Assessment of the importance of branches considering new energy access

D L Zhang¹ 4, S Yang¹, W X Huang²³, J Wu², Y Y Zhang¹, X Tian¹ and Z H Guo²

¹ Shandong Power Grid Co, Ltd, Economic and Technological Research Institute, Shandong Province, China
² Wuhan University, School of Electrical Engineering and Automation, Hubei Province, China
³ Email: hwx0102@whu.edu.cn

Abstract. Under the background of increasing penetration rate of new energy, the risk level of power system is getting higher and higher. Identifying the key branches of the system quickly and accurately is of great significance for improving the stability of power grid operation and preventing the occurrence of blackouts. This paper models the uncertain factors after the new energy is connected and establishes a grid risk assessment system. Based on the probabilistic power flow calculation, the comprehensive system risk index under the decommissioning of each branch is obtained as the branch importance through five indicators like power flow fluctuation risk and line active power over-limit risk. The improved IEEE-39 node system is used as an example for simulation calculation. The results verify the effectiveness of this method, which can distinguish the importance of branches, and provide references for safety early warning and differentiated planning.

Keywords. new energy; risk assessment; probability power flow; branch importance

1. Introduction
In recent years, several major power outages [1-2] almost all originated from the failure of individual components in the power grid, which caused the system to collapse after the failure was amplified by the unreasonable network architecture. Researches have shown that by identifying key network components, strengthening and reforming them through differentiated planning methods, the security level of the system can be significantly improved to avoid major power outages. At the same time, the access of new energy sources increases the uncertainty of grid operation, which has also become the direct cause of some major power outages [3]. Therefore, under the background of the increasing penetration rate of new energy, it is of great significance to comprehensively consider all kinds of uncertain factors, accurately and quickly evaluate the important branches of the network, and take reasonable preventive measures, so as to improve the safe and stable operation level of the whole power grid.

In this paper, a new method to evaluate the importance of branch is proposed. Based on probabilistic power flow calculation and risk theory [4,5], a branch importance evaluation model considering new

¹ Funding: Project Supported by the Science and Technology Program of State Grid Shandong Electric Power Company (SGSDJY00GPJS900089).
energy access is established. The effectiveness of this method is verified by an improved IEEE-39 bus system.

2. Evaluation ideas and processes

In this paper, the importance of a branch is measured by the impact on the system after the branch exits operation. In order to better deal with the uncertainty of the high proportion of new energy integration into the power system, this paper proposes the following model to deal with system uncertainties and adopts N-1 calibration based on probabilistic power flow. Probabilistic power flow [6,7] was first proposed by Borkowaka in 1974 to solve many uncertain factors in the process of power system analysis and make the calculation and analysis more suitable for the actual operation state of power grid. After the new energy is widely connected to the power grid, the randomness of the system is significantly improved, and probabilistic power flow algorithm is widely used in system analysis, including power system planning [8], static security analysis [9], power system risk assessment [10], etc.

2.1. Modeling of uncertain factors

In the power system with a high proportion of new energy, the main uncertainties include: wind, photovoltaic unit output and load fluctuations, etc. For different factors, we use the method shown in Table 1 to establish a probability model. The adopted mathematical model has been effectively verified in long-term engineering practice.

Table 1. Probabilistic Model of Uncertainty Factors

| Factor                | Model                      | Remarks                                           |
|-----------------------|----------------------------|---------------------------------------------------|
| Wind turbine output   | $P_{wind} = f_{wind}(v)$  | Wind speed $v$ obeys two-parameter Weibull distribution |
| Photovoltaic output   | $P_{pv} = f_{pv}(r)$      | The light intensity $r$ obeys the two-parameter beta distribution |
| Load fluctuation      | $P_{load} \sim N(\mu, \sigma^2)$ | The load obeys a normal distribution               |

2.2. System risk

Based on previous research [11-13], in order to comprehensively evaluate the impact on the system after the branch exits operation, this paper proposes a risk system as shown in Figure 1.

![Risk assessment system](image-url)

**Figure 1.** Risk assessment system.

The risk index can be defined as the product of accident probability and accident consequence, which is shown as follows:
Where, $Risk$ is the risk index value; $E$ is the accident; $Pr(E)$ is the probability of accident $E$; $Y_i$ is the specified running state, $Pr(Y_i|E)$ is the probability of system state $Y_i$ when $E$ happened.; $S(Y_i)$ is the severity when system operation status is $Y_i$. In order to better avoid the obscuration phenomenon [12], the exponential function is used as the severity function, which is shown as follows:

$$S_{ev}(\beta) = e^\beta - 1$$  \hspace{1cm} (2)

### 2.2.1. Power flow fluctuation risk.

Power flow fluctuation risk describes power flow fluctuation caused by system uncertainty. The power flow entropy [14] is used as the index of power flow fluctuation, and the second power function is used as the severity function, and it is consistent with the requirements of utility theory.

Then the risk calculation formula of power flow fluctuation is as follows:

$$R_{PFLC} = P_{PFLC} \cdot S_{evPFLC} = \frac{1}{N} \sum_{k=1}^{N} (H_{E,k} - \bar{H}_E)^2$$  \hspace{1cm} (3)

Where $N$ is the total number of sampling; $N_k$ is the total number of lines; $\bar{H}_E$ is the mean value of power flow entropy of $N$ iterations.

### 2.2.2. Risk of line active power overrun.

The over-limit situation is caused by the uncertain system description made by the risk index of line active power over-limit, then the risk index of line active power over-limit based on exponential risk function is defined as follows:

$$R_{LO} = \sum_{i \in M} R_{LO,i} = \sum_{i \in M} P_{ij} \times S_{evLO(i,j)}$$  \hspace{1cm} (4)

$$P_{ij} = \frac{N_{ij,over}}{N}$$  \hspace{1cm} (5)

$$S_{evLO(i,j)} = \frac{1}{N_{ij,over}} \sum_{k=1}^{N_{ij,over}} \left( \frac{P_{ij,k} - P_{ij,max}}{P_{ij,max}} \right)^2 - 1$$  \hspace{1cm} (6)

Where $M$ is the set of all branches of the system; $N_{ij,over}$ is the number of exceeding the maximum active power $P_{ij,max}$ that the branch $ij$ can withstand in its active power flow sample matrix; $N$ is the total number of active power flow samples of branch $ij$. $P_{ij}$ is the actual active power of the branch and $P_{max}$ is the maximum allowable branch power flow, both of which take the standard unit value.

### 2.2.3. Load shedding risk.

The load shedding risk index describes the load shedding caused by the line power flow over-limit. The risk index of load shedding is calculated as follows:

$$R_{LC} = P_{LC} \cdot S_{evLC}$$  \hspace{1cm} (7)

$$P_{LC} = \frac{N_{loadcut}}{N} = \sum_{k=1}^{N} P_k \cdot U_{L,k}$$  \hspace{1cm} (8)

$$S_{evLC} = \frac{1}{N_{loadcut}} \sum_{k=1}^{N_{loadcut}} \left( \frac{P_{loadcut} + \eta (P_{loadcut} - P_{load,rupt})}{P_{loadcut}} \right)^2 - 1$$  \hspace{1cm} (9)

Where, $U_{L,k}$ is the load loss state of the system in the $k$-th sampling state, which is a 0-1 variable. When 1 is selected, it means that load shedding is required, and when 0 is selected, it means that load shedding is not required; $P_k$ is the probability of state $K$; $N$ is the total number of sampling, $N_{loadcut}$ is the number of load shedding in $N$ samples; $P_{load}$ is the total amount of load shedding, $P_{load,rupt}$ is interruptible load and $\eta$ is non interruptible load compensation ratio.
2.2.4. Risk of new energy abandonment. The risk index of power loss describes the phenomenon of abandoning wind and light caused by excess power generation, the calculation formula of new energy abandonment risk is as follows:

\[ R_{NC} = P_{NC} \cdot S_{eeNC} \]  \hspace{1cm} (10)

\[ P_{NC} = \frac{N_{newcut}}{N} = \sum_{k=1}^{N} P_k \cdot U_{P,k} \]  \hspace{1cm} (11)

\[ S_{eeNC} = \frac{1}{N_{newcut}} \sum_{k=1}^{N_{newcut}} e^{P_{new,k} - 1} \]  \hspace{1cm} (12)

Where, \( U_{P,k} \) is the power loss state of the system in the k-th sampling state, which is a 0-1 variable; \( N_{newcut} \) is the number of abandoning wind and light in N samples; \( P_{newcut,k} \) is the power generation of wind, light and other new energy needed to be cut off at the k-th sample, and the new power abandonment in this paper is determined as the product of the system load shedding amount and the penetration rate of new energy; \( P_{new,k} \) is the total generation of new energy at the k-th sample.

2.2.5. Unit rescheduling risk. The calculation formula of unit rescheduling risk is as follows:

\[ R_{GR} = P_{GR} \cdot S_{eeGR} \]  \hspace{1cm} (13)

\[ P_{GR} = \frac{N_{re}}{N} = \sum_{k=1}^{N} P_k U_{R,k} S_{eeGR,k} \]  \hspace{1cm} (14)

\[ S_{eeGR} = \frac{1}{N_{re}} \sum_{k=1}^{N_{re}} e^{P_{re,k} - 1} \]  \hspace{1cm} (15)

Where \( N_{re} \) is the number of generator rescheduling in N samples; \( U_{R,k} \) is the state of generator rescheduling in order to eliminate the risk in the k-th sample, which is a 0-1 variable; \( P_k \) is the frequency of the k-th sampling state; \( P_{re,k} \) is the modulating power of conventional generator set rescheduling; \( P_{re,k} \) is the total power generation of conventional sets at a certain sampling time.

2.3 Branch importance

After quantifying the system risk after a branch exits operation, for different system risk indicators, due to their different units, they cannot simply be accumulated as the importance of the branch. TOPSIS method was first put forward by C.L. Hwang and K. Yoon in 1981. TOPSIS method ranks the closeness degree of limited evaluation objects to the idealized goals, so as to make decisions. Subjective evaluation methods are widely used in TOPSIS, such as analytic hierarchy process (AHP), fuzzy comprehensive evaluation method and so on, which are largely influenced by the subjective preference of decision-making experts, so that they are too casual to be objective. In the weight selection process of TOPSIS method, the entropy weight method [14] is adopted to reflect the information amount of indicators through the data variation, and determine the index weight, which can reduce the subjective factors in the decision-making process so as to make the results more objective and scientific. The decision-making steps of entropy weight TOPSIS method are as follows:

Step1: Weighted decision matrix is made by the decision matrix \( Y = (y_{ij})_{m \times n} \) and the weight vector \( W \) determined by entropy weight method:

\[ Z = YW = (z_{ij})_{m \times n} \]  \hspace{1cm} (16)

Step2: Determine the ideal solution \( Z^+ \) and the negative ideal solution \( Z^- \):

\[ Z^+ = \max \{z_{ij}\} \]  \hspace{1cm} (17)

\[ Z^- = \min \{z_{ij}\} \]  \hspace{1cm} (18)

Step3: Calculate the distance of each evaluation object to ideal solution and negative ideal solution:
Step4: Calculate the relative closeness $C_i$ of the evaluation objects and sort them:

$$C_i = \frac{D_i^+}{D_i^+ + D_i^-}$$  \hspace{1cm} (20)

The importance of branch is directly reflected by the overall risk level of the system after the branch is disconnected. In order to facilitate the evaluation and comparison of the overall risk level of the system, the comprehensive risk is constructed as the sum of the product of the risk index value and index weight value of each part, that is, the importance of branch $i$ can be calculated as follows:

$$R_{zi} = \sum_{j=1}^{5} w_j R_{ij}$$  \hspace{1cm} (21)

Where $R_{zi}$ is the importance of branch $i$, $R_{ij}$ is the $j$-th risk index after the disconnection of branch $i$, $\omega_j$ is the corresponding weight value.

3. Example analysis

IEEE 39 bus system is used as an example to test the above method and calculate the importance of each branch. The system consists of 39 nodes and 46 branches, whose structure is shown in the Figure 2. Considering that this paper focuses on the evaluation of branch importance after new energy access, the system is modified as follows:

1. The original units of node 30 and node 37 are changed into wind turbines with rated power of 250MW and 540MW; We assumed that the wind speed of the two wind power plants conforms to the two-parameter Weibull distribution, in which the shape parameter $k$ is 2.21 and 2.5 respectively, and the scale parameter $c$ is 8.55 and 8.8 respectively.

2. The original unit of node 33 is changed into photoelectric unit, and the rated power of the photoelectric unit is 632MW; the light radiation intensity of the power plant follows beta distribution, and the shape parameters are 0.6798 and 1.7788 respectively.

3. All loads obey normal distribution, the load value of the original example is taken as the mean value, and the standard deviation is 8% of the mean value; interruptible load accounts for 5%, and the compensation rate of uninterruptible load is increased to 5 times of interruptible load as punishment.

![Figure 2. IEEE-39 node system structure diagram](image)

![Figure 3. Normalized importance of each branch](image)

According to the method proposed in this paper, the branch importance of the network connected with new energy is evaluated. Table 2 shows the specific values of some risk indicators of some branches, and the results of importance of some branches are shown in Table 3. In order to intuitively compare the
relative importance of each branch, the importance of each branch is normalized. The normalized importance of all branches is shown in Figure 3.

| branch | $R_{PLC}$ | $R_{LC}$ | $R_{NC}$ |
|--------|-----------|----------|----------|
| 2-25   | 0.1425    | 0.3239   | 0.5167   |
| 4-14   | 0.1567    | 0.3167   | 0.5052   |
| 16-19  | 0.0587    | 0.3432   | 0.3932   |
| 21-22  | 0.1120    | 0.2049   | 0.2717   |
| 29-38  | 0.1081    | 0.2783   | 0.5286   |

Table 2 Risk index values of some branches

| branch | importance | branch | importance |
|--------|------------|--------|------------|
| 1-2    | 0.5479     | 16-19  | 0.4224     |
| 2-3    | 0.5742     | 17-27  | 0.2215     |
| 3-18   | 0.5452     | 21-22  | 0.2684     |
| 6-11   | 0.3939     | 23-36  | 0.4433     |
| 8-9    | 0.3839     | 26-29  | 0.2574     |

It can be seen from the results in the figure 3 that it is reasonable to reflect the importance of each branch by comprehensively considering the risk indicators of the system after each branch is returned. Branches 19-33, 2-30, 6-31 and 4-14 are of the highest importance. From the system structure diagram, branches 2-30 and 19-33 are directly connected with wind and solar farms respectively. Considering the impact of uncertainty on the system after new energy accessing, the high importance of these branches is very clear. Branches 6-31 and 4-14 are in the center of the whole system and connected with hub nodes, so the importance is relatively high. The results show that the proposed method is effective. At the same time, the access of new energy also makes the method more in line with the actual situation of the power system, which verifies the effectiveness of the method.

4. References

[1] Aiu Yun. Analysis on and Inspiration of the "9.13" Islanding and Outage of Brazilian Remote Northwest Power Grid [J]. Proceedings of the CSEE, 2018, 38(11): 3204-3213.
[2] Lin Weifang, Yi Jun, Guo Qiang, Wang Zhiwen, Jia Qi, Yu Fangfang. Analysis on Blackout in Argentine Power Grid on June 16, 2019 and Its Enlightenment to Power Grid in China [J]. Proceedings of the CSEE, 2020, 40(09): 2835-2842.
[3] Zeng Hui, Sun Feng, Li Tie, Zhang Qia-ning, Tang Junci, Zhang Tao. Analysis of "9-28" Blackout in South Australia and Its Enlightenment to China [J]. Automation of Electric Power Systems, 2017, 41(13).
[4] Chen Weihua, Jiang Quanyuan, Cao Yijia, Han Zhenxiang. Risk-based vulnerability assessment in complex power systems [J]. Power System Technology, 2005(04): 12-17.
[5] Zhang Cuibin, You Hao, Li Benyu, Shi Hengchu, Chen Jinfu. Assessment Method of Branch Importance Considering Topological Structure and Operation State [J]. Automation of Electric Power Systems, 2017, 41(07): 15-20.
[6] BORKOWSKA B. Probabilistic load flow [J]. IEEE Trans on Power Apparatus and Systems, 1974, 93(3): 752-759.
[7] Liu Yu, Gao Shan, Yang Shengchun, Yao Jianguo. Review on Algorithms for Probabilistic Load Flow in Power System [J]. Automation of Electric Power Systems, 2014, 38(23): 127-135.
[8] Yuan Yudong, Dong Lei. New Algorithm and Its Application to Probabilistic Load Flow of Power System [J]. Modern electric power, 2007(04): 5-9.
[9] Zhang Chuancheng. Application of Probabilistic Power Flow in Static Safety Analysis [D]. Beijing: North China Electric Power University, 2008.
[10] Yao Jianguo, Yang Shengchun, Wang Ke, Yang Zhenglin, Song Xiaofang. Concept and Research Framework of Smart Grid "Source-Grid-Load" Interactive Operation and Control [J]. Automation of Electric Power Systems, 2012, 36(21): 1-6+12.
[11] Bai Jiabin, Liu Tianqi, Cao Guoyun, Chen chen. Summary of power system vulnerability assessment methods [J]. Power System Technology, 2008, 32(S2): 26-30.
[12] Liu Ruoxi, Zhang Jianhua, Wu Di. Research on static security index of distribution network based on risk theory [J]. Power system protection and control, 2011, 39(15): 89-95.

[13] Wang Tao, Gao Chengbin, Gu Xueping, Liang Haiping. Power Betweenness Based Identification of Power Grid Critical Links [J]. Power System Technology, 2014, 38(07): 1907-1913.

[14] Lei Xunping, Qiu Guanghua. Empirical study about the carrying capacity evaluation of regional resources and environment based on entropy-weight TOPSIS model [J]. Acta Scientiae Circumstantiae, 2016, 36(01): 314-323.