \). If \( P \geq C_{\text{invest}} \), then pumped storage investment is economically workable. The calculation method of \( P \) is as follows:

\[
P = \frac{P_{\text{net}} \cdot \left(1 + i\right)^{n} - 1}{i \left(1 + i\right)^{n}}
\]

Among them \( i \) is the discount rate, \( n \) is the lifetime of pumped storage, and \( Q \) is the capacity of pumped storage.

4. Case analysis

The wind power, load data and various unit parameters in the calculation examples refer to literature[16].

4.1. Economic analysis of pumped storage under different models

Fig.1 daily operation curve of pumped storage under deterministic model and stochastic model

Fig.1 shows the daily operation curve of pumped storage under the deterministic unit commitment model and the stochastic unit commitment model. It can be seen from the figure that under the deterministic model, the unit pumps water from the 3rd to the 5th period and generates electricity from the 19th to 21st period; while under the stochastic model, the unit pumps water from the 3rd to the 7th period and generates electricity from the 15th ~ 16th, 19th ~ 21st time period, and the power output is higher than that under the deterministic model. Therefore, the call frequency of pumped storage units
under the stochastic model is higher than that under the deterministic model. The reason is that the stochastic unit combination model considers the uncertainty of wind power and load forecasting to generate various scenarios. In order to ensure that the system can operate safely and reliably in all forecast scenarios, sufficient spare capacity needs to be reserved when formulating a unit start-up and shutdown plan. The pumped storage unit has the characteristics of flexible operation and low start and stop cost, which makes it have more advantages compared with other types of units. Therefore, under the stochastic model, in order to meet the requirements of system reliability, pumped-storage units are called more frequently, and their pumping and generating power increases.

Fig.2 the net income of pumped storage under different models and capacity

The operation result of pumped storage scheduling will directly affect the operating cost saved for the system, that is, the profit situation. Fig.2 shows the calculation results of the net benefits of pumped storage under the two models. The change trend of the net income of pumped storage with capacity under different models is the same, that is, the net income increases first and then decreases with the increase of capacity. However, under the deterministic model, pumped storage can obtain the maximum net income at 600MW; and under the stochastic model, the capacity needs to reach 900MW to obtain the maximum net income. This is because the system operating cost saved by pumped storage under the stochastic model is higher than the cost saved under the deterministic model, and the fixed cost of pumped storage under the two models is the same (increasing with capacity). Therefore, it is possible that the optimal capacity of pumped storage under the stochastic model (that is, the capacity at the maximum net income) is greater than the optimal capacity under the deterministic model.

4.2. Analysis of the number of scenarios

| reduced number of scenes | net income ($ per day) | operating cost of the system ($ per day) | calculation time (s) |
|--------------------------|------------------------|----------------------------------------|----------------------|
| 10                       | 26140.29               | 725211                                 | 74                   |
| 30                       | 26169.04               | 726008.7                               | 263                  |
| 50                       | 26208.29               | 727097.7                               | 478                  |
| 100                      | 26417.96               | 732914.5                               | 1036                 |
| 500                      | no solution            | no solution                            | no solution          |

Table 1 shows the daily return of pumped storage based on the stochastic unit combination model, the daily operating cost of the system, and the calculation time changes with the number of reduced scenarios. As the number of reserved scenarios increases, the system needs to meet more wind power and load forecast scenarios, and the reliability of operation increases, but the required adjustment capacity also increases, which leads to an increase in the total cost of system operation. When the number of scenarios increases, the pumped-storage unit will be used more to ensure the reliability of the
system, so the saved operating costs (i.e., Revenue) will increase accordingly. In addition, the increase in the number of scenarios also doubles the number of optimization variables and constraints, the scale of calculation increases, and the difficulty of solving increases, which significantly increases the calculation time required to obtain the optimal solution.

On the other hand, the increase in the number of scenes also increases the probability of extreme scenes. Any unsatisfactory scenario will lead to unsolvable optimization problems. In the actual dispatch operation of the system, if it is simply ensured that all wind power and load fluctuations are met, the increase in system operating costs may be much higher than the loss due to insufficient regulation capacity and reduce the economic efficiency of system operation. Therefore, when solving the stochastic unit combination model based on the scene tree, the number of reduced scenes should not be too much or too little. In actual calculation and analysis, 10-30 scenes are usually reserved to meet the needs.

4.3. Impact analysis of wind power forecast error changes

The greater the wind power forecast error, the more regulation capacity the system needs, and therefore the higher the total operating cost. When the error reaches a certain value, the system will no longer provide enough regulation capacity to deal with the randomness of wind power output, and there will be no feasible solution in this case, and the pumped storage unit can increase the system's ability to respond to fluctuations in wind power output by providing more regulation capacity for the system.

Table 2 The influence of wind power forecast error on calculation results

| wind power forecast error % | operating cost of the system without pumped storage ($ per day) | operating cost of the system with pumped storage ($ per day) | net income of pumped storage ($ per day) |
|-----------------------------|---------------------------------------------------------------|-------------------------------------------------------------|----------------------------------------|
| 0                           | 731804.79                                                     | 708627.18                                                   | 23177.61                               |
| 10                          | 737348.39                                                     | 713248.77                                                   | 26140.29                               |
| 15                          | 746316.82                                                     | 722434.08                                                   | 23882.74                               |
| 20                          | 751351.29                                                     | 725211.00                                                   | 26140.29                               |
| 25                          | 757135.59                                                     | 731321.59                                                   | 25814.01                               |
| 30                          | no solution                                                   | 734927.26                                                   |                                         |
| 35                          | no solution                                                   | no solution                                                  |                                         |

Table 2 shows the impact of wind power forecast errors on system operating costs and benefits of pumped storage. When the wind power forecast error changes in the range of 0-25%, the optimal solution to the unit commitment problem can be obtained, and as the forecast error increases, the total operating cost of the system increases. The income of pumped storage changes irregularly because the forecast error indirectly affects the income of pumped storage by affecting the operating cost of the system. Although the total cost of the system with and without pumped storage increases with the increase in forecast error, the difference between the two changes at different speeds, that is, the income of pumped storage changes irregularly. In addition, it can be seen from Table 4-5 that when the system contains pumped storage units, there is still an optimal solution when the prediction error reaches 30%, while the system without pumped storage can only withstand 25% of the prediction error, which shows that the adjustment capability of the pumped storage unit enables the system to withstand greater wind power forecast errors.

5. Conclusion

This paper proposes a method for economic analysis of pumped storage based on a multi-scenario stochastic unit combination model. First, based on the statistical characteristics of wind power and load forecasting errors, a scenario tree model that comprehensively describes wind power and load forecasting errors is constructed. Secondly, a scenario modeling method based on associated nodes is used to build a stochastic unit combination model. Finally, the economy of pumped storage power
station is calculated based on the results of system analysis. The feasibility of the model is verified through the analysis of calculation examples, the calculation results under the deterministic unit combination model are compared and analyzed, and the influence of changes in different factors on the calculation results is analyzed from two aspects: the number of reduced scenarios and the change of wind power forecast errors.

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