Research Article

Research on Static and Dynamic Fragile Node Identification Algorithms Based on Uncertainty in New Energy

Yingming Lin,1 Haohuai Wang,2 Yang Liu,1 Shiming Li,1 Lei Li,3 and Dongjian Gu3

1Power Dispatching and Communication Center of Guangdong Power Grid Company, Guangzhou 510600, China
2CSG Power Dispatching Control Center, Guangzhou 510530, China
3Nari-Tech Nanjing Control Systems Ltd.,, Nanjing 211106, China

Correspondence should be addressed to Yingming Lin; 631505040409@mails.cqjtu.edu.cn

Received 17 January 2022; Revised 10 February 2022; Accepted 15 February 2022; Published 24 March 2022

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In order to identify the uncertain static and dynamic fragile nodes in new energy, the instability and randomness of new energy bring new challenges to the identification of vulnerable nodes in a power grid. Due to the characteristics of low cost and low energy consumption of new energy, people have paid much attention to the exploration and development of new energy. Due to the uncertainty of new energy, it is needed to properly analyze the uncertainty factors. To analyze the uncertainty factors in new energy using the framework of power big data artificial intelligence analysis based on cost-benefit analysis (CBA), it is required to carry out Fourier transform and extract the data characteristic matrix so that a vulnerability risk prediction index can be obtained by using a fuzzy convolution algorithm and binarization, and the safety form between the uncertainty factors in new energy and power stations can be evaluated. In this paper, a fuzzy neural network algorithm is proposed to identify the static and dynamic fragile nodes based on the uncertainty in new energy, so as to ensure the security and stability of the power generation system. The safety performance of the power station system is detected through different levels of early warning sensitivity. The simulation model of the above algorithm is constructed in MATLAB. The simulation results show that the proposed algorithm increases the sensitivity of the early warning system of the power station and the sensitivity of triggering the early warning system and improves the security of the power station system as a whole.

1. Instruction

Due to the increasing energy demand, new energy is considered the most attractive energy source. The new energy sources include wind energy, hydroelectric, ocean energy, geothermal energy, photovoltaic energy, etc. There are many studies on photovoltaic and wind energy sources due to the abundant availability of these sources everywhere on Earth. The objective is not only to get the energy but also to turn this obtained energy into proper use and to balance energy demand and supply.

In 2020, the Ministry of Finance, the National Development and Reform Commission, and the National Energy Administration issued several opinions on promoting the healthy development of nonaqueous renewable energy power generation, which defined in detail the concept of new energy, which is a renewable low emission energy type other than surface runoff potential energy (conventional hydropower station). Among them, wind power stations and photovoltaic power stations can be effectively developed under the current technical conditions. With the development of society, the requirement for an Internet power grid is increasing. Gradually, conventional energy is unable to meet the needs of industrial production. People are paying more and more attention to the environmental protection and regeneration characteristics of new energy to meet industrial needs, and new energy power generation has already entered the field of industrial production.

New energy, especially solar and wind energy, is highly uncertain due to dynamic climate conditions. A proper analysis of these uncertainties plays an important role in maintaining the stability and reliability of the system [1]. In
this context, a lot of work has been done. When new energy is connected to the power grid, due to the randomness of new energy, it has an impact on the stability of the power grid to a certain extent. In order to ensure the reliability of new energy connected to the power grid, the authors in [2] extract the minimum line during normal operation of the power grid by the Monte Carlo method to verify the fault repair time. The Monte Carlo method and the analytical method are commonly used methods for the reliability analysis of distribution networks [3, 4]. Experiments show that the newer energy is connected to the power grid, the higher the reliability of the power grid and the reserve capacity of the distribution station is directly proportional to the reliability of the power grid. In [5], the authors tested the reliability of a distribution network based on fuzzy spiking neural P system, considering the uncertainty of new energy access to the power grid and the deviation in the interactive power of tie lines between regions. Aiming at the problems existing in the cross-regional dispatching of new energy, the authors in [6] propose to design the decentralized collaborative debugging path of the multiregional interconnected systems according to the debugging level and solve the main problems and subproblems in the debugging problem respectively. The results show that this method effectively reduces the uncertainty impact on the safe operation of interconnected systems and improves the economic benefits of interconnected areas.

The power system plays an important role in China’s production and people’s lives. Every year, the state invests a large amount of conventional energy for power generation. In order to reduce the impact on the environment and improve the utilization of renewable energy, in recent years, the state has continuously increased its investment in wind power and photovoltaic power generation and organized a large number of scientific researchers to study its principles in order to explore more effective control measures and to promote the development of national power.

New energy power generation promotes the transformation of the power system. With the strong support of policies, new energy power generation has formed a large-scale industry. Through the analysis of the national support policies for new energy in the past decade, it is found that the policies in the field of new energy have been continuously refined and expanded in the power generation related industrial chain in order to promote the all-round development of the new energy power generation industry through policy guidance [7].

New energy power generation is to alleviate the contradiction between supply and demand of the power system and reduce the consumption of conventional energy. However, compared with conventional energy power generation, new energy has a certain instability and has a certain impact on the power grid. How to intervene with these effects by scientific and technological means is a problem that is necessary to solve. In this study, a fuzzy neural network algorithm is used to identify the static and dynamic fragile nodes based on the uncertainty in new energy so as to ensure the security and stability of the power generation system.

The structure of the remaining paper is as follows: section 2 describes the periodic fluctuation of energy demand in all seasons and discusses how this fluctuation can be balanced. Section 3 discusses the uncertainty of new energies such as wind energy and photovoltaic energy. Section 4 gives the proposed algorithm based on the uncertainty of new energy. Section 5 provides the performance evaluation of the algorithm. Section 6 concludes this work.

2. Certainty of Social Energy Demand

Social energy demand shows a relatively fixed periodic law in different cycles and a linear law of continuous growth over a long timeline. That is, in the annual cycle, the energy demand in winter and summer is large, and the energy demand in spring and autumn is small. In the weekly cycle, the energy demand on weekends is large, and the energy demand on rest days is small. In the single-day cycle, the energy demand during the day is large, and the energy demand at night is small.

Because of these laws, power supply enterprises have formulated the time-sharing electricity price policy of peak and flat valley, encouraged high-energy-consuming enterprises to make use of power supply at night, set gradient electricity prices, encouraged residents to reasonably plan their total electricity consumption for the whole year, and gave greater electricity price discounts to residents with small total electricity consumption for the whole year. However, under this measure, it is still not possible to effectively balance the periodic fluctuation of power demand [8].

Therefore, there are two measures to balance this volatility. First, the power supply enterprise operates its own peak shaving and valley leveling power stations and uses high-power power stations such as liquefied natural gas (LNG) or fuel oil that can be started and stopped quickly to balance the change in power load in a short period. Water potential energy storage facilities or weight potential energy storage facilities are also established in the power supply network to achieve effective peak shaving and valley leveling during the fluctuation period of power supply and demand. Second, we encourage the power generation enterprises to respond to the peak shaving and valley shaving dispatching order of power supply, the control section of coal-fired power plants, hydropower plants, and other utilization equipment, and to install energy storage facilities for photovoltaic and wind power plants to obtain the buffer capacity of power supply and demand.

Energy determines economic development. With the gradual increase of the proportion of China’s industry, the industrial sector has become the main energy growth sector for energy consumption. From the current situation, the growth of energy demand is sustainable, but energy is not
always renewable. There is a contradiction between the two, which promotes people's development and the exploration of new energy [9].

3. Uncertainty of Energy

In this section, the authors discuss the uncertainty of new energies such as wind energy and photovoltaic energy, their resources, and the problems associated with these resources.

3.1. Uncertainty of Photovoltaic Energy. Photovoltaic energy is subject to light intensity and light angle. The daily noon energy supply capacity is the strongest. Full load energy supply cannot be realized in the morning and evening, and there is no energy supply capacity at night. The curve is highly coupled with the energy demand curve of a single-day cycle, but there are also two problems:

First, the change curve of the energy supply capacity of a photovoltaic power station is relatively smooth, while the change of the energy one-day demand curve is closer to the trapezoidal curve.

Second, the energy supply capacity of a photovoltaic power station under strong light conditions in summer is strong, which corresponds to the peak power consumption in summer under the annual cycle, but its energy supply capacity under weak light conditions in winter is weak.

In addition, photovoltaic energy is seriously affected by cloudy, rainy, and hazy weather. A photovoltaic power generation system has a strong dependence on lighting resources. The time, intensity, and angle of sunlight directly affect the power output rate.

In Figure 1, the x-axis is labeled as hours in a day and the y-axis is labeled as energy demand. It can be seen that during the times around 0–8 and 19–24, the power demand is greater than that of photovoltaic power generation because the light energy is generally weak in this period. In the time period around 8–19, photovoltaic power generation is greater than or equal to the power demand because the light intensity in this period is strong and the light time is long.

In Figure 2, this curve is obtained from the difference between the curves of photovoltaic power generation and power demand in Figure 1. It can be clearly seen from Figure 2 that when the photovoltaic power generation capacity is large, the power demand is small, while when the photovoltaic power generation capacity is small, the power demand is large, which leads to the phenomenon of power generation waste and insufficient power demand.

3.2. Uncertainty of Wind Energy. Wind energy is subject to wind energy intensity. Under the annual curve of the northern region, wind power is strong in spring and autumn, but the energy demand in spring and autumn is small in comparison to the actual power demand. Due to the influence of extreme weather in winter and summer, there may be windy weather caused by large pressure differences. Wind energy facilities need to reduce wind energy utilization by adjusting blade attack angles to avoid risks. Annual wind power generation and power demand are shown in Figures 3 and 4.

In Figure 3, the x-axis is labeled as months in a year and the y-axis is labeled as energy demand. It can be seen that the curves of wind power generation and power demand intersect each other in a year, the size of wind power generation is related to the alternation of seasons, and the power generation in the periods from March to May and August to December is greater than that of power demand.

In Figure 4, the difference between the power demand curve and the wind power generation curve data is used to obtain Figure 4. It can be clearly seen from Figure 4 that when the wind power generation capacity is large, the power demand is small, while when the wind power generation capacity is small, the power demand is large, which leads to the phenomenon of power generation waste and insufficient power demand.

4. Static and Dynamic Combination Algorithm Based on Uncertainty of New Energy

In the development of wind energy and photovoltaic energy, two development objectives should be ensured.

First, all wind energy and photovoltaic energy shall realize full power development under the conditions allowed by technical conditions; that is, the additional electric energy
shall have sufficient energy storage facilities to balance the relationship between energy supply and demand.

Second, the charging and discharging efficiency of energy storage facilities should meet economic and business needs.

Under perfect conditions, the relationship between power generation capacity and energy storage capacity is given in the following formula:

\[
\int_{-\infty}^{\infty} S(t)dt - \int_{-\infty}^{\infty} C(t)dt = \int_{-\infty}^{\infty} \epsilon(t)dt + \int_{-\infty}^{\infty} D(t)dt, \tag{1}
\]

where \( S(t) \) is the time series function of power generation capacity, \( C(t) \) is the power demand timing function, \( D(t) \) is the time series function of energy storage capacity, and \( \epsilon(t) \) is the time series function of energy storage capacity loss. Based on this relationship, the vulnerability time series coefficient of the new energy power station is shown in the following formula:

\[
\tau(t) = \frac{\int_{-\infty}^{\infty} \epsilon(t)dt}{\int_{-\infty}^{\infty} S(t)dt}, \tag{2}
\]

where \( \tau(t) \) is the vulnerability time series coefficient of the new energy power station and other mathematical symbols are the same as in (1).

The vulnerability evaluation index of new energy power generation composed of the above formulas (1) and (2) can objectively reflect the vulnerability of new energy power stations equipped with energy storage facilities, but there are also some problems. That is, the four integral indexes in formula (1) and the two integral indexes in formula (2) have their own uncertainty, which are not typical periodic functions. Therefore, the actual evaluation \( \tau(t) \) and the statistical ability of values are weak. Thus, subsequent data mining is required to guide production. Its main data mining direction is data prediction and early warning based on curve estimation.

Therefore, under the artificial intelligence analysis framework of power big data based on CBA, it is necessary to carry out a Fourier transform and extract the data characteristic matrix, and then use the fuzzy convolution algorithm and binarization method to obtain the vulnerability risk prediction index. The above algorithm architecture is shown in Figure 5.

The basis function of Fourier transform is shown in the following formula:

\[
F(\omega) = \int_{-\infty}^{\infty} A \cdot f(t) \cdot e^{-i\omega t} dt. \tag{3}
\]

In the above equation, \( t \) is the traversal pointer of the sequence, \( \omega \) is the traversal pointer of the frequency variable, \( A \) is the detection accuracy correction variable, \( F(\omega) \) is the output function of Fourier transform, \( f(t) \) is the input function of Fourier transform, and \( -i\omega \cdot 2\pi \) is Fourier constant, where \( e \) is the natural constant.

The characteristic matrix obtained from the Fourier transform contains the strength of the main superimposed waveform, which is used to analyze uncertain data.

The node basis function of the fuzzy neural network based on sixth-order polynomial depth iterative regression is shown in the following formula:

\[
y = \sum_{i=1}^{n} A_{j} x_{i}^{5} , \tag{4}
\]

where \( A_{j} \) is the coefficient to be regressed of the \( j \)-th order polynomial, that is, each node in the formula contains 6 coefficients to be regressed from \( A_{0} \) to \( A_{5} \), \( j \) is the polynomial order, and the meanings of other mathematical symbols are the same as those in the previously mentioned formulas.

The output data of the multicolumn neural network is the output data that lies in the \([0, 1]\) interval. There is no distribution law for output data, so it needs to be binarized. An independent binarized neural network module is designed for each scheme to form a binarized multicolumn neural network. In a binarized neural network, binary values are used rather than floating values, which can be computed faster with less memory and power. The node basis function of the binarized neural network is as shown in the following formula:

\[
y = \sum_{i=1}^{n} \frac{1}{A_{j} + B \cdot e^{e^{i}}} , \tag{5}
\]

where \( e \) is the natural constant, and the approximate value here is \( e = 2.718281828 \); The meaning of other mathematical symbols is the same as formula (4).
5. Simulation Verification of Algorithm Efficiency

The Simulink module is loaded into MATLAB to build the simulation model for the above algorithm. The original data are the measured data of power supply company end grid connection of all 16 wind farms and 9 photovoltaic power plants in a city. When the neutral point offset reaches 50% of the cut-off setting value or the phase offset reaches 35% of the cut-off setting value, it is considered a high-risk state, and it is therefore necessary to give data early warning. The test points of early warning advance are set as 1 s, 5 s, 15 s, 30 s, and 60 s respectively.

We compare the vulnerability coefficient of formula (2) above τ(t) above the prewarning sensitivity of the forward prediction value directly estimated by the nonlinear curve under MATLAB and the forward prediction value given under the artificial intelligence analysis framework of power big data based on CBA is shown in Table 1.

In Table 1, early warning advance is the time advance from the high-risk state when the early warning is given, and sensitivity is the proportion of true positive data in positive data. It can be seen from Table 1 that both the early warning sensitivity estimated by the direct curve obtained by using the software directly and the early warning sensitivity obtained by using the fuzzy neural network algorithm are reduced according to the increase in the test point time of the early warning advance. The difference between the two can be made more obvious by making the following Figure 6 according to the data in Table 1.

It can be seen in Figure 6 that the curve trend of early warning sensitivity obtained by curve estimation is the same as that obtained by the fuzzy neural network algorithm. The difference is that the early warning sensitivity obtained by the fuzzy neural network algorithm is high at the same test point, and the difference becomes more and more obvious with the increase of early warning advance. This shows that the fuzzy neural network algorithm can identify the high-risk state more accurately.

In Table 2, early warning trigger conditions are the proportional relationship between the measured value of data and the setting value of fault removal when the early warning is given, and sensitivity is the proportion of true positive data in positive data.

It can be seen from Table 2 that under different early warning trigger conditions, the early warning sensitivity trend obtained by either direct curve estimation or fuzzy neural network algorithm is the same, from high to low according to the early warning trigger conditions and from low to high. In order to facilitate a more straightforward comparison of the data differences between the two, the following Figure 7 is made according to the data in Table 2.

As it can be seen in Figure 7 the early warning sensitivity estimated by the direct curve obtained by using the software directly and the early warning sensitivity obtained by using the fuzzy neural network algorithm are reduced according to the increase in the test point time of the early warning advance. The difference between the two can be made more obvious by making the following Figure 6 according to the data in Table 1.

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6. Conclusion

With the deepening of people’s exploration of new energy, new energy power generation is gradually applied to the power system. Due to the interference of natural factors, it affects the quality of power and the security of the power system [10]. This study analyzes the uncertain factors of wind power and photovoltaics affected by the outside world. Through the identification of fragile nodes with the combination of static and dynamic uncertainty in new energy, Fourier transform is carried out, and a data feature matrix is extracted under the artificial intelligence analysis framework of power big data based on CBA. Then the vulnerability risk prediction index is obtained by using a fuzzy convolution algorithm and binarization method. The simulation results show that the proposed fuzzy neural network algorithm identifies the high-risk state more accurately and the early warning sensitivity obtained is relatively stable.

With the continuous development of science and technology, the exploration and cognition of new energy are further improved, and the application level in relevant fields is also improved to promote the safe and stable development of power systems [11].

Data Availability

Data source: self-statistics of the study.

Conflicts of Interest

The authors declare that there are no conflicts of interest with the publication of this paper and that all authors have seen the manuscript and have agreed to submit it to your journal.

Table 2: Comparison of alert sensitivity based on alert trigger conditions.

<table>
<thead>
<tr>
<th>Sensitivity comparison</th>
<th>Alert trigger condition</th>
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<th>Alert trigger condition</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>[0.30,1.00]</td>
<td>[0.25,0.30]</td>
<td>[0.20,0.25]</td>
<td>[0.10,0.20]</td>
</tr>
<tr>
<td>Direct curve estimation</td>
<td>98.19</td>
<td>96.38</td>
<td>88.76</td>
<td>53.17</td>
</tr>
<tr>
<td>Fuzzy neural network</td>
<td>98.97</td>
<td>98.54</td>
<td>96.14</td>
<td>95.08</td>
</tr>
</tbody>
</table>

Figure 7: Comparison of early warning sensitivity under different early warning triggering conditions.

References