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Generation and Transmission Expansion Co-Planning Considering Wind Speed Correlation

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Abstract: Usually, outputs of the neighboring wind farms are strongly correlated due to being under similar conditions. However, conventional planning methods suppose wind farm outputs are mutually independent without considering the influence of wind speed correlation, which is not suitable for future power system with high proportion of renewable energy. In this paper, the co-planning approach of wind generation and transmission expansion is investigated considering the wind speed correlation. Firstly, the Nataf transformation and Cholesky decomposition are applied to describe the correlation of wind speed. Then, according to the cost-benefit analysis method, the objective function for describing the co-planning is established, which considers the investment cost, operation cost, reliability cost and the emission cost. The model was solved by the quantum-behaved particle swarm optimization algorithm based on stochastic simulation. Finally, the influence of wind speed correlation is analyzed via numerical results from South Brazil 46-bus system. From the simulation results, the model and algorithm are proved to be feasible. The method provided in this paper offers a useful tool for the dispatcher when the increasing wind energy is integrated into power systems.

Keywords: wind speed correlation, Nataf transformation, cost-benefit analysis, generation and transmission co-planning, quantum-behaved PSO.

Introduction

Wind power, which is a kind of the green, clean and renewable energy source, is being developed dramatically. The overall capacity is expected to reach 750 GW by 2020, showing an annual growth rate of more than 10% [1]. Therefore, the uncertainties and fluctuations associated with wind power call for reconsideration of the algorithms and methodologies for transmission network expansion planning (TNEP) to accommodate the increasing amount of uncertain generation. Besides, wind farms with close distance have the strong wind speed correlation. Reference [2] shows wind farms in Fujian province have the strong wind speed correlation. For this case, the research about TNEP with wind power (TNEP-WP) should also take account into the effect of wind speed correlation.

Recently, many works have focused on the development of modeling and solution methods for TNEP-WP. As one of the most popular methods, stochastic programming has applied to deal with the uncertainties in TNEP-WP problem [3]–[10]. In [3], a stochastic programming model for TNEP-WP is addressed, and then is solved by combining evolutionary algorithms and Benders decomposition. A two-stage stochastic programming approach for TNEP-WP is described in [4], where the joint distribution of the load and wind power is represented by the Gaussian copula. References [5] and [6] propose probabilistic multi-objective TNEP optimization frameworks. The uncertainties of wind power are tackled by the two-point estimation method [5] and the agglomerative hierarchical clustering method [6] respectively. In [7]–[8], Benders decomposition is employed to reduce the complexity and size of the optimization problem in the stochastic TNEP framework. The coordinated of wind farm integration and transmission network is developed based on multi-scenario in [9]. References [10] create representative load-wind scenarios via clustering for uncertainties.

In the above reference, the random and intermittent wind power outputs are assumed to be independent. And the relationship between the reliability and economy of the power grid is not well considered. In this paper, the integration of wind farms and transmission expansion are co-planned considering the correlation of wind speed. Furthermore, the wind speed data with a certain correlation is obtained by using the Nataf transformation, in which the other uncertain factors such as load forecast deviation, wind power output prediction error are both considered. Furthermore, an optimal co-planning model is proposed with the minimum total cost consisting of the investment cost, operation cost, reliability cost and emission cost. Then, the model is solved by the Quantum-behaved Particle Swarm Optimization (QPSO) based on the stochastic simulation algorithm.

The Model of Wind Speed Correlation

1) Nataf Transformation

To build the model of wind speed correlation, the Nataf transformation and Cholesky decomposition are used to convert the independent standard normal random variable to non-normal distribution relevant variables. The proposed method has good performance on the calculation speed and application robustness.

Using the marginal transformation, Liu and Der Kiureghian obtained the correlation standard normal random variables [11], which is shown as follows:

$$x_i = \phi^{-1}[F_i(v_i)] \quad i = 1, 2, ---, n \tag{1}$$

where $X = [x_1, x_2, ---, x_m]^T$; ϕ is the standard normal cumulative distribution function; and $F_i(v_i)$ is the wind speed cumulative distribution function.

The relationship between the correlation coefficient ρ_{ij} of the correlation standard normal random variable $\boldsymbol{X}$ and the wind speed correlation coefficient matrix $\mathbf{R}_0 = [\rho_{v, ij}]$ as follows:

$$\begin{aligned}\rho_{ij} &= \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}\left(\frac{x_i-\mu_i}{\sigma_i}\right)\cdot\left(\frac{x_j-\mu_j}{\sigma_j}\right) f_{X_i X_i}(x_i, x_j)\,dx_i\,dx_j \\ &= \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}\left(\frac{F_i^{-1}(\phi(y_i))-\mu_i}{\sigma_i}\right)\cdot\left(\frac{F_j^{-1}(\phi(y_j))-\mu_j}{\sigma_j}\right)\times\phi(y_i, y_j, \rho_{0,ij})\,dy_i\,dy_j\end{aligned} \tag{2}$$

Furthermore, $\mathbf{R}_0 = [\rho_{v, ij}]$ is decomposed by the Cholesky decomposition as

$$\mathbf{R}_0 = \mathbf{L}_0\mathbf{L}_0^T \tag{3}$$

Where $\boldsymbol{L}_0$ is the lower triangular decomposition matrix.

Then, the independent variables $\boldsymbol{U}$ with standard normal distribution are converted to the correlation variables. $\mathbf{Y} = [y_1, y_2, ---, y_m]^T$. The relation between $\boldsymbol{Y}$ and $\boldsymbol{U}$ is defined as

$$\mathbf{Y} = \mathbf{L}_0\mathbf{U} \tag{4}$$

At last, according to the inverse transform technique of equal-probability principle, one can obtain the wind speed with the correlation coefficient ρ as follows:

$$v_i = F_i^{-1}[\phi\,(y_i)] \quad i = 1, 2, ---, m \tag{5}$$

The above method is the process of the wind speed correlation by Nataf transformation.

2) The Solution for the Correlation Coefficient of the Wind Speed

It is difficult to get the analytical formula of Equation (2) directly, so it is transformed into the formula (6) as follow by using the integral space transformation method[12].

$$\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}\left(\frac{x_i-\mu_i}{\sigma_i}\right)\cdot\left(\frac{x_j-\mu_j}{\sigma_j}\right)f_{X_iX_i}(x_i,x_j)dx_idx_j=\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}\left(\frac{x_i-\mu_i}{\sigma_i}\right)\cdot\left(\frac{x_j-\mu_j}{\sigma_j}\right)\phi(u_i)\phi(u_j)du_idu_j \tag{6}$$

Then, the Gauss-Hermite integral method is applied to derive ρ_{ij}. And the wind speed correlation coefficient $\rho_{v,ij}$ is obtained by solving Equation (7) as follow

$$\rho_{v,ij}-\sum_{l=}^{m}\sum_{k=1}^{m}P_lP_k\left(\frac{x_{il}-\mu_i}{\sigma_i}\right)\left(\frac{x_{jk}-\mu_j}{\sigma_j}\right)=0 \tag{7}$$

where m is the number of the integral node; P_l and P_k are weigh values; (x_{il}, x_{jk}) are derived from Equations (8) and (9) as follow:

$$(y_{il}, y_{jk})^T = L_0(z_{il}, z_{jk})^T \tag{8}$$

$$(x_{il}, x_{jk})^T = (F_i^{-1}(\phi(y_{il})), F_j^{-1}(\phi(y_{jk}))) \tag{9}$$

The values of P_l , P_k, z_{il}, and z_{jk} in the above Equations can be got from the literature [12].

Mathematic Model

1) Objective Function

According to the cost-benefit analysis method, an objective function is built in the following, which is the minimum total cost C containing investment cost C_I and operation cost C_O of new wind turbines and transmission lines, reliability cost C_R of transmission network and emission cost C_E of ordinary generators.

$$\min C = C_I+C_o+C_R+C_E \tag{10}$$

The total investment cost includes ones of new wind turbines (WT) and transmission lines (TL):

$$C_I=\lambda_w\sum_{n=1}^{N_w}C_{Iw,i}\delta_{w,n}+\lambda_L\sum_{i,j\in\Omega}n_{ij}C_{IL,ij} \tag{11}$$

where N_w is the number of new WT ; Ω is the node set of transmission network; λ_w , λ_L are the equivalent annual value coefficients of the WT and TL respectively; $C_{Iw,n}$ is the investment cost of the nth WT; $C_{IL,ij}$, $n_{,ij}$ are respectively the investment cost of one line and the number of lines between the node i and j ; $\delta_{w,n}$ is a binary variable that is equal to 1 if the nth WT is constructed and 0 otherwise.

The total operation cost also consists of new wind generators and transmission lines:

$$C_O=\sum_{k=1}^{N_d}\left(\sum_{n=1}^{N_w}C_{Ow,n}P_{k,n}T_k+\sum C_{OL,ij}f_{k,ij}T_k\right) \tag{12}$$

where N_d is the number of load states; $C_{Ow,n}$, $C_{OL,ij}$ are the unit operation cost of the nth WT and the line ij respectively; $P_{k,n}$, $f_{k,ij}$ are respectively output of the nth WT and the active power flow through the line ij under the kth load state; T_k is duration of the kth load state.

The reliability and emission costs are calculated according to the following formula:

$$C_R=\sum_{k=1}^{N_d}C_{los}D_{los,k}T_k \tag{13}$$

$$C_E=\sum_{k=1}^{N_d}\sum_{r=1}^{N_g}C_{em}m_{em,k,r}T_k \tag{14}$$

where C_{los}, C_{em} are the unit losing-loads cost and unit emission cost respectively; $D_{los,k}$ and $m_{em,,k,r}$ is the power of lost loads and emission quality of the rth ordinary generator under the kth load state.

2) Constraints

Constraint conditions mainly include the power balance (15), the generation limits (16), and the line number limit each transmission line corridor (17), which are defined as follows:

$$\mathbf{P} - \mathbf{D} = \mathbf{B}\theta \tag{15}$$

$$P_i^{\min} \le P_{k,i} \le P_i^{\max} \qquad i \in N_g \tag{16}$$

$$0 \le n_{t,ij} \le n_{t,ij}^{\max} \qquad i, j \in \Omega \tag{17}$$

where ***P***, ***D*** are the active power vector of generators and loads respectively; ***B*** is the admittance matrix vector; ***θ*** is the phase angel vector of node voltages; $P_i^{\min}$ and $P_i^{\max}$ are the minimum and maximum available power output of the *i*the WT, respectively; $n_{t,ij}^{\max}$ is the maximum number of lines between node *i and j*.

Due to the random volatility of the wind power outputs and loads, some additional constraint conditions should be considered. In this paper, the uncertainty of the wind power prediction and load forecasting is considered within the 95% probability interval. Define the 95% probability interval of the wind power output as $\{P_W^{\min}, P_W^{\max}\}$. Define the 95% probability interval of the loads is $\{D_L^{\min}, D_L^{\max}\}$. The capacity constraint of lines is as follows:

$$P\left\{\left|f_{k,ij}\right| \le f_{ij}^{\max}\right\} \ge \beta \quad , \qquad i, j \in \Omega \tag{18}$$

Where $f_{ij}^{\max}$ is the maximum active power of the *i*the TL; β is the confidence level.

3) The prediction deviation

In the power system including wind farms, the prediction deviation is mainly considered from the load forecast and wind farm output prediction. Firstly, the load forecast deviation is as follows:

$$\tilde{D}_L(t) = \overline{D}_L(t) + \Delta D_L(t) \tag{19}$$

where $\tilde{D}_L(t)$ is the actual load; $\overline{D}_L(t)$ is the forecast load; $\Delta D_L(t)$ is the load forecast deviation, which is assumed to obey the normal distribution N $(0, \sigma_\kappa^2)$.

The wind farm output prediction deviation is

$$\tilde{P}_W(t) = \overline{P}_W(t) + \Delta P_W(t) \tag{20}$$

where $\tilde{P}_W(t)$ is the wind farm actual output value; $\overline{P}_W(t)$ is the wind farm output forecast value; $\Delta P_W(t)$ is the wind power output prediction deviation, which is assumed to obey the normal distribution N $(0, \sigma_w^2)$.

Solution Algorithm

1) Stochastic Simulation

In this paper, the model is solved by the QPSO based on the stochastic simulation whose procedure is as follows:

① set the counter $N' = 0$;

② generate randomly the variable samples of the output of WT, then put them into the formulus (18) to check, if they hold (18), then $N' = N' + 1$;

③ repeat '2)' above for *N* times until $N'/N > \beta$.

2) Quantum-Behaved Particle Swarm Optimization

In this paper, the QPSO has many advantages[14], such as the global convergence, faster convergence speed, fewer control parameters, stronger optimization ability, and so on.

The average best position *W*(*k*) is taken into QPSO to calculate the variable in the following iteration:

$$W(k) = \frac{1}{M}\sum_{i=1}^{M} w_i(k) = \left(\frac{1}{M}\sum_{i=1}^{M} w_{i,1}(k), \frac{1}{M}\sum_{i=1}^{M} w_{i,2}(k), \ldots, \frac{1}{M}\sum_{i=1}^{M} w_{i,N}(k)\right) \tag{21}$$

where *M* is the number of the swarm; *k* is the current number of iterations ; w_i is the local best position of the swarm *i*.

The iterative equation of the swarm is:

$$x(k+1) = w \pm \gamma \cdot \left| W_j(k) - x(k) \right| \cdot \ln[1/u] \tag{22}$$

where u = rand(0,1); γ is the contraction-expansion coefficient, which can be used to control the rate of convergence algorithm. The contraction-expansion coefficient is defined as

$$\gamma = (1 - 0.5) \times (Maxiter - k)/ Maxiter + 0.5 \tag{23}$$

where $Maxiter$ is the maximum number of the inner iterations.

The proposed QPSO is based on (21-23), the procedure is as follow:

① Generate the wind speed data of multi wind farms by inverse transformation of Nataf;

② Read the system data such as the prediction values of loads and wind power output, the probability distribution of prediction deviation. In addition, input the parameters of the quantum-behaved particle swarm optimization algorithm, such as maximum iteration number and particle swarm size;

③ Initialize the population. $\delta_{w,i}$, n_{ij} are randomly generated to form an individual, and the individual is tested according to the formula (15) ~ (18); if the individual is not feasible, the individual will be regenerated until the initial group is completed;

④ Calculate the average best position of particle swarm according to formula (21), and then calculate the fitness value of particles at the current location according to formula (10);

⑤ Update the position of the particle. The position of each particle is updated according to the formula (26), and the limit is verified. If it is beyond the limit, the particle is renewed. Besides, a random simulation is also used to verify whether the particle is satisfied with the predetermined confidence level, and if it doesn't meet the confidence level, the particle will be renewed. Then the fitness values of each particle are calculated. If they are superior to the extreme value of the current particle, the individual extremum is updated. If the individual extreme value of all particles is better than the current global extreme value, then update the global optimum;

⑥ Determine whether the number of iterations is reached. If it is not achieved, then go back to step '4)' and '5)', otherwise output the best particle as the optimal solution.

Analysis of Examples

1) Parameter Configuration

In this paper, the south Brazil 46-bus system is tested where 62 lines has been constructed and 79 new transmission line corridor may be built. Each pair of buses can be connected by 4 lines at most, which amounts to 316 candidate lines. The information about capacity and access node of the existing generators and the candidate wind farms are shown in table B1 in Appendix B. Loads are classed into the winner ones and summer ones, which was described in [15].

The relationship between the wind farm power output and the wind speed is as follows:

$$P(v) = \begin{cases} 0, v < v_{\mathrm{ci}} \\ \dfrac{v - v_{\mathrm{ci}}}{v_{\mathrm{r}} - v_{\mathrm{ci}}} P_r, v_{\mathrm{ci}} \le v < v_{\mathrm{r}} \\ P_{\mathrm{r}}, v_r \le v < v_{\mathrm{out}} \\ 0, v \ge v_{\mathrm{out}} \end{cases} \tag{24}$$

Where P_r is the rated power of a wind farm; υ_{ci}, υ_r and υ_{out} are the cut-in speed, rated speed and cut-out speed, which are 3,12 and 20 m/s, respectively. Load forecast deviation obeys the normal distribution $N(0, 20^2)$. The wind power prediction error factor is 0.02. The power loss value is 500USD/ MW·h. In QPSO, the number of swarms is 40, and the maximum number of iterations is 500. The confidence level β is set as 0.85.

2) Nataf Transformation

The wind speed distribution for every wind farm is assumed to follow the Weibull distribution, in which the scale and shape parameters are 8m/s and 2.2, respectively. The correlation coefficients between node 28 and 30 and between node 24 and 34 are both set as 0.5 respectively. The correlation coefficient matrix is defined as

$$\begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \tag{25}$$

In this paper, 5 integral nodes are selected to solve the correlation coefficient $\rho_{v,ij}$ of wind speed, which is 0.5124. Finally, wind speed simulation sequence for multi wind farms under moderate wind speed correlation is shown in Appendix A.

3) Results Analysis

The planning schemes in two cases - without considering wind speed correlation (case A) and considering one (case B) are shown in Fig.1, where the solid line represents the existing line, black dotted line represents the candidate line planned in two cases, blue and red dotted lines represent the candidate line planned only in case A and in case B respectively. 4 candidate wind farms are all to be integrated into the power system for satisfying load demand in two cases. In case B, no new line between the node 24 and 34 is to be constructed so as to avoid adverse effect of positive correlation between wind farms, where outputs of WTs increase or decrease simultaneously. The bus 24 supply more wind power to the bus 23. A new line between the node 34 and 35 is to be built. Since the correlation of wind farms with large rated capacity located at the bus 28 and 30 has a more significant influence on the power system, no line between the node 28 and 30 is to be connected. The wind power at the node 28 is transmitted to the node 16 and 22, while the wind power at the node 30 is transmitted to the node 29 and 26. In this way, two wind farms with large capacity can be isolated as far as possible to alleviate the negative effect due to strong correlations of wind speed.

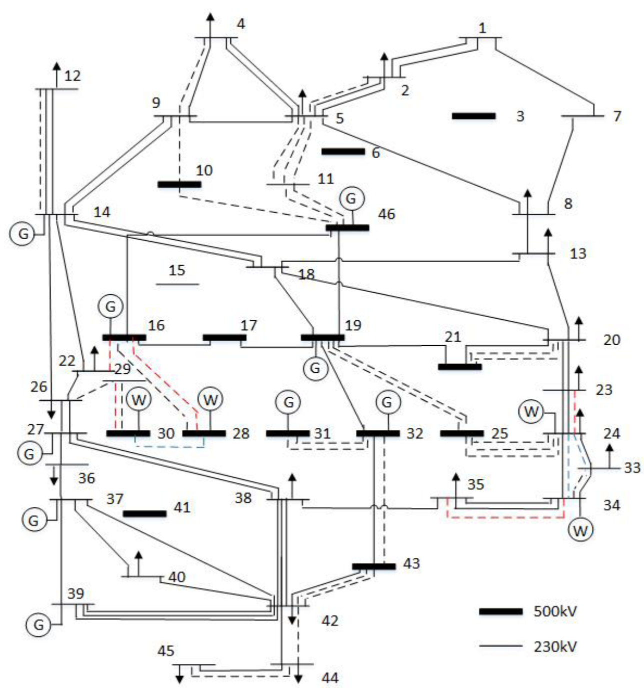

Figure1. *Comparison of planning schemes of South Brazil 46-bus system*

Table1. *Economic comparison of two planning schemes (cost/ million yuan)*

Planning scheme	Total cost	Investment cost	Operation cost	Other fees
case A	21546	1391	20139	16
case B	21293	1564	19715	14
cost-changing rate/%	-1.17	12.43	-2.11	-12.50

Table 1 illustrates the economic difference of two planning schemes – case A and case B. Compared with the planning scheme in case A, the investment cost rises by 12.43%, the operation cost falls by 2.11% and the total cost goes down 1.17%. Although the change rate of investment cost is much higher than that of operation cost, the operation cost of large-scale systems in case B goes down obviously because of the larger proportion of operation cost in the total cost. Therefore, with the increase of system scale, the economic benefits of generation and transmission expansion co-planning in case B are more significant than in case A.

Summary

This paper deals with generation and transmission expansion planning considering the wind speed correlation, and to enhance the reliability of the system, the reliability cost has been incorporated into the optimal model, in which the load forecast error and wind power output prediction error are considered. Meanwhile, the planning model is solved by the QPSO algorithm based on stochastic simulation. The main conclusions of this paper contain:

① Considering correlation of wind speed mainly affects the local planning scheme while has less impact on the overall one of large-scale systems. It should be avoided not to connect the buses where wind farms with strong correlation are integrated.

② Considering the correlation of wind power output may lead to the increase of investment cost, but the decrease of operation and other costs can offset this negative effect. The total economy depends on the proportion of each part of the total cost, and the economic benefit of large-scale system is better.

The main contribution of this paper is to propose a method of generation and transmission expansion considering wind power correlation. The specific impact of wind power correlation on the planning scheme also depends on the correlation degree of actual wind farms, the proportion of total cost components and other factors, which will be developed in the future work.

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References

1. QYResearch, China offshore wind power industry market research report, Market Res. Rep. Inc., Beijing, China, May 2016. https://www.researchmoz.us/china-offshore-wind-power-industry-2016 -market-research-report-report.htm
2. S. Reddy, P. R. Bijwe, Joint energy and spinning reserve market clearing incorporating wind power and load forecast uncertainties. IEEE Systems Journal. Commun. 9(2015), 152-164.
3. G. Chen, Z. Dong, and D. J. Hill, Transmission network expansion planning with wind energy integration: A stochastic programming model, Proc. IEEE PES Gen. Meeting, San Diego, CA, USA, 2012, pp. 1–10.

4. H. Park, R. Baldick, and D. P. Morton, A stochastic transmission planning model with dependent load and wind forecasts," IEEE Trans. Power Syst.,vol. 30, no. 6(2015) 3003–3011

5. A. Hajebrahimi, A. Abdollahi, and M. Rashidinejad, Probabilistic multi-objective transmission expansion planning incorporating demand response resources and large-scale distant wind farms, IEEE Syst. J., vol. 11, no. 2(2017) 1170–1181.

6. F. Ugranlı and E. Karatepe, Multi-objective transmission expansion planning considering minimization of curtailed wind energy, Int. J. Elect.Power Energy Syst., vol. 65(2015) 348–356.

7. J. Qiu, J. Zhao, and Z. Y. Dong, Probabilistic transmission expansion planning for increasing wind power penetration, IET Renewable Power Gener., vol. 11, no. 6(2017) 837–845.

8. C. Li, Z. Y. Dong, G. Chen, F. J. Luo, and J. Y. Liu, Flexible transmission expansion planning associated with large-scale wind farms integration considering demand response, IET Gener. Transmiss. Distrib., vol. 9,no. 15(2015) 2276–2283.

9. X.L. Wang, K. Zhang and P.L. Zeng, Coordinated planning of wind farm integration and transmission network based on multi-scenario, Electric Power Construction, vol. 36, no. 10(2015) 46–52.

10. F. Ugranli and E. Karatepe, Coordinated TCSC allocation and network reinforcements planning with wind power, IEEE Trans. Sustain. Energy, vol. 8, no. 4(2018) 1694–1705.

11. P. L. Liu, A. Der Kiureghian, Multivariate distribution models with prescribed marginals and co-variances. *Probabilistic Engineering Mechanics*, 1(1986), 105-112.

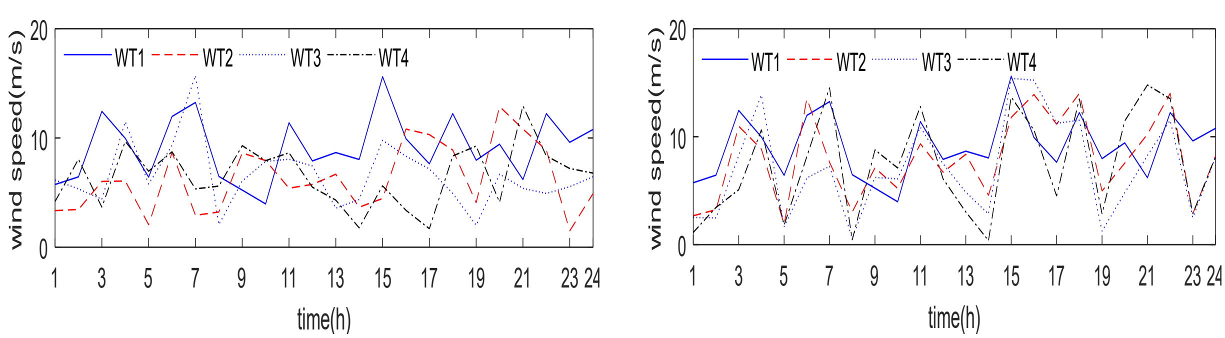
12. G. WANG, Global probabilistic seismic capacity analysis based on an improved point estimation method . *World Earthquake Engineering*, *4*(2008) 2-7

13. Y. Wang, C. Xu, W. Yue, A Stochastic Programming Model for Spinning Reserve of Power Grid Containing Wind Farms Under Constraint of Time-Varying Reliability. *Power System Technology*, 5(2013)1311-1316.

14. J. Sun, W. Fang, X. Wu, V. Palade, W. Xu,Quantum-Behaved Particle Swarm Optimization: Analysis of Individual Particle Behavior and Parameter Selection. *Evolutionary Computation*, 20(2013) 349–393.

15. Y. C. Huang, J. J. Yang, F. S. Wen, Transmission system planning considering capacity of accommodating intermittent generation sources. Automation of Electric Power Systems, vol. 37, no. 4(2013) 28–34.

Appendix A



(a) no correlation *(b) moderate correlation*

FigA1. *wind speeds time series with no correlation and moderate one*

TableA1. *Generation information of South Brazil 46-bus system*

Cenerators	node	Capacity (MW)	Cenerators	node	Capacity (MW)
G1	14	1257	G8	39	600
G2	16	2000	G9	46	700
G3	19	1670	W1	24	350
G4	27	220	W2	28	800
G5	31	700	W3	30	700
G6	32	500	W4	34	550
G7	37	300			

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