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Risk Reserve Constrained Economic Dispatch of Wind Power Penetrated Power System Based on UPSMC and SAGA Algorithms

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Abstract: A short-term Economic Dispatch (ED) model with risk constraint for wind penetrated power systems was built to face the challenge of scheduling spinning reserves brought from wind energies. The proposed model utilizes the probability of spinning reserve shortage as measurement of system risk and evaluates the risk by an Unequal Probabilities Sampling based Monte Carlo (UPSMC) method. A Genetic Algorithm (GA) improved with Simulated Annealing (SA) strategy is presented as SAGA to solve the problem. By comparing simulation results under different wind penetrations and risk constraints, coal consumptions will not always decrease with wind penetration and risk constraint but for most times. In addition, unit risk benefit has a trend to increase with wind penetration and decrease with risk constraint while contribution of unit wind generation has the contrary character. Simulation results also show that the proposed sampling method could improve the sampling efficiency and the SAGA method had better performance than traditional GA.

Keywords: Economic dispatch, genetic algorithm, monte carlo method, stochastic constraint, unequal probability sampling, wind energy

INTRODUCTION

The rapid increase of wind power penetration brings challenges to power systems especially for ED for the uncertainties of wind generations. ED consists of several phases and challenges in each phase would be different. For real-time ED, system requires considerable fast response generations or other power sources to settle the volatility of wind speeds in 5 to 10 min. For short-term ED, the main challenge is from the forecasting error of wind speeds, which might cause the spinning reserve shortage. Specifically, to satisfy loads with appropriate spinning reserves is the main duty of short-term ED in order to insure both economy and safety of power system. Short-term ED makes decisions based on forecasting values of wind speeds and loads, but forecasting values cannot match real ones at most times. Therefore, the spinning reserves determined by scheduling plan might be insufficient for system operating if they cannot satisfy the demand of large forecasting errors. Because the above reason, wind generations are not good power resources comparing with thermal generation from the perspective of ED. Nevertheless, system would prefer to utilize wind power as more as possible for they could offer clean energy and they are more reliable than other renewable energies.

However, traditional short-term ED model did not consider forecasting errors of wind power and those errors cannot be ignored since more and more wind power are integrated into electric power system (Miranda and Hang, 2005; Mangueira *et al*., 2008). Based on the challenge of wind generation, risk managements of power systems with wind generations gained great attentions in recent years. Wind generations usually make larger outputs during valley times of loads, hybrid power of wind and hydro can reduce risks of wind generations (Denault *et al*., 2009), but it is hard to carry out in water-stressed areas. Without extra reserves for wind energy, load-carrying abilities of wind generations would have a considerable difference with their average outputs (Billinton *et al*., 2009), which means a waste of clean energy. Utilized extra spinning reserves to increase wind penetration and to insure the security of system will be the choice for most power systems (Lu *et al*., 2008; Montes and Martin, 2007; Doherty and O'Malley, 2005). Extra reserves will hike up system cost, so ED programs need to balance the economy and safety. A two-objective ED model was built to balance the risk and cost in study (Lingfeng and Singh, 2008) and the authors assumed that system risk is a function of wind power penetration and system cost in their research. Algorithms of ED also obtained many attentions. In previous researches, ED problems mainly adopts the dynamic programming algorithm (Al-Kalaani, 2009), the priority order method, Genetic Algorithm (GA) (Amjady and

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Shirzadi, 2009; Dudek, 2007) and particle swarm optimization (Kumar *et al*., 2011; Wang and Singh, 2009). Generally, it is necessary to assess and control risks for ED of power system with wind generations to utilize wind energy economically and safely.

This study aims to satisfy the demand of risk management of power systems with large scale wind energy by proposing a risk reserve constrained ED model. The proposed model utilizes the probability of lacking spinning reserve as the measurement of system risk (Zhou *et al*., 2010) and assesses it with improved Monte Carlo method; and the challenge of nonlinear optimization and stochastic constraint are solved by the proposed SAGA method.

METHODOLOGY

ED model with risk constraint: The objective function was the coal consumptions and was given by:

$$\min f = \sum_{t=1}^{24}\sum_{i=1}^{Ng}\left\{ f_i\left[P_i(t)\right] + S_i(t)\right\}\cdot U_i(t) \tag{1}$$

Constraints of the model are as follow:

Active power balance constraint of system is expressed as Eq. (2):

$$\sum_{i=1}^{Ng} P_i^T(t)\cdot U_i(t) + \sum_{j=1}^{Nw} P_j^w(t) = PL(t) \tag{2}$$

Unit ramp rate constraints of every generators need considering in the model, as in Eq. (3):

$$DR_i \le P_i^T(t) - P_i^T(t-1) \le UR_i \tag{3}$$

All generations' commitments cannot outrage of their abilities:

$$P_{\min,i}^T \cdot U_i(t) \le P_i^T(t)\cdot U_i(t) \le P_{\max,i}^T \cdot U_i(t) \tag{4}$$

System risk measured by the probability of spinning reserve shortage cannot exceed the setting value:

$$Risk = \Pr\left\{\max\left\{\Delta P - P_{reserve}^{up}, \Delta P - P_{reserve}^{down}\right\} > 0\right\} \le r \tag{5}$$

Risk evaluation with UPSMC: As mentioned before, risk evaluations utilize UPSMC method. Monte Carlo method has already successfully solved the reliability and risk evaluation of complex system (Georgopoulou and Giannakoglou, 2010; Wu *et al*., 2008). However, traditional Monte Carlo faces an efficiency conundrum in reserve risk evaluations of wind power integrated system: it requires a huge number of sampling times to get stable sampling result. Reason of this problem is as follow:

Traditional Monte Carlo method adopted Same Probability Sampling (SPS) as the sampling method. SPS treats all samples equally in the sampling process, which means the selection probability of sample in each sampling is the same with its distribution probability. SPS would make good performances when all samples make equal contributions to sampling result. Nevertheless, extreme forecasting errors are the main reason of reserve risks. SPS method needs many sampling times to sample those samples in most cases for their sampled probabilities are small, which leads a large number of sampling times to acquire their contributions to get the risk value.

UPS method could improve sampling efficiency of traditional Monte Carlo method in the above situation. UPS utilizes another probability distribution of samples instead of the original one or adding a sampling probability instead of treating all individuals equally in sample space to pay more attentions on those small probability samples but with decisive contributions to the result (Qualite, 2008). In this way, those small probability but important samples could make their contributions to sample result in lower sample times than SPS. The sampling result needs to be restored in the final estimation (Dubnicka, 2007; Carrizosa, 2010). This study uses average distribution instead of initial distribution of wind speeds in stochastic sampling. Steps of risk assessment with UPSMC method are as follow:

1) Obtain the forecasting errors distributions of wind speeds and loads from history data, 2 volatility ranges for speeds and loads prediction errors are defined as:

$$\left[\Delta Ev_j^{\min}, \Delta Ev_j^{\max}\right] \text{ and } \left[\Delta EL_{\min}, \Delta EL_{\max}\right]$$

2) A $\Delta Ev_j(t)$ could be randomly generated from the above volatility ranges based on the average distribution. The corresponding wind speed could be evaluated as Eq. (6), which would have the same probability density with its forecasting error. Loop the step for all scheduling periods, which are 24 h in a day in this study:

$$v_j(t) = v_{f,j}(t)\cdot(1-\Delta Ev_j(t)) \tag{6}$$

3) Convert the wind speeds forecasting errors to the ones of wind power $\Delta P_{w,j}(t)$ by Eq. (7):

$$\Delta P_{w,j}(t) = P_w(v_j(t)) - P_w(v_{j,f}(t))$$

$$P_w(v) = \begin{cases} 0 & v < v_{ci} \text{ or } v \ge v_{co} \\ \dfrac{v - v_{ci}}{v_r - v_{ci}}\cdot \mathrm{P}_r^w & v_{ci} \le v < v_r \\ \mathrm{P}_r^w & v_r \le v < v_{co} \end{cases} \tag{7}$$

4) Generate forecasting errors of loads for all 24 h by utilizing the same method with wind speeds
5) Compute the sampling result. The reserve will be considered insufficient and the sampling result *Nr* will be 1 if the following inequalities are true, otherwise *Nr* will be 0

$$(\sum_{i=1}^{Ng}(U_i(t)\cdot(P_{\max,i}^T - P_i^T(t)) < \sum_{k=1}^{Nw}\Delta P_{w,j}(t)) - \Delta EL(t)) \ , \ \exists t \in [0,23] \ \ or$$
$$(\sum_{i=1}^{Ng}(U_i(t)\cdot(P_i^T(t) - P_{\min,i}^T) < -\sum_{k=1}^{Nw}\Delta P_{w,j}(t) + \Delta EL(t)) \ , \ \exists t \in [0,23] \tag{8}$$

6) Restore the sampling result as Eq. (9):

$$Nr' = p_{speed}\cdot p_{load} \big/ (p_{speed}'\cdot p_{load}')\cdot Nr \tag{9}$$

7) Suppose current sample times are *Ns*, calculate the frequency of reserve insufficient as Eq. (10):

$$Fr = \sum_{m=1}^{Ns} Nr_m' \Big/ Ns \tag{10}$$

8) Iterate Step 2) to 7) until matching the termination criterion. The stop criterion in this study is that the variation of *Fr* is no more than 10^{-5} in continuous 100 times or iteration time matches 10^6. Utilize the final value as the risk value of the evaluated plan

Solutions of ED model with SAGA:

Main optimization: This study applies a hybrid method of GA and SA programs as main optimization algorithm (Yildirim *et al*., 2006; Shi, 2009). The proposed program adopts the objective function as the fitness function. Comparing with traditional GA and SAGA could improve global search capability of GA by shrinking differences of surviving probabilities between poor and excellent individuals in early generations and enlarging it in late stage. Specifically, individuals will be selected to the next generation with the following probability:

$$\Pr_{sv} = \exp\{-(f_i - f_{\min})/Te\} \ , Te = T\cdot(R_{cool})^n \tag{11}$$

By an appropriate initial temperature, *Te* could shrink the difference of $f_i - f_{\min}$ in the initial stage of SAGA. The reduction effect could increase the diversity of populations to avoid the premature convergence and local optimum. In the late stage, *Te* will be far smaller than 1 generally, which could make a large difference of selected probabilities between 2 individuals even when their fitness values are close with each other. The magnification could keep powerful natural selection ability to accelerate the convergence speeds in late stage.

Generally, comparing with the traditional selection method, the proposed selection method owns some of their advances together, such as insuring the best individual into next generation, keeping diversity in early iterations and powerful natural selection ability in late periods.

Except the SA strategy in selection method, the proposed algorithm adopts decimal code, float point mutation and one point crossover strategies. Besides, the mutation and crossover rates are adaptive based on performances of generations by f_i in Eq. (11). Encoding for unit commitments is as Eq. (12), in which genes could directly stand for the outputs of thermal generations:

$$G = \begin{bmatrix} P_{1,1} & \cdots & P_{1,t} & \cdots & P_{1,T} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ P_{i,1} & \cdots & P_{i,t} & \cdots & P_{i,T} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ P_{Ng,1} & \cdots & P_{Ng,t} & \cdots & P_{Ng,T} \end{bmatrix} \tag{12}$$

Settling of constraints: Constraints 1-3 are linear or boundary limits, individuals could satisfy them by adjusting their genes. For constraint 1, the stochastic adjustment while is as follow:

1) Let $\Delta = \sum_{i=1}^{Ng} P_{i,t} + PW(t) - PL(t)$

2) Verify the termination condition as $|\Delta| \le \varepsilon$, in where ε is the threshold value and if validated then terminate else go to step (3)
3) Randomly select an *j* from [1, *Ng*] and refresh $P_{j,t}$ as Eq. (13) and then go to step (1):

$$\begin{aligned} P_{j,t} &= P_{j,t} + random\cdot(P_{\max,j}^T - P_{j,t}), \ if \ \Delta < 0 \\ P_{j,t} &= P_{j,t} - random\cdot(P_{j,t} - P_{\min,i}^T), \ if \ \Delta > 0 \end{aligned} \tag{13}$$

For constraints 2) and 3), program will forcibly change the outraged gene in the process of generating new individuals. For example, if $G_{i,t}$ of a new individual is larger than its maxim value, the program would utilize the maxim one as its value. Simply stochastic adjustment cannot resolve risk constraint effectively for its complexity. This study added a penalty term in the objective function to solve this constraint, as shown in Eq. (14):

$$\min f = \sum_{t=1}^{24}\sum_{i=1}^{Ng}\{f_i[P_i(t)] + S_i(t)\}\cdot U_i(t) + P\_Risk \tag{14}$$

A penalty coefficient multiplies by the outage risk makes the penalty term in Eq. (14). Since risk value is far less than objective function, the penalty term affects the optimal process only when the punishment coefficient is large enough. However, a large penalty coefficient would reduce the diversity of populations. The SAGA utilized SA strategy to solve the problem. SA strategy plays a similar role in risk penalty term as in individual saving problem. As shown in Eq. (15), it provides a small penalty coefficient of risk outraged plans when *Te* is large at the beginning of GA. This would allow scheduling plans over limit at first, which would enrich the populations to avoid precocious of GA. Punishment of outraged individuals would increase as *Te* becoming small to accelerate the obliterating speed of those out limit individuals. Generally, SA strategy improves GA by insuring diversity of populations in the initial stage while controlling eliminating speed of poor and individuals in the late stage:

$$P\_Risk = R \cdot Risk$$
$$R = \begin{cases} R_{initial} / Te & Risk > \mathrm{r} \\ 0 & Risk \le \mathrm{r} \end{cases} \tag{15}$$

System cannot always satisfy risk constraint when the installed capacity of wind generation is too large. The proposed ED model adopts shutting down some wind generations in this situation for the sake of security.

Process of SAGA: According to the above description, all steps of SAGA with constraints are as follow:

- Read the initial data, including parameters of generations, history and forecasting data of wind speeds and loads, parameters of GA and simulated annealing algorithm.
- Randomly create initial population and adjust all individuals to meet the power balance, unit ramp rate and output constraints.
- Assess risks of initial individuals.
- Compute the fitness function values and sort individuals by them.
- Validate termination conditions of maximum iteration and convergence precision, if satisfied go to step 6; else go to Step (7).
- Validate risk constraint of result of Step 5, if satisfied terminate programs and export result, else shut down one wind generation of the wind farm and go to Step (2).
- Calculate crossover rate and mutational rate.
- Carry the crossover and mutation process and adjust new individuals to meet linear and boundary constrains.
- Assess risks of new individuals.

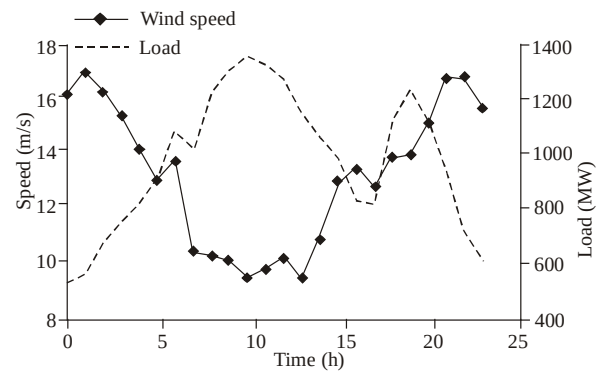

Fig. 1: Forecasting data of wind speeds and loads

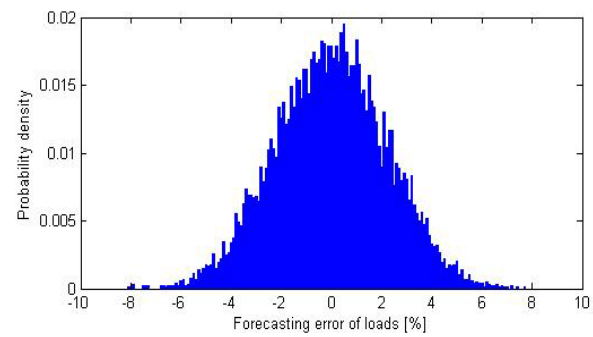

Fig. 2: Probability distribution of load forecast error

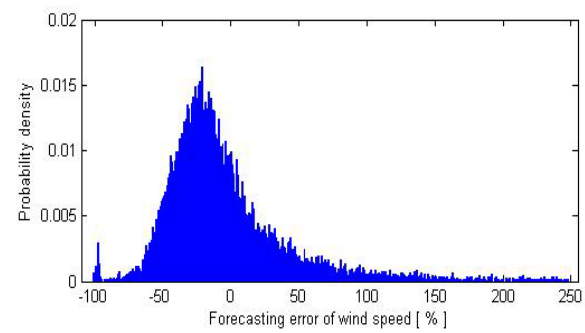

Fig. 3: Probability distribution of wind forecast error

- Compute the fitness function values of new individuals and sort all individuals.
- Select individuals with SA strategy to derivative next generation and go to Step (5).

Inputs and parameters: Use a system with 10 generators as the test system, parameters of the system are as reference (Sun *et al*., 2006). The total installed capacity of generations in the system is 1962 MW. As comparison, the study carried simulations under different installed capacities of wind farm from 0 to 600 MW. Figure 1 shows the utilized wind speeds and loads data. By utilizing the history data of Shanghai, Fig. 2 and 3 show the distribution of forecasting error of loads and wind speeds. Table 1 shows parameters of SAGA.

Table 1: Parameters of presented algorithm

Parameters	Population size	Convergence precision	Minimum crossover	Minimum mutation	R_{inital}	P_{WG}
Value	100	0.001	0.4	0.05	10	5
Parameters	Maximum iteration	Maximum crossover	Maximum mutation	R_{cool}	T	
Value	5000	0.8	0.2	0.9	10	

Table 2: Comparison of two sampling methods under different precision levels

Accuracy	Sampling method	Sampling times	Efficiency ratio
10^{-4}	I	5058	22.1%
	II	1119	
10^{-5}	I	20155	20.6%
	II	4163	
10^{-6}	I	45226	29.3%
	II	13248	
10^{-7}	I	332312	26.6%
	II	88340	

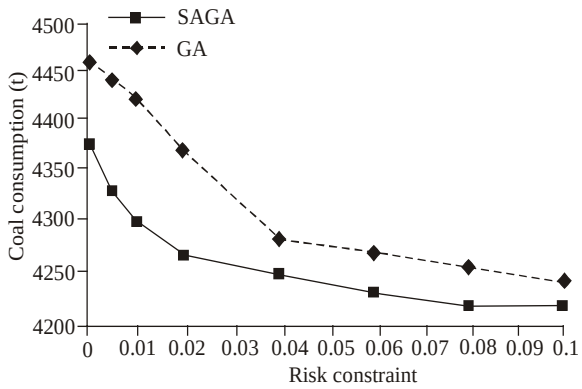

Fig. 4: Coal consumptions under different risk levels

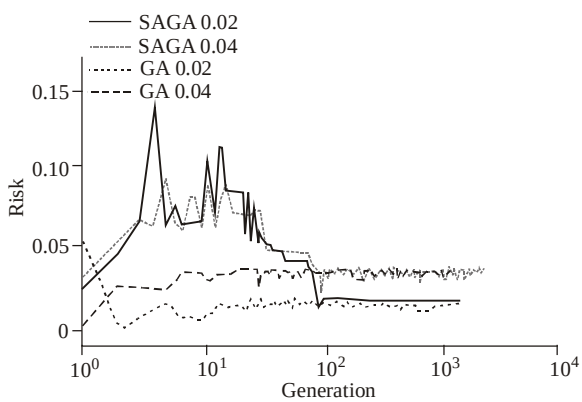

Fig. 5: Risks of optimization results in each generation

RESULTS AND DISCUSSION

Methods with SPS and UPS have been both carried in risk evaluation for comparison. Table 2 shows average sample times of the 2 methods in different accuracy levels. Method I accords to the original probability distribution, the methods II is the sampling method used in the designed program.

According the results shown in Table 2, for the utilized probability distributions of loads and wind speeds, the UPSMC decreases the numbers of sample times to 20~30%, respectively.

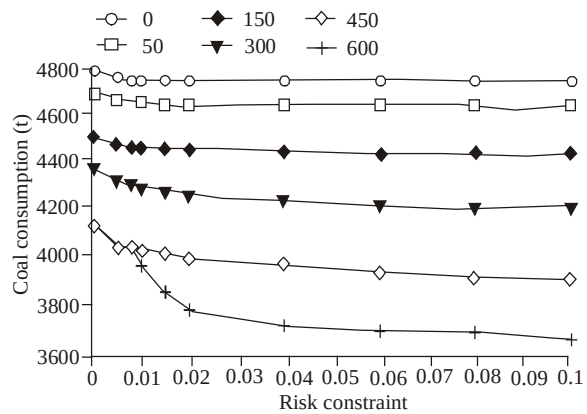

Fig. 6: Coal consumptions of different risk constraints under different wind penetration

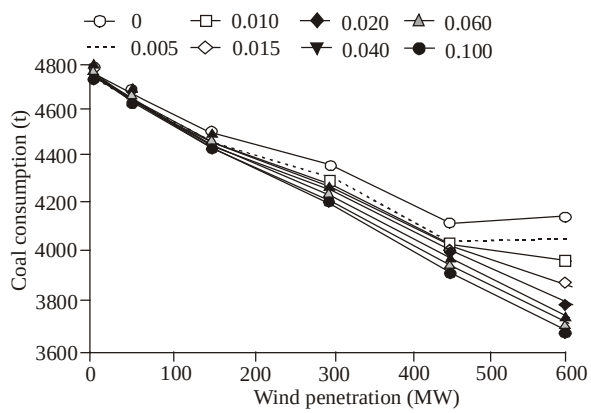

Fig. 7: Coal consumptions of different wind penetration under different risk constraints

In order to compare and discuss simulation results, the program utilized series of risk levels as inputs and solved ED with different methods. Figure 4 shows the coal consumptions under different risk levels with 300 MW installed wind generation based on the presented algorithm and the general GA, which would not contain SA strategy and with fixed crossover and mutation rate. The results show the improvement of SAGA comparing with general GA.

Figure 5 shows the risks of the best individual in every generation under risk constraints of 0.02 and 0.04. Comparing with GA, SAGA would allow individuals outrage of risk constraint in order to keep diversity of population. The results in late iterations all met risk constraints, which prove that the proposed ED model has the ability to control system risk.

Table 3: Scheduling strategy of thermal generations under risk constraint of 0 and 0.l

	Outputs of thermal generations [MW]									
	G1		G2		G3		G4		G5	
Time	0	0.1	0	0.1	0	0.1	0	0.1	0	0.1
0	0	0	331.84	367.00	0	0	0	0	35.150	0
1	0	0	317.02	382.00	0	0	0	0	42.850	0
2	187.48	198.82	290.86	304.59	0	0	0	0	25.110	0
3	195.27	397.76	373.74	197.14	0	0	0	0	25.970	0
4	375.16	454.03	281.58	227.88	0	0	0	0	25.240	0
5	441.32	454.66	322.55	334.76	0	0	0	0	25.680	0
6	411.21	454.67	421.00	407.39	0	0	85.650	88.850	33.080	0
7	407.95	454.64	380.02	356.52	0	0	80.970	127.26	69.570	0
8	448.92	454.89	451.33	433.17	0	98.900	129.82	128.35	87.500	25.110
9	454.87	454.76	454.87	443.86	0	128.21	129.35	128.87	110.91	72.720
10	438.02	454.97	455.00	455.00	0	129.92	62.420	129.98	160.91	122.58
11	449.93	454.82	443.15	454.73	0	98.720	122.28	129.80	134.69	115.87
12	418.18	454.94	450.54	454.74	0	0	124.28	129.88	141.75	160.35
13	421.03	451.25	440.53	442.23	0	0	49.450	83.510	146.43	110.42
14	401.89	454.95	347.40	454.48	0	0	123.90	0	101.33	64.990
15	440.48	455.00	294.51	378.69	0	0	73.030	0	51.940	26.210
16	435.46	450.65	211.67	228.73	0	0	0	0	57.280	25.020
17	339.56	326.26	318.11	329.57	0	0	0	0	45.240	47.140
18	432.21	453.60	419.10	439.95	64.29	0	0	0	72.840	94.900
19	435.29	454.98	448.94	454.99	77.76	0	75.430	0	62.550	144.76
20	371.41	452.78	451.97	411.12	0	0	46.560	0	88.990	95.010
21	397.23	398.11	314.77	312.71	0	0	0	0	43.950	45.070
22	315.51	198.42	202.42	344.49	0		0	0	25.020	0
23	258.31	0	162.01	445.50	0		0	0	25.090	0

	Outputs of thrmal generations [MW]									
	G6		G7		G8		G9		G10	
Time	0	0.1	0	0.1	0	0.1	0	0.1	0	0.1
0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0
8	22.90	0	0	0	0	22.90	0	0	0	0
9	45.84	0	0	0	16.14	45.84	0	0	0	16.14
10	80.00	0	50.00	0	46.14	80.00	0	50.00	0	46.14
11	62.16	0	25.65	0	16.14	62.16	0	25.65	0	16.14
12	39.60	0	25.66	0	0	39.60	0	25.66	0	0
13	30.02	0	0	0	0	30.02	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0
19	0	45.21	0	0	0	0	45.21	0	0	0
20	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0

Table 3 shows the optimal scheduling results at risk constraint of 0 and 0.1. As shown in Table 3, system needs to turn on more generations to provide more spinning reserve at the risk constraint of 0 compare with the one of 0.1, which makes the operation safer but more expensive. This explains why system cost would decrease with the increase of risk constraints.

Figure 4 also demonstrates a trend that coal consumptions would decrease as risk constraint grows while the sensitivities between them would become lower. In order to prove the point, this study carries simulations with series of wind penetrations.

Figure 6 and 7 show the coal consumptions under different wind penetrations and risk constraints. Curves in Fig. 6 illustrate the relations of coal consumption and risk constraint with wind penetrations of 0, 50, 150, 300, 450 and 600 MW, respectively, while the ones in Fig. 7 depict the connection of coal consumption and wind penetrations under different risk constraints,

which are 0, 0.005, 0.01, 0.015, 0.02, 0.04, 0.06 and 0.1, respectively.

As shown in Fig. 6, wind penetration would not affect the above trend, but it has effect on the slopes of curves, which are the benefit of enlarging unit risk constraint. From the variation of those slopes, unit risk benefit would increase with wind penetration but decrease with of risk constraint. Distances of adjacent curves in Fig. 7, which stands for the risk benefits of enlarging risk constraint from one to another, could also prove the above characteristic for those distances become smaller and smaller as increasing of risk constraint and decreasing of wind penetration.

Figure 7 also shows that coal consumptions decrease with wind penetration at most time and the only exception happens with risk constraint of 0. Consumption in the above condition is larger than the one with 450 MW, which can also be seen in Fig. 6. The exception shows the increase of wind penetration might make a rise of system cost when the risk constraint is small and wind penetration is large. Cost of system including 600 MW wind generation would be lower than the one including 450 MW while risk constraint increases up to 0.005 or larger, which supports the point that unit risk benefit would increase with installed capacity of wind generation.

Slopes of those curves in Fig. 7 stand for the saved consumptions per million watts installed capacity of wind penetration. From the variation of slopes in the figure, the contribution of unit wind generation has a general trend to decrease with the increase of wind penetration and the decline of risk level.

NOMENCLATURE

$f[P]$	Coal consumption of thermal generation at power P
S_i	Startup consumption of thermal generation *i*
U_i	State of thermal generation *i*, value 1 and 0 stand for running and shutting down, respectively
P^T, P^w	Power of thermal generation and wind farm
$P^T_{max,j}$, $P^T_{min,j}$	Maximum and minimum outputs of thermal generation *j*
UR_i, DR_i	The up and down ramp rate of thermal generation *i*
Ng, Nw	Numbers of thermal generators and wind farm
$P^{up}_{reserve}$, $P^{down}_{reserve}$	Reserve capacity of power system
$\Pr\{A\}$	Probability of event A
ΔP, ΔP_w	System and wind power variation caused by forecasting error
ΔEv^{min}, ΔEv^{max}	Minimum and maximum forecasting error of wind speed
ΔEL_{min}, ΔEL_{max}	Minimum and maximum forecasting error of load
v_j, v_f	Real and forecasting value of wind speed
ΔEv, ΔEL	Forecasting error of wind speed and load
v_{ci}, v_{co}	Cut in and cut out wind speeds of wind generator
v_r, P^w_r	The rated wind speed and rated power of wind farm
p_{speed}, p_{load}	The real probabilistic density of sampled wind speed and load
p_{speed}', p_{load}'	The changed probabilistic density of sampled wind speed and load which are used in the UPS
Te, T, R_{cool}	Temperature, initial temperature and cooling rate of SA
Nr, Nr'	Result of every sampling in UPS and the restored one
$P_{i,t}$	Coding of GA stands for the output of thermal generator *i* at time *t*
$PL(t)$ $PW(t)$	Load and total outputs of wind farms at time t
$\Pr_{sv,k}$	Selection probability of individual *k* in SAGA
f_k, f_{min}	Fitness value of individual *k* and the best one in each generation
P_Risk	Risk penalty term
R, $R_{initial}$	Penalty coefficient and its initial value
P_{WG}	Rated power of wind generation

CONCLUSION

With the development of smart grid, more and more wind power will penetrate into the grid, which brings challenges to both short-term and real-time ED problem. This study carries researches on short-term ED of power system with wind power penetration, proposes a short-term ED model considering risk constraint and adopts SAGA to optimize system cost. The proposed model solves the challenge of wind penetration by offering a risk control method. With the method, system could utilize the wind energy as possible as it could under the setting risk level. The ED model utilizes the probability of lacking reserves as the measurement of system risk and evaluates it by the UPSMC method. As shown in simulation results, the UPSMC could reduce sampling times to 20~30% compare with the traditional one for the utilized probability distributions. Meanwhile, the SAGA

method shows better performance than general GA. Coal consumptions would decrease with risk constraint, but the unit risk benefit would decrease with it and the reduction of wind penetration. Therefore, enlarging the same risk constraint would always more cost-effective while the risk constraint is small or the wind penetration is large. In the other hand, system cost would decrease with wind penetration at most situations and the exceptions, which stand for the system cost have a rise with wind penetration, only happens when the risk constraint is too small for a large wind penetration. Contribution of unit wind generation becomes smaller with the increase of wind penetration and the decline of risk level, which means wind generations would be more efficiency when the penetration is small or the risk constraint is large.

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