

Fault Diagnosis of Power Systems Using Intuitionistic Fuzzy Spiking Neural P Systems

Hong Peng, Jun Wang, Jun Ming, Peng Shi, *Fellow, IEEE*, Mario J. Pérez-Jiménez, Wenping Yu, and Chengyu Tao

Abstract—In this paper, intuitionistic fuzzy spiking neural P (IFSNP) systems as a variant are proposed by integrating intuitionistic fuzzy logic into original spiking neural P systems. Compared with a common fuzzy set, intuitionistic fuzzy set can more finely describe the uncertainty due to its membership and non-membership degrees. Therefore, IFSNP systems are very suitable to deal with fault diagnosis of power systems, specially with incomplete and uncertain alarm messages. The fault modeling method and fuzzy reasoning algorithm based on IFSNP systems are discussed. Two examples are used to demonstrate the availability and effectiveness of IFSNP systems for fault diagnosis of power systems. Case studies involve single fault, complex fault, and multiple faults with protection device failures and incorrect tripping signals.

Index Terms—Power systems, fault diagnosis, spiking neural P systems, intuitionistic fuzzy set.

I. INTRODUCTION

THE POWER system consists of many system elements, such as generators, transformers, bus bars and transmission lines, which are protected by protection systems comprised of protective relays (PRs), circuit breakers (CRs) and communication equipment. The supervisory control and data acquisition (SCADA) system is equipped together with electric power systems. Fault diagnosis of power systems is a process of discriminating the faulted system elements by tripping of protective relays and circuit breakers. When a fault event occurs, it can lead to a large amount of alarm messages in SCADA system. The alarm messages must be analyzed by dispatchers according to their operating experiences in order to

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identify the faults. However, the received data is often incomplete and tripping of protective relays and circuit breakers is sometime uncertain. Therefore, fault diagnosis is a difficult and complicated task since circuit breakers may fail to operate the multiple faults with the incomplete and uncertain alarm messages.

The expert systems (ES)-based methods have been used to deal with fault diagnosis of power systems [1]–[3]. The ES-based methods are suitable for operating logics of protective relays and circuit breakers as well as the diagnosis experience of operators. However, main drawbacks of the ES-based methods are the incapacity of generalization and the difficulty of validating and maintaining large rule base. With their attractive features, artificial neural networks (ANNs)-based systems have been employed as an intelligent fault diagnosis tool [4]–[6]. Nonetheless, most of the ANN-based diagnosis systems suffer from the “black-box” phenomenon since it is difficult to extract domain knowledge encoded in a trained network to explain its results intuitively. In addition, the performance of ANN-based diagnosis systems is highly restricted without the extensive confirmation of the quality of training process and the quantity of training samples. The fault diagnosis of power systems can be also formulated as an optimization problem. Some optimization techniques, such as genetic algorithms (GAs) [7], Honey-Bee Mating Optimization (HBMO) [8] and artificial bee colony (ABC) [9], were employed to solve the optimization problem. Since the outage area must be identified initially, the loss of a boundary CB alarm may lead to the failure of such methods. In fault diagnosis of power systems, a key problem is how to handle the incomplete and uncertain alarm messages of tripping of circuit breakers. Fuzzy logic provides a more usable and accessible technique to model the inaccuracy and uncertainty in fault diagnosis. Some techniques that incorporate fuzzy logic have been developed for fault diagnosis of power systems, for example, fuzzy logic (FL) [10], fuzzy relation (FR) [11] and fuzzy digraph models (FDM) [12]. Petri nets (PNs) are a useful tool for event modeling in a concurrent structure. However, it lacks the ability to handle uncertainty. Thus, fuzzy Petri nets (FPNs) [13], [14] that combine fuzzy logic with PNs have been employed to deal with the uncertainty existing in the operation of protective devices.

Membrane computing is a class of distributed parallel computing models inspired from the structure and functioning of living cells as well as interaction of living cells in tissues and organs, known as P systems [15], [16]. In past years, a various

of P systems and variants have been proposed and applied in a lot of real-world problems [17]–[27]. Spiking neural P systems (in short, SNP systems) are one of main forms of P systems. A SNP system can be viewed as a directed graph whose arcs represent the synaptic connections among the neurons [16], [28]–[30]. In recent years, a class of variants, which integrate different fuzzy logics in SNP systems, were developed, called the fuzzy spiking neural P system (in short, FSNP systems) [31]–[34]. Furthermore, FSNP systems have been used to deal with fault diagnosis of power systems [35]–[37]. Intuitionistic fuzzy set (IFS) has been proposed to deal with more finely the incompleteness and uncertainty [38]–[40]. IFS, which is a natural generalization of usual fuzzy set, seems to be useful in modeling many real life situations. IFS can finely characterize the membership level of an element x to fuzzy set A by providing two measures (membership and non-membership degrees) simultaneously. However, IFS has not been used to handle fault diagnosis problem of power systems.

In this paper a new variant is proposed by integrating IFS in SNP systems, called intuitionistic fuzzy spiking neural P systems (in short, IFSNP systems). The fault diagnosis model based on IFSNP systems is discussed in detail. Main contribution of this paper stays on proposing the IFSNP systems and developing a novel modeling method for fault diagnosis of power systems. Compared with the existing FSNP systems, differences of IFSNP systems include: (1) intuitionistic fuzzy number (IFN) is used to express alarm information and imprecise knowledge in fault diagnosis problems of power systems; (2) fuzzy reasoning mechanism of IFSNP systems is based on intuitionistic fuzzy logic; (3) diagnosis result (whether an element is a fault in a section) is described by a membership degree and a non-membership degree simultaneously. Therefore, the proposed IFSNP systems can better model the imperfect information, especially under imperfectly defined alarm information and imprecise knowledge in fault diagnosis of power systems.

The remainder of this paper is organized as follows. IFSNP systems are discussed in Section II, including the definition, modeling and reasoning methods. Three case studies of power systems with different structures are provided in Section III. Conclusions are finally drawn in Section IV.

II. IFSNP SYSTEMS

A. Definition

Let X be a universe of discourse. Intuitionistic fuzzy set (IFS) is a generalized fuzzy set introduced by Atanassov [38], shown as follows:

$$A = \{ \langle x, \mu_A(x), \nu_A(x) \rangle \mid x \in X \} \quad (1)$$

which is characterized by a membership function $\mu_A : X \rightarrow [0, 1]$ and a non-membership function $\nu_A : X \rightarrow [0, 1]$, with the condition

$$0 \leq \mu_A(x) + \nu_A(x) \leq 1, \quad \forall x \in X$$

where the numbers $\mu_A(x)$ and $\nu_A(x)$ denote the membership and non-membership degrees of the element x to the A , respectively.

For each IFS A in X , if $\pi_A(x) = 1 - \mu_A(x) - \nu_A(x)$, then $\pi_A(x)$ is called the indeterminacy degree or hesitation degree of x to A . Specially, if $\pi_A(x) = 1 - \mu_A(x) - \nu_A(x) = 0, \forall x \in X$, then the IFS A is reduced to a common fuzzy set.

For convenience, we call $\alpha = (\mu_\alpha, \nu_\alpha)$ an intuitionistic fuzzy number (IFN), where $\mu_\alpha \in [0, 1], \nu_\alpha \in [0, 1]$, and $\mu_\alpha + \nu_\alpha \leq 1$.

Let $\alpha = (\mu_\alpha, \nu_\alpha)$ and $\beta = (\mu_\beta, \nu_\beta)$ be two intuitionistic fuzzy numbers, and λ is a real number in $[0, 1]$. Three operations are introduced as follows:

- (1) $\alpha \oplus \beta = (\max(\mu_\alpha, \mu_\beta), \min(\nu_\alpha, \nu_\beta))$;
- (2) $\alpha \otimes \beta = (\mu_\alpha \cdot \mu_\beta, \nu_\alpha + \nu_\beta - \nu_\alpha \cdot \nu_\beta)$;
- (3) $\lambda \alpha = (\lambda \mu_\alpha, \lambda \nu_\alpha)$.

Let $S(\alpha) = \mu_\alpha - \nu_\alpha$ and $H(\alpha) = \mu_\alpha + \nu_\alpha$. For α and β , $\alpha < \beta$ if and only if (1) $S(\alpha) < S(\beta)$, or (2) $S(\alpha) = S(\beta)$ and $H(\alpha) = H(\beta)$.

Definition 1: An intuitionistic fuzzy spiking neural P system (IFSNP system, in short) of degree m is a construct

$$\Pi = (A, \sigma_1, \sigma_2, \dots, \sigma_m, \text{syn}, I, O) \quad (2)$$

where:

- (1) $A = \{a\}$ is the singleton alphabet (a denotes spike);
- (2) $\sigma_1, \sigma_2, \dots, \sigma_m$ are neurons of the form $\sigma_i = (\alpha_i, \tau_i, r_i)$, $i \in \{1, 2, \dots, m\}$ where:
 - (a) σ_i is an intuitionistic fuzzy number, denoting the initial value of spikes contained in σ_i ;
 - (b) τ_i is a real number in $[0, 1]$, denoting the confidence level associated with the neuron;
 - (c) r_i is a firing rule/spiking rule, of the form $a^\alpha \rightarrow a^\alpha$ or $a^\alpha \rightarrow a^\beta$, where α, β are two intuitionistic fuzzy numbers;
- (3) $\text{syn} \subseteq \{1, 2, \dots, m\} \times \{1, 2, \dots, m\}$, with $(i, i) \notin \text{syn}$ for $\forall 1 \leq i \leq m$ is the synapse graph, defining the synapses among neurons;
- (4) I and O denote the sets of input neurons and output neurons, respectively.

IFSNP systems are a variant of original SNP systems, which integrate intuitionistic fuzzy logic into their mechanisms. The firing mechanism of neurons can be described as follows: for a neuron σ_i , if its spiking rule is enabled, then the neuron fires and its spike value α is consumed, and then a spike with value β is generated; once the spike with value β is emitted, all successor neurons (with $(i, j) \in \text{syn}$) will receive the spike.

B. Modeling and Fuzzy Reasoning

In many applications fuzzy production rules have been commonly used in knowledge representation, where their antecedent and consequent use “AND” and “OR” operations to connect multiple propositions respectively. The following two types of fuzzy production rules have been used to construct fuzzy knowledge base:

Type 1: IF p_1 AND p_2 AND \dots AND p_{k-1} THEN p_k (CF= τ)

Type 2: if p_1 OR p_2 OR \dots OR p_{k-1} THEN p_k (CF= τ) where $p_1, p_2, \dots, p_{k-1}, p_k$ are k propositions, and τ is a real number in $[0, 1]$ and denotes the confidence factor (CF) of the fuzzy production rule.

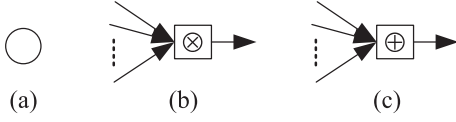


Fig. 1. Three types of neurons: (a) proposition neuron, (b) \otimes -type rule neuron and (c) \oplus -type rule neuron.

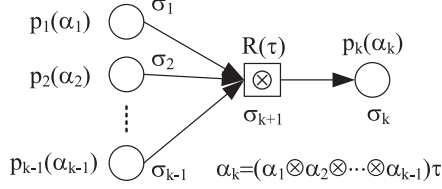


Fig. 2. Modeling type 1-fuzzy production rule based on IFSNP systems.

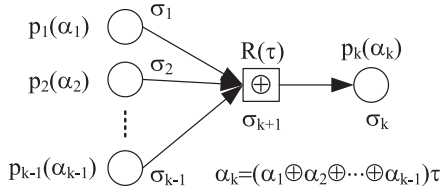


Fig. 3. Modeling type 2-fuzzy production rule based on IFSNP systems.

To model the fuzzy production rules, the neurons in IFSNP systems are further classified into three classes: proposition neurons, \oplus -type rule neurons and \otimes -type rule neurons. Proposition neurons are used to characterize fuzzy propositions in a fuzzy knowledge base. \otimes - and \oplus -type rule neurons are used to denote “AND”- and “OR”-type fuzzy production rules, respectively. Fig. 1 shows the three types of neurons.

A type 1-fuzzy production rule can be modeled by an IFSNP system, shown in Fig. 2. The reasoning procedure of IFSNP system can be described as follows. Initially, proposition neuron σ_i is assigned a spike with value α_i , $i = 1, 2, \dots, k-1$. Thus, the neurons fire and each emit a spike with value $\alpha_1, \alpha_2, \dots, \alpha_{k-1}$, respectively. Afterward, \otimes -type rule neuron σ_{k+1} receives $k-1$ spikes with value $\alpha_{k+1} = \alpha_1 \otimes \alpha_2 \otimes \dots \otimes \alpha_{k-1}$. Then, rule neuron σ_{k+1} fires and emits a spike (with value $\alpha_{k+1}\tau$) to the subsequent proposition neuron σ_k . Finally, neuron σ_k receives the spike. Therefore, computing result of the system is $\alpha_k = (\alpha_1 \otimes \alpha_2 \otimes \dots \otimes \alpha_{k-1})\tau$.

Fig. 3 shows another IFSNP system used to model a type 2-fuzzy production rule. The reasoning procedure of the IFSNP system can be described as follows. Initially, proposition neurons $\sigma_1, \sigma_2, \dots, \sigma_{k-1}$ are each assigned a spike, with values $\alpha_1, \alpha_2, \dots, \alpha_{k-1}$, respectively. Thus, the neurons fire and each emit a spike with value $\alpha_1, \alpha_2, \dots, \alpha_{k-1}$, respectively. Afterward, \oplus -type rule neuron σ_{k+1} receives $k-1$ spikes with value $\alpha_{k+1} = \alpha_1 \oplus \alpha_2 \oplus \dots \oplus \alpha_{k-1}$. Then, rule neuron σ_{k+1} fires and emits a spike (with value $\alpha_{k+1}\tau$) to the subsequent proposition neuron σ_k . Finally, neuron σ_k receives the spike. Therefore, computing result of the system is $\alpha_k = (\alpha_1 \oplus \alpha_2 \oplus \dots \oplus \alpha_{k-1})\tau$.

In the following, we describe the proposed fuzzy reasoning algorithm based on IFSNP systems. Suppose that the

TABLE I
FUZZY REASONING ALGORITHM BASED ON IFSNP SYSTEMS

Input: Π, α_i for $\forall \sigma_i \in I$;
Output: α_i for $\forall \sigma_i \in O$;
Begin
(1) Read C, D_1, D_2, E, δ_0 and θ_0 ;
(2) $t \leftarrow 1$;
(3) while (halting condition is not met)
(4) Proposition neurons evaluate and fire;
(5) $\delta_t \leftarrow (D_1^T \otimes \theta_{t-1}) + (D_2^T \oplus \theta_{t-1})$;
(6) Rule neurons evaluate and fire;
(7) $\theta_t \leftarrow E^T \oplus (C \odot \delta_t)$;
(8) $t \leftarrow t + 1$;
(9) endwhile
(10) Export all α_i of σ_i in O ;
End

considered IFSNP system Π contains m proposition neurons and n rule neurons (\oplus -type or \otimes -type). For convenience, several notions and operations are firstly introduced as follows.

(1) Vector $\theta = (\theta_1, \theta_2, \dots, \theta_m)$ denotes the values of spikes in the m proposition neurons, where θ_i is an intuitionistic fuzzy number, $1 \leq i \leq m$.

(2) Vector $\delta = (\delta_1, \delta_2, \dots, \delta_n)$ denotes the values of spikes in the n rule neurons, where δ_i is an intuitionistic fuzzy number, $1 \leq i \leq n$.

(3) Matrix $C = \text{diag}(c_1, c_2, \dots, c_n)$ is called the confidence matrix, where $c_i \in [0, 1]$ denotes confidence factor (CF) of i -th fuzzy production rule, $1 \leq i \leq n$.

(4) Matrix $D_1 = (d_{ij})_{m \times n}$ denotes the synapse connection from proposition neurons to \otimes -type rule neurons. If there is a directed arc from proposition neuron σ_i to \otimes -type rule neuron σ_j , then $d_{ij} = 1$; otherwise $d_{ij} = 0$, $1 \leq i \leq m$, $1 \leq j \leq n$.

(5) Matrix $D_2 = (d_{ij})_{m \times n}$ denotes the synapse connection from proposition neurons to \oplus -type rule neurons. If there is a directed arc from proposition neuron σ_i to \oplus -type rule neuron σ_j , then $d_{ij} = 1$; otherwise $d_{ij} = 0$, $1 \leq i \leq m$, $1 \leq j \leq n$.

(6) Matrix $E = (e_{ji})_{n \times m}$ denotes the synapse connection from rule neurons to proposition neurons. If there is a directed arc from rule neuron σ_j to proposition neuron σ_i , then $e_{ji} = 1$; otherwise $e_{ji} = 0$, $1 \leq j \leq n$, $1 \leq i \leq m$.

(7) $C \odot \delta = (c_1 \delta_1, c_2 \delta_2, \dots, c_n \delta_n)^T$.

(8) $D \otimes \theta = (\tilde{d}_1, \tilde{d}_2, \dots, \tilde{d}_n)^T$, where $\tilde{d}_j = d_{1j}\theta_1 \otimes d_{2j}\theta_2 \otimes \dots \otimes d_{mj}\theta_m$, $j = 1, 2, \dots, n$.

(9) $D \oplus \theta = (\tilde{d}_1, \tilde{d}_2, \dots, \tilde{d}_n)^T$, where $\tilde{d}_j = d_{1j}\theta_1 \oplus d_{2j}\theta_2 \oplus \dots \oplus d_{mj}\theta_m$, $j = 1, 2, \dots, n$.

Based on neuron's firing mechanism in IFSNP systems, fuzzy reasoning algorithm can be summarized in Table I.

III. CASE STUDIES

In this section, two different examples of power systems are used to illustrate and validate the availability and effectiveness of the proposed IFSNP systems: a six-bus 69kV distribution system and a 345kV transmission system. In the two examples, several cases are discussed, including single fault, complex fault and multiple faults. The diagnosis results of the proposed method are compared with other diagnosis methods.

TABLE II
LINGUISTIC TERMS AND THE CORRESPONDING
INTUITIONISTIC FUZZY NUMBERS (IFNs)

Linguistic terms	Intuitionistic Fuzzy Numbers (IFNs)
Extremely high (EH)	[1.00, 0.00]
Very very high (VVH)	[0.90, 0.10]
Very high (VH)	[0.80, 0.10]
High (H)	[0.70, 0.20]
Medium high (MH)	[0.60, 0.30]
Medium (M)	[0.50, 0.40]
Medium low (ML)	[0.40, 0.50]
Low (L)	[0.25, 0.60]
Very low (VL)	[0.10, 0.75]
Very very low (VVL)	[0.10, 0.90]
Extremely low (EL)	[0.00, 1.00]

TABLE III
THE CONFIDENCE DEGREES OF THE OPERATED PROTECTIVE DEVICES

Sections	Protective devices					
	Main		Nearby		Remote	
	Relays	CBs	Relays	CBs	Relays	CBs
L	VVH	VVH	VH	VH	H	H
B	VVH	VVH	-	-	H	H
T	VVH	VVH	VH	VH	H	H

A. Fault Diagnosis Model Based on IFSNP Systems

In this work, IFSNP systems are used to diagnose the faults of main sections, including transmission line, bus and transformer. In IFSNP systems, proposition neurons and rule neurons both are used to express the causal relationship between a fault section and its protective devices. The IFN value of proposition neuron is used to express the confidence degree of protective relay/circuit breaker, while rule neuron uses IFN value to express the probability of tripping the circuit breaker by protective operation. Considering the uncertainty of experts and senior dispatchers, fuzzy linguistic terms are used to describe the confidence degrees or probabilities, shown in Table II.

For each suspicious component in outage area, IFSNP systems is used to build its fault diagnosis model. The diagnosis procedure based on IFSNP systems has three steps: (1) retrieve the operational information of each device from SCADA system as the input data of IFSNP systems; (2) use fuzzy reasoning algorithm in Table I to obtain fault confidence levels of suspicious fault components; (3) distinguish the fault components according to the reasoning results.

In the IFSNP systems, the confidence factor (CF) is a real number in [0,1]. Based on the experience and protection level, it is considered that the confidence factor of rule neuron associated with both main protective and nearby backup devices is set to be 1.0, and the confidence factor of rule neuron associated with remote backup devices is set to be 0.9. If it involves multiple levels of protections, the certainty factors can be set to the value corresponding to the highest level of protections. At the same time, confidence degree of each protective device is also assigned according to past experience in fault diagnosis of power systems, including line, bus, protective relay

TABLE IV
THE CONFIDENCE DEGREES OF THE NON-OPERATED
PROTECTIVE DEVICES

Sections	Protective devices					
	Main		Nearby		Remote	
	Relays	CBs	Relays	CBs	Relays	CBs
L	L	L	L	L	L	L
B	ML	L	-	-	ML	L
T	ML	L	ML	L	L	L

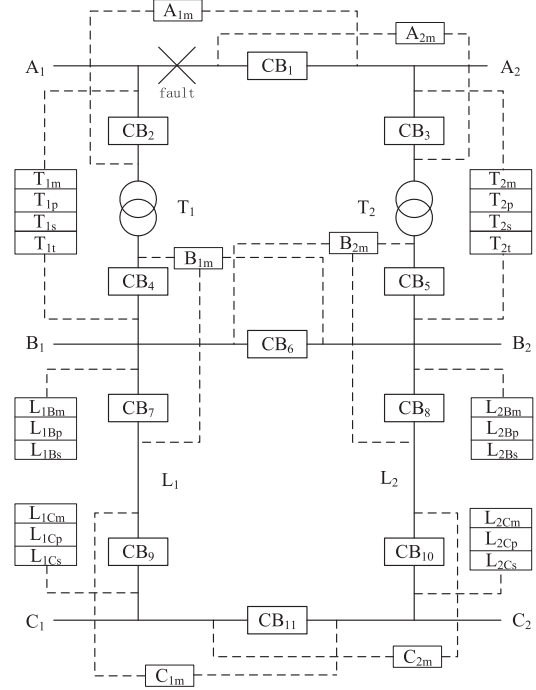


Fig. 4. A six-bus 69kV distribution system.

and circuit breaker. Tables III and IV provide the confidence degrees of the operated protective devices and non-operated protective devices, respectively. In addition, if the confidence level θ of a section satisfies the condition $\theta \geq (0.60, 0.30)$ the section is a fault; if $\theta \leq (0.40, 0.50)$ the section is not a fault; otherwise, it may be a fault.

B. Example I

The first system studied is a six-bus 69kV distribution system, shown in Fig. 4, which is adopted from [11]. This system consists of 10 system sections, 10 circuit breakers and 26 protective relays. Symbols are assigned as follows: $A/B/C, L, CB$ and T denote bus, line, circuit breaker and transformer, respectively. The 10 system sections have six buses (labeled by $A_1, A_2, B_1, B_2, C_1, C_2$), two transmission lines (labeled by L_1, L_2) and two transformers (labeled by T_1, T_2). The 10 CBs are labeled as $CB1, CB2, \dots, CB9, CB10$. The 26 protective relays are composed of 12 main protective relays (MPR) (labeled by $A_{1m}, A_{2m}, B_{1m}, B_{2m}$), 8 nearby backup relays (labeled by $T_{1p}, T_{1s}, T_{1t}, T_{2p}, T_{2s}, T_{2t}$) and 6 remote backup relays (labeled by $L_{1Bm}, L_{1Bp}, L_{1Bs}, L_{2Bm}, L_{2Bp}, L_{2Bs}, L_{1Cm}, L_{1Cp}, L_{1Cs}, L_{2Cm}, L_{2Cp}, L_{2Cs}$). This system

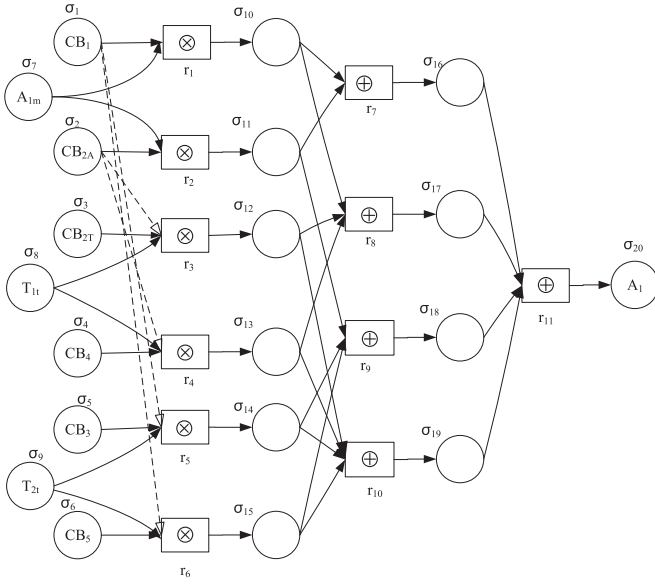


Fig. 5. The fault diagnosis model of bus A_1 based on IFSNP systems.

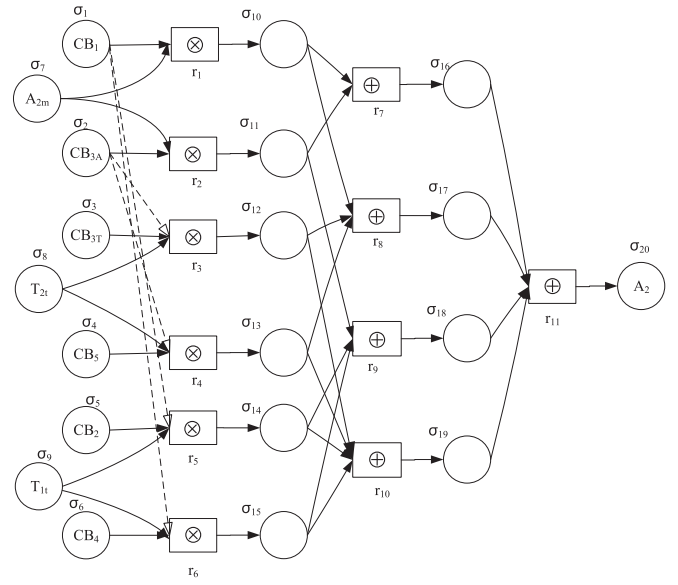


Fig. 6. The fault diagnosis model of bus A_2 based on IFSNP systems.

was used to test whether the proposed method can diagnose single fault, complex fault and multiple faults with rejection.

The diagnosis model of bus A_1 can be described by an IFSNP system consisted of 20 proposition neurons and 11 rule neurons, shown in Fig. 5. There are four assistant synapses, including (σ_1, r_5) , (σ_1, r_6) , (σ_2, r_3) and (σ_2, r_4) , marked by dashed lines with hollow arrow. For clarity, (σ_1, r_5) is regarded as an example to explain the meaning of these assistant synapses as follows: if CB_1 successfully opens, then the operation of T_{2t} , CB_3 and CB_5 is invalid, thus their values each are set to be $[0.0, 1.0]$; otherwise, the operation of T_{2t} , CB_3 and CB_5 is valid.

In the following, three cases are discussed, including single fault, complex fault and multiple faults.

Case 1 (Single Fault Without Failure Devices): Suppose that a fault occurs at the bus A_1 . The fault leads to the operation of main protective relays A_{1m} and the tripping of circuit breakers CB_1 and CB_2 without malfunction and rejection. The information retrieved from SCADA shows the protective relays A_{1m} operates and circuit breakers CB_1 and CB_2 trip.

The fault section can be diagnosed as bus A_1 by using the IFSNP system in Fig. 5. The proposed fuzzy reasoning algorithm can be used to conclude that output neuron σ_{20} has the fuzzy value of $[0.81, 0.19] (\geq VH)$. Therefore, A_1 can be recognised as a fault section with the confidence degree 0.81 according to the judgment condition given above. Note that A_1 is not a fault section only with the credibility of 0.19. This illustrates that the proposed IFSNP systems can accurately diagnose single fault.

Case 2 (Complex Fault With the Rejection of Circuit Breakers): Suppose that a fault occurs at the bus A_1 . The fault leads to the operation of main protective relays A_{1m} and trips circuit breakers CB_1 and CB_2 . But CB_2 fails to operate, thus the operation of remote backup relays T_{1t} leads to trip CB_2 again and CB_4 . The information obtained from SCADA shows that the protective relays A_{1m} and T_{1t} operate and circuit breakers CB_1 , CB_2 and CB_4 trip.

Fig. 5 shows the IFSNP system for fault diagnose of A_1 . Based on the IFSNP system, fault diagnosis process of A_1 can be achieved by the presented fuzzy reasoning algorithm. After fuzzy reasoning, we can obtain that fuzzy value of output neuron σ_{20} is $[0.81, 0.19]$. Based on the judgment condition, we can judge that A_1 is a fault section with high confidence degree ($\geq VH$). Therefore, the proposed method can well distinguish the fault section in the case of complex fault.

Case 3 (Multiple Faults With Rejection of Circuit Breakers): Suppose that multiple faults occur at the buses A_1 and A_2 . The fault at bus A_2 leads to the operation of main protective relays A_{2m} and trips circuit breakers CB_1 and CB_3 . The fault at bus A_1 leads to the operation of main protective relays A_{1m} and trips circuit breakers CB_1 and CB_2 , but CB_2 fails to operate. Thus, the operation of remote backup relays T_{1t} leads to trip CB_2 again and CB_4 . The information obtained from SCADA indicates that the protective relays A_{1m} , A_{2m} and T_{1t} operate and circuit breakers CB_1 , CB_2 , CB_3 and CB_4 trip.

The diagnosis models of the multiple faults can be also described by the IFSNP systems in Fig. 5 and Fig. 6, respectively. The presented fuzzy reasoning algorithm is used to conclude the diagnosis result in the case of multiple faults. Since A_1 and A_2 have a similar reasoning procedure, the reasoning procedure of bus A_1 as an example is illustrated as follows.

Initially, θ_0 and δ_0 can be determined according to the status information of protective relays and circuit breakers in the fault situation and Tables II, III and IV, in which θ_0 is a 20-dimensional vector and δ_0 is a 11-dimensional vector. The proposed fuzzy reasoning algorithm can be used to conclude that fuzzy value of output neuron δ_{20} for bus A_1 is $[0.81, 0.19]$. Similarly, we can conclude for bus A_2 that the fuzzy value of output neurons δ_{20} is also $[0.81, 0.19]$. Based on the judgment condition, A_1 and A_2 are simultaneously distinguished as the fault sections with high confidence level ($\geq VH$). Note that the confidence levels of them being not the fault sections are only 0.19. This indicates that the proposed IFSNP systems are

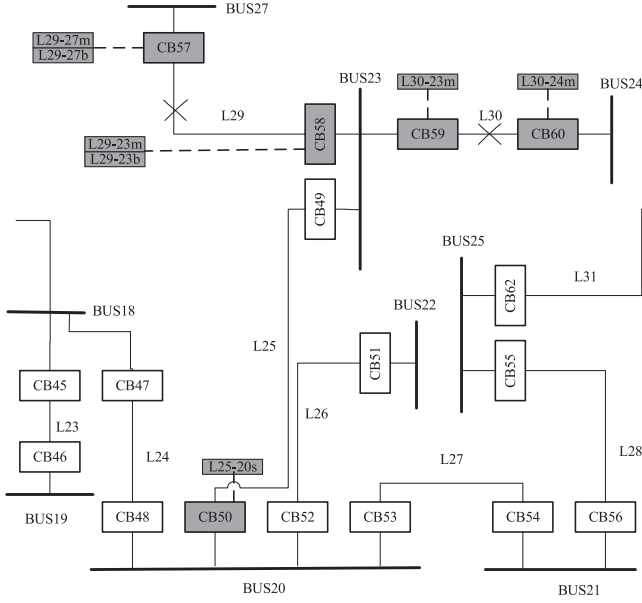


Fig. 7. A 345kV power transmission system. Here, “m” refers to the main protective relay, “b” denotes the nearby backup relay, and “s” represents the remote backup relay.

suitable to deal with the multiple faults with malfunction and rejection of circuit breakers.

C. Example II

The second system studied is a 345kV power transmission system, shown in Fig. 7, which is adopted from [12]. This system includes 18 system sections, 17 circuit breakers and 60 protective relays. Symbols are assigned as follows: BUS, L and CB denote bus, line and circuit breaker, respectively. The 18 system sections include nine buses (labeled by $BUS18, BUS19, \dots, BUS25, BUS27$) and nine transmission lines (labeled by $L23, L24, \dots, L31$). The 17 CBs are labeled as $CB45, \dots, CB60, CB62$. The 60 protective relays are composed of 26 main protective relays (MPR) (labeled by $BUS18m, \dots, BUS25m, BUS27m, L23 - xm, \dots, L31 - xm$), 17 nearby backup relays (labeled by $L23 - xb, \dots, L31 - xb$) and 17 remote backup relays (labeled by $L23 - xs, \dots, L31 - xs$). This system was used to test whether the proposed method can diagnose the multiple faults with rejection and incorrect tripping signals.

Case 4 (Multiple Faults With Rejection and Incorrect Tripping Signals): Suppose that multiple faults occur at the transmission line $L29$ and $L30$. The fault at line section $L30$ leads to the operation of main protective relays, $L30 - 23m$ and $L30 - 24m$, and the tripping of circuit breakers $CB59$ and $CB60$. The fault at line section $L29$ leads to the operation of main protective relays, $L29 - 27m$ and $L29 - 23m$, but the rejection of $CB57$ and $CB58$. Thus, nearby backup relays $L29 - 27b$ and $L29 - 23b$ operate to trip $CB57$ and $CB58$. There is also an obscure operation backup relay $L25 - 20s$, which causes $CB50$ to be tripped. Status information obtained from the SCADA system is as follows: the operated relays are $L30 - 23m, L30 - 24m, L29-27m, L29-23m, L29 - 27b, L29 - 23b$ and $L25 - 20s$, and the tripped CBs $CB50, CB57, CB58, CB59$ and $CB60$.

The fault diagnosis models of lines $L30$ and $L29$ can be built by two IFSNP systems, shown in Fig. 8 and Fig. 9, respectively. The two IFSNP systems contain each 23 proposition neurons and 13 rule neurons. In the two systems, proposition neurons, $\sigma_1, \dots, \sigma_{10}$ as the input, are used to denote the statuses of protective relays and circuit breakers in fault section, while proposition neuron σ_{23} as the output is used to denote the confidence degree of fault section. The initial values of all input neurons are determined according to Tables III and IV.

The IFSNP systems of lines $L30$ and $L29$ can be easily reasoned by using the proposed fuzzy reasoning algorithm. Since $L30$ and $L29$ have a similar reasoning procedure, line $L30$ as an example is illustrated as follow. Initially, θ_0 and δ_0 can be determined according to the status information of protective relays in the fault situation and Tables II–IV as follows, where θ_0 is a 23-dimensional vector and δ_0 is a 13-dimensional vector.

$$\delta_0 = [\mathbf{0}], \theta_0 = \begin{pmatrix} [0.90, 0.10] \\ [0.90, 0.10] \\ [0.90, 0.10] \\ [0.90, 0.10] \\ [0.25, 0.60] \\ [0.25, 0.60] \\ \mathbf{0} \end{pmatrix}.$$

According to fuzzy reasoning algorithm, computing results of each iteration are provided as follows.

For $t = 1$,

$$\delta_1 = \begin{pmatrix} [0.81, 0.19] \\ [0.81, 0.19] \\ [0.225, 0.64] \\ [0.225, 0.64] \\ \mathbf{0} \end{pmatrix}, \theta_1 = \begin{pmatrix} \mathbf{0} \\ [0.81, 0.19] \\ [0.81, 0.19] \\ [0.225, 0.64] \\ [0.225, 0.64] \\ [0.00, 0.90] \\ [0.00, 0.90] \\ \mathbf{0} \end{pmatrix}.$$

For $t = 2$,

$$\delta_2 = \begin{pmatrix} [0.81, 0.19] \\ [0.81, 0.19] \\ [0.81, 0.19] \\ [0.225, 0.64] \\ [0.81, 0.19] \\ [0.225, 0.64] \\ \mathbf{0} \end{pmatrix}, \theta_2 = \begin{pmatrix} \mathbf{0} \\ [0.81, 0.19] \\ [0.81, 0.19] \\ [0.81, 0.19] \\ [0.225, 0.64] \\ [0.81, 0.19] \\ [0.225, 0.64] \\ \mathbf{0} \end{pmatrix}.$$

For $t = 3$,

$$\delta_3 = \begin{pmatrix} \mathbf{0} \\ [0.81, 0.19] \end{pmatrix}, \theta_3 = \begin{pmatrix} \mathbf{0} \\ [0.81, 0.19] \end{pmatrix}.$$

For $t = 4$, we have $\delta_4 = [\mathbf{0}]$. Therefore, the halting condition is satisfied and the reasoning procedure ends. Thus, the fuzzy value of output neuron δ_{23} is $[0.81, 0.19]$. Based on the judgment condition, $L30$ is adjudged as a fault section with a confidence level VH.

Similarly, IFSNP system for $L29$ can be reasoned, and the reasoning result of $L29$ is $[0.64, 0.19]$. Note that

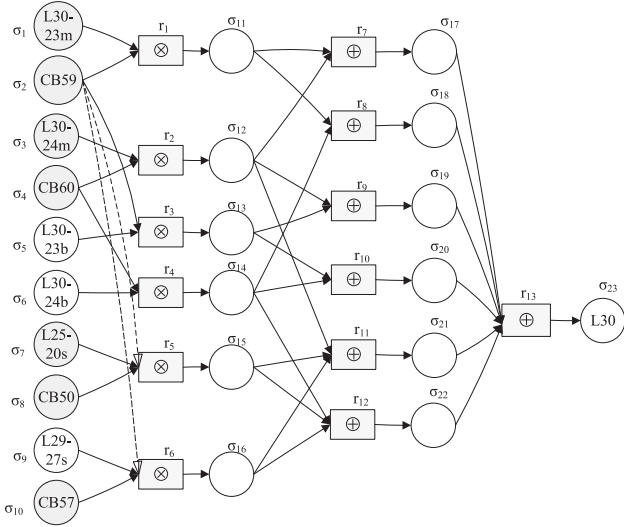


Fig. 8. The fault diagnosis model of line L30 based on IFSNP systems.

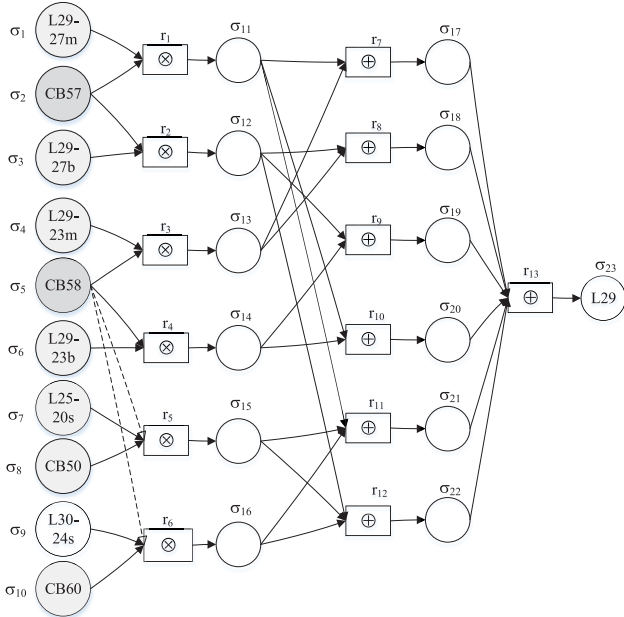


Fig. 9. The fault diagnosis model of line L29 based on IFSNP systems.

$MH < [0.64, 0.19] < H$ meets. Therefore, L29 is a fault section according to the judgment condition. The diagnostic result of L29 is same to L30 although there is the rejection in sections of L29.

The example indicates that in the case of multiple faults with rejection and incorrect tripping signals the proposed IFSNP systems can accurately diagnose fault sections.

D. Comparison Analysis With Other Methods

In the recent, example II has been studied in several literatures, such as fuzzy logic (FL) [10], fuzzy relations (FR) [11], fuzzy graph (FG) [12] and FSNP systems [35]. Chin [10] combined classical fuzzy logic with cause-effect network to deal with the uncertainty in fault diagnosis of power systems. Min *et al.* [11] presented a fault method based on fuzzy relations, where the relationship between the operated protective

TABLE V
THE COMPARISON RESULTS OF THE PROPOSED METHOD
WITH OTHER METHODS ON EXAMPLE II

IFSNP systems	FL [10]	FR [11]	FG [12]	FSNP systems [35]
L29, L30	L30	L30	L29, L30	L30

devices and the fault section candidates was modeled and reasoned by fuzzy matrix. Chen [12], fuzzy graph was used to propose a fault diagnosis method. Tu *et al.* [35], FSNP systems were applied to deal with fault diagnosis problem of power systems. In these four methods, classical fuzzy logic and reasoning mechanism were used to express and handle the uncertainty in fault diagnosis of power systems. In this work, a fault diagnosis problem can be described by a set of fuzzy production rules, and then rule neurons and proposition neurons are used to express the fuzzy rules and the fuzzy propositions in them respectively. Moreover, fault diagnosis is implemented based on the firing mechanism of neurons, and IFNs are used to express the uncertainty in fault diagnosis problems.

The comparison results of the proposed fault diagnosis model based on IFSNP systems with these methods on example II are provided in Table V. It can be observed from Table V that IFSNP systems and FG methods can diagnose the faults L29 and L30, however, FL, FR and FSNP systems can distinguish only the fault L30. More importantly, the proposed fault diagnosis model not only can correctly identify all the fault sections but also provides two measures of each fault section (membership degree and non-membership degree). Thus, IFSNP systems can distinguish a fault section with high confidence level (higher membership degree and lower non-membership degree). In addition, the comparison results of IFSNP systems with FSNP systems indicate that IFN has stronger ability to characterize the uncertainty in fault diagnosis problem of power systems than classical fuzzy number. The comparison demonstrates that fault diagnosis model based on IFSNP systems is effective for fault diagnosis of power systems.

IV. CONCLUSION

This paper developed IFSNP systems and presented a novel fault diagnosis model based on IFSNP systems for power systems. The IFSNP systems are a kind variant that integrates IFN in SNP systems, therefore, the proposed modeling method is capable of representing uncertain knowledge in fault diagnosis of power systems and dealing with alarm messages from the SCADA system. Moreover, IFSNP systems can more finely and accurately distinguish whether an element is a fault section by providing its membership and non-membership degrees simultaneously. Therefore, IFSNP systems can help the dispatchers more intuitively and effectively to identify all the fault sections. The case studies on a six-bus 69kV distribution system and a 345kV transmission system demonstrate that the proposed diagnosis method can effectively and accurately deal with single fault, complex fault and multiple faults with rejection and incorrect tripping signals. The proposed fault diagnosis model requires status information provided by

SCADA system, so it is unable to handle fault diagnosis if SCADA system is not equipped with power systems. In such an application scenario, this is a limitation of IFSNP systems. In addition, the time between the tripping of breakers during a fault is worth considering because they can provide additional information, especially in the systems where stepped-distance and differential protection (and possibly breaker failure protection) are used. However, the current version of IFSNP systems does not contain time factors, so it can not handle the situation. Our further work is to extend IFSNP systems to discuss fault diagnosis in this situation.

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