Contingency Screening and Ranking Considering Volatility of Wind Power

Di Wang, Huaidong Liu, and Lezhao Yi
Ministry of Education Key Laboratory of Smart Grid (Tianjin University), Tianjin, China
Email: di002369@yahoo.com, hdongliu@126.com, yilezhao@tju.edu.cn

Xiran Wang
Economy Research Institute of State Grid Zhejiang Electrical Power Company, Zhejiang, China
Email: pkwxr@163.com

***Abstract*—In order to avoid only considering seriousness of fault in contingency screening and ranking, a new method is proposed which is based on probabilistic insecurity index. In this paper, randomness, economy and volatility of wind power and load are considered. Besides, probability density functions of wind power and load are used to modify the model of expected loss. Firstly, according to typical fault set, dynamic security region and probabilistic insecurity index are determined. Then the volatility of wind power and load could be transformed into the volatility of generator trip and load shedding. Finally, based on modified model of expected loss, the proportion of expected loss of each contingency in fault set can be computed. Then use this proportion to screen and rank contingencies. Simulations on New England 10-generator 39-bus system show that based on this new method, contingencies could be screened and ranked rationally and accurately.**

***Index Terms*—contingency screening and ranking, probabilistic insecurity index, volatility of wind power and load, expected loss**

I. INTRODUCTION

Wind power is an important renewable energy. Its development is conducive to energy conservation and emission reduction. However, its randomness, fluctuation and uncontrollability are challenges to traditional contingency screening and ranking strategies. A large number of power failure accidents around the world suggest that it is necessary to attach great importance to power systems security problems. Thus establishing, screening and ranking anticipated fault set are of great importance to the safe and stable operation of power system [1]-[3].

Great numbers of indexes, like state index and stability margin index, could be used to screen and rank faults [4]-[10]. But in these cases only seriousness of contingency is considered. Faults probability, parameter uncertainty and economic loss are neglected. Thus, expected loss, based on probabilistic insecurity index, is a better index which could evaluate the operation of power system accurately.

Manuscript received October 1, 2016; revised December 14, 2016.

Both generator trip and load shedding are important emergency control measures. Currently, studies of emergency control measures are mainly based on conventional power network structure. And the characteristics of wind power are not considered. In Ref. [11], detailed post-fault action process of power system and safety control device are studied. This study suggests that after the integration of large-scale wind power, the volatility of wind power would influence the effectiveness of generator trip inevitably. Ref. [12]-[15] suggest that in wind-thermal combined system, in order to maintain controllability of post-fault frequency and voltage, the proportion of thermal generator trip should not be high. Wind generator trip should be considered. Normally, the volatility of wind power could be eliminated by electric power system control. But in failure period, local power flow may change fast as a result of volatility of wind power. Thus, the fluctuation of wind power should be considered when expected loss index is used to screen and rank contingencies.

In this paper, a new contingency screening and ranking method is presented. In order to consider volatility of wind power and load, probability density functions of wind power and load are used to modify expected loss model. Also, faults probability, parameter uncertainty and economic loss are considered. On the other hand, using dynamic security region to calculate probabilistic insecurity index can simplify calculation and increase calculation speed.

II. PROBABILISTIC INSECURITY INDEX

A. Dynamic Security Region

Dynamic security region $\Omega(i,j,t)$ is a vector set of active power in power injection space. i refers to prefault network structure. j refers to post-fault network structure. t refers to the duration of this fault. When an active power vector $\boldsymbol{Y}$ is given, if a power system can maintain synchronism after a fault, this vector $\boldsymbol{Y}$ is in dynamic security region $\Omega(i,j,t)$. Otherwise, this vector is out of dynamic security region. Many simulation experiments suggest that the boundary of dynamic

doi: 10.18178/ijoee.4.4.199-203

security region can be approximated by one or numbers of hyperplane which can be expressed as follows [16]:

$$\boldsymbol{A}\boldsymbol{Y}^{\mathrm{T}} = \sum_{i=1}^{n} a_i y_i = a_0 \tag{1}$$

where $\boldsymbol{A} = [a_1, a_2 \cdots a_n]$ is equation coefficient of hyperplane, and $\boldsymbol{Y} = [y_1, y_2 \cdots y_n]$ is critical active power vector. Also, n represents the dimensions of injection space. Besides, a_0 is watch variable. Normal value is 1 and conservative value is 0.9. Since dynamic security region method is a real-time algorithm, this new proposed method is suitable for real time framework.

B. Probabilistic Insecurity Index

Ref. [17] proposes a kind of probability insecurity model. Its physical significance refers to the unstable probability of power system after a contingency. But weather condition, fault type, line parameter and other factors are neglected in this model. This feature limits its engineering application. Using transmission line as an example, define probabilistic insecurity index $P_{in\sec}(l_i)$ as:

$$P_{\mathrm{insec}}(l_i) = P_{\mathrm{w}}(l_i)\alpha_{\mathrm{k}} \sum_{w=0}^{1} \beta_{\mathrm{w}} \int_0^{x_0(l)} f_{\mathrm{x}}(x) \int_0^{+\infty} f_{\mathrm{r}}(r) \int_0^{+\infty} f_{\tau}(\tau) M_{\Omega(l,k,r,x,\tau)}(y)\,\mathrm{d}\tau\,\mathrm{d}r\,\mathrm{d}x \tag{2}$$

where i is the number of transmission line. w refers to weather condition. $w=0$ refers to normal weather and $w=1$ refers to bad weather. $P_w(l_i)$ is fault probability function of line l_i in weather condition w. k refers to the type of fault. $k=1$ represents single-phase earthing fault. $k=2$ represents two-phases earthing fault. $k=3$ represents two-phase short circuit fault and $k=4$ refers to three-phase short circuit fault. α_k is the proportion of fault k. β_{w} is the proportion of weather condition w. x is the distance between fault location and initial point of the line. $x_0(l_i)$ is the length of transmission line l_i. $f_{\mathrm{x}}(x)$ is probability density function of x. r refers to fault resistance value. $f_{\mathrm{r}}(r)$ is probability density function of r. τ is fault-clearing time. $f_\tau(\tau)$ is probability distribution function of τ. $M_{\Omega(l,k,r,x,\tau)}(y)$ refers to security measure of certain faulty.

III. Probability Model of Random Factors

A. Probability Model of Fault Occurrence

Fault occurrence probability can be depicted by Poisson distribution. Ref. [18] proposes a fault occurrence probability model of transmission line considering normal and bad weather condition. This probability model can be expressed as:

$$P_{\mathrm{w}}(l_i) = 1 - e^{-\lambda_{\mathrm{tc}}(w)t} \tag{3}$$

$$\lambda_{\mathrm{tc}}(w) = \begin{cases} \lambda_0 \dfrac{N+S}{N}(1-\beta_1) & w=0 \\ \lambda_0 \dfrac{N+S}{N}\beta_1 & w=1 \end{cases} \tag{4}$$

where λ_0 is mean failure rate of line l_i. N refers to duration of normal weather. S refers to duration of bad weather. β_1 refers to the proportion of fault in bad weather condition.

B. Probability Model of Fault Type

The probability of these four faults, Single-phase earthing fault, two-phases earthing fault, two-phase short circuit fault and three-phase short circuit fault, can be obtained by using history data statistics.

C. Probability Model of Fault Location

Ref. [19] proposes a probability model based on discrete distribution and history data statistics. If transmission line is divided into M sections, then this probability of fault location at u can be depicted as:

$$P_{\mathrm{u}} = \frac{f_{\mathrm{u}}}{\sum_{u=1}^{M} f_{\mathrm{u}}} \tag{5}$$

where f_{u} is the number of fault occurring at u section.

D. Probability Model of Fault Resistance

Assume that fault resistance obeys logarithmic normal distribution. Its probability density function can be depicted as:

$$f_{\mathrm{r}}(r) = \begin{cases} \dfrac{1}{r\sqrt{2\pi}\sigma} e^{-\frac{(\ln r-\mu)^2}{2\sigma^2}} & r>0 \\ 0 \quad r<1 \end{cases} \tag{6}$$

E. Probability Model of Fault-Clearing Time

Assume that the sum of actuation time of protection relay and breaker time obeys normal distribution. And detection time is not considered in this paper. Then this probability density function can be expressed as [20]:

$$f(\tau) = \frac{1}{\sigma_\tau\sqrt{2\pi}} \exp\left(-\frac{(\tau-\mu_\tau)^2}{2\sigma_\tau^2}\right) \tag{7}$$

F. Uncertainty Model of Wind Power

Assume that wind turbines are variable speed turbines. Then output power characteristic can be depicted as:

$$P_{wind} \begin{cases} 0, 0 \le v < v_{\mathrm{i}} \\ a + bv^3, v_{\mathrm{i}} \le v < v_{\mathrm{r}} \\ P_{\mathrm{r}}, v_{\mathrm{r}} \le v \le v_0 \\ 0, v > v_0 \end{cases} \tag{8}$$

$$a = \frac{P_{\mathrm{r}} v_{\mathrm{i}}^3}{v_{\mathrm{i}}^3 - v_{\mathrm{r}}^3} \tag{9}$$

$$a = \frac{P_{\mathrm{r}} v_{\mathrm{i}}^3}{v_{\mathrm{i}}^3 - v_{\mathrm{r}}^3} \tag{10}$$

where v_i is cut-in wind speed. v_r is rated wind speed. v_0 is cut-out wind speed. P_{r} is rated power.

For the sake of simplification, neglect wake effects and assume that each wind turbine is the same. Then the total wind power of wind farm can be expressed as:

$$w_{\mathrm{av}} = P_{\mathrm{w}} N_{\mathrm{w}} \tag{11}$$

where P_{w} is the power of one wind turbine. w_{av} is the available wind power. N_{w} is the number of wind turbines. Then the probability density function of w_{av} can be depicted as:

$$f_{w_{\mathrm{av}}}(w_{\mathrm{av}}) = \frac{1}{3\sqrt{2\pi}\sigma_v b^{1/3} N_{\mathrm{w}}^{1/3}} (w_{\mathrm{av}} - aN_{\mathrm{w}})^{-2/3} \tag{12}$$

$$\exp\left(-\frac{[(\frac{w_{\mathrm{av}} - aN_{\mathrm{w}}}{bN_{\mathrm{w}}})^{1/3} - \bar{v}]^2}{2\sigma_v^2}\right) \tag{13}$$

G. Uncertainty Model of Load

Uncertainty model of load can be expressed by load forecasting error which obeys normal distribution. Its probability density function is as follows:

$$f_{\Delta P_{\mathrm{L}}}(\Delta P_{\mathrm{L}}) = \frac{1}{\sqrt{2\pi}\sigma_{\mathrm{L}}} \exp(-\Delta P_{\mathrm{L}}^2 / (2\sigma_{\mathrm{L}}^2)) \tag{14}$$

ΔP_{L} is load forecasting error. σ_{L} is standard deviation of forecasting error.

IV. Expected Loss Considering Volatility of Random Factor

After fault, the loss cost of power system mainly includes cost of applied prevention measures and cost of unstability. Assuming that the fluctuated value of wind power and load is small compared with the value of generator trip and shedding load, the dynamic security region remains unchanged. According to the function of hyperplane, the output of wind farm is linear to the value of generator trip and the fluctuated load value is linear to the value of shedding load. Then the probability density function of the value of generator trip and shedding load can be calculated easily. The loss cost can be depicted as follows [21], [22]:

$$I_{\mathrm{m}}^{\mathrm{c}} = I_{\mathrm{ms}} + I_{\mathrm{mo}} + I_{\mathrm{mD}} \tag{15}$$

where I_{ms} is the cost of device maintenance, device shutdown and device boot. I_{mo} refers to opportunity cost of power generation which can be depicted as formula [16]. I_{mD} is load lost cost which can be expressed as formula [19].

$$I_{\mathrm{mo}} = (\mathrm{C}_{\mathrm{new}} - \mathrm{C}_{\mathrm{old}}) \cdot h \cdot \int_{a-}^{a+} f_{\mathrm{lost}}(P_{\mathrm{lost}}) dP_{\mathrm{lost}} \tag{16}$$

where C_{new} is unit generation cost in fault period. C_{old} is prefault unit generation cost. h refers to the duration of fault. P_{lost} is the value of generator trip.

$$a- = P_f - (1 - p_{\mathrm{w}}) P_f \tag{17}$$

$$a+ = P_f + (1 - p_{\mathrm{w}}) P_f \tag{18}$$

P_f is predicted value of wind power and p_{w} refers to confidence coefficient.

$$I_{\mathrm{mD}} = C_{\mathrm{pen}} \cdot h \cdot \int_{b-}^{b+} f_{\mathrm{shed}}(P_{\mathrm{shed}}) dP_{\mathrm{shed}} \tag{19}$$

C_{pen} refers to load loss of unit power and P_{shed} is the value of shedding load.

$$b- = P_{\mathrm{load}} - (1 - p_{\mathrm{load}}) P_{\mathrm{load}} \tag{20}$$

$$b+ = P_{\mathrm{load}} + (1 - p_{\mathrm{load}}) P_{\mathrm{load}} \tag{21}$$

P_{load} is predicted value of load and p_{load} refers to confidence coefficient.

When fault k occurs at line l, expected loss S_{l_k} is as follows:

$$S_{l_k} = P_{\mathrm{insec}}(l_k) \cdot I_{\mathrm{mk}}^{\mathrm{c}} \tag{22}$$

V. Contingency Screening and Ranking

To implement the proposed new method, the major steps are briefly explained in sequence as follows:

Step 1: According to history data statistics, typical fault set $L = (l_1, l_1, \cdots l_{nf})$ is established.

Step 2: Based on each fault in typical fault set, calculate dynamic security and probabilistic insecurity index $P_{\mathrm{insec}}(l)$.

Step 3: Calculate probability density functions of wind power and load. Moreover, according to these functions, probability density functions of the value of generator trip and shedding load can be obtained.

Step 4: Calculate loss cost $I_{\mathrm{m}}^{\mathrm{c}}$ and expected loss S_{l_k}.

Step 5: Calculate the proportion K_k of expected loss of each fault in fault set.

$$K_k = \frac{S_{l_k}}{\sum_{i=1}^{n} S_{l_i}} \tag{23}$$

Threshold value ξ is given. If $K_k \geq \xi$, then this fault k is in the candidate set. If $K_k < \xi$, then this fault k is out of the candidate set.

Step 6: Examine fault set to ensure that all faults in this fault set have been considered. Assume that this candidate set $S = (l_1, l_1, \cdots l_m)$ has m faults. Screen and rank them according to their expected loss.

VI. SIMULATION

In this section, simulation is presented based on 10-generator 39-bus New England system. The detailed network topology of this system is shown in Fig. 1. Assume that wind power is at bus 37 replacing the original synchronous generators with the same generating capacity. A fiercely fluctuating load, like charging station, is at 16. Beyond that, the value of ξ is 0.001. $k = 4$ and $w = 0$.

Detailed information is depicted in Table I. Symbol + suggests that this fault is in candidate set and symbol - suggests that this fault is out of candidate set. We can also find that faults 3-4, 26-27, 3-18, 17-18, 25-26, 4-5, 7-8, 1-2 are out of candidate set. Because these faults are not serious fault, it is not necessary to take any safety control measures. But for these faults in candidate set, safety control measures must be taken. Furthermore, we can easily find that the probabilistic insecurity index of fault 26-29 is quite small, but its expected loss is quite large. Thus it is reasonable to put this fault in candidate set. In this case, if we use traditional method to screen contingencies, this fault may be neglected and may cause serious consequences. Moreover, screen and rank the contingencies in candidate set again without considering the volatility of wind power and load. Results are shown in Table II. It can be found that the order of fault 8-9 is changed and fault 6-7 is removed out of the candidate set. Besides, expected loss in Table II is slightly different with that in Table I. Therefore, this new method can screen and rank contingency accurately and rationally.

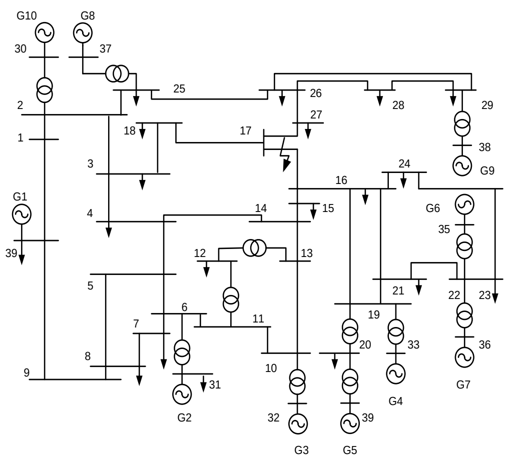

Figure 1. 10-generator 39-bus new England system

TABLE I. DATA TABLE CONSIDERING VOLATILITY

Typical fault set	Probabilistic insecurity index (10^{-4})	Expected loss (ten thousand yuan)	K_k	Selection
28-29	0.71164	90.96877	0.52240	+
23-24	0.91157	8.26624	0.05260	+
26-29	0.00830	8.22115	0.05910	+
8-9	1.00000	7.61435	0.05003	+
2-3	0.88472	6.76163	0.04676	+
10-11	0.99999	6.37794	0.04177	+
15-16	0.91361	5.60906	0.04043	+
1-39	0.92698	5.20249	0.03300	+
22-23	0.08865	4.60153	0.02723	+
21-22	0.36231	2.01720	0.01983	+
9-39	0.14711	1.00726	0.00696	+
6-7	0.00167	0.51720	0.00064	+
26-28	0.00739	0.30212	0.00197	+
3-4	0.00001	0.05050	0.00032	-
26-27	0.00001	0.02080	0.00013	-
3-18	0.00001	0.02060	0.00013	-
17-18	0.00010	0.01170	0.00007	-
25-26	0.00002	0.01150	0.00006	-
4-5	0.00001	0.00970	0.00006	-
7-8	0.00001	0.00960	0.00006	-
1-2	0.00001	0.00880	0.00006	-

TABLE II. CANDIDATE SET WITHOUT CONSIDERING VOLATILITY

Typical fault set	Probabilistic insecurity index (10^{-4})	Expected loss (ten thousand yuan)	K_k	Selection
28-29	0.71164	81.6591	0.52240	+
26-29	0.00830	9.23790	0.05910	+
23-24	0.91157	8.30480	0.05260	+
8-9	1.00000	7.82030	0.05003	+
2-3	0.88472	7.30938	0.04676	+
10-11	0.99999	6.52970	0.04177	+
15-16	0.91361	6.31942	0.04043	+
1-39	0.92698	5.15870	0.03300	+
22-23	0.08865	4.25640	0.02723	+
21-22	0.36231	3.10038	0.01983	+
9-39	0.14711	1.08849	0.00696	+
26-28	0.00739	0.30770	0.00197	+
6-7	0.00167	0.09970	0.00064	-

VII. CONCLUSION

This paper, based on probabilistic insecurity index, proposes a new contingency screening and ranking method. A large number of experimental data suggest that the volatility of wind power and load would have negative impact on the effectiveness of generator trip and load shedding. Thus it is necessary to consider the fluctuation of wind power and load in contingency screening and ranking. The expected loss model can be modified by using probability density functions of wind power and load. Clearly, randomness, economy, volatility and severity are all considered in this new method. Simulations on New England 10-generator 39-bus system shows that based on this new method, contingencies could be screened and ranked accurately and rationally.

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Di Wang was born in China in 1992. He received a B.S. degree in electrical engineering from Fuzhou University. Currently, he is pursuing a M.S. degree in Tianjin University. He has worked on power system analysis, planning and power market.

Huaidong Liu was born in China in 1963. He received a Ph.D. degree from Tsinghua University. Currently, he is a professor in Tianjin University. He has worked on power system analysis, planning, energy storage and power market.

Lezhao Yi was born in China in 1993. He received a B.S. degree in electrical engineering from Tianjin University. Currently, he is pursuing a M.S. degree in Tianjin University. He has worked on power system analysis, planning and smart grid.

Xiran Wang was born in China in 1989. He received a B.S. degree and a M.S. degree in electrical engineering from Tianjin University. Currently, he is working at economy research institute of state grid Zhejiang electrical power company. He has worked on power system analysis and planning.