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, especially 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 modeling method and fuzzy reasoning algorithm based on IFSNP systems as a variant are proposed by integrating intuitionistic fuzzy sets (IFs) into original spiking neural P systems (SNPs), which are suitable for dealing with fault diagnosis of power systems, especially with incomplete and uncertain alarm messages. Therefore, IFSNP systems are very suitable to deal with fault diagnosis of power systems, especially 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 modeling method and fuzzy reasoning algorithm based on IFSNP systems as a variant are proposed by integrating intuitionistic fuzzy sets (IFs) into original spiking neural P systems (SNPs), which are suitable for dealing with fault diagnosis of power systems, especially with incomplete and uncertain alarm messages.

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 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 alarm information and imprecise knowledge in fault diagnosis [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:

\[
A = \{ \langle x, \mu_A(x), \nu_A(x) \rangle \mid x \in X \}
\]

(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 \( \alpha = (\mu_A, \nu_A) \) an intuitionistic fuzzy number (IFN), where \( \mu_A \in [0, 1] \), \( \nu_A \in [0, 1] \), and \( \mu_A + \nu_A \leq 1 \).

Let \( \alpha = (\mu_A, \nu_A) \) and \( \beta = (\mu_\beta, \nu_\beta) \) be two intuitionistic fuzzy numbers, and \( \lambda \) 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 \( \alpha \) and \( \beta \), \( \alpha < \beta \) 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

\[
\Pi = (A, q_1, q_2, \ldots, q_m, \text{syn}, I, O)
\]

(2)

where:

(1) \( A = \{a\} \) is the singleton alphabet (\( a \) denotes spike);
(2) \( q_1, q_2, \ldots, q_m \) are neurons of the form \( q_i = (\alpha_i, \tau_i, r_i) \), \( i \in \{1, 2, \ldots, m\} \) where:

(a) \( \alpha_i \) is an intuitionistic fuzzy number, denoting the initial value of spikes contained in \( \alpha_i \);
(b) \( \tau_i \) 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 \( \alpha, \beta \) are two intuitionistic fuzzy numbers;
(3) \( \text{syn} \subseteq \{1, 2, \ldots, m\} \times \{1, 2, \ldots, m\} \), with \( (i, j) \notin \text{syn} \) 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 \( \sigma_i \), if its spiking rule is enabled, then the neuron fires and its spike value \( \alpha \) is consumed, and then a spike with value \( \beta \) is generated; once the spike with value \( \beta \) 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 \( p_1 \) \( \text{AND} \) \( p_2 \) \( \text{AND} \) \( \ldots \) \( \text{AND} \) \( p_{k-1} \) THEN \( p_k \) (CF=\( t \))

Type 2: if \( p_1 \) OR \( p_2 \) OR \( \ldots \) OR \( p_{k-1} \) THEN \( p_k \) (CF=\( t \))

where \( p_1, p_2, \ldots, p_{k-1}, p_k \) are \( k \) propositions, and \( t \) is a real number in \( [0,1] \) and denotes the confidence factor (CF) of the fuzzy production rule.
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 \(\sigma_i\) is assigned a spike with value \(\alpha_i\), \(i = 1, 2, \ldots, k - 1\). Thus, the neurons fire and each emit a spike with value \(\alpha_1, \alpha_2, \ldots, \alpha_{k-1}\), respectively. Afterward, \(\otimes\)-type rule neuron \(\alpha_{k+1}\) receives \(k - 1\) spikes with value \(\alpha_{k+1} = \alpha_1 \otimes \alpha_2 \otimes \ldots \otimes \alpha_{k-1}\). Then, rule neuron \(\alpha_{k+1}\) fires and emits a spike with value \(\alpha_{k+1}\) to the subsequent proposition neuron \(\sigma_1\). Finally, neuron \(\sigma_k\) receives the spike. Therefore, computing result of the system is \(\alpha_k = (\alpha_1 \otimes \alpha_2 \otimes \ldots \otimes \alpha_{k-1}) \tau\).

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 \(\sigma_1, \sigma_2, \ldots, \sigma_{k-1}\) are each assigned a spike, with values \(\alpha_1, \alpha_2, \ldots, \alpha_{k-1}\), respectively. Thus, the neurons fire and each emit a spike with value \(\alpha_1, \alpha_2, \ldots, \alpha_{k-1}\), respectively. Afterward, \(\oplus\)-type rule neuron \(\alpha_{k+1}\) receives \(k - 1\) spikes with value \(\alpha_{k+1} = \alpha_1 \oplus \alpha_2 \oplus \ldots \oplus \alpha_{k-1}\). Then, rule neuron \(\alpha_{k+1}\) fires and emits a spike (with value \(\alpha_{k+1}\)) to the subsequent proposition neuron \(\sigma_i\). Finally, neuron \(\sigma_k\) receives the spike. Therefore, computing result of the system is \(\alpha_k = (\alpha_1 \oplus \alpha_2 \oplus \ldots \oplus \alpha_{k-1}) \tau\).

In the following, we describe the proposed fuzzy reasoning algorithm based on IFSNP systems. Suppose that the considered IFSNP system \(\Pi\) 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 \(\theta = (\theta_1, \theta_2, \ldots, \theta_m)\) denotes the values of spikes in the \(m\) proposition neurons, where \(\theta_i\) is an intuitionistic fuzzy number, \(1 \leq i \leq m\).

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

(3) Matrix \(C = diag(c_1, c_2, \ldots, c_n)\) 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 \(\sigma_i\) to \(\otimes\)-type rule neuron \(\sigma_j\), 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 \(\sigma_i\) to \(\oplus\)-type rule neuron \(\sigma_j\), then \(d_{ij} = 1\); otherwise \(d_{ij} = 0\), \(1 \leq i \leq m, 1 \leq j \leq n\).

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

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)

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

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 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 θ ≥ (0.60, 0.30) the section is a fault; if θ ≤ (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 A1, A2, B1, B2, C1, C2), two transmission lines (labeled by L1, L2) and two transformers (labeled by T1, T2). The 10 CBs are labeled as CB1, CB2, ..., CB9, CB10. The 26 protective relays are composed of 12 main protective relays (MPR) (labeled by A1m, A2m, B1m, B2m), 8 nearby backup relays (labeled by T1p, T1s, T1p, T1s, L1Bp, L2Bp, L1Cp, L2Cp) and 6 remote backup relays (labeled by T1r, T2r, L1Br, L2Br, L1Cr, L2Cr). This system

Fig. 4. A six-bus 69kV distribution system.
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 $(\sigma_1, r_5)$, $(\sigma_1, r_6)$, $(\sigma_2, r_5)$ and $(\sigma_2, r_4)$, marked by
dashed lines with hollow arrow. For clarity, $(\sigma_1, r_5)$ is regarded
as an example to explain the meaning of these assistant
synapses as follows: if $CB_1$ successfully opens, then the operation
of $T_{2t}$, $CB_2$ and $CB_3$ is invalid, thus their values each
are set to be $[0, 1.0]$; otherwise, the operation of $T_{2t}$, $CB_2$
and $CB_3$ 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 $A_{1_{m}}$ and the tripping of circuit breakers
$CB_1$ and $CB_2$ without malfunction and rejection. The informa-
tion retrieved from SCADA shows the protective relays $A_{1_{m}}$
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 algo-
rithm can be used to conclude that output neuron $\sigma_{20}$ 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 $A_{1_{m}}$
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 $A_{1_{m}}$ 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 neu-
ron $\sigma_{20}$ is $[0.81, 0.19]$. Based on the judgment condition, we
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
$A_{2_{m}}$ and trips circuit breakers $CB_1$ and $CB_3$. The fault at bus $A_1$
leads to the operation of main protective relays $A_{1_{m}}$
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 $A_{1_{m}}$, $A_{2_{m}}$ 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, respec-
tively. 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 rea-
soning procedure of bus $A_1$ as an example is illustrated as
follows.

Initially, $\theta_0$ and $\delta_0$ can be determined according to the sta-
tus information of protective relays and circuit breakers in
the fault situation and Tables II, III and IV, in which $\theta_0$ is a
20-dimensional vector and $\delta_0$ is a 11-dimensional vector. The
proposed fuzzy reasoning algorithm can be used to conclude
that fuzzy value of output neuron $\delta_{20}$ for bus $A_1$ is $[0.81, 0.19]$.
Similarly, we can conclude for bus $A_2$ that the fuzzy value of
output neurons $\delta_{20}$ 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
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, ..., BUS25, BUS27) and nine transmission lines (labeled by L23, L24, ..., L31). The 17 CBs are labeled as CB45, ..., CB60, CB62. The 60 protective relays are composed of 26 main protective relays (MPR) (labeled by BUS18m, ..., BUS25m, BUS27m, L23 − xM, ..., L31 − xM), 17 nearby backup relays (labeled by L23 − xb, ..., L31 − xb) and 17 remote backup relays (labeled by L23 − xs, ..., L31 − xs).

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, σ1, ..., σ10 as the input, are used to denote the statuses of protective relays and circuit breakers in fault section, while proposition neuron σ23 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, θ0 and δ0 can be determined according to the status information of protective relays in the fault situation and Tables II–IV as follows, where θ0 is a 23-dimensional vector and δ0 is a 13-dimensional vector.

\[ δ_0 = [0], θ_0 = \begin{pmatrix} [0.90, 0.10] \\ [0.90, 0.10] \\ [0.90, 0.10] \\ [0.90, 0.10] \\ [0.25, 0.60] \\ [0.25, 0.60] \end{pmatrix} \]

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

For \( t = 1 \),

\[ δ_1 = \begin{pmatrix} [0.81, 0.19] \\ [0.81, 0.19] \\ [0.225, 0.64] \\ [0.225, 0.64] \\ 0 \end{pmatrix} , θ_1 = \begin{pmatrix} 0 \\ [0.81, 0.19] \\ [0.81, 0.19] \\ [0.225, 0.64] \\ [0.225, 0.64] \end{pmatrix} \]

For \( t = 2 \),

\[ δ_2 = \begin{pmatrix} [0.81, 0.19] \\ [0.81, 0.19] \\ [0.81, 0.19] \\ [0.225, 0.64] \\ [0.225, 0.64] \end{pmatrix} , θ_2 = \begin{pmatrix} 0 \\ [0.81, 0.19] \\ [0.81, 0.19] \\ [0.81, 0.19] \\ [0.225, 0.64] \end{pmatrix} \]

For \( t = 3 \),

\[ δ_3 = \begin{pmatrix} 0 \\ [0.81, 0.19] \end{pmatrix} , θ_3 = \begin{pmatrix} 0 \\ [0.81, 0.19] \end{pmatrix} \]

For \( t = 4 \), we have \( δ_4 = [0] \). Therefore, the halting condition is satisfied and the reasoning procedure ends. Thus, the fuzzy value of output neuron δ23 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 line L29 can be reasoned, and the reasoning result of L29 is [0.64, 0.19]. Note that
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 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
The authors would like to thank the anonymous reviewers for their very insightful and constructive suggestions, which have helped greatly improve the presentation of this paper.

ACKNOWLEDGMENT

The 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.

REFERENCES