PAPER • OPEN ACCESS

Fault identification using wavelet transform and Petri networks

To cite this article: Liu Fang et al 2021 IOP Conf. Ser.: Earth Environ. Sci. 645 012033

View the article online for updates and enhancements.

You may also like

- Fault identification using piezoelectric impedance measurement and modelbased intelligent inference with prescreening Q Shuai, K Zhou, Shiyu Zhou et al.

- Impact of microsecond-pulsed plasmaactivated water on papaya seed germination and seedling growth Deng-Ke Xi, , Xian-Hui Zhang et al.
- Perspective-Micro Photosynthetic Power Cells Hemanth Kumar Tanneru, Kiran Kuruvinashetti, Pragasen Pillay et al.





DISCOVER how sustainability intersects with electrochemistry & solid state science research



This content was downloaded from IP address 3.129.19.251 on 03/05/2024 at 04:55

Fault identification using wavelet transform and Petri networks

Liu Fang¹, Jian Hangli^{2*}, Sun Qian², Wang Zhi¹, Chen Fan¹, Liu kai¹, Yuan Shanshan¹, Jia Mengqing¹, Li Jiang^{2*}

¹ State Grid Luoyang Electric Power Supply Company, Luoyang, Henan, 471000, China

² School of Electrical Engineering, Northeast Electric Power University, Jilin City, Jilin Province, 132012, China

Corresponding author's e-mail: 2202000261@neepu.edu.cn

Abstract. This paper proposes the fault identification methods by using fuzzy Petri networks for the advanced application of the micro phasor measurement unit (µPMU) in the distribution network. Firstly, μ PMUs are placed at multi buses of the radial distribution network, and the measured impedance is obtained by µPMU. Then, the transient characteristics of the threephase fault current are extracted by the wavelet transform and Petri networks. Finally, the simulation verifies the effectiveness of the proposed method in 10kV distribution networks.

1. Introduction

In recent years, advanced applications based on micro phasor measurement units (µPMU) are studied by researchers. Based on synchronous monitoring and characteristics of electrical parameters, the μPMU measurement data can improve the accuracy of fault identification and location.

The electrical parameters will change suddenly when a failure occurs in the distribution network. Reference [1,2] proposed a method for deep-learning to identify the fault type. Reference [3-6] proposed a method of applying deep neural networks to get the precise fault type in the distribution network. The results demonstrated that the proposed identification method based on the deep network architecture had higher identification accuracy and reliability.

Reference[7] proposed a new fault location algorithm based on decision-tree topology; reference [8] proposed fault traveling wave-based fault location method. Reference [9] presents a new method for locating a fault in distribution systems using synchronous measurement, which was provided by phasor measurement units (PMUs) with high accuracy and a timestamp. Reference [10,11] delineated the traveling-wave-based fault-location technique for transmission grids via wide-area synchronized voltage measurements. This paper presents a novel method of fault identification combined with µPMU measurement data.

Firstly, the fundamental idea of impedance-based fault identification is introduced in Section 1. Then, the proposed fault identification algorithm by using wavelet transform and Petri networks is illustrated in Section 2 and Section 3. Finally, the effectiveness of the proposed identification algorithm is demonstrated in Section 4.

2. Impedance-based fault identification

The μ PMU can measure voltage and current phasors in real-time [12-15], and the impedance curve from B to E for the single-phase short-circuit is shown in Figure.1.



Figure1. Single-phase short-circuit impedance curve from B to E

The μ PMUs distributed in the whole network can divide the grid into multiple sub-regions, which can measure the voltage phasors at the boundary μ PMU installation and the current phasor flowing into the sub-region in real-time. Figure.2 shows the partial grid topology of an individual distribution network.



Figure2.The partial topology of a specific distribution network

When a fault occurs in a distribution network, the equivalent impedance amplitude will be significantly reduced. The impedance curve from the voltage and current phasors at that moment can be used to identify the fault type and fault section. To analyze the impedance relationship between the normal and fault conditions, a ratio variable s is defined, taking the single-phase impedance as an example, as follows:

$$s_A^r = \frac{Z_{Aent,nml}^r}{Z_{Aent}^r} = \frac{\left| \dot{U}_{Aent,nml}^r / \dot{I}_{Aent,nml}^r \right|}{\left| \dot{U}_{Aent}^r / \dot{I}_{Aent}^r \right|}$$
(1)

Where $Z_{Aent,nml}^{r}$ is the measurement impedance amplitude of phase A at the monitoring node r under the normal operation condition; Z_{Aent} is the measurement impedance amplitude of phase A at the monitoring node r under the abnormal operation condition; $\dot{U}_{Aent,nml}^{r}$ and $\dot{I}_{Aent,nml}^{r}$ respectively represent the voltage and current phasors of phase A at the monitoring node r under normal operation condition. Similarly, the ratio variables of phase B and C are shown in (2) and (3)

Similarly, the ratio variables of phase B and C are shown in (2) and (3)

$$s_B^r = \frac{Z_{Bent,nml}^r}{Z_{Bent}^r} = \frac{\left| \dot{U}_{Bent,nml}^r / \dot{I}_{Bent,nml}^r \right|}{\left| \dot{U}_{Bent}^r / \dot{I}_{Bent}^r \right|}$$
(2)

$$s_{c}^{r} = \frac{Z_{Cent,nml}^{r}}{Z_{Cent}^{r}} = \frac{\left| \dot{U}_{Cent,nml}^{r} \middle| \dot{I}_{Cent,nml}^{r} \right|}{\left| \dot{U}_{Cent}^{r} \middle| \dot{I}_{Cent}^{r} \right|}$$
(3)

Set the ratio threshold s_{set}^r . The fault maybe occur at node r when $s^r > s_{set}^r$. Firstly, the impedance ratio coefficients at a monitoring node are calculated by using (1)-(3). If one of the given three

conditions $s_A^r > s_{A,set}^r$, $s_B^r > s_{B,set}^r$, and $s_C^r > s_{C,set}^r$ is met, the fault identification algorithm is started to identify which type is suit for measurement impedance. When the impedance characteristics meet the threshold within the given section under the fault conditions, it can be judged that a fault occurs in the given section.

3. Fault identification by µPMU measurement data

In recent years, scholars at domestic and abroad have proposed a large number of fault identification methods based on the transient signals [16,17]. This section presents a fault identification method based on hybrid fuzzy Petri nets (HFPN), whose framework is shown in Figure 3 [18,19].



Figure 3. Fault identification framework

The fault characteristics extracted from three-phase and zero sequence currents are taken as the input value of the Fuzzy Petri networks. The energy by using wavelet transform for measurement data is taken as the characteristic value in the Fuzzy Petri networks. The function of the fuzzy logic module is to get the fuzzy value suitable for the input of the fuzzy Petri networks and identify the fault type through the given sample set and comparison process.

3.1 Wavelet transform in fault identification

3.1.1Principle of Wavelet Transform

Wavelet transform uses the variable-scale functions to decompose various time-varying signals into the identification indexes [20, 21]. The wavelet packet based on wavelet transform can map any signal to a set of basis functions, which can be composed of a wavelet expansion, which can get the decomposition sequence in the different frequency domains.

The wavelet transforms for time-varying signals f(t) is mainly to find a set of coefficients that can measure the similarity relationship $(W\Psi f)(q,p)$ between time-varying signals f(t) and the function family $\Psi_{q,p}(t)$. A selected energy finite function $\Psi(t)$ can be obtained through translation transformation, as follows:

$$\psi_{p,q}(t) = \left| p \right|^{-\frac{1}{2}} \psi \ge \left(\frac{t-q}{p} \right) \tag{4}$$

Where p is the expansion factor, q is the translation factor.

$$C_{\Psi} = \int_{\mathbb{R}} \frac{\left|\hat{\Psi}(\omega)\right|^2}{|\omega|} d\omega < \infty$$
(5)

Where $\hat{\Psi}(\omega)$ is the Fourier transform of $\Psi(t)$; Ψ is called the admissible wavelet or basis wavelet.

2020 International Conference on Smart Grid and Energy Engineering

IOP Publishing

IOP Conf. Series: Earth and Environmental Science 645 (2021) 012033 doi:10.1088/1755-1315/645/1/012033

$$(WT\Psi f)(p,q) = |q|^{-\frac{1}{2}} \int_{\mathbb{R}} f(t) \Psi\left(\frac{t-q}{p}\right) d\omega$$
(6)

Where $p, q \in R$, $p \neq 0$, $\overline{\psi}(t)$ and $\psi(t)$ are conjugated with each other.

Wavelet transform is affected by the frequency and time characteristic of the signal. If the wavelet transform is applied to actual engineering, it is necessary to discretize the wavelet transform. Let $p = p_0^m$ and $q = nq_0 p_0^m$, the form of wavelet expansion is shown, as follows:

$$\Psi_{nn}(t) = p_0^{-m/2} \Psi\left(\frac{t - nq_0 p_0^m}{p_0^m}\right)$$
(7)

Where $p_0, q_0 \in R, m, n \in Z, p_0 > 1, q_0 > 0$.

Therefore, the discrete wavelet transform is expressed as follows:

$$(DWT\Psi f)(m,n) = \int_{\mathbb{R}} f(t)\overline{\Psi}_{mn}(t)dt$$
(8)

By selecting P_0 and q_0 , the signal can be decomposed into a group of signals without information redundancy between them. The signal can be decomposed to obtain the characteristics of the signal on the time and frequency scales in the different frequency ranges.

3.1.2 Fault characteristic extraction

The zero-sequence currents in the distribution network can be extracted from the three-phase currents IA, IB, and IC when a fault occurs. The electrical parameters are decomposed by wavelet packet transform using a db4 wavelet basis, 8-layer wavelet decomposition waveform with high-frequency signal coefficient $d_1(k) - d_8(k)$, and low-frequency signal coefficient $a_8(k)$ are shown in Figure 4. The 8-layer wavelet decomposition waveforms of the zero-sequence current under the A-phase grounding fault (AG) are also obtained in Figure 4.

The high-frequency energy values EA, EB, EC, ED corresponding to the four currents IA, IB, IC, and I0 can be obtained by (9) as follows:

$$E_{\delta} = \sum_{j=1}^{S} \sum_{k=1}^{100} \left| d_{\delta j}(k) \right|^{2}$$

$$E_{0} = \sum_{j=1}^{S} \sum_{k=1}^{100} \left| d_{0j}(k) \right|^{2}$$
(9)

Then apply (10) to obtain the normalized values of high-frequency energy eA, eB, eC, e0, as follows:

$$e_{\delta} = E_{\delta} / \max(E_A, E_B, E_C, E_0)$$

$$e_0 = E_0 / \max(E_A, E_B, E_C, E_0)$$
(10)

Where: δ means A, B, C three-phases, The high-frequency energy value E_{δ} in formula (9) is unified and standardized to obtain e_{δ}

The four eigenvalues will reflect their different characteristics when the different faults occur. We can distinguish the various types of faults by using fuzzy Petri networks in this section.

doi:10.1088/1755-1315/645/1/012033



Figure 4. 8-layer wavelet decomposition waveforms of zero sequence current under AG

3.2Fuzzy processing

The concept of fuzzy logic is proposed by simulating the thinking mode of the human brain's uncertainty concept judgment and reasoning. The respective members in the fuzzy set form a fuzzy group based on the corresponding relationship between each element. A mapping relationship (11) can be used to describe the fuzzy function and the fuzzy set $\mu: x \to [0,1]$, as follows:

$$A = \left\{ \left(x, \mu_A(x) \right) \middle| x \in X \right\}$$
⁽¹¹⁾

Where X is the domain of discourse; x is the element in domain X; $\mu_A(x)$ is the functional function of the fuzzy set, describing the degree between x in the set A.

In Fuzzy processes, a fault occurs, zero-sequence current will appear, and zero-sequence wavelet energy increases. "high" in the fuzzy language can be used to indicate the increase of wavelet energy; on the contrary, "low" is used to indicate that the wavelet energy does not change much.

The linear performance functions of the three-phase current characteristic and the zero-sequence current characteristic are analyzed in Figure 5.



Figure 5. performance for Fuzzy function

IOP Conf. Series: Earth and Environmental Science 645 (2021) 012033 doi:10.1088/1755-1315/645/1/012033

3.3 Fuzzy reasoning Petri networks

3.3.1 Definition

Fuzzy reasoning Petri net (FRPN) can be defined as follows:

$$FRPN = \left\{ P, T, I, O, \theta^0, U \right\}$$
(12)

IOP Publishing

Where $P = \{p_1, p_2, ..., p_n\}$ is the collection of places; $T = \{t_1, t_2, ..., t_m\}$ is the set of changes; I is the input matrix, $I = [\delta_{ij}]$; δ_{ij} is the logical quantity, $\delta_{ij} \in [0,1]$; if p_i is not the input of t_j , $\delta_{ij} = 0$, i = 1, 2, ..., n, j = 1, 2, ..., m; if p_i is the input of t_j , the value of δ_{ij} is the weight of this directed arc; O is the output matrix, $O = [\gamma_{ij}]$. γ_{ij} is the logical quantity, $\gamma_{ij} \in [0,1]$; if p_i is not the output of t_j , $\gamma_{ij} = 0$, i = 1, 2, ..., n, j = 1, 2, ..., m; if p_i is the logical quantity, $\gamma_{ij} \in [0,1]$; if p_i is not the output of t_j , $\gamma_{ij} = 0$, i = 1, 2, ..., n, j = 1, 2, ..., m; if p_i is the output of t_j , the value γ_{ij} is the credibility of the rule; $\theta_{P_i}^0$ represents the confidence that the state P_i is the initial logical state of the proposition $\theta_{P_i}^0 \in [0,1]$, $\theta^0 = [\theta_{P_1}^0, ..., \theta_{P_n}^0]^T$, i = 1, 2, ..., n; U is the rule confidence matrix, $U = diag(\mu_1, ..., \mu_m)$, and μ_j is the confidence degree of the rule T_j .

3.3.2 Process

Two operators \oplus and \otimes are respectively defined as:

 \oplus :X \oplus Y=Z, X, Y, and Z are all m×n matrices, $Z_{ij} = \max(X_{ij}, Y_{ij})$;

 \otimes :X \otimes Y=W, X, Y, W are m×q, q×n, m×n matrices, $W_{ij} = \max_{1 \le k \le a} (X_{ik} \cdot Y_{kj});$

The reasoning factor $neg\theta^k$ is used in the reasoning process as follows:

$$neg\theta^k = \mathbf{1}_m - \theta^k = \overline{\theta^k} \tag{13}$$

Where: 1m is an m-dimensional vector with all unit elements; k is an inference step; $neg\theta^k$ is an m-dimensional vector. The intermediate variable v^k can be obtained as follows:

$$v^{k} = I^{T} \otimes \left(neg \theta^{k} \right) = I^{T} \otimes \overline{\theta^{k}}$$
(14)

Where: T_i is a false confidence, j = 1, 2, ..., n. Thus, confidence ρ^k is obtained

$$\rho^{k} = negv^{k} = neg\left(I^{T} \otimes \left(neg\theta^{k}\right)\right) = \overline{I^{T} \otimes \overline{\theta^{k}}}$$
(15)

Where: ρ^k is an m-dimensional vector.

Finally, the next state is obtained by the following iterative steps

$$\theta^{k+1} = \theta^k \oplus \left[\left(O \cdot U \right) \otimes \overline{I^T \otimes \overline{\theta^k}} \right]$$
(16)

In summary, the inference algorithm can be obtained:

Algorithm 1

(1)Input data j = 1, 2, ..., n;

(2)Let reasoning step k = 0;

OObtain the operators and intermediate variables of formula (13) ~ formula (15);

(4) Calculate θ^{k+1} according to formula (16);

(5) If $\theta^{k+1} \neq \theta^k$, k = k+1, return to step (3) to recalculate θ^{k+1} ; otherwise $\theta^{k+1} = \theta^k$, terminate the algorithm.

3.3.3 Model

The wavelet energy of the three-phase current and zero-sequence current is the input of FRPN, the extracted wavelet energy of the three-phase current and zero-sequence current is used as the input of HFPN, and the data is further processed through the fuzzy Petri net. The model of FRPN is obtained in Figure 6.



4. Simulation analysis

The 10kV 50Hz distribution networks are established in PSCAD in Figure 7 to generate transient waveforms under different faults, such as single-phase grounding fault (AG), AB two-phase grounding fault (ABG), phase A to phase B (AB), and three-phase fault (ABC). Two μ PMUs are placed at nodes 1, and 4. The main parameters in Figure 8 include line positive sequence resistance $r_1 = 0.124 \Omega/km$, zero sequence resistance $r_0 = 0.124 \Omega/km$, positive sequence inductance $l_1 = 0.2292 mH/km$, zero-sequence inductance $l_0=0.6875 mH/km$, positive sequence capacitance $c_1 = 250 nF/km$, and zero sequence capacitance $c_0 = 375 nF/km$.



Figure 7. 10kV distribution network

The faults occur at 0.35s between nodes 2 and 3 in Figure 7, in which the transition resistance is set to 10Ω . The transient waveforms from the μ PMU installed at node 1 are imported into MATLAB, and the fault eigenvalue is calculated by 8-layer wavelet decomposition. The high-frequency energy EA, EB, EC, E0 for the currents are obtained by (2), and the characteristic fault values are calculated by (3), which are shown in Table 1.

IOP Conf. Series: Earth and Environmental Science 645 (2021) 012033

IOP Publishing doi:10.1088/1755-1315/645/1/012033

Tab. I Fault eigenvalues under different faults								
Fault type	$e_{_{A}}$	$e_{\scriptscriptstyle B}$	e_{C}	e_0				
AG	1	0.1347	0.1272	0.0634				
ABG	1	0.4078	0.0041	0.0538				
AB	1	0.9283	0.0020	0				
ABC	1	0.4475	0.6382	0				

Tab 1 Fault air 1

The eigenvalues in Table 1 are processed by Fuzzy logic, and the initial states of the FRPN are obtained in Table 2.

Tab.2 Initial state of FPN					
Fault type	FPN Initial state				
AG	$\theta^{0} = [1\ 0\ 0\ 1\ 0\ 1\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\$				
ABG	$\theta^{0} = [1\ 0\ 0.7546\ 0.2454\ 0\ 1\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\$				
AB	$\theta^{0} = [1\ 0\ 1\ 0\ 0\ 1\ 0\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\$				
ABC	$\theta^{0} = [1\ 0\ 0.8241\ 0.1759\ 1\ 0\ 0\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\$				

The output status and the probability of FRPN are shown in Table 3. It can be seen from Table 3 that Algorithm 1 can accurately identify the fault types and obtain the probability of occurrence under the different faults.

Tab.3 Output of FRPN						
Fault type	output state	probability				
AG	$\theta^3 = [1001011010000001000000000]^T$	AG/1				
ABG	$\theta^3 = [100.75460.245401100.2454000.7546]$					
	$0000.245400000.7546000]^{^{T}}$	ABG/0.7546				
AB	$\theta^3 = [1\ 0\ 1\ 0\ 0\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\$	AB /1				
ABC	$\theta^3 = [100.82410.1759100100000.1759]$					
	$0.8241000000.17590000.8241]^{^{T}}$	ABC/0.8241				

The fault eigenvalue and identification results by using Algorithm 1 are analyzed in Tables 4 and 5 under different positions and transition resistances. Tab 4 Fault identification results under different locations

rab.4 Fauti identification results under different locations										
Fault location	e	4	$e_B e_C$		e_0	Outcome and probability				
2km	1	0.	1109	0.1326	0.0738	AG/1				
4km	1	0.	1224	0.9403	0.0672	AG/1				
6km	1	0.	1347	0.1272	0.0634	AG/1				
8km	1	0.0	0864	0.1158	0.0815	AG/1				
Tab.5 Fault identification results under different transition resistances										
Transition resistance	$e_{_{A}}$	$e_{\scriptscriptstyle B}$	e_{C}	e_0	Outcome and probability					
0Ω	1	0.8824	0.0017	0	AB/1					
10Ω	0.9283	1	0.0020	0	AB/1					
30Ω	1	0.7037	0.0013	0	AB/1					
50Ω	1	0.4538	0.0022	0	AB/0.8452					

The simulation results show that the proposed method is adaptive for identifying the fault type under different conditions, and gives the probability of occurrence.

5. Conclusion

This article proposes a fault identification method by using the impedance-based fault starting index, wavelet transform, and Petri networks. The eigenvalue of fault current is extracted by wavelet transform, and the eigenvalue is fuzzified, which improves the accuracy of fault identification from energy viewpoints. In the FRPN algorithm, I_0 is introduced into the input to identify the grounding fault. It can be seen from the simulation results that the proposed *Algorithm 1* is more accurate than that of other methods.

ACKNOWLEDGEMENTS

This research is supported by *Synchronous Phasor Measurement and Fault Location Technology based on NB-IoT in Distribution Networks*,2020 Scientific Development Plan of State Grid Henan Province Electric Power Company, No. 5217A020000Y

REFERENCES

- H. Liang, Y. Liu, G. Sheng, and X. Jiang, "Fault-cause identification method based on adaptive deep belief network and time-frequency characteristics of traveling wave," in IET Generation, Transmission & Distribution, vol. 13, no. 5, pp. 724-732, 2019.
- [2] M. Benidris, J. Mitra, and C. Singh, "Integrated Evaluation of Reliability and Stability of Power Systems," in IEEE Transactions on Power Systems, vol. 32, no. 5, pp. 4131-4139. 2017.
- [3] S. Motepe, A. N. Hasan and R. Stopforth, "Improving Load Forecasting Process for a Power Distribution Network Using Hybrid AI and Deep Learning Algorithms," in IEEE Access, vol. 7, pp. 82584-82598. 2019.
- [4] R. Kou and Y. Wang, "Transmission Line Fault Identification Based on BP Neural Network," 2019 IEEE Innovative Smart Grid Technologies - Asia (ISGT Asia), Chengdu, China, 2019, pp. 991-994. 2019.
- [5] H. Zhao, Y. Qi and H. Jia, "Medium voltage distribution network traveling wave fault location method based on wavelet packet energy spectrum," 2011 International Conference on Advanced Power System Automation and Protection, Beijing, 2011, pp. 1650-1655. 2011.
- [6] S. Xue, L. Chen and G. Liu, "Resource State Prediction in the Grid Based on Neural Network," 2009 Fifth International Conference on Natural Computation, Tianjin, 2009, pp. 294-298.2009.
- [7] N. Zhang, Y. Sun, D. Liu, Z. Li, C. Li, and G. Hu, "FL-TN: A fault location algorithm based on tree topology for smart grid," 2019 Chinese Control And Decision Conference (CCDC), Nanchang, China, 2019, pp. 6221-6225. 2019.
- [8] Li Zewen, Hua Huanhuan, Deng Feng, Zeng Xiangjun, and Yu Kun, "Power grid fault traveling wave network location method," 2013 IEEE Industry Applications Society Annual Meeting, Lake Buena Vista, FL, 2013, pp. 1-6. 2013.
- [9] J. Ren, S. S. Venkata, and E. Sortomme, "An Accurate Synchrophasor Based Fault Location Method for Emerging Distribution Systems," in IEEE Transactions on Power Delivery, vol. 29, no. 1, pp. 297-298, Feb. 2014.
- [10] M. Korkali, H. Lev-Ari, and A. Abur, "Traveling-Wave-Based Fault-Location Technique for Transmission Grids Via Wide-Area Synchronized Voltage Measurements," in IEEE Transactions on Power Systems, vol. 27, no. 2, pp. 1003-1011. 2012.
- [11] P. Jafarian and M. Sanaye-Pasand, "A traveling-wave-based protection technique using wavelet/PCA analysis", IEEE Trans. Power Del, vol. 25, no. 2, pp. 588-599. 2010.
- [12] J. Lu and X. Shan, "WAMS based power grid disturbance recognition and system response assessment, Beijing, 2011, pp. 615-618. 2011.
- [13] S. Yang and B. Zhang, "A WAMS information based transient stability real-time detection scheme for a multi-machine system," 12th IET International Conference on Developments in Power System Protection (DPSP 2014), Copenhagen, 2014, pp. 1-5. 2014.
- [14] R. Kateb, P. Akaber, M. H. K. Tushar, M. Debbabi, and C. Assi, "Delay aware measurements gathering in WAMS communication network,"(GlobalSIP), Montreal, QC, 2017, pp. 1090-1094. 2017.
- [15] X. Liu, X. Zeng, L. Yao, et al." Power System State Estimation Based on Fusion of WAMS/SCADA Measurements: A Survey," 2018 2nd IEEE Conference on Energy Internet

and Energy System Integration (EI2), Beijing, 2018, pp. 1-6. 2018.

- [16] Yang Jianwei, He Zhengyou. Power system fault transient identification method based on hybrid fuzzy Petri nets[J]. Power System Technology, 2012.
- [17] Zhang Jun. Research on Intelligent Fault Diagnosis and Harmonic Source Location of Distribution Network [D]. Southwest Jiaotong University, 2012.
- [18] Chen Jun, Liu Xin, Wang Liping, Zheng Zhong, Ye Xiang, Ren Jie. Research on Fault Diagnosis and Location Method of Petri Net Intelligent Substation Protection Control[J]. China Test, vol. 45, no. 10, pp. 128-134. 2019.
- [19] Bobbio, G. Franceschinis, R. Gaeta and L. Portinale, "Exploiting Petri nets to support fault tree based dependability analysis," Proceedings 8th International Workshop on Petri Nets and Performance Models (Cat. No.PR00331), Zaragoza, Spain, 1999, pp. 146-155. 1999.
- [20] Y. Zheng, Y. Xu and Z. Xiao, "A traveling wave fault location system based on wavelet transformation," 2019 IEEE Green Energy and Smart Systems Conference (IGESSC), Long Beach, CA, USA, 2019, pp. 1-6.2019.
- [21] W. Fluty and Y. Liao, "Electric Transmission Fault Location Techniques Using Traveling Wave Method and Discrete Wavelet Transform," 2020 Clemson University Power Systems Conference (PSC), Clemson, SC, USA, 2020, pp. 1-8. 2020.