A new approach to fault-line selection of small current neutral grounding system

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ABSTRACT
In this paper, a new approach combining BP neural network with fuzzy Petri net (FPN) is developed to deal with the issue of fault-line selection of the small current neutral grounding system. First, the preliminaries of the FPN are briefly introduced. Then, the model of the fault-line selection is detailedly described to explain the new feature representation that fuses multiple fault features of the lines, including the wavelet energy, the active component and the fifth harmonic component. Finally, the simulation model of the fault-line selection is constructed, and the simulation experiments are carried out to verify the effectiveness of the new approach, which could be superior to the traditional fault-line selection approaches.

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1. Introduction
With the rapid development of the electric power system, the structure of the distribution network is increasingly becoming more complex. However, the accuracy of the fault-line selection cannot be satisfied for the small current neutral grounding system by using the traditional fault-line selection methods. Therefore, the accurate fault-line selection approach of the small current neutral grounding system is of great importance and becoming a hot research topic in recent years (Ji et al., 2018; Qian, Huang, & Ruan, 2014).

In the past decades, a large amount of methods have been proposed by researchers from different countries, e.g. transient methods, steady-state methods and artificial intelligent methods, which usually use only few features for the fault-line selection. For example, the problem of fault-line selection has been analysed by using an active component method, but it is susceptible to the series and parallel resistances (Pang & Chen, 2009). The wavelet analysis has been adopted in Chen (2017), but the accuracy of this method is limited due to various issues, such as different frequency of the lines and great difference of the waveforms. In Sun et al. (2016), the fifth harmonic has been used to analyse the line faults, but the amplitude of the fifth harmonic is prone to be disturbed by the unbalanced current. In Zhao and Yin (2013), the wavelet has been combined with BP neural network for the fault-line selection, but it still suffers some defects, including erroneous or missing judgement, unstable accuracy, etc.

To deal with the aforementioned problems, a new approach combined with BP neural network and fuzzy Petri net (BPNN-FPN) is developed in this paper to handle the issue of fault-line selection of small current neutral grounding system, which combines the fault features of the steady and transient states, i.e. the fusion of active component, fifth harmonic and wavelet analysis. By fusing the fault features extracted by these methods, the new approach outperforms the traditional approaches on the fault-line selection of small current neutral grounding system. The contribution of this paper can be summarized as follows: (1) A BPNN-FPN approach combined with multiple fault features is proposed to handle the problem of fault-line selection of small current neutral grounding system. (2) A simulation model is constructed to simulate the line faults and to train the BPNN-FPN. (3) The effectiveness and superiority of the proposed approach are verified by comparing with other traditional methods.

The remainder of this paper can be organized as follows. Section 2 addresses the preliminaries of the FPN. Section 3 introduces the fault-line selection model of the small current neutral grounding system. In Section 4, the simulation experiments are presented and the simulation results are discussed. Finally, the conclusion of this paper is given in Section 5.
2. Preliminaries of FPN

An FPN is defined as follows (Li, Yu, & Lara-Rosano, 2000):

\[ \text{FPN} = \{P, T, I, O, \lambda, \mu, M, W\}, \]

where \( P = \{p_1, p_2, \ldots, p_n\} \) and \( T = \{t_1, t_2, \ldots, t_m\} \) stand for respectively the limited set of place and transition; \( I \) and \( O \) denote respectively the input and output functions that reflect the mapping relationship between the transitions and the places; \( M \) denotes the mapping relationship that represents the mark values of the corresponding places, i.e. \( p_i \in P(i=1, 2, \ldots, n) \), \( P \to [0, 1] \); \( \lambda = \{\lambda_1, \lambda_2, \ldots, \lambda_m\} \) represents the threshold of the transitions, which can reflect the degree of support of the premise to the conclusion in the fuzzy rule generation; and \( \mu = \{\mu_1, \mu_2, \ldots, \mu_m\} \) represents the reliability of the transition \( t_j(j=1, 2, \ldots, m) \).

In this paper, an S-type function (Gong, Liu, Wang, Zhang, & Hou, 2016) is defined as follows:

\[ y(x) = \frac{1}{1 + e^{-b(x-k)}}, \quad x = \sum_{i=1}^{n} M(p_i) \times w_i, \quad k = \lambda(t_i), \]

where \( b \) is set to be a constant that is large enough. Then, \( y(x) \approx 1 \) if \( x > k \), \( e - b(x - k) \approx 0 \); otherwise, \( y(x) \approx 0 \) if \( x < k \), \( e - b(x - k) \approx \infty \). So that, the value of \( y(x) \) can be taken as a criterion of the transition, i.e. the transition is enabled or not enabled when \( y(x) \approx 1 \) or \( y(x) \approx 0 \).

The continuous function of transition fire is defined by

\[ z(x) = y(x) \times \mu(t_i) \times x, \]

where \( z(x) = \mu(t_i) \times x > 0 \) represents the mark value of the output place according to the transition fire if \( y(x) \approx 1 \); and the mark value of the output places will be remained unchanged if the transition is not fired, i.e. \( y(x) \approx 0, z(x) = 0 \).

BPNN has a strong ability of self-learning and self-adaption, which can be applied to the optimization of parameters such as weights, thresholds and reliability values of the FPNs. In this paper, the back-propagation of BPNN is introduced into the FPN model, whose parameters are obtained by repeatedly learning from the training samples (Huang & Chen, 2002).

The cost function is formulated to evaluate the error between the theoretical value and the true value, which is expressed by

\[ E = 2^{-1} \sum_{i=1}^{n} \sum_{j=1}^{m} (M_i(p_j) - M_i^E(p_j))^2, \]

where \( M_i(p_j) \) and \( M_i^E(p_j) \) represent respectively the real and expected mark values of the output place. Furthermore, the parameters of the transition are updated by repeatedly learning and optimization as follows:

\[ \Delta w_{ik}(k+1) = \Delta w_{ik}(k) - \eta \frac{dE}{dw_{ik}(k)}, \]

\[ \Delta \mu_{ik}(k+1) = \Delta \mu_{ik}(k) - \eta \frac{dE}{d\mu_{ik}(k)}, \]

\[ \Delta \lambda_{ik}(k+1) = \Delta \lambda_{ik}(k) - \eta \frac{dE}{d\lambda_{ik}(k)}, \]

where \( x = 1, 2, \ldots, m \).

3. Fault-line selection model

First, the zero-sequence current values of \( p \) loops in the period of \( T \) are acquired, and the zero-sequence current

![Figure 1. Structure of FPN for fault-line selection.](image)
Figure 2. Flow diagram of fault-line selection.
of each set is decomposed into five layers using a db10 wavelet (Peng, Zhou, & Gao, 2015). The wavelet energy value $E_j$ of each line can be calculated by

$$E = \sum_{i=0}^{31} \sum_{\mu=0}^{m} (S_{5j}(\mu))^2,$$

and the corresponding eigenvector values are obtained by normalization and expressed as $(E_1, E_2, \ldots, E_p)^T$. Then, the active component $P_j$ of each line is calculated by

$$P = \frac{1}{T} \int_{t-T}^{t} (V(t) \times I(t))dt,$$

and the corresponding normalized eigenvector values are obtained as $(P_1, P_2, \ldots, P_p)^T$. Moreover, the fifth harmonic component $H_j$ of each line can be calculated, and the normalized vector values are obtained as $(H_1, H_2, \ldots, H_p)^T$. Finally, the three vectors are connected together to construct the input sample data of the FPN model, i.e. $(E_1, E_2, \ldots, E_p, P_1, P_2, \ldots, P_p, H_1, H_2, \ldots, H_p)^T$. The number of input node is set as 3$p$, and the outputs are the corresponding $p+1$ lines, including $p$ lines and one bus line. The structure of the FPN for fault-line selection is shown in Figure 1, where a large number of training samples are sent into the FPN network, which is trained by using BPNN. The training of FPN network can be accomplished after the convergence of parameters, and the reliability of each fault mode can be predicted by inputting the test samples. The flow diagram of fault-line selection is depicted as Figure 2.

4. Simulation experiments

4.1. Simulation model

The fault model of the small current neutral grounding system is constructed as shown in Figure 3, which includes four loops, i.e. L1–L4. The grounding fault is simulated by using MATLAB/Simulink, where the length of L1–L4 is set as 18.1 km, 21.5 km, 16.8 km and 20.7 km respectively. It is worth noting that the setting of length is not too long due to the actual condition of the distribution lines.

In the following simulation experiments, the line faults are loaded on the loops of L1–L4 and the A phase of the bus line, and the faults are simulated with various fault phase angles, grounding resistances and fault distances. The wavelet energy, active power component and fifth harmonic component of each distribution line, which includes 500 sample groups, are calculated by using respectively the wavelet function, Active & Reactive Power module and Fourier function of MATLAB/Simulink.

In the 500 sample groups, 400 of which are randomly selected to be the training samples of the BPNN-FPN network, and the other 100 sample groups are used for the network test. The test samples are distributed to L1, L2, L3, L4 and the bus line with 15, 25, 20, 18 and 22 sample groups. It is worth noting that these samples are comprehensive enough to ensure the effectiveness of the predicted results. The fault codes are listed in Table 1, where 1 and 0 of the network output represent respectively the fault or normal states of the corresponding line; and the lines are marked as 1–5 for easier statistical analysis. The transition rules of the small current fault-line selection system are listed in Table 2, where $b$ is set as 5000 and $\lambda_i (i = 1, 2, \ldots, 5)$ are set as 0.5.

4.2. Simulation results

In the simulation, the acquired 400 groups of sample data are put into the constructed FPN to optimize the parameters such as weights, reliability values and thresholds. The training is stopped when the value of cost function is smaller than the set threshold value after 40 iterations.
Figure 4. Variation of the transition reliability.

Figure 5. Variation of the representative weights.

Figure 4 shows the variation of the transition reliability with the increasing iteration, and the variations of partial representative weights are shown in Figure 5 for simplicity.

It is clear that the variation of the transition reliability and the representative weights is beginning to converge after 20 iterations, which can conclude the following rules. (1) For the parameter of reliability, the values of $\mu_1, \mu_2$ and $\mu_4$ are decreasing to the stable values, which means that the corresponding reliability of the fuzzy rule generation is descending. Instead, the reliability is higher for $\mu_3$ and $\mu_5$ with the ascending values. (2) For the parameter of weight, the ascending $w_{12}$ and $w_{31}$ indicate a greater support for the corresponding fault lines than the initial conditions. Conversely, the descending $w_{23}, w_{41}$ and $w_{52}$ indicate that the arc has less support for the transition triggering. Finally, the learnt parameters are used for the FPN, and the test errors of the real
and expected output are demonstrated in Figure 6. In the experiment, an total accuracy rate of 98% is achieved for BP-FPN and only 2 erroneous judgements occur in the 100 groups of test sample data as shown in Table 3. Comparatively, the fault-line selection results using FPN and BPNN (Jiang, Ren, Liu, Li, & Chen, 2017; Zang, Jiang, Xue, & Yin, 2014) are also listed in Table 3, whose performances are not as good as the proposed method.

5. Conclusion

In this paper, a new approach based on BPNN and FPN is proposed for the fault-line selection of the small current neutral grounding system. By fusing the multiple fault features of the lines, the accuracy of the fault-line selection is promoted comparing with some traditional approaches, and the performances of the BPNN-FPN model have been verified by simulation experiments. In the future, we will focus on the application of the artificial intelligence and intelligent optimization algorithms for the problem of fault-line selection and other fault diagnostic problem of the electric power system (Cui & Liu, 2017; Luo, Song, Liang, & Dobaie, 2018; Sheng, Zhang, & Gao, 2014; Song, Wang, & Sheng, 2016; Song, Wang, & Zou, 2017; Song, Wang, Zou, Xu, & Alsaadi, 2017; Xu et al., 2018; Zeng et al., 2018; Zhang, Song, & Zhao, 2017; Zhao, Song, Zhang, & Xu, 2017; Zhao, Zou, & Song, 2017).

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References

Chen, L. (2017, February). Research on approach of single-phase grounding faulty line detection in coal mine grid based on wavelet analysis. Coal Mine Machinery, 38(2), 160–162.

Cui, L., & Liu, Y. (2017, August). Complex open-circuit fault detection of the IGBT in a three-level inverter. Journal of Shandong University of Science and Technology (Natural Science), 36(4), 108–114.

Gong, M., Liu, Y., Wang, L., Zhang, C., & Hou, L. (2016, July). Fault diagnosis of mine hoist based on optimizing fuzzy petri networks. Industry and Mine Automation, 42(7), 50–53.

Huang, X., & Chen, Y. (2002, October). Wavelet based data compression technique in fault location using travelling wave signal, in Proceedings of International Conference on Power System Technology, pp. 1132–1136, Kunming, China.

Ji, P., Pei, Y., Zhao, S., Bai, C., Wu, W., Liang, L., & Tang, Z. (2018, June). A novel location method for single-phase grounding fault for distribution network based on transient technique, in Proceedings of the 30th Chinese Control and Decision Conference (CCDC’18), pp. 5190–5193, Shenyang, China.

Jiang, X., Ren, L., Liu, M., Li, Y., & Chen, P. (2017, January). Research on fault line detection for non-effectively earthed
system based BP neural networks algorithm. *Journal of Shan-
dong University of Technology (Natural Science Edition)*, 31(1),
67–70.
Li, X., Yu, W., & Lara-Rosano, F. (2000, November). Dynamic
knowledge inference and learning under adaptive fuzzy Petri
net framework. *IEEE Transactions on Systems Man and Cyber-
netics–Part C*, 30(4), 442–450.
Luo, Y., Song, B., Liang, J., & Dobaie, A. M. (2018, October). Finite-
time state estimation for jumping recurrent neural networks
with deficient transition probabilities and linear fractional
uncertainties. *Neurocomputing*, 260, 265–274.
Pang, Q., & Chen, S. (2009, December). Artificial immune
algorithm based faulty line detection method for indirectly
grounding power system. *Power System Protection and Con-
trol*, 37(24), 27–31.
Peng, P., Zhou, Y., & Gao, Y. (2015, October). Ground fault line
selection method in distribution network using GA optimal
network. *Proceedings of the CSU-EPESA*, 27(10), 65–69.
Qian, H., Huang, Z., & Ruan, D. (2014, August). Single phase-to-
earth fault location of small current grounding system with
distributed generation. *Electric Machines and Control*, 18(8),
17–23.
Sheng, L., Zhang, W., & Gao, M. (2014, March). Relationship
between Nash equilibrium strategies and $H_2/H_{\infty}$ control
of stochastic Markov jump systems with multiplicative
noise. *IEEE Transactions on Automatic Control*, 59(9), 2592–
2597.
Song, B., Wang, Z., & Sheng, L. (2016, April). A new genetic
algorithm approach to smooth path planning for mobile
robots. *Assembly Automation*, 36(2), 138–145.
Song, B., Wang, Z., & Zou, L. (2017, January). On global
smooth path planning for mobile robots using a novel mul-
timodal delayed PSO algorithm. *Cognitive Computation*, 9(1),
5–17.
Song, B., Wang, Z., Zou, L., Xu, L., & Alsaadi, F. E. (2017). A
new approach to smooth global path planning of mobile
robots with kinematic constraints. *International Journal of
Machine Learning and Cybernetics*, 1–13. doi:10.1007/s13042-
017-0703-7.
Sun, Q., Zhang, K., Liu, J., Yi, L., Song, X., & Li, Y. (2016, August).
Research on single-phase fault earth fault line selection
method for the distribution network based on fifth harmonics
and wavelet reconstruction. *Electrical Measurement and Instru-
ment*, 53(16), 1–4.
Xu, L., Cao, M., Song, B., Zhang, J., Liu, Y., & Alsaadi, F. E. (2018,
May). Open-circuit fault diagnosis of power rectifier using
sparse autoencoder based deep neural network. *Neurocom-
puting*, 311, 1–10.
Zang, C., Jiang, B., Xue, X., & Yin, J. (2014). Fault location
algorithm based on wavelet optimizing neural network.
*Application of Electronic Technique*, 40(6), 55–58.
Zeng, N., Zhang, H., Song, B., Liu, W., Li, Y., & Dobaie,
A. M. (2018, January). Facial expression recognition via
learning deep sparse autoencoders. *Neurocomputing*, 273,
643–649.
Zhang, J., Song, B., & Zhao, H. (2017, October). A new
approach to fault diagnosis of three-phase full-bridge recti-
fier with integrated feature extraction, in *Proceedings of 2017
Chinese Automation Congress (CAC)*, pp. 6817–6821, Jinan,
China.
Zhao, H., Song, B., Zhang, J., & Xu, L. (2017, August). Fractional-
order PID controller design based on PSO algorithm. *Jour-
nal of Shandong University of Science and Technology (Natural
Science)*, 36(4), 60–65.
Zhao, F., & Yin, D. (2013, September). Fault line selection based
on wavelet packet and improved BP neural network for
power distribution grid. *Process Automation Instrumentation*,
34(9), 4–8.
Zhao, Z., Zou, L., & Song, B. (2017, August). $H_{\infty}$ filtering for a
class of networked systems with distributed delays and one-step
random delays. *Journal of Shandong University of Science and
Technology (Natural Science)*, 36(4), 101–107.