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Fault Section Estimation for Power Systems Based on Adaptive Fuzzy Petri Nets

Z. Y. He
School of Electrical Engineering, Southwest Jiaotong University, Cheng Du, Si Chuan,610031, China
e-mail: hezy@home.swjtu.edu.cn

J.W. Yang
School of Electrical Engineering, Southwest Jiaotong University, Cheng Du, Si Chuan,610031, China

Q.F. Zeng
School of Electrical Engineering, Southwest Jiaotong University, Cheng Du, Si Chuan,610031, China

T.L. Zang
School of Electrical Engineering, Southwest Jiaotong University, Cheng Du, Si Chuan,610031, China

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Abstract

Due to the advantages of Fuzzy reasoning Petri-nets(FPN)on uncertain and incomplete information processing. It is a promising technique to solve the complex power system fault-section estimation problem. Therefore, we propose a novel estimation method based on Adaptive Fuzzy Petri Nets (AFPN), in this algorithm, the AFPN is used to build a dynamic fault diagnosis fuzzy reasoning model, where the weights in fuzzy reasoning are decided by the incomplete and uncertain alarm information of protective relays and circuit breakers. The validity and feasibility of this method is illustrated by simulation examples. Results show that the fault section can be diagnosed correctly through fuzzy reasoning models for ten cases, and the AFPN not only takes the descriptive advantages of fuzzy Petri net, but also has learning ability as neural network..

Keywords: Fault-section estimation, Power system, fault AFPN.

1. Introduction

The aim of fault section estimation is identifying faulty components in power system based on the operation information of protective relays and circuit breakers. A section of power system means a power apparatus, a transmission line, bus bars, or a transformer, etc. which can be separated from the rest of the system by breakers. It is of great significance for the real-time fault diagnosis to recover the power system rapidly after fault occurs. In recent years, Expert System (ES) technique [1]-[4], Artificial Neural Networks (ANN) technique [5]-[7], optimization technology such as Boltzman machine [8], Genetic Algorithm (GA) [9]-[11], Tabu Search (TS) [12] and many other methods has been applied to fault diagnosis of electric power system.

In practical applications, a lot of transmission data and detection information from Energy Management System (EMS) are incomplete, and the tripping of protective relays and circuit breakers are somehow uncertain. At present, what researchers are interested in is how to deal with the uncertainty and incompleteness of fault information, data error and information redundancy. Thus some relevant research efforts are engaged in to seek an effective approach to the fault diagnosis of Electric Power Systems (EPS) in face of the situation with incomplete and uncertain information [13]–[15], in which the fuzzy logic proves its special ability in dealing with such uncertainty and incompleteness. Meanwhile, the Petri net shows the characteristics of parallel information processing and concurrent operating function, and the ability of clearly describing the relation of protective relays, circuit breakers and concurrent operating mechanism can also be got in the Petri net. It is a very suitable and useful modeling tool for fault diagnosis. Hence some methodologies of modeling and analysis for the fault diagnosis of EPS based on Petri nets are presented [16]–[17].

Combining with Petri nets and fuzzy logic, a new type of fault diagnosis model has been proposed [18]. Based on this model, fault section can be estimated correctly, and a satisfactory

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result can also be achieved even in the situation with large amount of incomplete and uncertain alarm information. To search for the optimal design of the structure of FPN diagnosis models and the matrix reasoning execution algorithm, not only a new formal definition of FPN but some discussion about several key issues in implementation of FPN for fault section estimation are given in [19] which proposes a control center implementation solution which is adaptive to changes of input data, power system and protection system configuration.

The fault diagnosis method based on FPN can provide correct diagnostic result, especially, compared with other methods [1]-[6], it can perfectly process the problem of information uncertain and data incompleteness [18]-[19]. However, it has no ability of adjusting its weights and threshold value according to the knowledge updating or the network topology changing. Because of lack of adjustment (learning) mechanism in FPN, it can't cope with potential changes of actual power systems, in [20] introduces the conception "adaptive" into FPN, called Adaptive Fuzzy Petri Nets (AFPN). AFPN not only takes the descriptive advantages of fuzzy Petri net, but also has learning ability as neural network. It can be used for knowledge representation and reasoning, and it has the most important advantage that it is suitable for dynamic knowledge.

This paper is structured as follows: A formal definition of AFPN is given in Section II and its performance is improved by considering characteristics of protective relays. The implementation of APFN for fault diagnosis is described in Section III. In Section IV, some cases are studied to validate merits of this method. The conclusions are given in Section V.

2. The Definition Of AFPN and its training method

2.1. *The Definition of AFPN*

A AFPN is a 9- tpule[21]:

$$AFPN = \{P, T, D, I, O, \alpha, \beta, Th, W\} \quad (1)$$

Where

$P = \{p_1, p_2, \cdots, p_n\}$ set of places;

$T = \{t_1, t_2, \cdots, t_n\}$ set of transitions;

$D = \{d_1, d_2, \cdots, d_n\}$ set of propositions;

$I(O): T \to P^\infty$ input (output) function which defines a mapping from transition to bags of places

$\alpha: P \to [0,1]$ association function which assigns a real value which defined as the certainty factor of the token in place, between 0 to 1 to each places.

$\beta: P \to D$ is bijective mapping between the pro-position and place label for each nod;

If $\beta(p_i) = d_i$ $\alpha(p_i) = y_i$ $y_i \in [0,1]$ certainty factor of proposition d_i is y_i. $|P| = |D|, P \cap T \cap D = \phi$

$Th = \{\lambda_1, \lambda_2, \cdots, \lambda_n\}$ is set of a threshold value λ_i from 0 to 1 to transition $t_i, Th(t_i) = \lambda_i$

$W = W_I \cup W_O$ is sets of input weights w_i and output weights μ_i which assign weights value w_i or μ_i from 0 to 1 to all the arcs of a net.

2.2. *The rules of AFPN*

The rules and reasoning algorithm of AFPN are given through a simple power network sample, and then adaptive algorithm is introduced base on it.

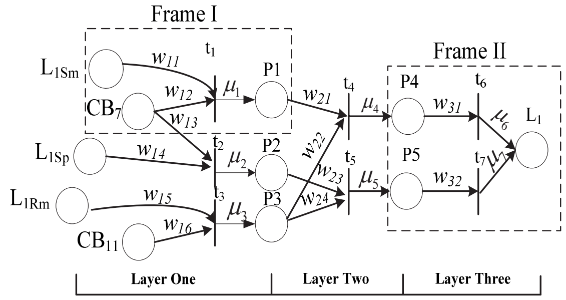


Fig. 1 The sub model of AFPN of power system fault diagnosis

Fig.1 is a sub model of power system fault diagnosis base on AFPN, which was used for estimate whether line L1 in Fig.4 is faulty. Only main protective relays, receiving terminal prime backup protective relay and their corresponding circuit breakers are included.

As show in Fig.1 the rules of improved AFPN are:

A place is called source place if the place only has output transitions, such as place L1sm, place CB7, place L1sp etc., and a place is called sink place if the place only has input transitions like place L1.

A place p is called enable place if it is an input place of a transition, but its corresponding proposition is a precondition for reasoning the corresponding proposition of the output place of the transition, not participate in reasoning it. If p has token and $\alpha(p) > 0$, we select $\alpha(p) = 1$ .Place a_3 is enable place in Fig.2.

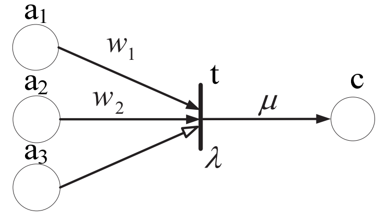


Fig.2 Improved AFPN graph of condition conjunctive rule

The AFPN improved model has three fuzzy production rules. In Fig.1 includes two of them.

The first rule is called conjunctive rule such as frame I shows, the mathematic expression is:

$R: IF \quad a_1 \quad AND \quad a_2 AND \cdots AND \quad a_n \quad THEN \quad c$

$Th(t) = \lambda, W_O = \mu, W_I = w_i, i = 1, 2, \cdots, n$

The second rule is called disjunctive rule such as frame II shows, the mathematic expression is:

$R: IF \quad a_1 \quad OR \quad a_2 \quad OR \cdots OR \quad a_n \quad THEN \quad c$

$Th(t_i) = \lambda_i, W_O = \mu_i, W_I = w_i, i = 1, 2, \cdots, n$

Moreover, the last rule is called condition conjunctive rule, which is used for the situation that considering bus coupling circuit breaker, the mathematic expression is:

$R: WHEN \quad a_3 \quad IS \quad TURE, IF \quad a_1 \quad AND \quad a_2 \quad THEN \quad c$

$Th(t) = \lambda, W_O = \mu, W_I = w_i, i = 1,2$

2.3. *Reasoning algorithm of AFPN*

The reasoning algorithm for conjunctive rule is, only if all the input places p_j of t have tokens, and the certainty factor of these places are $\alpha(p_j) > 0, j = 1,2,\cdots n$, t is enable. When t is enable, t can fire and product new tokens with new certainty factor CF (t) put into each output places, then all tokens in input places are removed.

$$CF(t) = \begin{cases} (\sum_j \alpha(p_j) * w_j) * \alpha(p_i), & \sum_j \alpha(p_j) * w_j > Th(t) \\ 0, & \sum_j \alpha(p_j) * w_j < Th(t) \end{cases}$$

Where p_i is enable place, if there is no enable place we select $\alpha(p_i) = 1$. We can use a continuous function *G(x)* to approximate *CF (t)*μ*

$$G(x) = x \cdot \mu \cdot f(x) \tag{2}$$

Where

$$x = \sum_j \alpha(p_j) \cdot w_j \tag{3}$$

And $f(x)$ is a sigmoid function which approximates the threshold of *t*

$f(x) = \dfrac{1}{1 + e^{-b(x - Th(t))}}$,where b is a large enough number. When $x > Th(t)$,then $f(x) \approx 1$; and when $x < Th(t)$, then $f(x) \approx 0$.

For example, in frame I if place L1sm and place CB7 have tokens with certainty factors, transition t1 fire and products a new token with certainty factor CF(t1), the mathematic expression is:

If $\alpha(L_{1Sm}) > 0, \alpha(CB_7) > 0$, then t1 fire and $\alpha(P1) = G(CF(t1)) = (\alpha(L_{1sm}) \bullet w_{11} + \alpha(CB_7) \bullet w_{12}) \bullet \mu \bullet f(CF(t1)) \quad CF(t1) > Th(t1)$

Especially, the new token with certainty factor CF (t1) cannot put into output place and will be destroyed by G(CF(t1))=0, when CF(t1) < Th(t1).

The reasoning algorithm of disjunctive rule is the same, but certainty factor is set to the max one when the output place has more than one input transitions fire.

Such as in frame II, if $\alpha(P4) > 0$, $\alpha(P5) > 0$, transitions *t6* and *t7* fire at the same time product new tokens with certainty factors. Use *G(x1)* and *G(x2)* denote respectively, the final result is $\alpha(P(L1)) = MAX(G(x_1), G(x_2))$,

Where

$$G(x_1) = \alpha(P4) \bullet w_{31} \bullet \mu \bullet f(\alpha(P4) \bullet w_{31})$$
$$G(x_2) = \alpha(P5) \bullet w_{32} \bullet \mu \bullet f(\alpha(P5) \bullet w_{32})$$

The fuzzy reasoning of AFPN is used to get certainty factor of the set of consequence propositions from certainty factor of the set of antecedent propositions.

The example is shown as follows:

In Fig.1,*P ={L1Sm,CB7, L1Sp,L1Rm,CB11,P1,P2,P3,P4,P5,L1}*. If tokens with certainty factors are put into places L_{1Sm}, CB_7, L_{1Sp}, L_{1Rm} and CB_{11}, then

(i) t1, t2, t3 are fire

$$x_1 = \alpha(L_{1\mathrm{Sm}})w_{11} + \alpha(\mathrm{CB}_7)w_{12}$$
$$x_2 = \alpha(L_{1\mathrm{Sp}})w_{14} + \alpha(\mathrm{CB}_7)w_{13}$$
$$x_3 = \alpha(L_{1\mathrm{Rm}})w_{15} + \alpha(\mathrm{CB}_{11})w_{16}$$

then

$$\alpha(p_{\mathrm{L1}}(11)) = x_1\mu_1 / (1 + \mathrm{e}^{-b(x_1 - T_\mathrm{h}(t_1))})$$
$$\alpha(p_{\mathrm{L1}}(12)) = x_2\mu_2 / (1 + \mathrm{e}^{-b(x_2 - T_\mathrm{h}(t_2))})$$
$$\alpha(p_{\mathrm{L1}}(13)) = x_3\mu_3 / (1 + \mathrm{e}^{-b(x_3 - T_\mathrm{h}(t_3))})$$

(ii) t4 and t5 are fire

$$x_4 = \alpha(p_{\mathrm{L1}}(11))w_{21} + \alpha(p_{\mathrm{L1}}(13))w_{22}$$
$$x_5 = \alpha(p_{\mathrm{L1}}(12))w_{23} + \alpha(p_{\mathrm{L1}}(13))w_{24}$$

then

$$\alpha(p_{\mathrm{L1}}(21)) = x_4\mu_4 / (1 + \mathrm{e}^{-b(x_1 - T_\mathrm{h}(t_4))})$$
$$\alpha(p_{\mathrm{L1}}(22)) = x_5\mu_5 / (1 + \mathrm{e}^{-b(x_2 - T_\mathrm{h}(t_5))})$$

(iii) t6 and t7 are fire

$$x_6 = \alpha(p_{\mathrm{L1}}(21))\mu_6 / (1 + \mathrm{e}^{-b(\alpha(p_{\mathrm{L1}}(21)) - T_\mathrm{h}(t_6))})$$
$$x_7 = \alpha(p_{\mathrm{L1}}(22))\mu_7 / (1 + \mathrm{e}^{-b(\alpha(p_{\mathrm{L1}}(22)) - T_\mathrm{h}(t_7))})$$

Then the adaptive algorithm will be given based on it.

2.4. *Adaptive Learning Algorithm*

Generally, the threshold values λ, input weight values *w* in FPN are given by expert experiences with uncertain factors [19]. Output weight values *μ* are not defined in FPN. These values in AFPN may be trained and adaptive updated, and use these updated values will let calculate consequence more approximate real value.

In Fig.1, assume that threshold values and output weight values are known and only input weight values are updated, select the real data of certainty factor of sink place is *O*, the output error is $e = \alpha(L1) - O$ and the input weight in each layer is updated as

$$W^{(n)}(k+1) = W^{(n)}(k) - \gamma \dot{G}^{(n)} e^{(n)} \Lambda^{(n)} \tag{4}$$

Where, γ is adaptive gain; $\Lambda^{(n)}$ is input of *n*_th layer, for example in Fig.1,

$$\Lambda^{(3)} = [\alpha(P4), \alpha(P5)]^T \tag{5}$$

W (k) is weight at the time of *k*; $\dot{G}$ is the derivative of the function *G*

$$\dot{G} = \frac{d}{dx}\left[\frac{\mu \cdot x}{1 + e^{-b(x - Th(t))}}\right] = \frac{\mu x b e^{-b(x - Th(t))}}{(1 + e^{-b(x - Th(t))})^2} + \frac{\mu}{1 + e^{-b(x - Th(t))}} \tag{6}$$

The adaptive learning will be end, if the error between reasoning results $\alpha(L1)$ and real data or expect data *O* is an arbitrarily small number, formula is as follow:

$$E = \frac{1}{2}\sum(\alpha(L1) - O)^2 < \varepsilon \quad (7)$$

Where ε is an arbitrarily small number which is selected according to expected accuracy.

The AFPN improved model is a three-layer model, the error for each layer is different. There are some more rules about how to calculate the errors of each layer [20]:

Firstly, like Layer Three in Fig.1, when the layer has a composite disjunctive rule. We assume *e6*; *e7* and *e* represent the output error of transition *t6*, *t7*, and the final output error, respectively.

When there is only *t6* fire $\quad e_6 = e\cdot\mu_6, e_7 = 0$

When there is only *t7* fire $\quad e_6 = 0, e_6 = e\cdot\mu_7$

When *t6* and *t7* fire at the same time

$$e_6 = e\cdot\frac{\mu_6}{\mu_6+\mu_7}, e_7 = e\cdot\frac{\mu_7}{\mu_6+\mu_7}$$

Secondly, if it's a composite conjunctive rule and *t* fire, output error

$$e^{(k-1)} = e^{(k)}\cdot\mu^{(k)} \quad (8)$$

The adaptive learning algorithm of AFPN is as follows [20]:

(i) Select a set of initial input weight values.

(ii) Select r sets of input data. For one set of input data, according to the reasoning algorithm, calculate the certainty factors of sink places, the final error e and each layer error e^k, use these to adjust the input weights and the next set of input data.

(iii) Assumed there are *q* sink places, let output O^* be approximated except output O, until $E = \frac{1}{2}\sum_{i=1}^{r}\sum_{j=1}^{q}(O^* - O)^2 < \varepsilon$.

For example in Fig.4 (a), the places $P_I = \{A_{1m}, CB_1, CB_2, CB_3, T_{1s}, T_{2s}, X_s, CB_x\}$, and transitions $T = \{t_1, t_2, t_3, t_4, t_5, t_6, t_7, t_8, t_9, t_{10}\}$ which divide into three layers $T_1 = \{t_1, t_2, t_3, t_4, t_5, t_6\}, T_2 = \{t_7, t_8\}, T_3 = \{t_9, t_{10}\}$.

(i) When $\alpha(A_{1m}) = \alpha(T_{2s}) = \alpha(CB_1) = \alpha(CB_2) = \alpha(CB_3) = 1 > 0$, t1, t2, t3 ,t5 are enable

$$x_1 = \alpha(CB_1)\cdot w_1 + \alpha(A_{1m})\cdot w_2 = 1$$
$$x_2 = \alpha(CB_2)\cdot w_3 + \alpha(A_{1m})\cdot w_4 = 1$$
$$x_3 = \alpha(CB_3)\cdot w_6 + \alpha(A_{1m})\cdot w_5 = 1$$

Then for $x_1 > \lambda_1, x_2 > \lambda_2, x_3 > \lambda_3, x_5 > \lambda_5$, t1, t2, t3, t5 fire, move tokens to places p1, p2, p3, p5 with certainty factors as follows:

$$\alpha(p1) = x_1\cdot\mu_1 / (1 + e^{-b(x_1-\lambda_1)}) = 0.858$$
$$\alpha(p2) = x_2\cdot\mu_2 / (1 + e^{-b(x_2-\lambda_2)}) = 0.858$$
$$\alpha(p3) = x_3\cdot\mu_3 / (1 + e^{-b(x_3-\lambda_3)}) = 0.858$$
$$\alpha(p5) = x_5\cdot\mu_5 / (1 + e^{-b(x_5-\lambda_5)}) = 0.579$$

(ii) Then, t7 is enable while t8 is not

$$x_7 = \alpha(p1)\cdot w_{13} + \alpha(p3)\cdot w_{14} + \alpha(p3)\cdot w_{15} = 1.287$$

For $x_7 > \lambda_7$, t7 fire, move tokens to places p7 with certainty factors as follows:

$$\alpha(p7) = x_7\cdot\mu_7 / (1 + e^{-b(x_7-\lambda_7)}) = 1.287$$

At last t9 is enable and fire

$$\alpha(A1) = \alpha(p7)\cdot 1\cdot\mu_9 / (1 + e^{-b(\alpha(p7)*0.5-\lambda_9)}) = 1.287$$

(iii) Then start adaptive learning algorithm for update input weights, we calculator e=0.287, $e^{(2)}$=0.287, $e^{(1)}$=0.246.

$$\begin{bmatrix} w13 \\ w14 \\ w15 \end{bmatrix} = W^{(2)}(1) = W^{(2)}(0) - \gamma \dot{G}^{(2)} e^{(2)}\Lambda^{(2)} = \begin{bmatrix} 0.483 \\ 0.483 \\ 0.483 \end{bmatrix}$$

$$\begin{bmatrix} w1 \\ w2 \\ w3 \\ w4 \\ w5 \\ w6 \end{bmatrix} = W^{(1)}(1) = W^{(1)}(0) - \gamma \dot{G}^{(1)} e^{(1)}\Lambda^{(1)} = \begin{bmatrix} 0.485 \\ 0.485 \\ 0.485 \\ 0.485 \\ 0.485 \\ 0.485 \end{bmatrix}$$

(iv) Then use the new input weights in next time fuzzy reasoning calculator and adaptive learning, until $E = \frac{1}{2}\sum(O^* - O)^2 < \varepsilon$.

3. Implementation oF APFN for Fault Diagnosis

3.1. *The improved Fault Diagnosis Model Based on AFPN*

As shown in Fig.3 from [18], a local sketch map of operational principle and protection configuration of protective relay system of an EPS is given, in which 28 system elements, 84 protective relays and 40 circuit breakers are included.

28 system elements are listed as: A1,…,A4; T1,…,T8; B1,…,B8; L1,…,L8; and 40 circuit breakers are in turn as: CB1,CB2,…,CB40; for the 84 protective relays, in which 36 main protective relays may be enumerated as A_{1m},…,A_{4m}; T_{1m},…,T_{8m}; B_{1m},…,B_{8m}; L_{1Sm},…,L_{8Sm}; L_{1Rm},…,L_{8Rm}; and 48 backup protections are in turn as: T_{1p},…,T_{8p}; T_{1s},…,T_{8s}; L_{1Sp},…,L_{8Sp}; L_{1Rp},…,L_{8Rp}; L_{1Ss},…,L_{8Ss}; L_{1Rs},…,L_{8Rs}.

Referring to [18] and according to principles of relay protection, topological graph of network and fuzzy production rules of AFPN. We use three layers combined into a fault diagnosis model in each element, e.g. Fig.3, and the same to others.

In Layer One, each transition has two or more input places which input weight, one output place which output weight. Input places are source places which represent operated protective relays or tripped circuit breakers. Output place describes that one protective relay is operated and its corresponding circuit breaker is tripped; it also can be combined with diagnosis criterions according to principles of relay protection. Input weight is an adaptive operator used to make fuzzy reasoning result more accurate (the same in Layer Two and Layer Three), and output weight represents the certainty factors of the event that protective relay and circuit breaker are operated correctly.

In Layer Two, input places are output places in Layer One. Output places represent diagnosis criterions or one of fuzzy reasoning results. Output weight represents the certainty factors of the diagnosis criterions, it is selected as 1 in our model (the same in Layer Three).

In Layer Three, output place is sink place corresponding with fault diagnosis consequence. If there is one input place for a transaction, the input weight is 1 and not to be adaptive.

These models are show in Fig.4, including four types elements of the power system.

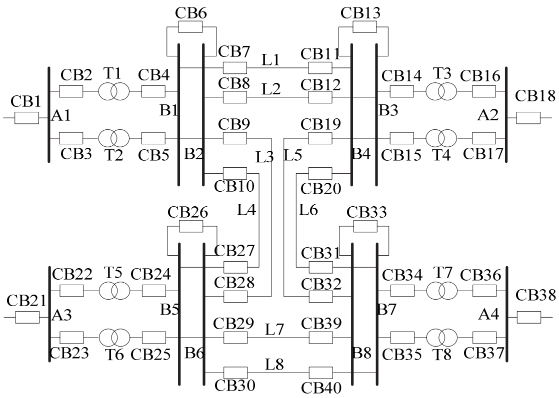
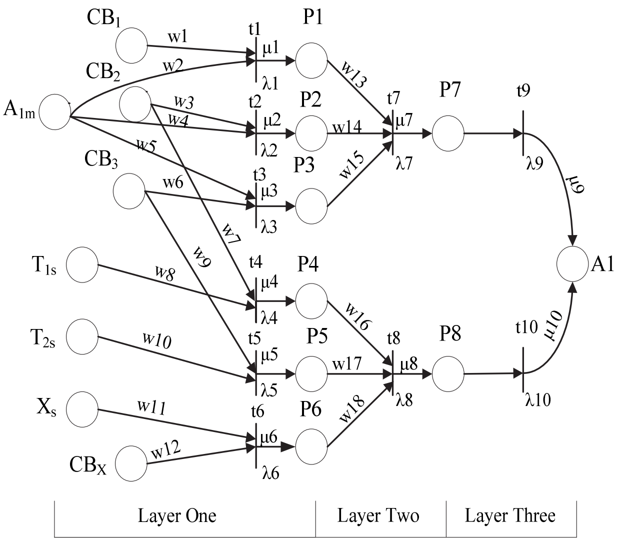
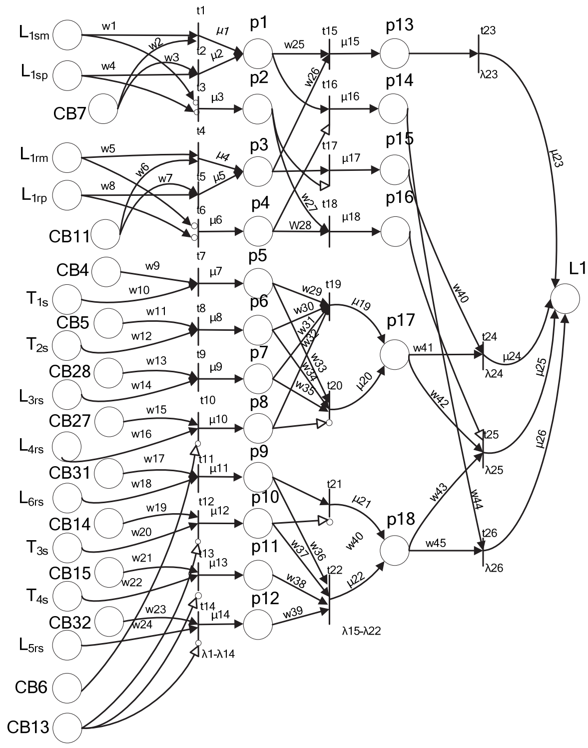


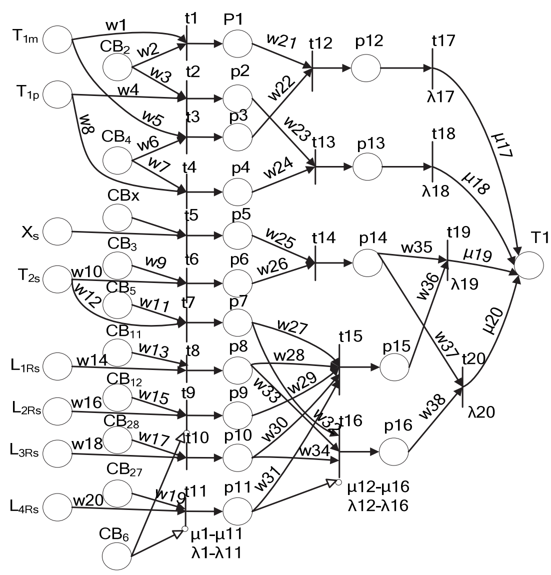
Fig. 3 A sample of power networks



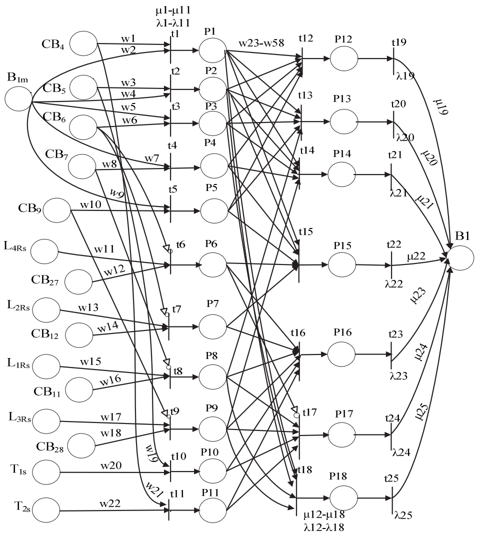
(a)



(b)



(c)



(d)

Fig. 4 Improved fault diagnosis model of power system based on AFPN：(a) bus A (b) Line L (c) transform T (d) bus B

3.2. *Determination of Parameter*

The certainty factors of protective relays or circuit breakers that tripped correctly are calculated based on statistic data.

As the calculation method shown in [22], the certainty factor of main protective relay operated correctly is ratio of its operated correctly times and total times during the 12 months, and then its average value is got by the formula as follows:

$$R = \frac{\sum^{N} \mathrm{P}}{N} \tag{9}$$

Where, *R* denotes the certainty factors of main protective relay or circuit breaker which is operated correctly; *P* is probability for protective relay or circuit breaker which is operated correctly in one year; *N* is number of years.

So, here certainty factor of line main protective relay operated correctly is R_L=0.991. As the same R_T=0.776, R_B=0.856.

Based on statistic data from [24],[25], 275373 times of circuit breakers were triggered in 2004, the number of accident and fault accrued to 392; in 2005, 295101 times of circuit breakers were triggered, while accident and fault happened 654 times. So certainty factor of circuit breaker that is triggered correctly is R_{CB}=0.998.

Assumed that event A is circuit breaker that is triggered correctly, event B is the protective relay that operates correctly. Then the certainty factor of protective relay that operated correctly is signed as P (B). The certainty factor of circuit breaker that is triggered correctly is signed as P (A|B), because the circuit breaker is triggered following correspond protective relay operates. The certainty factor of both protective relay and circuit breaker operated correctly is P(AB)=P(A|B)*P(B).

Based on calculation results from statistics, we assume that the certainty factor of circuit breaker be triggered correctly is 0.998, the certainty factor of line main protective relay operates correctly is 0.99, the certainty factor of bus main protective relay operates correctly is 0.86, and the certainty factor of transformer main protective relay operates correctly is 0.78. The certainty factor of primary or second backup protective relay is assumed as 0.1 or 0.2 lower than corresponding main protective relay. Calculation results of P (AB) are shown as Table 1.

Table 1 Contrast of the Two Methods Applied to Fault Detection

P(AB)	MAIN PROTECTIVE RELAYS	PRIMARY BACKUP PROTECTIVE RELAYS	SECOND BACKUP PROTECTIVE RELAYS
LINE	0.988	0.888	0.788
BUS	0.858	0.758	0.659
TRANSFORMER	0.778	0.679	0.579

The output weights in Layer One are selected as Table 1.

Initial values of input weights are selected as 0.5 or 0.3(Bus B).

The expected training results of all 28 elements are selected as 1.

Based on characteristics of sigmoid function, here we set b=300, $\gamma = 0.07$, Th(t)=0.5. When power system fault occurs, the information about which protective relays or circuit breakers are triggered will be sent from SCADA to control center. If the information includes CB1 is triggered, the antecedent proposition of place CB1 in Fig.4 (a) model is true. So put token into place CB1, and select the certainty factor of the antecedent proposition of place CB1 is 1. And if there is no information about CB1 is triggered, the antecedent proposition of place CB1 in Fig.4 (a) model is false. So no token put into place CB1, and select the certainty factor of the antecedent proposition of place CB1 is 0.

4. Simulation Studies

In order to verify the effectiveness of the method proposed in this paper, the same representative cases from various fault types of the power system shown in Fig.3 are extracted to carry out simulation.

Determination of cases

In this paper, all of the 28 element models need training samples for input weights learning. And the cases from 7 to 15 are used for input weights learning of each element model. Each of these cases is combined with no more than four elements' fault data, including one appointed element's and others on random. Fault data set of single element is composed of protective relays and circuit breakers information when fault occur to it. For example, the fault data set of L1 and B1 is shown as Table 2 and Table 3, where"…" represents 1 or 0. One of the cases in L1 model may as Table 4 shown, only has the fault data of L1 and B1, where L1 is appointed element and B1 is stochastic, "…"represents the state value of protective relay or circuit breaker is 0. The case is the combination of L1 and B1 fault data sets.

4.1. *Simulation result*

Error curves of line, bus and transformer models are shown in Fig.5, error *e* is an arbitrarily small number after 50 times, and the iteration times are less than the times in AFPN model [26]. Parts convergence curves of input weights in L1 and B1 models after training are shown as Fig.6. Fig.6(a) shows input weights for main protective relays, prime backup protective relays and their circuit breakers. Fig.6(b) shows input weights of main protective relay and its circuit breakers. All of them tend to convergent.

After training of input weighs for all elements in the system, we can get correct fault diagnosis results from the test of all simple fault cases, then we choose the fault cases from [23] to test, the results are shown in Table 4. The certainty factors value of the result is calculated by the formula below:

$$CF = (1 - |x - 1|) \times 100\% \tag{10}$$

Where, x is the fuzzy reasoning result.

Compared with results in [23], we can see that the method in this paper can get correct results to complex cases from Table 4. Case 1 to case 7 are calculated by AFPN improved models and FPN models. Compared with results from [18], it expresses that correct and accurate results can be obtained after input weights updating by AFPN improved method in this paper. Especially in case 7, Ref. [18] gives incorrect information of L8 faulted with true value is 0.693. Case 1 to case 5 are used in AFPN improved models and AFPN classical models simulation; the results show that the proposed method can give more accurate results. In case 8 to case 10, we assume that the faulted data is lost or wrong in transmission process. Compared case 5 with case 8, AFPN improved method can get correct result when the data of CB5 is lost. In case 9, it also can give CF of T3 and A2 when the data of CB16 is lost. We assume the circuit breaker CB32 is operated, but the data is lost in transmission process, compared case 7 with case 10, the AFPN improved method can give the result that the CF of bus B8 occurs fault, but cannot get the result that line L5occurs fault. Case 8 to case 10 show that the data is lost in transmission process, they only has effect to the corresponding elements.

Table 2 Fault Data Set of L1

	L_{1sm}	L_{1rm}	L_{1sp}	L_{1rp}	L_{3rs}	L_{4rs}	L_{5rs}	L_{6rs}	T_{1s}	T_{2s}	T_{3s}	T_{4s}	CB_4	CB_5	CB_6	CB_7	CB_{11}	CB_{14}	CB_{15}	CB_{24}	CB_{27}
1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0
2	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
n-1	1	0	0	1	1	1	0	0	1	1	0	0	1	1	0	0	0	0	0	0	1
n	0	1	1	0	0	0	1	1	0	0	1	1	0	0	0	0	0	1	1	0	0

Table 3 Fault Data Set of B1

	B_{1M}	L_{1RS}	L_{2RS}	L_{3RS}	L_{4RS}	T_{1S}	T_{2S}	CB_4	CB_5	CB_6	CB_7	CB_9	CB_{11}	CB_{12}	CB_{27}	CB_{28}
1	1	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0
2	1	0	1	1	0	0	0	1	1	0	1	1	0	1	1	0
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
N-1	1	1	0	0	1	0	0	1	1	1	0	0	1	0	0	1
N	1	1	1	1	1	1	1	1	1	0	0	0	1	1	1	1

Table 4 One of Fault Data The Paper Use

	B_{1m}	…	L_{1sm}	L_{1rm}	…	L_{1sp}	L_{2r}	L_{3ss}	L_{3r}	T_{1m}	…	CB_4	CB_5	CB_6	CB_7	CB_9	CB_{10}	CB_{11}	CB_{12}	…	CB_{27}	…
1	1	…	1	1	…	0	1	0	1	0	…	1	1	0	1	1	0	1	1	…	1	…

4.2. *Fault Classification Tests in Simulation*

The system shown in Fig.5 is used for simulation tests. The current as well as the voltage transient of each phase, which is measured in one end, is analyzed in the case of fault classification. Their performances are similar to each other. Therefore, we only illuminate the test results of voltage transient to verify the algorithm. The sampling frequency is set to be 20kHz and we take the 200-sample-long sequence, i.e. half-cycle data after fault inception, as the input of WSE.

In order to test the noise immunity of WSE, different density of white noise has been added of the SNR value of the system in Fig.5 has been varied between 10 and 40. The SNR value would have some influence on the classification results. Take A-phase-to-ground fault as an example, the WSE values and classification results are shown respectively in Fig.10 and Table 3.

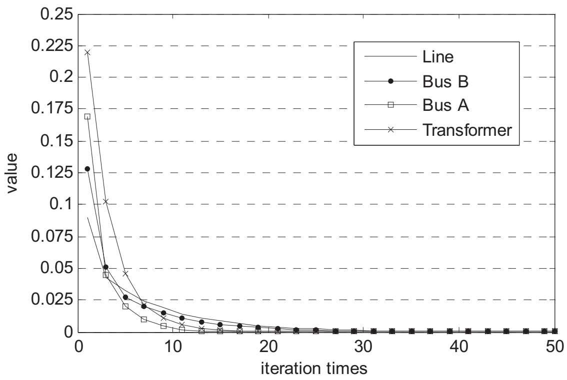
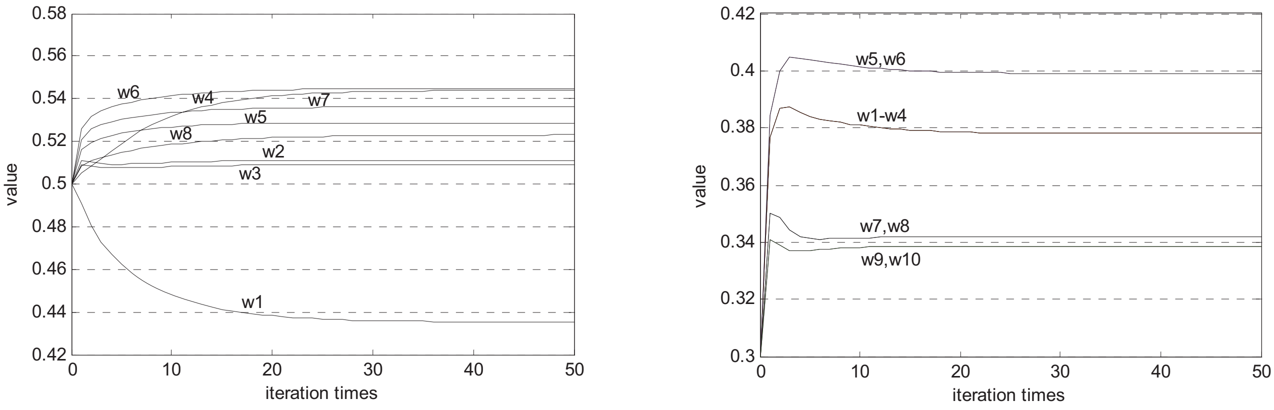


Fig. 5 Error curves of above four models in 50 times training



(a) (b)

Fig. 6 Parts of input weights learning results of model (a) L1 model (b) B1 model

Table 5 Fault Diagnosis Results of Samples

CASE NUMBER	FAULT DATA	FAULT DIAGNOSIS RESULT	CLASSICAL MODEL RESULT[26]	FPN MODEL RESULT[18]	FAULT DATA ANALYSIS
1	protective relays B_{1m}, L_{2Rs}, L_{4Rs} are operated and circuit breakers CB4, CB5, CB7, CB9, CB12, CB27 are tripped	B1 CF=100%	B1 CF=99.97%	B1 Truth Value(TV) is 0.703	CB6 refuse operation
2	protective relays B_{1m}, B_{2m}, L_{1Sm}, L_{1Rp}, L_{2Sp}, L_{2Rm} are operated and circuit breakers CB4, CB5, CB6, CB7, CB8 ,CB9, CB10, CB11, CB12 are tripped	B1,L1,B2,L2 CF are 100%, 99.999%, 100%, 99.999% respectively	B1,L1,B2,L2 CF are 100%, 99.99%, 100%, 99.99% respectively	B1,B2,L1,L2 TV are 0.967, 0.985, 0.972, 0.972, respectively	L_{1Rm}, L_{2Sm} refuse operation
3	protective relays T_{5s},T_{6s} are operated and circuit breakers CB22, CB23, CB24, CB25 are tripped	A3 CF=100%	A3 CF=99.98%	A3 TV is 0.648	A_{1m} refuse operation
4	protective relays L_{1Sm}, L_{1Rp}, L_{2Sp}, L_{2Rp}, L_{7Sp}, L_{7Rm}, L_{8Sm}, L_{8Rm} are operated and circuit breakers CB7, CB8, CB11, CB12, CB29, CB30, CB39, CB40 are tripped	L1,L2,L7, L8 CF are 100%, 100%, 100%, 100% respectively	L1,L2,L7, L8 CF are 99.99%, 100%, 100%, 100% respectively	L1,L2,L7, L8 TV are 0.972, 0.938, 0.972, 0.99, respectively	L_{1Rm}, L_{2Rm}, L_{2Sm}, L_{7Sm} refuse operation
5	protective relays B_{1m}, L_{1Sp}, L_{1Rm} are operated and circuit breakers CB4, CB5, CB6, CB7, CB9, CB11 are tripped	B1, L1 CF are 100%, 99.999% respectively	B1, L1 CF are 100%, 99.99% respectively	B1, L1 TV are 0.967, 0.972, respectivly	L_{1sm}, refuse operation
6	protective relays T_{3p}, L_{7Sp}, L_{7Rp} are operated and circuit breakers CB14, CB16, CB29, CB39 are tripped	T3, L7 CF are 100%, 99.997% respectively	No this sample	T3, L7 TV are 0.938, 0.938, respectively	T_{3m}, L_{7Sm}, L_{7Rm}, refuse operation
7	protective relays T_{7m}, T_{8p}, B_{7m}, B_{8m}, L_{5Sm}, L_{5Rp}, L_{6Ss}, L_{7Sp}, L_{7Rm}, L_{8Ss} are operated and circuit breakers CB19, CB20, CB29, CB30, CB32, CB33, CB34, CB35, CB36, CB37, CB39 are tripped	T7,T8,B7,B8,L5,L7 CF are 100%, 100% 100%, 100%, 100%, 100%, respectively	No this sample	T7,T8,B7,B8,L5,L7,L8 TV are 0.99, 0.938, 0.703, 0.985, 0.972, 0.972, 0.693, respectively	T_{8m}, L_{7Sm}, L_{5Rm},CB31, CB40, refuse operation
8	protective relays B_{1m}, L_{1Sm}, L_{1Rm} are operated and circuit breakers CB4, CB6, CB7, CB9, CB11 are tripped	B1, L1 CF are 79.391%, 99.999% respectively	No this sample	No this sample	CB5 was lost
9	protective relays T_{3p}, A_{2m} are operated and circuit breakers CB14, CB17, CB18 are tripped	T3,A2 CF are 75%, 66.667% respectively	No this sample	No this sample	T_{3m} refuse operation, CB16 was lost
10	protective relays T_{7m},T_{8p},B_{7m}, B_{8m},L_{5Sm} ,L_{5Rp} ,L_{7Sp} ,L_{7Rm} ,L_{8Ss} are operated and circuit breakers CB19, CB29, CB30, CB31, CB33, CB34, CB35, CB36, CB37, CB39 are tripped	T7,T8,B7, L7 CF are 100% , 100%, 100% , 100% , respectively B8 is 81.411%	No this sample	No this sample	T_{8m},L_{7Sm}, CB40, refuse operation, CB32 was lost

5. Conclusion

With fuzzy petri nets as basic tool, and according to fault diagnosis characteristics, a new improved type of diagnosis analysis method using self-adaptive petri nets with fuzzy logic is presented in this paper. The logical testifying and cases simulation validate the feasibility and effectiveness of this method. Several conclusions can be got as shown below:

(i) The training times of AFPN improved models are less than AFPN classical models in the same cases, and AFPN improved models can give more accurate results.

(ii) Output weights are selected based on statistic data describes the right times of protective relays and circuit breakers are operated, by this way a better explanation and realistic basis can be given to the places in Layer Two. Thus, the subjective ness of the proposed method can be reduced.

(iii) The input weights in AFPN improved models are updated by using BP algorithm which not only increases the accurate of diagnosis result, but also describes the mathematic relations between protective relays, circuit breakers and elements in power networks based on AFPN improved models.

(iv) The method in this paper has a good capability of fault-tolerance. It can still get diagnosis results even though the fault data lose by various reasons.

(v) The method has a good ability of parallel processing, simple reasoning procedure, and quick diagnosis speed. It also has such advantages as high flexibility and adaptability.

6. References

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