Robust coordinated capacity allocation for wind generation and energy storage in power systems

Xiaobin Wang, Sheng Fan and Gang Wang
Fuyang Power Supply Bureau, Hangzhou, Zhejiang Province, China

Email 1421997054@qq.com

Abstract. Aiming at locating and sizing of wind generation and energy storage in power system planning stage simultaneously, a bi-level optimization model is constructed. The first stage is mainly used to allocate the capacity of wind farms considering the total cost of establishment, operation and maintenance from both wind generation and energy storage. The second stage is applied for allocating energy storage to address the violations of wind generation. Robust optimization theory and genetic algorithm are used to solve the model. The effectiveness of the proposed model is validated by the Garver’s 6-bus system.

1. Introduction
Under the situation of fossil energy shortage and environmental pollution, the utilization of renewable energy is a promising way. Wind power generation is the most widely used due to its technology development and commercial prospect. However, the volatile and intermittent of wind power pose serious challenges to the power grid and restrict the capacity of wind power integrated. It is a common way to assemble energy storage to suppress wind generation fluctuation, which is helpful for increasing the admission capacity of wind power. Coordinate allocation of wind farms and energy storage will be a great benefit to the power systems integrated with large scale wind power from the perspectives of both economic and security.

The methods of researches on capacity allocation for wind generation and energy storage in power systems can be categorized as stochastic optimization [1-2] and robust optimization [3-9]. In the stochastic optimization, the decision maker has the probability distribution for the random parameters observed in the problem. And he/she aims to minimize the expected cost. In the robust optimization, on the other hand, there is no prior information on the parameter probabilities and only a set of discrete (sometimes continuous) uncertain parameters are at hand. In such cases, decision makers aim to minimize the worst-case cost.

Above researches choose to assemble energy storage after the wind farms are located, however, the decomposition-based allocating approach cannot achieve the optimal results because the lack of global coordination of different devices.

This paper proposes a bi-level optimization model based on robust optimization for locating and sizing both wind farms and storage, which is rarely researched to the best of the authors’ knowledge [10]. The optimization target is to reduce the total economic cost of establishment, operation and maintenance from both wind generation and energy storage when the operational security constraints violated by random wind generations are satisfied. To solve the problem, a linear robust optimization method and genetic algorithm are used. The validity of the method is demonstrated by an example of revised Garver’s 6 bus system.
The rest of the paper is organized as follows. In the next section the optimization model is presented. In section 3 and 4, solution method and case studies are illustrated. In section 5, conclusion and discussion are provided.

2. Wind power-storage joint allocation model

Configuration of wind power is helpful to reduce fuel costs of thermal power units, but requires more rotating reserve capacity of AGC units. Energy storage is needed when reserve capacity is insufficient to suppress wind power fluctuations. To judge wind power revenue and energy storage expenditure, optimization target of comprehensive income is considered, which consist of the cost of installation, maintenance and fuel cost. Node sets of wind powers, thermal power plants, adjustable units, non-adjustable units, energy storage devices and loads are expressed by the element W, T, G, U, E, L, respectively.

The objective function of first stage is to minimize comprehensive cost.

\[ f_1 = \min C = C_{\text{initial}} + C^{\text{om}} + C^{\text{fuel}} - E^{\text{grid}} \]  

where \( C \) is the comprehensive income of power system, \( E^{\text{grid}} \) denotes the electricity income, \( C_{\text{initial}} \) denotes the construction cost, \( C^{\text{om}} \) denotes the maintenance cost, \( C^{\text{fuel}} \) denotes the fuel cost. \( E^{\text{grid}} \), \( C_{\text{initial}} \), \( C^{\text{om}} \), \( C^{\text{fuel}} \) are represented as follows.

\[ C_{\text{initial}} = \rho_w^p \sum_{n=1}^{NY} S_{W,n} + \rho_e^p \sum_{j=1}^{NY} S_{E,j} \]  

where \( \rho_w^p \), \( \rho_e^p \) denotes the installation cost per unit capacity. \( n_W, n_E \) denotes the number of wind powers and energy storages in the power system. \( S_{W,n}, S_{E,j} \) denotes the capacity of the i-th wind power and j-th energy storage.

\[ C^{\text{om}} = \sum_{n=1}^{NY} \left( \frac{1 + \alpha_{\text{om}}^{\text{w}}}{{1 + a}} \right)^{n-1} \rho_w^{\text{om}} \sum_{i=1}^{n_W} S_{W,i} + \left( \frac{1 + \alpha_{\text{om}}^{\text{e}}}{{1 + a}} \right)^{n-1} \rho_e^{\text{om}} \sum_{j=1}^{n_E} S_{E,j} \]  

where \( NY \) denotes the number of programming year. \( \rho_w^{\text{om}}, \rho_e^{\text{om}} \) denotes the maintenance cost per unit capacity per year of wind powers and energy storages. \( \alpha_{\text{om}}^{\text{w}}, \alpha_{\text{om}}^{\text{e}} \) denotes the growth rate of \( \rho_w^{\text{om}}, \rho_e^{\text{om}} \) per year. \( a \) denotes the discount rate.

\[ C^{\text{fuel}} = 8760 \sum_{n=1}^{NY} \left( \frac{1 + \alpha_{\text{fuel}}^{\text{w}}}{{1 + a}} \right)^{n-1} \rho_{\text{fuel}}^{\text{w}} \sum_{i=1}^{n_W} P_{W,i} \]  

where \( \rho_{\text{fuel}}^{\text{w}} \) denotes the fuel cost of thermal power plants. \( \alpha_{\text{fuel}}^{\text{w}} \) denotes the growth rate of \( \rho_{\text{fuel}}^{\text{w}} \); \( P_{W,i} \) denotes the average output of thermal power plants at node \( i \).

\[ E^{\text{grid}} = 8760 \sum_{n=1}^{NY} \left( \frac{1 + \alpha_{\text{grid}}^{\text{w}}}{{1 + a}} \right)^{n-1} \rho_{\text{grid}}^{\text{w}} \sum_{i=1}^{n_W} S_{W,i} + \left( \frac{1 + \alpha_{\text{grid}}^{\text{e}}}{{1 + a}} \right)^{n-1} \rho_{\text{grid}}^{\text{e}} \sum_{j=1}^{n_E} P_{E,j} \]  

where \( \rho_{\text{grid}}^{\text{w}}, \rho_{\text{grid}}^{\text{e}} \) denotes the electricity income of wind powers and thermal power plants per generation capacity. \( \alpha_{\text{grid}}^{\text{w}}, \alpha_{\text{grid}}^{\text{e}} \) denotes the growth rate of \( \rho_{\text{grid}}^{\text{w}}, \rho_{\text{grid}}^{\text{e}} \); \( P_{W,i} \) denotes the average output of i-th wind power.

Constraints of first stage is as follows.

\[ 0 \leq S_{W,i} \leq \overline{S}_{W,i} \]  

where \( \overline{S}_{W,i} \) denotes the permissible maximum capacity of wind power of configurable nodes.

The objective function of second stage is to minimize the sum of energy storage capacity.

\[ f_2 = \min \sum_{j=1}^{n_E} S_{E,j} \]  

Second stage is based on DC power flow model. Constraints of second stage are as follows.
1) Nodal power balance

\[ \sum_{i=1}^{n_l} P_{L,i} = \sum_{j=1}^{n_{u,n}} P_{U,j} + \sum_{k=1}^{n_{G,k}} P_{G,k} + \sum_{y=1}^{n_{w,y}} P_{w,y} \]  

(8)

where \( P_{L,i} \), \( P_{U,j} \), \( P_{G,k} \) represents the average output of i-th load, j-th non-adjustable unit, k-th adjustable unit, respectively. \( n_l, n_{u,n}, n_{G,k} \) denotes the number of load, non-adjustable unit, adjustable unit, respectively.

2) Linear decision rule of power compensation

\[ \sum_{i=1}^{n_l} M_{\bar{a}_i} + \sum_{j=1}^{n_{G,j}} G_{\bar{a}_j} = 1, \ M_{\bar{a}_i}, G_{\bar{a}_j} \geq 0, \ \bar{a}_i = 1, \ldots n_{WB} \]  

(9)

where \( M_{\bar{a}_i} \), \( G_{\bar{a}_j} \) denotes the power balance sensitivity coefficient of energy storage and adjustable units, which represent the power adjustment of i-th energy storage and j-th adjustable unit when the power fluctuation of the k-th wind power happens.

3) Transmission capability constraints

\[ -\bar{F} \leq T(P_L - P_U - P_G - P_w + (M + G - I)\Delta P_w) \leq \bar{F} \]  

(10)

where \( \bar{F} \) denotes the deterministic limits of transmission capacity. \( P_L, P_U, P_G, P_w \) denotes the average output of load, non-adjustable unit, adjustable unit, wind power, respectively. \( \Delta P_w \) denotes the uncertain deviation between the real-time wind power output and the mean value, where \( \Delta P_{\bar{w}_l} \leq \Delta P_{\bar{w}_u} \leq \bar{P}_{\bar{w}} \). \( \bar{P}_{\bar{w}}, \bar{P}_{\bar{w}} \) denotes the upper bound and lower bound of output deviation of wind power. \( T \) denotes the power transfer allocation matrix, expressed as follows.

\[ T = X \begin{bmatrix} B^{+1} & 0 \\ 0 & 0 \end{bmatrix} \]  

(11)

where \( X \) is a matrix consist of vector \( X_k \). For k-th branch from bus \( i \) to \( j \), \( X_k \) can be expressed as follows.

\[ X_k = \begin{bmatrix} \cdots & \cdots & \cdots & \cdots \\ \cdots & X_y & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots \end{bmatrix} \]  

(12)

4) Operating range constraints of adjustable unit

\[ P_G \leq P_{\bar{G}} - M\Delta P_w \leq P_{\bar{G}} \]  

(13)

where \( P_{\bar{G}}, P_{\bar{G}} \) denotes the maximum and minimum output of adjustable unit. \( -M\Delta P_w \) denotes the reverse adjustment of adjustable unit to absorb the wind power fluctuation.

5) Operating range constraints of energy storage device

\[ -S_G \leq -G\Delta P_w \leq S_G \]  

(14)

where \( -G\Delta P_w \) denotes the reverse adjustment of energy storage device. \( S_G \) denotes the capacity of energy storage device.

3. Solution method

3.1. Robust linear optimization theory

The second stage model proposed in previous sections can be expressed as a linear optimization model considering uncertain data:

\[ \min \ cx \]
\[ \text{s.t.} \ A x \leq b \]
\[ l \leq x \leq u \]  

(15)
where $x \in \mathbb{R}^n$ is the decision variable; $l, u \in \mathbb{R}^n$ is the lower and upper bounds of $x$; $c \in \mathbb{R}^n$ is the coefficient matrix and vector; $b \in \mathbb{R}^m$ is a deterministic vector. And we assume that uncertain data only exist in matrix $A \in \mathbb{R}^{m \times n}$. The element of $A$ is denoted by $a_{ij} \in [a^l_{ij}, a^u_{ij}]$, $i=1, \ldots, m$, $j=1, \ldots, n$; the mean value of $a_{ij}$ is $\overline{a}_{ij}$.

Robust optimization theory [11] provides a solution to immune the uncertain data in (13). We introduce the uncertainty set with a robustness budget $\Gamma_i (\Gamma_i \leq |J_i|)$, which can be defined as:

$$\mathcal{R}_i(\Gamma_i) = \{a_{ij} \in [\overline{a}_{ij} - \beta_{aij} t^u_{ij}, \overline{a}_{ij} + \beta_{aij} t^l_{ij}], 0 \leq \beta_{aij} \leq 1, \sum_{i=1}^{m} \beta_{aij} \leq \Gamma_i \}, \quad i=1, \ldots, m, \forall k \in J_i$$

(16)

where $a_{ij}$ denotes the uncertain data vector in row $i$ of matrix $A$, $i=1, \ldots, m$; $\beta_{aij}$ depends on the robustness quota $\Gamma_i$, which is used for adjusting the conservative degree of $\mathcal{R}_i(\Gamma_i)$. By increasing $\Gamma_i$ from $\Gamma_{i1}$ to $\Gamma_{i2}$ ($\Gamma_{i1} \leq \Gamma_{i2}$), the conservative level of the solution will be lower. $t^u_{ij} = \overline{a}_{ij} - a^l_{ij}$, $t^l_{ij} = a^u_{ij} - \overline{a}_{ij}$; $J_i$ represents the set of uncertain data in row $i$ of matrix $A$, and $|J_i|$ represents the number of elements in set $J_i$.

With the dual theory, the robust counterpart of (15) and (16) can be given in (17):

$$\min_{x, z, p} \sum_{j=1}^{n} \overline{a}_{ij} x_j + \Gamma_i z_i + \sum_{k=1}^{m} p_{ik} \leq b_i, i=1, \ldots, m$$

$$z_i + p_{ik} \geq t^u_{ij} x_j, \quad i=1, \ldots, m, \forall k \in J_i$$

$$z_i + p_{ik} \geq -t^l_{ij} x_j, \quad i=1, \ldots, m, \forall k \in J_i$$

$$z_i \geq 0, p_{ik} \geq 0, \quad i=1, \ldots, m, \forall k \in J_i$$

$$l \leq x \leq u$$

(17)

where $z_i$ and $p_{ik}$ ($i=1, \ldots, m, \forall k \in J_i$) are auxiliary variables. The robust counterpart (17) is a determined linear programming.

3.2. Solution process

To solve the programming expressed by formula (1)-(14), the genetic algorithm is used to generate dispersed wind power capacity vector. A genetic algorithm is a search heuristic that is inspired by Charles Darwin’s theory of natural evolution. This algorithm reflects the process of natural selection where the fittest individuals are selected for reproduction in order to produce offspring of the next generation.

After determination of wind power capacity, the original problem can be translated into stochastic linear optimization expressed by formula (15). Using robust linear optimization theory, the robust optimal storage capacity in a certain wind power capacity can be obtained. By multiple iterations through genetic algorithm, the optimal wind power and storage capacity will be produced. The algorithm flow chart is as Figure 1.

4. Case study

4.1. Case condition

As shown in Figure 2, the revised Garver’s 6-bus system [12] is used to verify the effectiveness of the introduced approach. The parameters of bus and branch are shown in Table 1-2. The capacity limit of configurable wind powers is shown in Table 3. $d$ denotes the load; $g^{\text{max}}$ and $g^{\text{min}}$ denote the upper and lower limits of adjustable units; $n_{ij}$ denotes the number of transmission lines between node $i$ and
$j$: $x_j$ denotes the imaginary part of admittance of each branch; $f_y$ denotes the active power limit of single line between node $i$ and $j$.

Figure 1. Flowchart of algorithm.

Figure 2. Garver’s 6 bus test system.

Figure 3. Power balance sensitivity coefficients of storages and adjustable units.

Table 1. Bus parameters (MW).

| Bus | $d$ | $g_{\text{max}}$ | $g_{\text{min}}$ |
|-----|-----|------------------|------------------|
| 1   | 100 | 150              | 120              |
| 2   | 300 | -                | -                |
| 3   | 50  | 280              | 200              |
| 4   | 200 | -                | -                |
| 5   | 300 | -                | -                |
| 6   | -   | 500              | 300              |

Table 2. Branch parameters.

| Branch | $n_{ij}$ | $x_{ij}$ | $f_{ij}$/MW |
|--------|----------|----------|-------------|
| 1-2    | 1        | 0.4      | 100         |
| 1-4    | 1        | 0.6      | 80          |
| 1-5    | 1        | 0.2      | 100         |
| 2-3    | 1        | 0.2      | 100         |
| 2-4    | 1        | 0.4      | 100         |
| 2-6    | 4        | 0.3      | 100         |
| 3-5    | 2        | 0.2      | 100         |
| 4-6    | 2        | 0.3      | 100         |
Table 3. Capacity limit of configurable wind powers (MW).

| Bus | 1   | 2   | 3   | 4   | 5   | 6   |
|-----|-----|-----|-----|-----|-----|-----|
| $S_p$ | 50  | -   | 100 | 100 | 50  | -   |

4.2. Case result
Solver CPLEX in the interface YALMIP of MATLAB [13] is used for optimization. The solution time for this case is 300s. The optimal capacity and location of wind power and storage are given, as shown in Table 4.

Table 4. Optimal allocation of wind powers and energy storages (MW).

| Bus | 1   | 2   | 3   | 4   | 5   | 6   |
|-----|-----|-----|-----|-----|-----|-----|
| Energy storage (MW) | 7.2 | 0   | 0   | 0   | 29.4| 0   |
| Wind power (MW)     | 49  | 0   | 50  | 81  | 49  | 0   |

As shown in Table 4, the configuration capacity is lower than configurable capacity, which certifies the joint allocation method has optimization effect.

The power balance sensitivity coefficients of storages and units are shown in Figure 3. As shown in Figure 3, the fluctuation of wind power is completely eliminated through the regulation capability of AGC units and energy storage equipment. Each AGC unit has the ability to regulate the fluctuation of wind power besides balancing the active power under the mean output of wind power. Node 3 unit can absorb the fluctuation of wind power of the node completely. The energy-saving power of Node 6 unit is transferred to the wind farm of Node 1, 4 and 5 through the grid. Node 5, which has no AGC units, is a weak link in the network. It is limited by the transmission capacity of the grid and the regulation capacity of the unit, and its original regulation capacity is weak, so it needs a lot of energy storage to eliminate.

4.3. The influence of grid transmission capacity and unit regulation capacity
Table 5 compares wind storage allocation results under different grid transmission capacity and unit regulation capacity. Case 1 is the original case, case 2 is the case when the transmission power limit of the line is increased to 1.2 times, case 3 is the case when the node 3 unit is changed to 240MW non-AGC unit.

Table 5. Comparison of the allocation of wind power-storage under different transmission and unit regulation capacity (MW).

| Bus | 1   | 2   | 3   | 4   | 5   | 6   |
|-----|-----|-----|-----|-----|-----|-----|
| Energy storage (MW) case 1 | 0   | 0   | 0   | 0   | 37.4| 0   |
|     case 2 | 3.5 | 3.1 | 3.2 | 3.3 | 3.8 | 3.1 |
|     case 3 | 10.4| 3.4 | 7.5 | 3.8 | 31.6| 3.4 |
| Wind power (MW) case 1 | 49  | 0   | 50  | 81  | 49  | 0   |
|     case 2 | 49  | 0   | 71  | 97  | 46  | 0   |
|     case 3 | 49  | 0   | 21  | 81  | 47  | 0   |

From the comparison of case 1 and case 2, it can be seen that when the power flow constraint is relaxed, the allocation capacity of energy storage decreases, and the allocation points change from 5 nodes concentrated in weak links to balanced distribution of each node, and the installed capacity of wind power increases. This shows that the transmission capacity of the original grid structure is inadequate, resulting in limited flexible resource adjustment range, which limits the wind power admittance capacity of the power system. Line expansion can be considered to expand the absorption...
capacity. From the comparison of case 1 and case 3, it can be seen that the allocation of energy storage needs to be increased when the installed capacity of wind power is reduced after the unit of Node 3 loses its regulation capacity. This is because of the limitation of the adjustable operation range of the unit, the adjustment of power balance that cannot be participated in needs to be supplemented by the energy storage device.

5. Conclusion and discussion
A bi-level optimization model for capacity allocation of both wind farms and energy storage is proposed. The result shows that the model is more effective than optimizing wind power and energy storage capacity step by step. Furthermore, it assists the analysis of weak lines in the power systems so as to provide advice for expansion planning. In future work, we will try to introduce partial statistical information into the robust optimization to reduce the conservatism.

Reference
[1] Abbey C, Joós G 2009 A stochastic optimization approach to rating of energy storage systems in wind-diesel isolated grids[J] IEEE Transactions on Power Systems 24(1) 418-426
[2] Vrakopoulou M, Margellos K, Lygeros J and Andersson G 2013 A probabilistic framework for reserve scheduling and N-1 security assessment of systems with high wind power penetration IEEE Transactions on Power Systems 28(4) 3885-3896
[3] G Wang, Q Bian, H Xin and Z Wang 2018 A robust reserve scheduling method considering asymmetrical wind power distribution IEEE/CAA Journal of Automatica Sinica 5 961-967
[4] Natapol Korprasertsak, Thananchai Leephakpreeda 2019 Robust short-term prediction of wind power generation under uncertainty via statistical interpretation of multiple forecasting models Energy 180 387-397
[5] Xu Wang, Zhaohong Bie, Fan Liu, Yu Kou 2019 Robust dispatch for Integrated Electricity and Natural Gas System Considering Wind Power Uncertainty Energy Procedia 159 130-135
[6] Yumin Zhang, Xueshan Han, Ming Yang, Bo Xu, Yuanchun Zhao, Hefeng Zhai 2019 Adaptive robust unit commitment considering distributional uncertainty International Journal of Electrical Power & Energy Systems 104 635-644
[7] Farshad Golnary, Hamed Moradi 2019 Dynamic modelling and design of various robust sliding mode controls for the wind turbine with estimation of wind speed Applied Mathematical Modelling 65 566-585
[8] Shuang Yuan, Chaohua Dai, Ai Guo, Weirong Chen 2019 A novel multi-objective robust optimization model for unit commitment considering peak load regulation ability and temporal correlation of wind powers Electric Power Systems Research 169 115-123
[9] Yachao Zhang, Jian Le, Feng Zheng, Yi Zhang, Kaipei Liu 2019 Two-stage distributionally robust coordinated scheduling for gas-electricity integrated energy system considering wind power uncertainty and reserve capacity configuration Renewable Energy 135 122-135
[10] Dutta S, Sharma R 2012 Optimal storage sizing for integrating wind and load forecast uncertainties[C] Innovative Smart Grid Technologies(ISGT) IEEE 1-7
[11] Kang S C 2008 Robust linear optimization using distributional information. Boston: Boston University
[12] Chen Yan, Wen Jin-yu, Cheng Shi-jie 2011 Minimum load-curtailment in transmission network planning considering integrated wind farms Proceedings of the CSEE 31(34) 20-27
[13] Löfberg J 2004 YALMIP: A toolbox for modeling and optimization in MATLAB 2004 IEEE International Symposium on Computer Aided Control Systems Design 284-289