Optimization method of external power transmission based on complementary characteristics of wind power and photovoltaic

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Abstract. The large-scale development of renewable energy power is faced with challenges such as the reverse distribution of wind and photovoltaic resources and power loads. The main challenge currently facing is the randomness and volatility of renewable energy power generation. Based on the concept, this paper studied the bundled transmission capacity planning. First, this paper proposed new energy output characteristics based on probability theory. According to the historical data of wind power and photovoltaic power generation, this paper considered the timing output characteristics and output change characteristics of wind power and photovoltaic power generation under different time scales. Then, the optimization model is established based on the objective function of minimizing total cost. Finally, this paper solved optimization problems with reinforcement learning algorithms and determined the installed capacity of thermal power. The research results of this paper have a certain significance for the bundled delivery of wind power and photovoltaics in new energy-rich areas.

1. Introduction
In recent years, with the rapid economic development, global energy consumption has increased dramatically and fossil energy has been overexploited and utilized. It has brought about global environmental pollution and energy crisis problems[1]. With the rapid development of renewable energy such as wind and photovoltaic energy, low-carbon has become the transformation direction of the global energy system[2].

Large-scale uncontrollable clean energy is connected to the grid, but a large number of wind farms, light fields, and electricity load are geographically far away. The construction of long-distance transmission lines to send large-scale wind power and photovoltaic power to the load center for consumption is an important measure to solve this contradiction[3, 4]. However, pure wind power transmission is greatly affected by natural conditions, and its limitations are also obvious. Therefore, to improve the economy of wind-photovoltaic-thermal bundled delivery, it is necessary to research the capacity configuration of wind-photovoltaic-thermal bundled delivery[5].

Because of the optimization of new energy source structures, domestic and foreign scholars have carried out many types of research. WANG[6] aimed at minimizing the net loss of the system and studied the optimal configuration of distributed generation by improving the particle swarm optimization algorithm, but he did not consider the randomness and timing of distributed generation power. Liu[7] based on the timing characteristics of the wind turbine, photovoltaic power, and load demand in different
seasons. He studied the multi-objective optimization problem of minimizing DG investment cost, power purchase cost, and voltage deviation. It is particularly important to use clean energy as much as possible without losing the economy of thermal power units and study and demonstrate reasonable wind power and thermal power installed capacity and proportions [8]. Therefore, the optimization model of wind-photovoltaic-thermal bundled delivery is presented in this paper, which needs consider the characteristics of wind power and photovoltaic output.

2. The analysis of wind power generation and photovoltaic power characteristics

2.1. The annual utilization hours

\[ T_{\text{year}} = \frac{E_{\text{total}}}{\sum_{i=1}^{S} C_{W_i}} \]  

In the formula, \( E_{\text{total}} \) is the total annual wind power/photovoltaic power generation; \( C_{W_i} \) is the installed wind power/photovoltaic capacity of \( i \) unit; \( S \) is the total number of wind power/photovoltaic installed in the system.

2.2. The average quarterly power

\[ W_{\text{quarter}} = \frac{\sum_{i=1}^{N_q} P_i}{N_q} \]  

In the formula, \( N_q \) is the number of sampling values in the season; \( P_i \) is the average power of wind power/photovoltaic per hour.

2.3. The average monthly power

\[ W_{\text{month}} = \frac{\sum_{i=1}^{N_m} P_i}{N_m} \]  

In the formula, \( N_m \) is the number of sampled values in the month.

2.4. The index of daily characteristic

\[ P_a = \frac{\sum_{i=1}^{N} P_{i,t}}{N} \quad (t = 1,2,...,24) \]  

In the formula, \( P_{i,t} \) is the wind power/photovoltaic output at time \( t \).

3. Reinforcement Learning

Deep reinforcement learning is usually based on the Markov decision process. The result of interaction between agent and environment at the next moment is only related to the current environment state and has nothing to do with the previous environment state. A typical MDP process consists of five elements \( (S, A, R, P, \gamma, \pi) \). \( S \) represents a collection of environmental states. \( A \) represents the set of actions that decision-makers can take on the environment. \( R \) represents the reward function, that is, the reward that the agent gets after taking some action in a certain state. \( P \) represents the probability of state transition, it can be determined by the environment. \( \gamma \) represents the discount rate of reward. \( \pi \) represents the set of strategies. In a Markov decision process, the cumulative discounted return is defined by

\[ G_t = r_t + \gamma P_{t+1} + \gamma^2 P_{t+2} + \cdots \]
The state value function $v^\pi(s)$ is defined as the expected value of cumulative discount return:

$$v^\pi(s) = E(G_t | s_t = s)$$  \hspace{1cm} (6)

The action value function $q^\pi(s,a)$ is defined as the expected value of cumulative discount return after executing action $a$ in state $s$.

$$q^\pi(s,a) = E(G_t | s_t = s, a_t = a)$$  \hspace{1cm} (7)

According to state value function and action value function, the action dominance function $A^\pi(s,a)$ can be defined by the following formula (8)

$$A^\pi(s,a) = q^\pi(s,a) - v^\pi(s)$$  \hspace{1cm} (8)

It can be proved theoretically that there is an optimal strategy $\pi$ in the Markov decision process $\pi^*$. It can make the state value function of any state under this strategy greater than that of other strategies.

$$A^\pi(s) = \max_\pi v^\pi(s)$$  \hspace{1cm} (9)

The purpose of reinforcement learning is to learn the optimal strategy $\pi^*$ through the interaction between the decision-maker and the environment.

$$v^\pi(s) = \max_a \left[ r(s,a) + \gamma \sum_{s' \in S} P_{ss'} v^\pi(s') \right]$$  \hspace{1cm} (10)

$$q^\pi(s,a) = \max_a \left[ r(s,a) + \gamma \sum_{s' \in S} P_{ss'} \max_a q^\pi(s',a') \right]$$  \hspace{1cm} (11)

In the formula, $s'$ represents the subsequent state of state $s$. The optimal state value function and action-value function of the current state can be expressed by the optimal state value function and action-value function of the next state.

4. The optimal configuration of wind power and photovoltaic capacity

We take the minimum power generation cost as the objective function. We consider equipment investment costs, fuel costs, operation and maintenance costs, load loss costs, and network fees to establish an objective function.

$$\min c = C_I + C_M + C_L + C_R$$  \hspace{1cm} (12)

In the formula, $c$ represents the power generation cost of the entire bundled power generation system during the entire life cycle. $C_I$ represents the total investment cost during the entire life cycle; $C_M$ represents the total maintenance cost during the entire life cycle; $C_F$ represents the fuel power generation cost during the entire life cycle; $C_N$ represents the network fee during the entire life cycle; $C_R$ represents the penalty for load loss during the entire life cycle cost.

The constraints of the above optimization model are as follows:

The minimum technical output of thermal power

$$P_{j,t}^c \geq (1 - \rho) P_C$$  \hspace{1cm} (13)

In the formula, $\rho$ represents the minimum output rate of the thermal unit; $P_C$ represents the installed capacity of the thermal power unit.

The planning capacity constraints for wind power and photovoltaic

$$C_{\min}^w \leq C_w^p \leq C_{\max}^w$$  \hspace{1cm} (14)
In the formula, $C^{wp}$ represents the planned installed capacity of the wind and photovoltaic; $C_{\text{max}}^{wp}$ and $C_{\text{min}}^{wp}$ respectively represent the upper and lower limits of the installed capacity of the wind power and photovoltaic.

The constraint of compensation capacity per minute for thermal power units

$$C_c \geq C_{\text{wp}}^{\text{m}}$$

(15)

In the formula, $C_c$ represents the compensation capacity of the thermal power unit per minute; $C_{\text{wp}}^{\text{m}}$ represents the change of wind and wind combined output per minute by two.

5. Case studies and results analysis

5.1. The power generation analysis

We conducted statistical analysis on the historical data of a certain region in 2018.

The average power generation in seasons are shown in Table 1:

| Class     | Year | Spring | Summer | Autumn | Winter |
|-----------|------|--------|--------|--------|--------|
| Wind      | 1790 | 0.253  | 0.167  | 0.175  | 0.223  |
| Photovoltaic | 1316.6 | 0.184  | 0.151  | 0.126  | 0.139  |

The annual power generation is shown in Figure 1.

![Figure 1](image.png)

Figure 1. The monthly average output of wind power and photovoltaic

The index of daily characteristic is shown in Table 2.

| Season   | Wind     | Photovoltaic |
|----------|----------|--------------|
| Year     | 0.00-0.86| 0.01-0.91    |
| Spring   | 0.08-0.86| 0.13-0.90    |
| Summer   | 0.05-0.67| 0.13-0.90    |
| Autumn   | 0.05-0.67| 0.05-0.88    |
| Winter   | 0.00-0.84| 0.01-0.91    |

5.2. The analysis of complementary characteristics of wind power and photovoltaic

When the wind power and the photovoltaic installed capacity ratio is 1:1, the 24-hour average power generation curve is shown in Figure 2.
5.3. The analysis of power capacity optimization results
Take the historical output data of wind power and photovoltaics in the region in 2018 as an example to optimize the capacity of the wind and photovoltaic bundling power generation system. The installed capacity ratio of wind power and photovoltaic is 6:1, and the planned capacity of the wind and photovoltaic base is planned to be 1000~4000MW. The supporting thermal power unit adopts 3×600MW units, and the minimum technical output is 30% of the rated capacity. Our compensation rate is 3%/min, the investment cost of thermal power units is 3800 yuan/kW, the coal consumption of thermal power units is 300g/kWh, the life span is 25 years, and the coal price for the planned year is 600 yuan/t. Through simulation calculations, as the transmission capacity increases, the overall installed capacity of wind power and photovoltaics is also gradually increasing. The unit power generation cost shows a trend of first decreasing and then increasing. It reaches its lowest point when the transmission capacity is 1900MW. At this time, the installed wind power capacity is 1900MW, the installed photovoltaic capacity is 380MW, the investment cost is 16.150 billion yuan, the fuel cost is 36.619 billion yuan, the operation and maintenance cost is 11.167 billion yuan, the network cost is 21.767 billion yuan, the shortcoming cost is 105 million yuan, and the unit cost is 0.3432 yuan/kWh. The utilization hours of wind power, photovoltaic power, and thermal power are 1,596, 1,300, and 3596 hours respectively. The available electricity is 3901.08GWh, and the waste electricity is 374.68 GWh.

6. Conclusion
This paper analyzed the complementary characteristics of wind power and photovoltaics, which lays the foundation for the follow-up wind-photovoltaic bundled delivery. This paper implemented the problem of wind, photovoltaic, and thermal power capacity planning for external power transmission through reinforcement learning. The wind-photovoltaic-thermal bundled delivery will greatly reduce the system's requirements for peak-shaving capacity of thermal power units, reduce the peak-shaving pressure of the receiving end grid, ensure the smooth transmission of power from the transmission channel, and reduce power supply costs.

References
[1] Zhang Y., Shan B. (2010) China’s power system development and operation: main challenges and countermeasure. Electric Power., 50: 1-6.
[2] Lu Z., Li H., Qiao Y. (2016) Power system flexibility planning and challenges considering high pro-portion of renewable energy. J. Automation of Electric Power Systems, 40: 147-158.
[3] Liu Z., Zhang Q., Dong C., at al. (2014) Efficient and Security Transmission of Wind, Photovoltaic and Thermal Power of Large-scale Energy Resource Bases Through UHVDC Projects. J. Proceedings of the CSEE, 34: 2513-2522.
[4] Bilil H, Aniba G, Maaroufi M. (2014) Multiobjective optimization of renewable energy penetration rate in power systems. J. Energy Procedia, 50: 368-375.

[5] Yi B., Xu J., Fan Y. (2016) Inter-regional power grid planning up to 2030 in China considering renewable energy development and regional pollutant control: A multi-region bottom-up optimization model. Applied Energy, 184: 641-658.

[6] Abdi S., Afshar K. (2013) Application of IPSO-Monte Carlo for optimal distributed generation allocation and sizing. J. INT. J. ELEC. POWER, 44: 786-797.

[7] Liu K., Sheng W., Liu Y., et al. (2015) Optimal siting and sizing of DGs in distribution system considering time sequence characteristics of loads and DGs. J. INT. J. ELEC. POWER, 69: 430-440.

[8] Yin M., Ge X., Wang C., et al. (2010) Analysis of issues about China’s large-scale wind power development. J. Electric Power, 2010, 43: 59-62.