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Qin He and Tang Wenbo

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He Qin, Wenbo Tang

Nanjing University of Posts and Telecommunications, No. 9 Wenyuan Road, Qixia District, Nanjing, Jiangsu, China

158984663@qq.com

Abstract. In order to evaluate safety of the Microgrid(MG) after distributed energy resources and different types of loads accessed in or disconnected, chaotic time series and RBF neural network are essential and beneficial tools. In this paper, Voltage Security Assessment Index(VSAI) is established to assess whether the MG is able to achieve equilibrium state for voltage. The application of Solar Photo Voltaic(SPV) or Wind Turbine(WT) generation alone is tested in the process of the phase space reconstruction and compared to the consorted hybrid example. Chaos algorithm can be used to define and optimal the RBF center and the connection weights of out put layer, which can further improve the convergence speed of RBF neural network. Comparing the result of output between actual and prediction in three different conditions, if the difference of their values is above or below a certain threshold, the safety of MG will be judged unsafe. Test is conducted on an autonomous MG bus feeder to verify the usefulness of the posed system. The research conclusion shows that chaotic time series and RBF neural network is effective and feasible for the safety evaluation of MG.

Index Terms—Microgrid(MG),voltage security assessment index(VSRI), phase space reconstruction, chaotic time series, RBF neural network.

1. Introduction

A microgrid is a small-scale power grid that can be operated independently or in combination with the main electrical grid. Distributed renewable energy sources(such as wind turbines, photo-voltaic), energy storage systems and loads are composition of a MG[1,2]. When a disturbance happening, MG will disconnect from main grid and switch to islanded mode, otherwise it may operate in grid-connected mode. Considering randomness of renewable energy sources, the safety of MG with island operation capability faces many challenges such as voltage flicker, fluctuation and dip which should be solved [3].

Many studies and papers have been published to discuss the impact of microgrid on safety of distribution network, however, few publications handle the safety of interior microgrid, especially in aspect of voltage. Paper[4] proposes a approach based on fault tree analysis(FAT) to evaluate the safety of islanded microgrid with the specific operation time, but the approach may be not applicable in common situation. Combine the advantages of rough set with the advantages of artificial neural

network, [5] proposed a way that pretreat the input data of neural network in the way of rough set, use the key part of input data as input to the network and improves the level of evaluation. Combination of safety engineering, factor analysis and neural network in Paper [6] to evaluate whether the system is safety, however this new security assessment way only for transmission grid system and it can not handle the safety of the MG with DGs and different loads.

This paper is organized as follows. Section 2 focuses on dynamic voltage security assessment at point of common coupling(PCC) of microgrid. Section 3 describes the proposed a evaluation method of the microgrid safety which uses chaotic time series and RBF neural network. In Section 4, simulation studies are offered to prove the usefulness of the posed method. Finally, Section 5 concludes the paper.

2. Dynamic voltage security assessment of microgrid

In this paper, a dynamic voltage security criterion originated from the VSAI[7] is used to evaluate whether the system can achieve a equilibrium state for voltage after disturbance.

Voltage Security Assessment Index[7]: VSAI is calculated from a time series data of the rms values of the voltage at point of common coupling(PCC) in the microgrid. Assuming the i th node voltage sequence as $V_i = [V_i^1, V_i^2, \dots, V_i^m]^T$, and the following steps about computation of the VSAI.

a) Calculate the moving average value of the i th node voltage at j th moment from N available measurements as follows:

$$\text{if}(j \leq N) : v_j = \sum_{k=1}^j V_i^k / j, \\ j \in 1, 2, \dots, N \quad (1)$$

$$\text{if}(j > N) : v_j = \sum_{k=j-N+1}^j V_i^k / N, \\ j \in N+1, N+2, \dots, m$$

b) Calculate the percentage discrepancy C_i^j between the node voltage measured at j th moment V_i^j and the moving average value $V_i^{(j)}$.

$$C_i^j = |V_i^j - V_i^{(j)}|, (j \in 1, 2, \dots, m) \quad (2)$$

c) Calculating the value by eliminating the area under the percentage discrepancy curve by N at j th moment as follows:

$$\text{if } j \leq N : U_i^{(j)} = \sum_{k=1}^j (C_i^k + C_i^{k-1}) / 2j, \\ j \in 1, 2, \dots, N, \quad (3)$$

$$\text{if } j > N : U_i^{(j)} = \sum_{k=j-N+1}^j (C_i^k + C_i^{k-1}) / 2N, \\ j \in N+1, N+2, \dots, m.$$

d) At j th moment the VSAI is define as:

$$VSAI_i^{(j)} = U_{th} - U_i^{(j)} \quad (4)$$

Where U_{th} is security threshold value.

3. A evaluation method based on chaos theory and RBF neural network

3.1. Judgement of the chaotic time series

Lyapunov exponent can judge whether the dynamic voltage time sequence with chaotic characteristic[8]. The computing steps as follows:

Suppose the dynamic voltage time series is $V\{v_1, v_2, \dots, v_N\}$.

1) Count the delay time τ and the embedding dimension m of the dynamic voltage time series, and the average period p .

2) Reconstruct the phase space with the help of τ and m .

$$V(t_i) = (v_i, v_{i+\tau}, \dots, v_{i+(m-1)\tau}) \in R^n \quad (5)$$

where $i = 1, 2, \dots, M; N = M + (m-1)\tau$ and define the reconstructed phase space as $\{V_j, j = 1, 2, \dots, M\}$.

3) Find the nearest point V_j^\wedge , and calculate the shortest distance to the particular reference point V_j , shown as follows:

$$d_j(0) = \min_X \|V_j - V_j^\wedge\| \quad (6)$$

4) Count the distance $d_j(i)$ between every dot of the reconstructed phase space after i discrete-time paces.

$$d_j(i) = |V_{j+i} - V_{j+i}^\wedge| \quad (7)$$

Where, $i = 1, 2, \dots, \min(M-j, M-j)^\wedge$.

5) Compute the mean line $v(i)$.

$$v(i) = \frac{1}{q\Delta t} \sum_{j=1}^q \ln d_j(i) \quad (8)$$

in which, q means the number of non-zero $d_j(i)$ and Δt is the sampling time of the dynamic voltage time series.

6) Obtain the largest Lyapunov exponent λ by computing the slope of regression line.

3.2. Reconstruction of phase space

Assuming the a th node voltage sequence of length b as $\{V_a^b, a = 1, \dots, 13; b = 1, 2, \dots, n\}$, and according to the theory of Takens[9], the new reconstructed phase space as follows:

$$V = [V_a^1, V_a^2, \dots, V_a^c]^T \quad (9)$$

where c is the number of phase points in reconstructed phase space and expressed as:

$$c = b - (m-1)\tau \quad (10)$$

where m is embedding dimension and τ is delay time.

And according to (10), it is necessary to find appropriate the embedding dimension m and the delay time τ in the process of reconstruction.

3.2.1. The selection of the delay time τ

Considering the non-linear characteristics between dynamic voltage time series in microgrid, this paper utilizes the mutual information function to determine the delay time, and comparing impacts of DGs in different situations on the delay time, and the calculation formula as follows:

$$I(\tau) = \sum_{v_a^b, v_a^{b+\tau}} P(v_a^b, v_a^{b+\tau}) \log_2 \left[\frac{P(v_a^b, v_a^{b+\tau})}{P(v_a^b)P(v_a^{b+\tau})} \right] \quad (11)$$

Where $P(v_a^b)$ and $P(v_a^{b+\tau})$ are the normalized distributions of v_a^b and $v_a^{b+\tau}$, and $P(v_a^b, v_a^{b+\tau})$ is their joint distribution.

3.2.2. The selection of the embedding dimension m

In this paper, using the GP method proposed by Grassberger and Procaccia, and the main steps are as follows:

- 1) Give a smaller value m_0 first and calculate the delay time for the dynamic voltage time series $\{V_a^b, a=1,2,\dots,30, b=1,2,\dots,n\}$, which corresponds to a reconstructed phase space.
- 2) Calculate the correlation function :

$$C(r) = \lim_{N \rightarrow \infty} \frac{1}{N} \sum_{i,j=1}^N \theta(r - |Y(t_i) - Y(t_j)|) \quad (12)$$

where $|Y(t_i) - Y(t_j)|$ is the distance between the phase point $Y(t_i)$ and $Y(t_j)$, $\theta(z)$ is the Heaviside function, $C(r)$ represents the odds that the distance between two dots on the phase space attractor is less than r .

3) In a suitable scope of r , the relationship between the dimension d of attractor and the cumulative distribution function $C(r)$ should fulfill the logarithmic linear, $d(m) = \ln C(r) / \ln r$, Thus fit out the correlation dimension $d(m_0)$ corresponding to m_0 .

4) Increase the value of the embedding dimension $m_1 > m_0$, and repeat the process of the steps 2 and 3 until the estimated value of the correlation dimension $d(m)$ is no more change with the increase of m in a fixed scope of deviation. The d obtained at this moment is the correlation dimension of the attractor.

3.2.3. The forecast of the RBF neural network

In this paper, the steps of prediction as follows:

1) Use the given dynamic voltage data of microgrid as the predicted time series, and according to the G-P algorithm and the mutual information method in chaos theory, calculating the optimal embedding dimension m and the delay time τ . Then getting the reconstruction of the phase space:

$$V = [V_a^1, V_a^2, \dots, V_a^c]^T \quad (13)$$

2) Use the dynamic voltage data of microgrid after reconstructed as the input data, half of the data as the training sample input and the other half as the test sample input.

3) Train the neural network by using dynamic voltage data at PCC in MG system as training samples, and build network construction by debugging reasonable parameter, finally obtain the forecast data by the test sample.

4. Simulation

The method introduced in the article is tested on a MG bus feeder which includes an actual 115KV/4.16KV 50-HZ distribution line. The model shown in Figure.1 is taken from the IEEE 13 feeder test system, and the distributed generation are imploded into the MG feeder at bus 9 for simulation. According to a design standard in [10], bus 9 is chosen as a connected bus.

Bus 14 represents a concentrated load between distributed load lines 1 and 4.. It is invisible and situated at 2/3 the distance from bus 4.

This paper uses dynamic voltage data at bus 14 of the MG, under the situation of the solar PV/wind turbo integrated into the MG independently or hybrid of them connected with the MG. The voltage magnitude may change with the access of solar PV and turbo energy to the MG, and further threaten the safety of MG.

The base voltage size is 0.985 pu at 14 point without any distributed generations through power flower calculation. Three different colour lines represent voltage changes at three different condition in Figure2.

4.1. Demonstrate the effectiveness of the VSAI.

There are many factors that affect the intensity of solar radiation at a place in one day, such as rainfall, cloud cover and temperature etc, and most of them occur in the transient[10]. The curve of voltages may change at node 14 in short time, while the entire MG transfers from the state of parallel operation of the solar PV and wind turbine to the state in which only the wind turbine is in operation at this time. And when solar PV stop working, as shown in Fig.3, the voltage starts to fall at $t = 12s$, the corresponding curve of VSAIs at 14th node of MG system also begins to fall from 0. When the fault at the 14th node stops and the voltage at 14th node is in another safe situation, the VSAI also returns to 0. Therefore, whether the node voltage is in a safe state can be determined according to the value of VSAI .

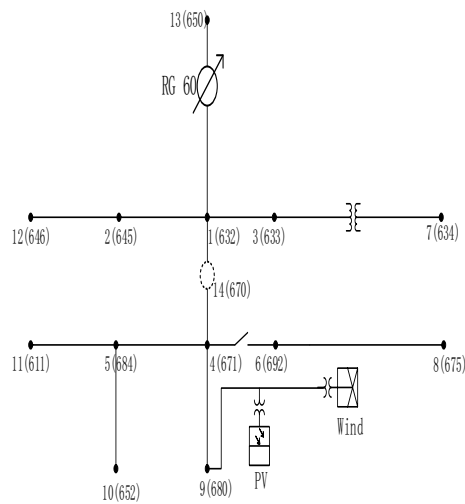


Figure 1. The structure of MG bus feeder.

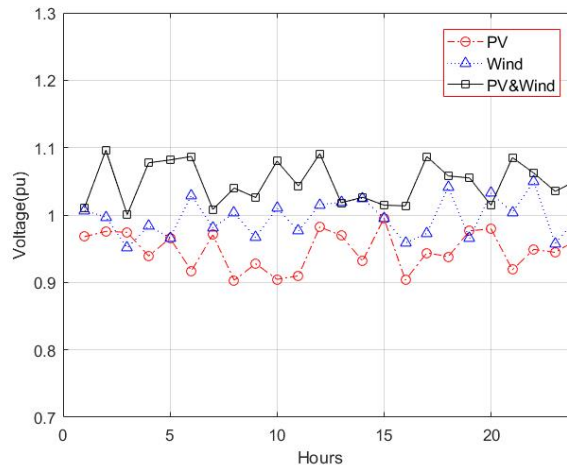


Figure 2. Voltages graph at bus 14 because of PV, wind and hybrid PV/wind.

4.2. Determine the existence of chaos.

According to the theory of the small amount of data method which is proposed in the front part of the article. The largest Lyapunov exponent of the dynamic voltage data is $\lambda = 1.3972$ by the calculation of the Matlab programming. Because of $\lambda > 0$, the chaotic feature of dynamic voltage sequence can be determined.

4.3. Reconstruction of the phase space.

Reconstruct the new phase space of dynamic voltage sequence (9):

$$V = [V_a^1, V_a^2, \dots, V_a^c]^T \quad (9)$$

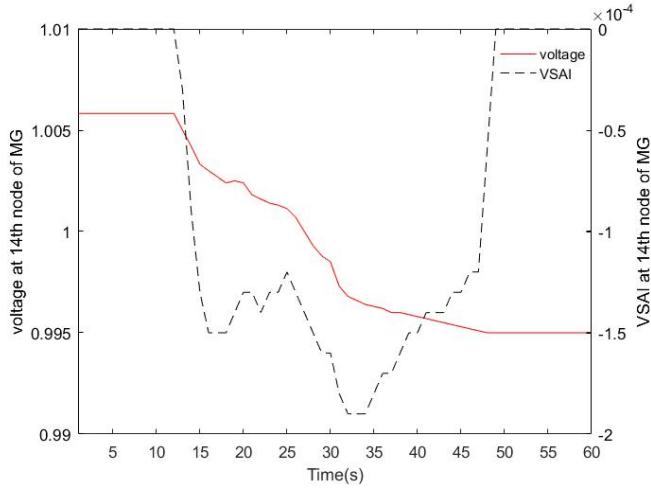


Figure 3. Safety case---voltage and VSAI at critical MG.

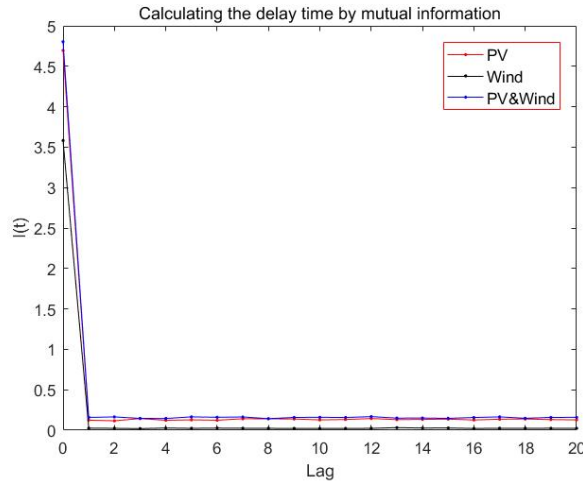


Figure 4. Delay time of the new phase space.

The delay time $\tau_{PV} = \tau_{Wind} = \tau_{PV\&Wind} = 1$ at three different conditions is shown in Figure.4 which means the delay time has no relationship with the ways of the distributed generation assess to the MG system.

The following step is computing the embedding dimension through the way of GP algorithm and which is shown in Fig.5. The embedding dimension is $m = 6$ when the solar PV generation provide energy only for the MG system, the $m = 9$ when the Wind turbine operates independently in the MG system, and the $m = 10$ when both of them work together. And the more bigger of the embedding dimension, the more evolutionary information of dynamic voltage time series will be revealed when it is in appropriate interval. So hybrid of SPV and WT generation integrated into the MG system can provide a more suitable embedding dimension and a more stable voltage output.

4.4. Chaos theory and neural network prediction.

The output of distributed generation is always affected by environmental factors, and changes in environmental factors occur in an instant, and due to this reason, the evaluation system must be able to

assess changes in the system over a short period of time. Evaluate the safety of the MG system within half an hour, take seconds as the sampling time unit, and the evaluation system can assess the safety of the MG system sensitively according to the environmental changes.

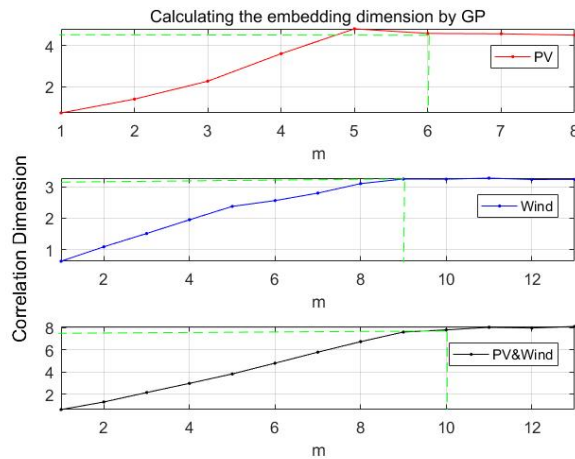


Figure 5. Embedding dimension of the new phase space.

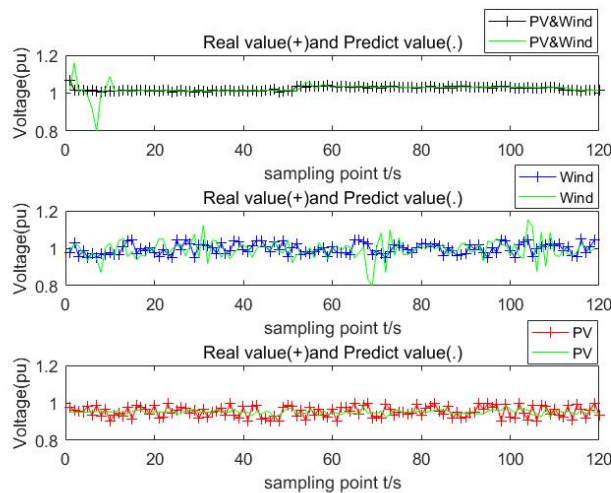


Figure 6. The contradistinction of real value and predict value.

According to Fig.6, the voltage magnitude fluctuates around 0.9 pu or 1.0 pu when the SPV or WT integrated into the Microgrid system independently, and the voltage magnitude is more stable around 1.05 pu when hybridization of SPV and WT connected with the Microgrid system.

The absolute error of the hybridization of SPV and WT is the smallest and the smoothest in Fig.7, and the maximum absolute predict error of it is 0.18, and the other is between 0 ~ 0.2 .

5. Conclusion

A new method has been suggested for evaluating the safety of MG, following an accident, promoting self-healing of the MG. The proposed scheme can judge whether the dynamic voltage at PCC of the MG is in safety status through a dynamic voltage safety criterion drafted exploiting a Voltage Security Assessment Index (VSAI). This scheme uses chaotic time series method to analyze the data of dynamic voltage at PCC of the MG, and calculated that , which means the series of dynamic voltage with

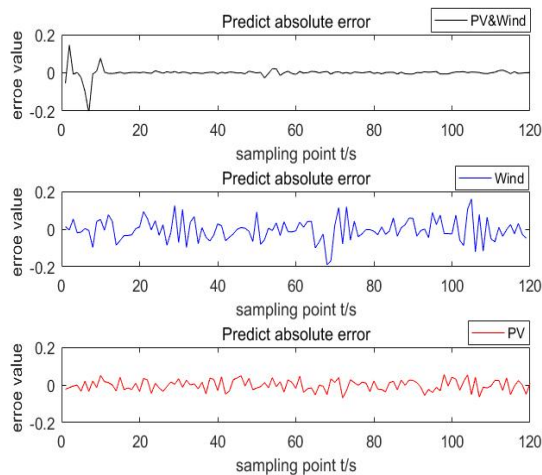


Figure 7. The prediction absolute error curve.

chaotic characteristics. The hybridization of SPV and WT generation can provide a more stable voltage output and it also acts as a remedy to voltage suppression problem in the MG system by comparing three different situations in which distributed generation is integrated into the MG. The result of the maximum absolute error is 0.18 proves the advantage of combining chaotic time series theory with RBF neural network.

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