Research on Low Carbon Dispatching of Hybrid Power Generation System with Wind Power and Pumped Storage Station

Yichun Wu¹, Yonghui Li², Xiaotong Xu², Jie Huang¹, Caifang Li¹

¹ Anhui Electrical Engineering Professional Technique College, Hefei 230022, China
² School of Electrical Engineering, Wuhan University, Wuhan 430072, China

Abstract. The joint operation of wind farms and pumped-storage plants is an effective solution to the challenge that large scale wind power integration brings to the economic operation of power grid. In the low carbon dispatching of the hybrid power system with wind power and pumped storage, the economic efficiency is met by considering the environmental benefits. In this paper, the modeling and optimization algorithm of low carbon scheduling problem for hybrid system with wind power, thermal power and pumped storage station is studied. Firstly, the wind power scenario model is built based on the probability distribution of wind power prediction error. Then a two-stage stochastic programming model is established based on day-ahead scheduling and hour-ahead scheduling. Secondly, the improved differential evolution based the ε-constraint method and Pareto non-dominance sorting is applied to solve the low carbon scheduling problem for multi-objective optimization with mixed integer programming. Finally, an example is provided to verify the feasibility of the proposed algorithm by the use of MATLAB software.

1. Introduction

Wind power has greatly developed in recent years. Due to the uncertainty of wind power, the large-scale wind power integration brings great difficulties to grid security dispatching. In order to absorb the wind power as far as possible and ensure the efficiency of wind farm, it is necessary to provide sufficient peak shaving and frequency regulation capacity for wind power. Pumped storage is also widely used to smooth out wind power fluctuations. Therefore, combined operation with pumped storage station is an effective measure to smooth the active power output of the wind farm and maintain the safe and stable operation of the power grid.

The optimization scheduling of dispatching power system with wind power and pumped storage station has been drawn a widely concern in recent years. In the hybrid power system, the optimal objective [1-3] has mainly the minimum abandon wind power, the minimum fluctuation of wind output power, the minimum running cost of the unit, the maximum economic benefit of joint operation, etc. Meanwhile, combining several single objectives is required to achieve multi-objective optimization of the system if necessary [4-5]. Moreover, the dispatching model of power system is gradually changed from traditional economic scheduling to low carbon scheduling which satisfies the economic efficiency of the power system and takes into account the environmental benefits at the same time.

The low carbon scheduling of hybrid power generation system with wind power and pumped-storage station is a multi-objective optimization problem. The research on the solution that involves mixed integer variables such as genetic algorithm, particle swarm optimization and differential
evolution has been relatively mature, and their modified algorithm has been widely used in the industry applications. In reference [6], genetic algorithm is adopted to research the optimal operation of wind-pumped storage combined system. In reference [7], the binary particle swarm algorithm for the day-ahead scheduling model is presented. In reference [8], the differential evolution algorithm is applied to the unit combination problem. On the basis of the existing research, the algorithm is further improved to optimize the process, and develop the computing speed and convergence rate. In this paper, the two-stage stochastic programming[9] scheduling method is applied to research the low carbon scheduling of hybrid power generation system. Firstly, according to the probability distribution of wind power prediction error, the most representative set of scenarios can be obtained. Then the scheduling scheme is divided into two phases which are day-ahead scheduling phase and hour-ahead scheduling phase to establish the two-stage stochastic optimization model. Finally, the improved differential evolution algorithm based on the \( \varepsilon \)-constraint method and Pareto non-dominance sorting is used to solve the multi-objective optimization problem including the mixed integer linear programming in the low carbon scheduling.

2. Two-stage stochastic optimal scheduling model for hybrid system

2.1. Wind power probability model
Due to the random fluctuation of wind power, the scenario modeling of wind farms is established with probabilistic approaches. Firstly, the autoregressive moving average model is utilized to forecast the output power of wind power [10]. Then the operational scenarios of the future are generated and a set of initial scenarios is set up. Given that the operation time is related to the size of the scenarios, the scenarios have to be reduced. According to the rule that the probability distance after the reduction of scenarios is minimal [11], the initial set of scenarios is truncated. Finally, a small but representative set of optimal scenarios and the corresponding probability density are obtained.

2.2. Unit combination model of hybrid system

2.2.1. Two-stage stochastic optimization scheduling. In the optimization scheduling, the decision variables are the on-off state and the active power output of the units during each time period. By the two-stage stochastic optimization method [10], the optimization problem of the unit combination can be separated into two independent optimization stages: one of the stages have discrete variables only and the other have continuous variables only. The day-ahead dispatch is the first stage to determine the start-stop status of the units while the hour-ahead dispatch is the second stage to determine the output and load distribution at each period after the start of the units.

In the day-ahead scheduling phase, the start-up or shut-down strategy of each thermal power unit is determined. Taken the minimization of the unit cost as well as the minimization CO\(_2\) emission as the two objective functions, the operation schedule of the thermal power unit and pumped storage power station in each scenario is developed based on the set of optimal wind power scenarios.

In the hour-ahead scheduling phase, the net load fluctuation of system is smoothed out to avoid changing the power output from thermal power units as far as possible and avoid increasing the running cost. On the basis of the start-up and shut-down strategy, according to the latest hour-ahead wind power prediction, the power distributions of the selected thermal power units and pumped storage units are fixed to make more accurate scheduling policies in time.

2.2.2. Objective function. For the joint system, the multi-objective function is set up to reduce the cost of the unit and the CO\(_2\) emission as the optimization objective.

(1) Unit cost
The costs of wind farms and pumped storage power stations are mainly consisted in construction costs. The operation cost of the pumped storage power station is generated only when the two working conditions of pumping and generating are converted, then it can be ignored compared to the thermal
power unit \(^{[12]}\). This paper does not consider construction costs, so the objective function about economic efficiency of the hybrid system only considers the cost of the thermal power unit. The cost of thermal power unit is mainly composed of two parts, namely, start-up and shut-down costs and operating expense. The expected value model is expressed as:

\[
\min C = \sum_{t=1}^{T} \sum_{i=1}^{I} C_i (1-u_i)u_i' + \sum_{i=1}^{I} \beta_i \sum_{t=1}^{T} \sum_{i=1}^{I} u_i'[F(P_{G,i}')] \\
C_i' = C_{i,us}^{hs}, T_{down} \leq T_{off} \leq t_{ih} \\
C_i' \cdot T_{off} \geq t_{ih} \\
F(P_{G,i}') = a_i(P_{G,i}')^2 + b_i P_{G,i} + c_i
\]

where \( C \) is the total cost, \( I \) is the number of thermal power unit, \( T \) is the time period of hour-ahead dispatch, \( H \) is the number of optimal scenario. \( u_i' \) denotes the start-up state of unit \( i \) during \( t \) time, \( \beta_i \) is the probability of scenario \( h \). \( C_i' \) is the start-up cost of unit \( i \) during \( t \) time, \( T_{off} \) is the continuous shut-down time, \( t_{ih} \) is the critical time of hot start-up, \( C_{i,us}^{hs} \) is the cost of hot start-up, \( C_{i,us}^{cs} \) is the cost of cold start-up. \( F(P_{G,i}') \) is the fuel fee for the unit \( i \) during the \( t \) time under the scenario \( h \), \( P_{G,i}' \) is the output power of the thermal power unit \( i \) in the \( t \) period, \( a_i, b_i, c_i \) are the correlation coefficients.

(2) \( \text{CO}_2 \) emissions

\[
\min E_c = \sum_{t=1}^{T} \sum_{i=1}^{I} \beta_i \sum_{h=1}^{H} G(P_{G,i}') \\
G(P_{G,i}') = a_i(P_{G,i}')^2 + b_i P_{G,i} + c_i
\]

where \( E_c \) are the carbon emissions, \( G(P_{G,i}') \) are the carbon dioxide emissions for the unit \( i \) during the \( t \) time period under the scenario \( h \), which is a quadratic polynomial of the output power \( P_{G,i}' \) of the thermal power unit \( i \) in the \( t \) period, \( a_i, b_i, c_i \) are the correlation coefficients.

2.2.3. Constraints. The constraints are divided into equality constraints and inequality constraints.

(1) Inequality constraints

Inequality constraints include minimum start-stop time constraints for thermal power units, climbing constraints of thermal power units, the upper and lower bound constraints of active power for thermal power units, spinning reserve constraint for system, the upper and lower bound constraints of power generation and pumping power in pumped storage stations, water flow constraints of pump generation and pumping in pumped storage stations, bound constraints of storage capacity of pumped storage stations, which are expressed as the following formula (6) \~ (12) respectively.

\[
(u_i' - u_i)(T_{i,down} - T_{i,up}) \geq 0 \\
(u_i' - u_i)(-T_{i,down} - T_{i,up}) \geq 0 \\
P_{G,i,down} \leq u_i' P_{G,i} - u_i P_{G,i} \leq P_{G,i,up} \\
u_i' P_{G,i} \leq P_{G,i} \leq u_i' P_{G,i} \\
\sum_{i=1}^{I} u_i' P_{G,i} - P_{G,i} \geq 0 \%
\]

\[
0 \leq P_{G,i} \leq P_{G,i} \\
0 \leq P_{G,i} \leq P_{G,i}
\]
where \( T^t_i \) is the continuous running time or shutdown time of the unit \( i \) at time \( t \), it is positive when continuous in service, and negative when continuous shutdown; \( T^{min}_i \) and \( T^{off}_i \) are the minimum running time and downtime respectively; \( P^\prime_{r,down} \) and \( P^\prime_{r,sp} \) are the upper and lower climbing power limit, respectively; \( P^\prime_{g_k} \) and \( P^\prime_{p_k} \) are respectively the power generation and pumping power of the storage power station; \( q^\prime_{g_k} \) and \( q^\prime_{p_k} \) are respectively the water flow of power generation and pumping in storage power stations; \( \overline{q}_{g_k} \) and \( \overline{q}_{p_k} \) are respectively the upper limit of power generation and pumping water flow; \( r^t_i \) is the storage capacity of the upper reservoir in the storage power station at the time of \( t \); \( \overline{r}^t_i \) and \( \underline{r}^t_i \) are respectively the maximum capacity and minimum capacity of the upper reservoir.

(2) Equality constraints

Equality constraints include total power balance constraint of the system, the constraint that the power generation and pumping of pumped storage power station do not take place at the same time, power- water flow balance constraint of pumped storage power station, dynamic balance constraint of reservoir capacity in pumped storage power station, initial and terminating capacity constraints of the storage power station, which are respectively expressed as the following formula (13) ~ (17).

\[
\sum_{k=1}^{n} u^t_i P^\prime_{g_k,h} + \sum_{k=1}^{n} P^\prime_{g_k,h} - \sum_{k=1}^{n} P^\prime_{p_k,h} + P^\prime_{wind, h} - P^\prime_D = 0
\]

\[
P^\prime_{g_k} - P^\prime_{p_k} = 0
\]

\[
\begin{align*}
P^\prime_{g_k} &= d_1 (q^\prime_{g_k})^2 + d_2 q^\prime_{g_k} \\
P^\prime_{p_k} &= d_1 (q^\prime_{p_k})^2 + d_2 q^\prime_{p_k}
\end{align*}
\]

\[
r_{k}^{i+1} - r_{k}^{i} + (q_{g_k} - q_{p_k}) \Delta t = 0
\]

\[
\begin{align*}
r_{k}^{0} &= r_{k}^{ini} \\
r_{k}^{T} &= r_{k}^{end}
\end{align*}
\]

where \( P^\prime_{g_k,h} \) and \( P^\prime_{p_k,h} \) are respectively the power generation and pumping power of the storage power station during the time \( t \) under the scenario \( h \), \( P^\prime_{wind, h} \) is the output power of the wind farm during the time \( t \) under the scenario \( h \), \( P^\prime_D \) is the total load of the system during the \( t \) time period. \( d_1, d_2, d_3 \) and \( d_4 \) are the correlation coefficients of power and water flow in the storage power station. \( r_{k}^{ini} \) and \( r_{k}^{end} \) are respectively the initial and terminal storage capacity of the reservoir in the pumped-storage station.

3. Multi-objective optimization algorithm

3.1. Improved differential evolution algorithm

In the low carbon power scheduling, the multi-objective optimization problem contains two kinds of variables: one is the 0/1 integer decision variable \( u^t_i \), representing the on-off state of thermal power units in each time period, the other is the continuous variable \( P^\prime_{g_k,h} \), which determines the power output of thermal units in each period. It can be seen from the model that the multi-objective optimal scheduling problem is a nonlinear, high-order and nonconvex problem. To solve this problem, an improved differential evolution algorithm will be given as follows:

1. The variation factor and crossover probability are dynamically adjusted in the improved algorithm. By adopting the dynamic adjustment strategy to the parameters such as variation factor and crossover probability, the differential evolution algorithm can make global search in the initial stage of
searching and maintain the diversity of the population. In the later period of search, the differential evolution algorithm focuses on local search to improve the accuracy of the algorithm.

(2) In the selecting operation, the individual is sorted and selected by using fast non-dominating hierarchical sorting strategy. In the early stage of evolution, the ε-constraint method is used to improve the usage of high quality genes in the unfeasible solutions, so that the algorithm can more effectively select the optimal solution set of the objective function.

3.2. Key steps of differential evolution algorithm

3.2.1. Initial population formation. In the beginning of differential evolution algorithm for low carbon power scheduling, the initial population of 0/1 integer decision variable about on-off state and continuous variable about active power output of thermal power units in each period are generated. Since the on-off state of the thermal power units under each time period determines whether their active output value is 0 or not, the two kinds of variables can’t be considered completely independently. Firstly, the initial on-off state and initial output value are randomly generated. Secondly, the initial active power output values are fixed to 0 when the initial states of the units are shutdown at that time period, then the initial population can be generated.

3.2.2. Mutation operation. Due to the large number of elements contained in the population, the constraints are also complex. It is helpful to select 5 parent individuals to do mutation operation, which is beneficial to increase the randomness and global character, and then good optimization results can be achieved.

By adopting the dynamic adjustment strategy to variation factor, the searching capability of the difference evolution algorithm is improved to enhance the accuracy of the algorithm. Variation factor $F$ is generally a value between $[0, 2]$. At the beginning of the search, variation factor $F$ should be a little larger, which is beneficial to the global search and prevent premature convergence. In the later time period, with the advance of population evolution, the $F$ value should be reduced continuously to ensure the convergence of the algorithm. The dynamic value of $F$ is based on equation (18).

$$F = F_{\text{min}} + (F_{\text{max}} - F_{\text{min}})(1 - \frac{G}{G_{\text{max}}})$$

where $F_{\text{min}}$ and $F_{\text{max}}$ are the lower and upper limits of the scaling factor, $G$ is the current iteration number, $G_{\text{max}}$ is the maximum number of iteration.

3.2.3. Crossover operation. In the process of crossover operation, the on-off state of the units is particularly concerned. After the crossover, if the new value indicating the on-off state of the units gets 0, the value of active power output of the corresponding units is fixed to 0.

The crossover probability $c_r$ is the key to affect the behavior and performance of genetic algorithm, which is generally between $[0, 1]$. In the early stage, the value of $c_r$ should be a little smaller to maintain population diversity, and then global search capability can be improved. In the later period, the proportion of the variation vectors in the population should be enhanced to improve the local searching ability, so crossover probability $c_r$ should be increased. The dynamic value equation of crossover probability $c_r$ is as follows:

$$c_r = c_{\text{rmin}} + \frac{G}{G_{\text{max}}}(c_{\text{rmax}} - c_{\text{rmin}})$$

where $c_{\text{rmin}}$ and $c_{\text{rmax}}$ are the lower and upper limits of the crossover probability.

3.2.4. Selecting operation. The standard differential evolution algorithm adopts the greedy selection method to combine the experimental individuals generated after the cross mutation and the current parent to form a wide range of search. The algorithm should guarantee better population diversity to
avoid premature and make the effective solution of multi-objective optimization problem distributed evenly in the studied space. In this paper, the non-dominated sorting strategy in NSGA-II \cite{13} is introduced into differential evolution algorithm. The fast non-dominated sorting strategy is adopted to preferentially recruit non-dominated individuals which are selected by comparing their crowding degrees at the same level. The best individual is chosen so that the high-quality individuals selected in each generation are distributed in the entire Pareto domain. Then the diversity of each generation population is maintained. Simultaneously, the elite reservation strategy is introduced to update the Pareto optimal solution set to prevent the loss of high quality solution.

The differential evolution algorithm usually uses the comparison rule of the feasible priority solution to select the high quality solution, but this method is not applicable when the feasible solution is not appeared at the initial stage of calculation. In order to solve the optimization problem effectively, the \(\varepsilon\)-constraint method \cite{14} with improved rules is adopted. In this method, the unfeasible solution that has a better objective function on the boundary of the feasible domain can be selected into the population in the early stage of evolution, so that the high-quality genes of the outstanding unfeasible solution can be retained. With the increase of evolutionary generation, the number of unfeasible solutions in the population can be reduced by decreasing the relaxation degree gradually. The population is completely made up of feasible solutions until the relaxation is zero. Based on the non-dominant ranking strategy of the same level, the optimal solution is sorted, then several good individuals are put into the Pareto candidate solution set, which would continue to participate in the evolution of the next generation.

4. Example

In order to verify the proposed method, the IEEE-10 machine benchmark system which has one pumped-storage station, wind farm with a number of fans, and equivalent overall load.

Based on the original predictive power curve of the wind farm, 100 initial scenes are generated according to the scenario sampling method of ARMA. According to the principle that the probability distance is the shortest after the reduction of scenarios, a heuristic synchronous recursive reduction method in this paper is used to reduce the initial scenarios. Finally, the optimal set of 5 optimal random prediction wind power curves is obtained. The probability of occurrence of each scene is 0.1, 0.12, 0.5, 0.18 and 0.1, respectively.

Nine sets of Pareto optimal solutions are finally obtained by calculating in MATLAB. The optimal solution of each group corresponds to a feasible scheduling scheme for thermal power units, the objective function value of each scheduling scheme are shown in figure 1.

![Figure 1. The cost and CO\(_2\) emissions of each optimal plan](image)

The algorithm optimizes two objective functions simultaneously and then nine sets of optimal solutions all meet the requirements of carbon emissions, therefore economic efficiency can be the main goal for the selection of optimum solutions. In this case, "scheme 1" among all optimum solutions is selected as the final scheduling strategy due to the lowest cost. The optimization results of the corresponding objective function are as follows: running cost is $397127 and CO\(_2\) emissions are 57480kg.

Taking "scheme 1" as an example, all the calculated parameters are verified to meet the constraint conditions, which indicates the feasibility of this scheme. The case proves the reliability of the calculation results and verifies the feasibility of the algorithm.
5. Conclusion
This paper proposes a method to solve the multi-objective optimal scheduling problem of hybrid power system with wind power and pumped-storage station. Firstly, a two-stage stochastic programming model of classical test system is established based on the scenario modeling method of wind power uncertainty. Then the improved algorithm is proposed to calculate the stochastic expectation model. The obtained solution indicates that the optimization result on the objective function is effective, and the model of multi-objective stochastic optimization scheduling is suitable for solving the optimization of low carbon scheduling for hybrid system with uncertain wind power.

Acknowledgments
This work was supported by the Key Natural Science Research Project of Universities of Anhui (KJ2015A363).

References
[1] Zou J, Lai X, Wang N B. 2015, Mitigation of Wind Curtailment by Coordinating With Pumped Storage. Power System Technology, 39(9), pp 2472-2477. (in Chinese)
[2] Xu F, Chen L, Jin H P, et al. 2013, Modeling and Application Analysis of Optimal Joint Operation Pumped Storage Power Station and Wind Power. Automation of Electric Power System, 37(1), pp 149-154. (in Chinese)
[3] Xiao B, Cong J, Gao X F, et al. 2014, A Method to Evaluate Comprehensive Benefits of Hybrid Wind Power-Pumped Storage System. Power System Technology, 38(2), pp 400-404. (in Chinese)
[4] Li Z W. 2011, Multi-objective Optimization of System Combined Wind Power with Pumped Storage Power. Lanzhou University of Technology. (in Chinese)
[5] Yu J, Ren J W, Zhou M. 2013, A Chance-Constrained Programming Based Dynamic Economic Dispatch of Wind Farm and Pumped-Storage Power Station. Power System Technology, 37(8), pp 2116-2122. (in Chinese)
[6] Wang L, Zhou Z, Wei Z Y, et al. 2014, Research on Optimal Operation of Hybrid Wind Power and Pumped Hydro Storage System. Power System and Clean Energy, 30(2), pp 70-75. (in Chinese)
[7] Zong Jin. 2012, Two-stage Power Generation Dispatch Model and Algorithm for Power Systems Including Wind Power and Pumped Storage Station. North China Electric Power University. (in Chinese)
[8] Wang S Y, Wang X H, Xiao J M. 2010, Application of Differential Evolution Algorithm in Combination of Units. Journal of Jiangnan University(Natural Science Edition), 9(4), pp 455-458. (in Chinese)
[9] Oskouei M Z, Yazdankhah A S. 2015, Scenario-based stochastic optimal operation of wind, photovoltaic, pump-storage hybrid system in frequency-based pricing. Energy Conversion & Management, 105, pp 1105-1114.
[10] Boone A. 2013, Simulation of Short-term Wind Speed Forecast Errors using a Multi-variate ARMA(1,1). Time-series Model. Electrical Engineering Electronic Engineering Information Engineering, pp 1-89.
[11] Zhang B H, Shao J, Wu X S, et al. 2013, Unit commitment with wind farms using scenario tree and chance-constrained programming. Power System Protection and Control, 41(1), pp 127-135. (in Chinese)
[12] Zhang L D, Yin M H, Bu J, et al. 2015, A Joint Optimal Operation Model of Wind Farms and Pumped Storage Units Based on Cost-Benefit Analysis. Power System Technology, 39(12), pp 3386-3392. (in Chinese)
[13] Deb K, Agrawal S, Pratap A, et al. 2000, A Fast Elitist Non-dominated Sorting Genetic Algorithm for Multi-objective Optimization: NSGA-II[M]/ Parallel Problem Solving from Nature PPSN VI. Springer Berlin Heidelberg, pp 849-858.
[14] Zheng J G, Wang X, Liu R H. 2012, $\varepsilon$-Differential Evolution Algorithm for Constrained Optimization Problems. *Journal of Software, 23*(9), pp 2374-2387. (in Chinese)