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Evolution model of power failure considering new energy uncertainty

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Abstract. In order to explore the impact of new energy uncertainty on power failure and the choice of new energy buses in interconnected power grid, evolution model of non-sequential Monte-Carlo power failure is proposed. Assessment of power failure risk in interconnected power grid under multi-scenario is proposed to study the access of new energy. Firstly, the model of the uncertainty of wind power and photovoltaic power generation is set. Secondly, the non-sequential Monte-Carlo method is used to obtain the output of new energy, and a power failure evolution model is established based on SOC-Power Failure model. Finally, doing power failure evolution simulation in IEEE118 grid by this model in different scenario, the RISK value is obtained by integrating the LOLP, ELOL and EPFB indicators by AHP method, and the best access scenarios of new energy are determined by RISK value. The scenarios of new energy with the lowest power failure risk and the weak lines in the power grid are verified, which verifies the feasibility of the model and the practicability of the multi-scenario simulation.

1. Introduction

In order to solve a series of problems such as global energy shortage, climate warming, and environmental degradation, new energy represented by wind power and photovoltaic becomes more and more popular and makes great progress. The increasing of new energy brings a series of effects on the structure, operation and safety of traditional power systems. First of all, the uncertainty of new energy output poses a challenge to the operation of power grids. At the same time, in order to solve the problem of new energy consumption, the connection between different regional power grids is getting closer and closer. Taking China as an example, new energy power generation is gradually developed from small-scale development to large-scale development of long-distance transmission [1].

Domestic and foreign scholars have done a lot of research on the simulation of power system blackout evolution process. Article [2] proposes the OPA model to simulate the changes in power system components, line capacity, load and power generation. Article [3] optimizes the OPA model and considers the effects of scheduling, communication, relay protection, automation and other factors in power grid. SOC-Power Failure model is constructed to make the evolution of power failure [4].

All of the above models effectively simulate the evolution process of power system blackout accidents. With the increasing of new energy penetration in power system, the traditional power outage accident evolution model undoubtedly needs to keep pace with the time, and the uncertainty of new energy output is also needed to be considered. This paper considers the uncertainty of new energy generation output represented by wind power and photovoltaic, and forms an improved evolution model of power failure. The comprehensive LOLP, ELOL and EPFB indicators are formed by AHP

method [5]. The RISK value assesses the blackout risk of the interconnected grid under different new energy access scenarios.

2. Evolution model of power failure considering new energy

2.1. New Energy Uncertainty Model
The new energy generation of power system is mainly based on wind power and photovoltaic power generation. The uncertainty of wind power output is due to the volatility of wind speed. The uncertainty of photovoltaic power output is derived from the volatility of solar radiation. The wind speed fluctuation obeys the two-parameter Weibull distribution, and the solar irradiance obeys the Beta distribution. Combined with the probability density function of wind speed and solar irradiance, the corresponding wind power output P_w and photovoltaic power output P_s can be obtained. The probability density function of wind power output and photovoltaic power output can be expressed as follows:

$$f(P_w) = \frac{A}{\alpha B}(\frac{P_w - \beta}{\alpha B})^{A-1} \exp(-(\frac{P_w - \beta}{\alpha B})^A) \qquad (1)$$

$$f(P_s) = \frac{\Gamma(a+b)}{P_m \Gamma(a)\Gamma(b)}(\frac{P_s}{P_m})^{a-1}(1 - \frac{P_s}{P_m})^{b-1} \qquad (2)$$

Where: A is the shape parameter of the Weibull distribution; B is the scale parameter; α and β are the coefficients related to the wind speed and rated output power of the fan; P_m is the maximum output power of the solar cell; a and b are the shape parameters of the Beta distribution; Γ is Gamma function.

2.2. Evolution of non-sequential Monte Carlo power failure
The non-sequential Monte Carlo method defines parameters by random sampling. Each sample is independent of each other, and multiple samples can obtain the expected values of the corresponding parameters, which can be expressed as:

$$E(F) = \frac{1}{N}\sum_{i=1}^{N} F(X_i) \qquad (3)$$

Where: $E(F)$ is the expected value of the sample parameter; N is the sample number; $F(X_i)$ is the function value of sample.

The SOC-Power Failure model characterizes the process of power outages that cause power outages. In the actual simulation process, the impact is simulated by randomly selecting load nodes to increase the disturbance. Similarly, in order to simulate the impact of new energy access on the evolution of the power grid, the output is obtained by the non-sequential Monte Carlo method according to the probability density of the wind and solar, then the simulation model of the power outage accident is simulated until the power outage occurs.

If the scale r of the object satisfies the relationship between the frequency N above the scale r:

$$N = cr^{-D} \qquad (4)$$

Where: c is a constant to be determined; D is a power law value, indicating that the object satisfies the power law distribution. Double logarithmic transformation of equation:

$$\lg N = C - D\lg r \qquad (5)$$

Where: $C = \lg c$

The research shows that the power system's power outage scale and frequency meet the power law relationship, and the power law relation can be used to verify the feasibility of power failure evolution model [6].

3. Assessment indicators of power failure risk
Combined with the existing researches on the risk assessment of power grid by domestic and foreign scholars, this paper obtains the RISK value by the LOLP, ELOL and EPFB.

3.1 Accident loss load probability LOLP

$$LOLP = \sum_{i \in L} p_i \qquad (6)$$

Where: p_i is the probability of power failure state i in the evolution of power failure; L is the set of power failure state in the evolution of power failure.

3.2 Accident loss load expectation value ELOL

$$ELOL = \sum_{i \in L} p_i L_i \qquad (7)$$

Where: L_i is the amount of load that is cut off during the power outage state i during the evolution of the power failure.

3.3 Accident related node expectation value EPFB

$$EPFB = \sum_{i \in L} p_i B_i \qquad (8)$$

Where: B_i is the number of nodes that need to load when the power outage state i in the process of power failure accident evolution.

3.4 Comprehensive power outage risk value RISK
The weights of the indicators obtained by the AHP method are shown in Table 1.

Table1．The weight values of different indicators

indicators	LOLP	ELOL	EPFB
weights	0.539	0.297	0.164

The power failure risk value RISK can be calculated by equation (9).

$$RISK = \sum_{i=1}^{n} w_i \times r_i' \qquad (9)$$

4. IEEE118 grid

Based on the IEEE118 grid, this paper studies the power failure risk of new energy access to the interconnected grid under different new energy penetration, and explores suitable new energy access points from the perspective of power outage risk. In order to verify the feasibility of the power failure evolution model proposed in this paper, the scale-frequency relationship of the blackout accident generated by this model is compared with the power law relationship and the traditional energy is not considered. The power law relationship fitted by the scale and frequency of the blackout accident obtained by the model and the traditional model is shown in Fig. 1.

The power-law relationship and the significant correlation coefficient obtained by the two models are shown in Table 2.

Table 2 Power law relation and significant level

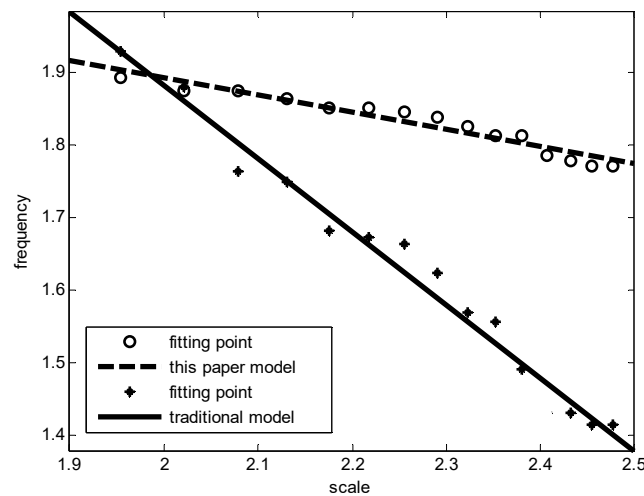| model	power law relation	significant level
traditional model	lg$N$=1.998-1.012lg$r$	0.965
this paper model	lg$N$=1.919-0.237lg$r$	0.989

Figure1. Power law relation

It can be seen from Fig. 1 and Table 2 that the power failure obtained by the power failure evolution model considering the new energy uncertainty proposed in this paper has the power law characteristic, which is consistent with the power law characteristic of the actual blackout accident, which verifies the paper. At the same time, the power law characteristics obtained by using this model to obtain power failure accidents are significantly improved in significance compared with the power law characteristics obtained by the traditional model.

This model is used to study the choice of new energy access to the interconnection grid access point, the new energy represented by wind power and photovoltaic is divided into 8 scenes. Under the new energy penetration rate of 10% and 20%, using MATLAB to simulate the evolution of non-sequential Monte Carlo blackouts considering new energy uncertainty for each scene, the non-sequential Monte Carlo new energy output sampling frequency is 100, and the number of incidents 200. The data of the corresponding power outage accidents in each scene are obtained through simulation, and the power outage risk value RISK is calculated. When the new energy penetration rate is 10% and 20%, the RISK value curve obtained by sorting the RISK values of different new energy access points in 8 new energy access modes from large to small is shown in Fig. 2.
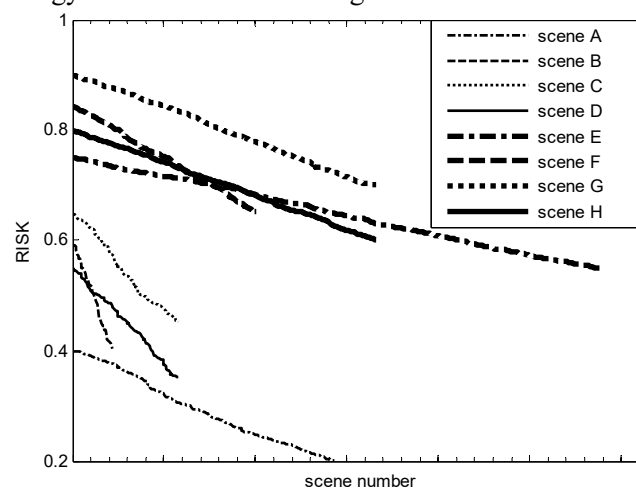

Figure2. Curve of RISK

The scene with the lowest RISK value in the different new energy access modes is taken as the representative of the access mode for further analysis, and is sequentially defined as scene A to scene I. In the four scenarios where the new energy penetration rate is 10%, the RISK value of scene A is the

lowest, and the RISK value of scene C is the highest; in the four scenarios where the new energy penetration rate is 20%, the RISK value of scene E is the lowest, the scene G is the highest.

5. Conclusion

In the past, the evolution model of power failure mostly simulates the occurrence of power failure from the perspective of load changes, and the considerations are relatively simple. In order to take into account of the impact of new energy output uncertainty on power failure, the evolution model of power failure is established. This paper adds new energy output model to the evolution model of power failure to form non-sequential Monte Carlo power failure evolution model. And the model is applied to the IEEE118 grid. The model provides a reference for grid planners to choose new energy access nodes about grid interconnection and reliability construction of the grid.

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