Fault Diagnosis of Electric Power Systems Based on Fuzzy Reasoning Spiking Neural P Systems

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Abstract—This paper proposes a graphic modeling approach, fault diagnosis method based on fuzzy reasoning spiking neural P systems (FDSNP), for power transmission networks. In FDSNP, fuzzy reasoning spiking neural P systems (FRSN P systems) with trapezoidal fuzzy numbers are used to model candidate faulty sections and an algebraic fuzzy reasoning algorithm is introduced to obtain confidence levels of candidate faulty sections, so as to identify faulty sections. FDSNP offers an intuitive illustration based on a strictly mathematical expression, a good fault-tolerant capacity due to its handling of incomplete and uncertain messages in a parallel manner, a good description for the relationships between protective devices and faults, and an understandable diagnosis model-building process. To test the validity and feasibility of FDSNP, seven cases of a local subsystem in an electrical power system are used. The results of case studies show that FDSNP is effective in diagnosing faults in power transmission networks for single and multiple fault situations with/without incomplete and uncertain SCADA data, and is superior to four methods, reported in the literature, in terms of the correctness of diagnosis results.

Index Terms—Electric power system, fault diagnosis, fuzzy production rules, fuzzy reasoning, fuzzy reasoning spiking neural P system, linguistic term, trapezoidal fuzzy number.

I. INTRODUCTION

WHEN operating electric power systems (EPS), one of the key objectives is to supply reliable and stable power to customers. Impacted by various factors such as disturbances and equipment failures, interruption of power service or even blackout may happen in power systems [1], [2]. To reduce the loss caused by the two latter undesired events, it is essential for dispatchers to quickly identify the faulty sections in the power system to restore power supply. When a fault occurs, a large number of alarm messages from supervisor control and data acquisition (SCADA) systems are poured into dispatchers' consoles in a short period of time. These messages are often incomplete and uncertain [3]–[6]. Thus, it is necessary to develop

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a good method to help dispatchers evaluate where the faults are and which sections fail [4].

Fault diagnosis of a power system is a complicated process because it contains lots of sections such as generators, transmission lines, bus bars and transformers which are protected by a protective system consisting of protective relays, circuit breakers (CBs) and communication equipments [5]. In recent decades, fault diagnosis has been implemented by various approaches, such as expert systems (ES) [1], [2], fuzzy logic (FL) [3]–[7], artificial neural networks (ANNs) [8], [9], Petri nets (PNs) [4], [5], [10], Bayesian networks (BNs) [11], [12], multi-agent systems (MAS) [13], [14], optimization methods (OM) [15]–[17], cause-effect networks (CE-Nets) [6], [7], [18], and information theory (IT) [19], [20]. Each method has its own merits and demerits.

ES is the earliest artificial intelligence method for power system fault diagnosis. ES makes full use of experts' knowledge, but it has a slow inference speed due to its sequential search nature, and the difficulties of designing and maintaining a rule-based knowledge system [2], [18]. FL expresses imprecision and uncertainty, but it needs to be combined with other methods [18], [20]. ANNs have the advantages of good tolerance and strong learning ability, and the disadvantages of the empirical design of network structures and parameters, premature convergence and the need for numerous samples [18]. The major features of PN-based methods are graphical knowledge representation and parallel information processing, however, bad tolerance and combinatorial explosion in large power networks are their weaknesses [6]. Fault diagnosis models based on BNs are intuitive and can find relationships of causality between data, but it is difficult for these methods to obtain accurate prior probabilities and model complex power grid [12], [20]. In MAS, several agents corresponding to several methods cooperate to fulfill fault diagnosis, but how to properly combine different methods and how these agents cooperate are unsolved issues [13], [20]. Although OM may obtain globally optimal solutions of a complex fault diagnosis problem, it is not easy to construct an objective function reflecting the discrepancy between the expected and actual states of protective devices and to adjust the parameters in the optimization model [16], [18]. CE-Nets are a graphical tool for knowledge representation with easy algebraic reasoning and parallel information processing ability, but their fault tolerance needs to be improved and their forward reasoning strategy makes CE-Nets unable to visually represent all possible combinations of main, first and second protections [18], [21]. IT-based methods are a novel approach emerging with the informatization of power systems. To a certain extent, these methods deal with the uncertainty in

failure processes with fast diagnosis speed, but it is difficult to dynamically describe the fault information needed [20]. Therefore, much attention should be paid to the improvements of the aforementioned methods and the exploration of new ones to solve fault diagnosis problems.

This paper discusses a novel fault diagnosis approach for power systems by using membrane systems or P systems, which are theoretical computing devices in the area of membrane computing. As a newly attractive research field of computer science, membrane computing, formally introduced by Păun [22], aims at abstracting computing models from the structure and the functioning of living cells, as well as from the way that cells are organized in tissues or higher order structures. A spiking neural P system (SN P system) is the type of P system inspired by the neurophysiological behavior of neurons sending electrical impulses (spikes) along axons from presynaptic neurons to post-synaptic neurons in a distributed and parallel manner [23]. An SN P system can be considered as a set of nodes representing neurons in a directed graph whose arcs express synaptic connections among neurons. The contents of each neuron are composed of several copies of a single object type. Likewise, each neuron has a finite set of firing (spiking) and forgetting rules. Firing rules send information between neurons in the form of spikes and forgetting rules remove spikes from neurons. The rules associated with each neuron are used in a sequential manner, but neurons communicate with each other in parallel. Recently, SN P systems have become a hot topic in membrane computing [24]–[30].

SN P systems are a class of distributed and parallel computing models with good understandability and dynamics [28], [29]. The fault occurrence in power systems is a discrete and dynamical process [4]–[6]. Thus, SN P systems can be used for diagnosing faults in power systems. In the preliminary work, we discussed the knowledge representation ability of FRSN P systems [26], [27]. To successfully fulfill diagnosis knowledge representation and reasoning, an FRSN P system with real numbers was presented in [28], where only one transformer was considered. In these systems, the potential value that a spike can take within a neuron and the truth value of a fuzzy proposition (or confidence factor of a production rule) are represented by real numbers in [0, 1]. In [21], an approach based on the FRSN P system, presented in [28], for fault diagnosis of power systems was discussed and three different applications were used to verify its effectiveness. How to handle the incompleteness and uncertainty of the alarm information in different power systems is worth further discussing.

To handle incompleteness and uncertainty in power transmission network fault diagnosis in electric power systems, a method based on FRSN P systems, FDSNP, is developed in this paper. In FDSNP, an FRSN P system with trapezoidal fuzzy numbers is introduced to model candidate faulty sections and an algebraic fuzzy reasoning algorithm of the FRSN P system is presented for matrix-based fault reasoning to obtain confidence levels of candidate faulty sections and identify faulty sections. In order to make the process of building diagnosis models based on FRSN P systems easily understandable, fault fuzzy production rule sets to obtain the relationships between protective devices and faults are presented.

The main contribution of this work is summarized as follows. This study provides a fault diagnosis method based on FRSN
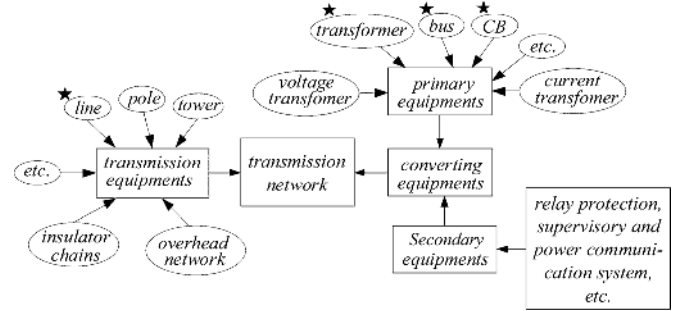

Fig. 1. Equipments and sections in a power transmission network.

P systems with trapezoidal fuzzy numbers for power transmission networks. The main ideas of this method include the introduction of trapezoidal fuzzy numbers into FRSN P systems, the fuzzy reasoning algorithm within the framework of FRSN P systems with trapezoidal fuzzy numbers and the fault fuzzy production rule sets based on syntactical ingredients of FRSN P systems with trapezoidal fuzzy numbers. The use of trapezoidal fuzzy numbers is helpful to express potential values of spikes contained in neurons and the fuzzy truth values of the neurons and consequently allows us to handle incompleteness and uncertainty in power systems. The presented reasoning algorithm uses an easily understandable description and has various kinds of synaptic matrices to describe relationships among faulty sections, protective relays and their CBs more flexible and effective. The fault fuzzy production rule sets for main sections including transmission lines, buses and transformers in transmission networks can offer the causality between the faults and the statuses of protective relays and their corresponding CBs in an intuitive and visual way.

The remainder of this paper is organized as follows. Section II states the problem to solve. Section III presents FDSNP. Following, seven case studies are provided in Section IV. Conclusions are finally drawn in Section V.

II. PROBLEM DESCRIPTION

Strictly speaking, fault diagnosis includes fault detection, fault section identification, fault type estimation, failure isolation and recovery [17]. Among the five processes, fault section identification is especially important [4], [5]. A power transmission network is composed of transmission equipments and converting equipments, as each of which consists of many kinds of sections as shown in Fig. 1. In this paper, we focus on the fault diagnosis of a power transmission network because it is one of the major networks in power systems. In this study, the faults of lines, buses and transformers in power transmission networks are diagnosed by using the statuses of protective relays and circuit breakers (CBs) because they are normally read from a power SCADA system. The protective relays consist of main protective relays (MPRs), first backup protective relays (FBPRs) and second backup protective relays (SBPRs). It is worth pointing out that there is not any FBPR for buses. Fig. 2 shows a schematic illustration of the transmission network with sections and protective relays considered in this study.

Protective relays of transmission lines are of two types: sending end protective relays and receiving end protective relays. To illustrate the operational rules of different
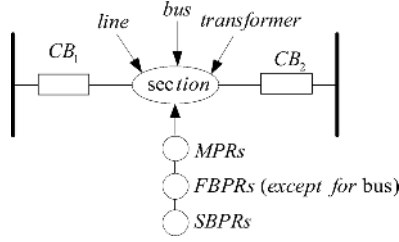
Fig. 2. Schematic illustration of the power transmission network with sections and protective relays considered in this study.
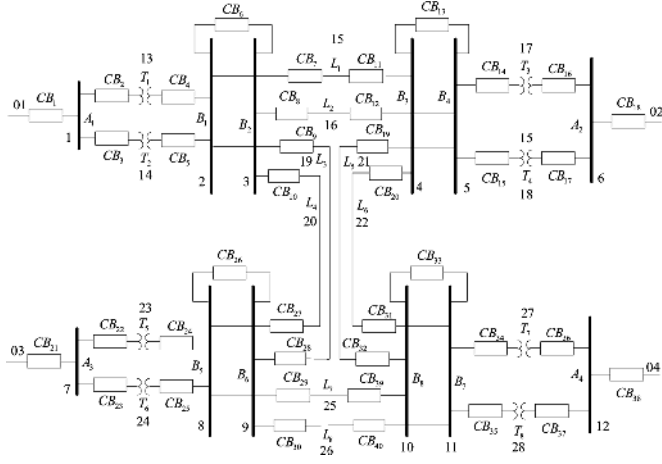

Fig. 3. Local sketch map of the protection system of an EPS.

types of protections, a local sketch map of the protection system of an EPS is chosen from [4], [17] and shown in Fig. 3, which includes 28 system sections, 40 CBs and 84 protective relays. For the convenience of description, some notations are described as follows. A single bus, double bus, transformer and line are represented by A, B, T, and L, respectively. S and R represent the sending and receiving ends of the line L, respectively. m, p, and s denote the main protection, the first backup protection and the second backup protection, respectively. The 28 sections ($S_1 \sim S_{28}$) are labeled as $A_1, \ldots,$ $A_4, T_1, \ldots, T_8, B_1, \ldots, B_8, L_1, \ldots, L_8$ and the 40 CBs ($C_1 \sim C_{40}$) are labeled as $CB_1, CB_2, \ldots, CB_{40}$. The 84 protective relays are composed of 36 main ones, $r_1 \sim r_{36}$ represented by $A_{1m}, \ldots, A_{4m}, T_{1m}, \ldots, T_{8m}, B_{1m}, \ldots, B_{8m}, L_{1Sm}, \ldots,$ $L_{8Sm}, L_{1Rm}, \ldots, L_{8Rm}$, and $r_{37} \sim r_{84}$ denoted as $T_{1P}, \ldots,$ $T_{8P}, T_{1s}, \ldots, T_{8s}, L_{1Sp}, \ldots, L_{8Sp}, L_{1Rp}, \ldots, L_{8Rp}, L_{1Ss}, \ldots,$ $L_{8Ss}, L_{1Rs}, \ldots, L_{8Rs}$.

The operational rules of the protective relays for the three kinds of sections, lines, buses and transformers, are described in [17] as follows.

1) *Protective relays of lines*

Both ends of a line have their own main, first and second protections. When the main protective relays of a line operate, CBs connected to the line are tripped. For example, if line L_7 fails, MPRs L_{7Sm} and L_{7Rm} are operate to trip CB_{29} and CB_{39}, respectively. Likewise, when the main protections of a line fail to operate, the first backup protective relays operate to trip CBs connected to the line. For example, if line L_7 fails and main protection relay (MPR) L_{7Sm} fails to operate, first backup protective relay (FBPR)
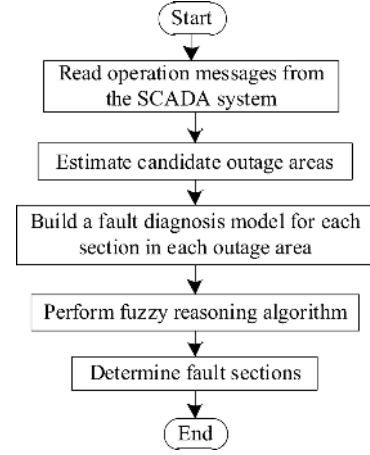
L_{7Sp} operates to trip CB_{29}. If line L_7 fails and MPR L_{7Rm} fails to operate, FBPR L_{7Rp} operates to trip CB_{39}. When the adjacent regions of a line fail and their protections fail to operate, the second backup protections operate to protect the line. For example, if section B_8 fails and CB_{39} fails to trip off, second backup protective relay (SBPR) L_{7Ss} operates to trip CB_{29}. If section B_5 fails and CB_{29} fails to trip off, SBPR L_{7Rs} operates to trip CB_{39}.

2) *Protective relays of buses*

When the main protective relays of a bus operate, all CBs direct connected to the bus will be tripped. For example, if bus A_1 fails, MPR A_{1m} operates to trip CB_1, CB_2, and CB_3. Similarly, if bus B_8 fails, MPR B_{8m} operates to trip CB_{32}, CB_{33}, and CB_{39}.

3) *Protective relays of transformers*

When the main protective relays of a transformer operate, all CBs connected to the transformer are tripped. For example, if transformer T_3 fails, MPR T_{3m} operates to trip CB_{14} and CB_{16}. Likewise, when the main protections of a transformer fail to operate, the first backup protective relays operates to trip CBs connected to the transformer. For example, if transformer T_3 fails and MPR T_{3m} fails to operate, FBPR T_{3p} operates to trip CB_{14} and CB_{16}. When the adjacent regions of the transformer fail and their protections fail to operate, the second backup protections operate to protect the transformer. For example, if bus A_2 fails and CB_{16} fails to trip off, SBPR T_{3s} operates to trip CB_{16} to protect T_3.

In this study, FDSNP is used to fulfill fault diagnosis of main sections, transmission lines, buses and transformers, in power transmission networks when some incomplete and uncertain status information about protective relays and CBs is detected. The flowchart of FDSNP is shown in Fig. 4. First, the status information is read from the SCADA system. Second, outage areas are identified to obtain the suspected fault sections using network topology analysis method [10], [31]. Third, a fault diagnosis model for each section in each candidate outage area is built. Then, each fault diagnosis model performs a fuzzy reasoning algorithm to obtain fault confidence levels of suspicious fault sections. Finally, faulty sections are determined according to their fault confidence levels. The key ingredients and steps of FDSNP are presented in detail in Section III.

Fig. 4. Flowchart of FDSNP.

III. FDSNP

This section presents a graphic modeling approach, FDSNP, for fault diagnosis of power transmission networks based on FRSN P systems with trapezoidal fuzzy numbers. We first give the definition of an FRSN P system with trapezoidal fuzzy numbers and then describe its algebraic fuzzy reasoning algorithm. Subsequently, the fault fuzzy production rule sets for main sections including transmission lines, buses and transformers in power transmission networks are presented. Finally, FDSNP is algorithmically illustrated.

A. FRSN P Systems With Trapezoidal Fuzzy Numbers

Definition 1: An FRSN P system with trapezoidal fuzzy numbers (with degree $m \geq 1$) is a construct

$$\Pi = (O, \sigma_1, \ldots, \sigma_m, syn, in, out)$$

where
1) $O = \{a\}$ is a singleton alphabet (a is called spike);
2) $\sigma_1, \ldots, \sigma_m$ are neurons of the form $\sigma_i = (\theta_i, c_i, r_i), 1 \leq i \leq m$, where
   a) θ_i is a trapezoidal fuzzy number in $[0, 1]$ representing the potential value of spikes (i.e., the value of electrical impulses) contained in neuron σ_i;
   b) c_i is a trapezoidal fuzzy number in $[0, 1]$ representing the fuzzy truth value corresponding to neuron σ_i;
   c) r_i represents a firing (spiking) rule associated with neuron σ_i of the form $E/a^\theta \rightarrow a^\beta$, where E is a regular expression, and θ and β are trapezoidal fuzzy numbers in $[0, 1]$.
3) $syn \subseteq \{1, 2, \ldots, m\} \times \{1, 2, \ldots, m\}$ with $i \neq j$ for all $(i, j) \in syn, 1 \leq i, j \leq m$, is a directed graph of synapses between the linked neurons;
4) $in, out \in \{1, 2, \ldots, m\}$ indicate the input neuron set and the output neuron set of Π, respectively.

In an FRSN P system, the pulse value contained in each neuron is not the number of spikes represented by a real number, but a trapezoidal fuzzy number in $[0, 1]$, which can be interpreted as the potential value of spikes contained in neuron σ_i. The motivation for the introduction of trapezoidal fuzzy numbers comes from three aspects. First of all, due to experts' subjectivity, professional knowledge acquisition has various uncertainties. Subsequently, human knowledge in the real world, such as knowledge in fault diagnosis process, is usually expressed by using linguistic terms with a certain degree of uncertainty. For example, we often use fuzzy concepts (*absolutely-false, very-low, low, medium-low, medium, medium-high, high, very-high, absolutely-high*) to describe a degree of uncertainty. In addition, the knowledge in practical applications may contain a certain degree of uncertainty. For instance, the operation process of protective devices in fault diagnosis usually includes uncertainly protective messages such as maloperation and misinformation.

The *trapezoidal fuzzy number* in *Definition 1* can be parameterized by a 4-tuple $\tilde{A} = (a_1, a_2, a_3, a_4)$, as shown in Fig. 5, where a_1, a_2, a_3 and a_4 are real numbers such that $a_1 < a_2 <$
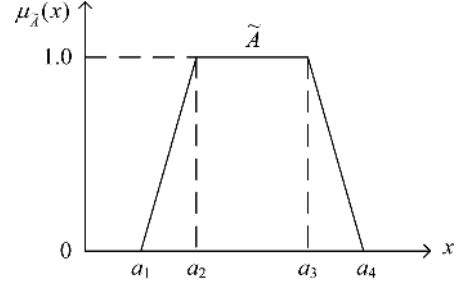

Fig. 5. Trapezoidal fuzzy number.

$a_3 < a_4$, which are the four horizontal axis values of the trapezoid. The membership function $\mu_{\tilde{A}}(x)$ of the trapezoidal fuzzy number $\tilde{A}$ is defined as follows:

$$\mu_{\tilde{A}}(x) = \begin{cases} 0, & x \leq a_1 \\ \frac{x - a_1}{a_2 - a_1}, & a_1 < x \leq a_2 \\ 1, & a_2 < x \leq a_3 \\ \frac{a_4 - x}{a_4 - a_3}, & a_3 < x \leq a_4 \\ 0, & x > a_4. \end{cases} \tag{1}$$

Let $\tilde{A}$ and $\tilde{B}$ be two trapezoidal fuzzy numbers, $\tilde{A} = (a_1, a_2, a_3, a_4)$ and $\tilde{B} = (b_1, b_2, b_3, b_4)$. The arithmetic operations of the trapezoidal fuzzy numbers $\tilde{A}$ and $\tilde{B}$ are listed as follows. More operations can be seen in [6] and [32].
1) Addition $\oplus$: $\tilde{A} \oplus \tilde{B} = (a_1, a_2, a_3, a_4) \oplus (b_1, b_2, b_3, b_4) = (a_1 + b_1, a_2 + b_2, a_3 + b_3, a_4 + b_4)$;
2) Multiplication $\otimes$: $\tilde{A} \otimes \tilde{B} = (a_1, a_2, a_3, a_4) \otimes (b_1, b_2, b_3, b_4) = (a_1 \times b_1, a_2 \times b_2, a_3 \times b_3, a_4 \times b_4)$.

We define four logic operations as follows, where A and B are trapezoidal fuzzy numbers, and a, b are real numbers.
1) *Minimum operator* $\wedge$: $a \wedge b = min(a, b)$;
2) *Maximum operator* $\vee$: $a \vee b = max(a, b)$;
3) *and* $\bigwedge$: $A \bigwedge B = (a_1, a_2, a_3, a_4) \bigwedge (b_1, b_2, b_3, b_4) = ((a_1 \wedge b_1), (a_2 \wedge b_2), (a_3 \wedge b_3), (a_4 \wedge b_4))$;
4) *or* $\bigvee$: $A \bigvee B = (a_1, a_2, a_3, a_4) \bigvee (b_1, b_2, b_3, b_4) = ((a_1 \vee b_1), (a_2 \vee b_2), (a_3 \vee b_3), (a_4 \vee b_4))$.

We also define a scalar multiplication operation as follows, where A is a trapezoidal fuzzy number and b is a real number.
1) *Scalar Multiplication*: $bA = b(a_1, a_2, a_3, a_4) = (ba_1, ba_2, ba_3, ba_4)$.

With regard to the pulse value θ_i, if $\theta_i > (0, 0, 0, 0)$, neuron σ_i contains a spike with value θ_i, otherwise, the neuron contains no spike. The firing condition $E = a^n$ means that the spiking rule associated with neuron σ_i can be applied if and only if the number of spikes that neuron σ_i receives at any computational step equals n, otherwise, the firing rule cannot be applied. If the number of spikes that neuron σ_i receives is less than n, neuron σ_i performs the operation $\bigwedge$ or $\bigvee$ on the potential values carried by these spikes to update its pulse value.

According to their usage, in an FRSN P system the neurons are divided into two categories: *proposition neurons* and *rule neurons*. Each neuron σ_i corresponds to either a proposition or a fuzzy production rule, which will be described later in this section. Thus, the trapezoidal fuzzy number c_i can be understood as either the fuzzy truth value of a proposition or the certainty factor of a fuzzy production rule.

Definition 2: A *proposition neuron*, as shown in Fig. 6, corresponds to a proposition in the fuzzy production rules. Such a neuron is represented by the symbol P.

The fuzzy truth value of a proposition neuron equals to the fuzzy truth value of the proposition corresponding to this neuron. If such a proposition neuron receives one spike, i.e., $n = 1$, it will fire and emit a spike. The parameter β of the firing rule contained in such a proposition neuron is identical to θ. If a proposition neuron is an input, then its pulse value θ equals to the fuzzy truth value c of this neuron. Otherwise, if there is only one presynaptic rule neuron, then θ equals to the pulse value transmitted from this neuron. In any other case, θ equals to the result of the operation $\bigwedge$ on all pulse values received from its presynaptic rule neurons.

There are three types of *rule neurons*: *general*, *and* and *or*, which are represented by the three symbols $\ominus$, $\bigwedge$ and $\bigvee$, respectively. We use R to denote a rule neuron. If the number of spikes a rule neuron receives equals the number of its presynapses, it will fire and emit a spike. In what follows we define each type of rule neurons.

Definition 3: A *general* rule neuron $\ominus$, as shown in Fig. 7 (i), corresponds to a fuzzy production rule which has only one proposition in the antecedent part of the rule. The consequent part of the fuzzy production rule may contain one or more propositions.

A *general* rule neuron has only one presynaptic proposition neuron and one or more postsynaptic proposition neurons. The fuzzy truth value of a *general* rule neuron equals to the certainty factor of the fuzzy production rule corresponding to its neuron. If a *general* rule neuron receives a spike with potential value θ and its firing condition is satisfied, then the neuron fires and produces a new spike with potential value $\beta = \theta \otimes c$.

Definition 4: An *and* rule neuron $\bigwedge$, as shown in Fig. 7 (ii), corresponds to the fuzzy production rule which has more than one proposition with an *and* relationship in the antecedent part of the rule. The consequent part of the fuzzy production rule contains only one proposition.

An *and* rule neuron has more than one presynaptic proposition neuron and only one postsynaptic proposition neuron. The fuzzy truth value of an *and* rule neuron equals to the certainty factor of the fuzzy production rule corresponding to its neuron. If an *and* rule neuron receives k spikes with potential values $\theta_1, \theta_2, \ldots, \theta_k$, respectively, and its firing condition is satisfied, then the neuron fires and produces a new spike with the potential value $\beta = (\theta_1 \bigwedge \ldots \bigwedge \theta_k) \otimes c$.

Definition 5: An *or* rule neuron $\bigvee$, as shown in Fig. 7 (iii), corresponds to the fuzzy production rule which has more than one proposition with an *or* relationship in the antecedent part of the rule. The consequent part of the fuzzy production rule contains only one proposition.

An *or* rule neuron has more than one presynaptic proposition neurons and only one postsynaptic proposition neuron. The fuzzy truth value of an *or* rule neuron equals to the certainty factor of the fuzzy production rule corresponding to its neuron. If an *or* rule neuron receives k spikes with potential values $\theta_1, \theta_2, \ldots, \theta_k$, respectively, and its firing condition is satisfied, then the neuron fires and produces a new spike with the potential value $\beta = (\theta_1 \bigvee \ldots \bigvee \theta_k) \otimes c$.
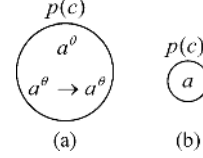

Fig. 6.   (a) Proposition neuron and (b) its simplified form.
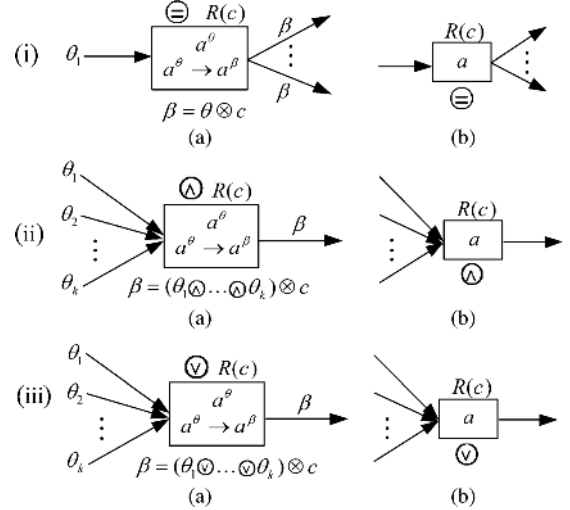

Fig. 7.   Rule neurons. (i) A *general* rule neuron (a) and its simplified form (b); (ii) An *and* rule neuron (a) and its simplified form (b); (iii) An *or* rule neuron (a) and its simplified form (b).
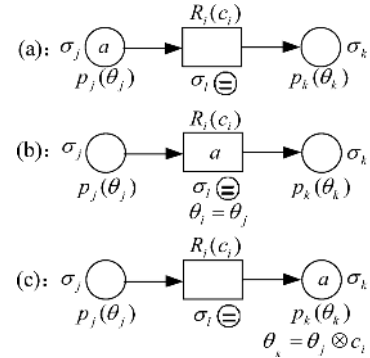

Fig. 8.   Modeling process of *Type 1* using one FRSN P system.

In what follows, we use FRSN P systems to model these *fuzzy production rules*, which will be used to model fault diagnosis in power systems. We consider four types of fuzzy production rules. An FRSN P system is used to model one or more fuzzy production rules. In the following description, $R_i (i = 1, \ldots, N_r)$ is the ith fuzzy production rule, N_r represents the number of fuzzy production rules, c_i is a trapezoidal fuzzy number in [0, 1] representing the certainty factor of R_i, p_j $(1 \leq j \leq N_p)$ is the jth proposition appearing in the antecedent or consequent part of R_i, N_p represents the number of proportions, and θ_j is a trapezoidal fuzzy number in [0, 1] representing the fuzzy truth value of proposition p_j.

Type 1: $R_i(c_i) : p_j(\theta_j) \rightarrow p_k(\theta_k)$ $(1 \leq j, k \leq N_p)$. The modeling process of this rule type by using one FRSN P system is shown in Fig. 8, where (a), (b), and (c) represent spike a being transmitted from input neuron σ_j to output neuron σ_k. The fuzzy truth value of the proposition p_k is $\theta_k = \theta_j \otimes c_i$.
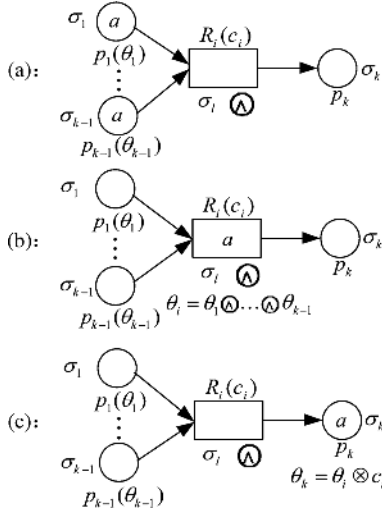
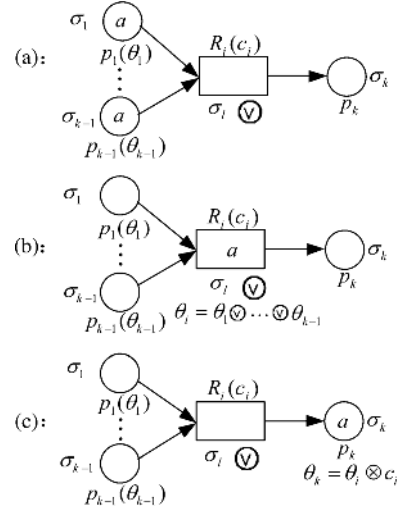Fig. 9. Modeling process of *Type 2* using one FRSN P system.

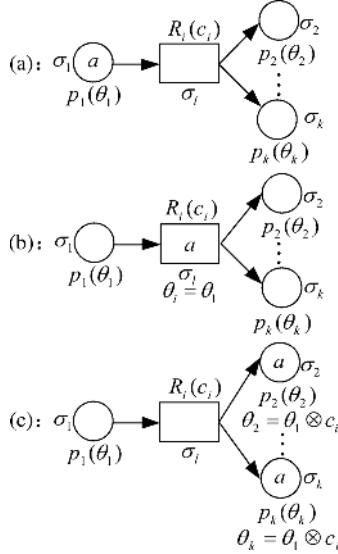Fig. 10. Modeling process of *Type 3* using one FRSN P system.

Fig. 11. Modeling process of *Type 4* using one FRSN P system.

Linguistic Terms	Trapezoidal Fuzzy Numbers
absolutely-false (AF)	(0, 0, 0, 0)
very-low (VL)	(0, 0, 0.02, 0.07)
low (L)	(0.04, 0.1, 0.18, 0.23)
medium-low (ML)	(0.17, 0.22, 0.36, 0.42)
medium (M)	(0.32, 0.41, 0.58, 0.65)
medium-high (MH)	(0.58, 0.63, 0.80, 0.86)
high (H)	(0.72, 0.78, 0.92, 0.97)
very-high (VH)	(0.975, 0.98, 1, 1)
absolutely-high (AH)	(1, 1, 1, 1)

which are represented by the trapezoidal fuzzy numbers shown in Table I.

B. Fuzzy Reasoning Algorithm

This subsection presents an algebraic fuzzy reasoning algorithm for FRSN P systems with trapezoidal fuzzy numbers. If the fuzzy truth values of the propositions corresponding to the input proposition neurons are given, the algorithm reasons out the fuzzy truth values of other unknown propositions corresponding to the other proposition neurons in the FRSN P system. The reasoning results are the fuzzy truth values of the propositions corresponding to the output neurons.

Let us assume that the FRSN P system used for knowledge representation and reasoning contains s proposition neurons and t rule neurons, each of which may be *general, and* or *or* rule neurons. Thus, the total number of neurons is $m = s + t$. To explain this reasoning algorithm, we first introduce some vectors and matrices as follows.

1) $\boldsymbol{\theta} = (\theta_1, \theta_2, \ldots, \theta_s)^T$ is a vector containing the fuzzy truth values of the s proposition neurons, where θ_i is a trapezoidal fuzzy number in [0, 1] representing the pulse value contained in the ith proposition neuron, $1 \leq i \leq s$. If there is not any spike contained in a proposition neuron, its pulse value is "*unknown*" or (0, 0, 0, 0).

2) $\boldsymbol{\delta} = (\delta_1, \delta_2, \ldots, \delta_t)^T$ is a vector containing the fuzzy truth values of the t rule neurons, where δ_j is a trapezoidal fuzzy number [0, 1] representing the pulse value contained in

Type 2: $R_i(c_i) : p_1(\theta_1) \wedge \ldots \wedge p_{k-1}(\theta_{k-1}) \rightarrow p_k(\theta_k)$. The process of this rule type modeled by using one FRSN P system is shown in Fig. 9, where (a), (b), and (c) represent spike a being transmitted from input neurons $\sigma_1, \sigma_2, \ldots, \sigma_{k-1}$ to output neuron σ_k. The fuzzy truth value of the proposition p_k is $\theta_k = (\theta_1 \wedge \ldots \wedge \theta_{k-1}) \otimes c_i$.

Type 3: $R_i(c_i) : p_1(\theta_1) \rightarrow p_2(\theta_2) \wedge \ldots \wedge p_k(\theta_k)$. The process of this rule type modeled by using one FRSN P system is shown in Fig. 10, where (a), (b), and (c) represent spike a being transmitted from input neuron σ_1 to output neurons $\sigma_2, \sigma_3, \ldots, \sigma_k$. The fuzzy truth values of the propositions $p_2, p_3, \ldots, p_k$ are identical, i.e., $\theta_2 = \theta_3 = \ldots = \theta_k = \theta_1 \otimes c_i$.

Type 4: $R_i(c_i) : p_1(\theta_1) \vee \ldots \vee p_{k-1}(\theta_{k-1}) \rightarrow p_k(\theta_k)$. The process of this rule type modeled by using one FRSN P system is shown in Fig. 11, where (a), (b), and (c) represent spike a being transmitted from input neurons $\sigma_1, \sigma_2, \ldots, \sigma_{k-1}$ into output neuron σ_k. The fuzzy truth value of the proposition p_k is $\theta_k = (\theta_1 \vee \ldots \vee \theta_{k-1}) \otimes c_i$.

The fuzzy truth values of the propositions appearing in the fuzzy production rules and the certainty factor of each fuzzy production rule can also be described by using linguistic terms,

the jth rule neuron, $1 \leq j \leq t$. If there is not any spike contained in a rule neuron, its pulse value is "*unknown*" or $(0, 0, 0, 0)$.

3) $\boldsymbol{C} = diag(c_1, c_2, \ldots, c_t)$ is a diagonal matrix, where c_j $(1 \leq j \leq t)$ is a trapezoidal fuzzy number representing the certainty factor of the jth fuzzy production rule.

4) $\boldsymbol{D}_1 = (d_{ij})_{s \times t}$ is a synaptic matrix representing the directed connection from proposition neurons to *general* rule neurons. If there is a directed arc (synapse) from the proposition neuron σ_i to the *general* rule neuron σ_j, $d_{ij} = 1$, otherwise, $d_{ij} = 0$.

5) $\boldsymbol{D}_2 = (d_{ij})_{s \times t}$ is a synaptic matrix representing the directed connection from proposition neurons to *and* rule neurons. If there is a directed arc (synapse) from the proposition neuron σ_i to the *and* rule neuron σ_j, $d_{ij} = 1$, otherwise, $d_{ij} = 0$.

6) $\boldsymbol{D}_3 = (d_{ij})_{s \times t}$ is a synaptic matrix representing the directed connection from proposition neurons to *or* rule neurons. If there is a directed arc (synapse) from the proposition neuron σ_i to the *or* rule neuron σ_j, $d_{ij} = 1$, otherwise, $d_{ij} = 0$.

7) $\boldsymbol{E} = (e_{ji})_{t \times s}$ is a synaptic matrix representing the directed connection from rule neurons to proposition neurons. If there is a directed arc (synapse) from the rule neuron σ_j to the proposition neuron σ_i, $e_{ji} = 1$, otherwise, $e_{ji} = 0$.

Subsequently, we introduce following three multiplication operations.

1) $\odot$: $\boldsymbol{C} \odot \boldsymbol{\delta} = (c_1 \otimes \delta_1, c_2 \otimes \delta_2, \ldots, c_t \otimes \delta_t)^T$. Likewise, $\boldsymbol{D}^T \odot \boldsymbol{\theta} = (\bar{d}_1, \bar{d}_2, \ldots, \bar{d}_t)^T$, where $\bar{d}_j = d_{1j}\theta_1 \oplus d_{2j}\theta_2 \oplus \ldots \oplus d_{sj}\theta_s$, $j = 1, 2, \ldots, t$.

2) $\odot$: $\boldsymbol{D}^T \odot \boldsymbol{\theta} = (\bar{d}_1, \bar{d}_2, \ldots, \bar{d}_t)^T$, where $\bar{d}_j = d_{1j}\theta_1 \bigwedge d_{2j}\theta_2 \bigwedge \ldots \bigwedge d_{sj}\theta_s$, $j = 1, 2, \ldots, t$.

3) $\circledast$: $\boldsymbol{E}^T \circledast \boldsymbol{\delta} = (\bar{e}_1, \bar{e}_2, \ldots, \bar{e}_s)^T$, where $\bar{e}_i = e_{1i}\delta_1 \bigvee e_{2i}\delta_2 \bigvee \ldots \bigvee e_{ti}\delta_t$, $i = 1, 2, \ldots, s$.

What follows is a description of a fuzzy reasoning algorithm for an FRSN P system.

Input: the fuzzy truth values of the propositions corresponding to the input proposition neurons

Output: the fuzzy truth values of the propositions corresponding to the output proposition neurons

Step 1) Let $g = 0$ be the reasoning step;

Step 2) Set initial values of $\boldsymbol{D}_1, \boldsymbol{D}_2, \boldsymbol{D}_3, \boldsymbol{E}, \boldsymbol{C}$ and the termination condition $\boldsymbol{0}_1 = (unknown, unknown, \ldots, unknown)^T_t$. The initial values of $\boldsymbol{\theta}$ and $\boldsymbol{\delta}$ are set to $\boldsymbol{\theta}_g = (\theta_{1g}, \theta_{2g}, \ldots, \theta_{sg})$ and $\boldsymbol{\delta}_g = (\delta_{1g}, \delta_{2g}, \ldots, \delta_{tg})$, respectively.

Step 3) g is increased by one.

Step 4) The firing condition of each input neuron ($g = 1$) or each proposition neuron ($g > 1$) is evaluated. If the condition is satisfied and there is a presynaptic rule neuron, the neuron fires and transmits a spike to the next rule neuron.

Step 5) Compute the fuzzy truth value vector $\boldsymbol{\delta}_g$ according to (2):

$$\boldsymbol{\delta}_g = \left(\boldsymbol{D}_1^T \odot \boldsymbol{\theta}_{g-1}\right) \oplus \left(\boldsymbol{D}_2^T \odot \boldsymbol{\theta}_{g-1}\right) \oplus \left(\boldsymbol{D}_3^T \circledast \boldsymbol{\theta}_{g-1}\right). \quad (2)$$

Step 6) If $\boldsymbol{\delta}_g = \boldsymbol{0}_1$, the algorithm stops and outputs the reasoning results, otherwise, it go to *Step 7)*.

Step 7) Evaluate the firing condition of each rule neuron. If the condition is satisfied, the rule neuron fires and transmits a spike to the next proposition neuron.

Step 8) Compute the fuzzy truth value vector $\boldsymbol{\theta}_g$ according to (3). Go to *Step 3)*:

$$\theta_g = \boldsymbol{E}^T \circledast (\boldsymbol{C} \odot \delta_g). \quad (3)$$

C. Fault Fuzzy Production Rule Sets

To obtain the causality between a fault and the statuses of its protective devices, in this subsection we present fault fuzzy production rule sets for main sections including transmission lines (L), buses (B) and transformers (T) in transmission networks.

The fault fuzzy production rules consist of propositions and certainty factors. A certainty factor represents the degree of confidence that a fault occurs. Each rule has one certainty factor. Due to the uncertainty of the knowledge of experts and senior dispatchers, we use linguistic terms to describe certainty factors.

In the sequel, we introduce the fault fuzzy production rule sets for three main sections: lines, buses and transformers.

A line has six types of protections: sending end main protections, sending end first backup protections, sending end second backup protections, receiving end main protections, receiving end first backup protections and receiving end second backup protections. The fault fuzzy production rule set for lines contains nine rules, in which the meaning of each proposition is shown in Table II:

$$R_1(c_1 = AH): \ (p_1 \ and \ p_2 \ operate)$$
$$\bigwedge (CB_1 \ and \ CB_2 \ trip) \to L \ fails$$
$$R_2(c_2 = AH): \ (p_1 \ and \ p_4 \ operate)$$
$$\bigwedge (CB_1 \ and \ CB_4 \ trip) \to L \ fails$$
$$R_5(c_3 = AH): \ (p_1 \ and \ p_6 \ operate)$$
$$\bigwedge (CB_1 \ and \ CB_6 \ trip) \to L \ fails$$
$$R_3(c_4 = AH): \ (p_3 \ and \ p_2 \ operate)$$
$$\bigwedge (CB_3 \ and \ CB_2 \ trip \to L \ fails$$
$$R_4(c_5 = AH): \ (p_3 \ and \ p_4 \ operate)$$
$$\bigwedge (CB_3 \ and \ CB_4 \ trip) \to L \ fails$$
$$R_7(c_6 = AH): \ (p_3 \ and \ p_6 \ operate)$$
$$\bigwedge (CB_3 \ and \ CB_6 \ trip) \to L \ fails$$
$$R_6(c_7 = AH): \ (p_5 \ and \ p_2 \ operate)$$
$$\bigwedge (CB_5 \ and \ CB_2 \ trip) \to L \ fails$$
$$R_8(c_8 = AH): \ (p_5 \ and \ p_4 \ operate)$$
$$\bigwedge (CB_5 \ and \ CB_4 \ trip) \to L \ fails$$
$$R_9(c_9 = VH): \ (p_5 \ and \ p_6 \ operate)$$
$$\bigwedge (CB_5 \ and \ CB_6 \ trip) \to L \ fails.$$

The fault fuzzy production rule set for buses contains two rules, in which the meaning for each proposition is shown in

TABLE II
MEANING OF EACH PROPOSITION IN RULE SET OF L

P_1	sending end main protections of L	CB_1	CB_s related to P_1
P_2	receiving end main protections of L	CB_2	CB_s related to P_2
P_3	sending end first backup protections of L	CB_3	CB_s related to P_3
P_4	receiving end first backup protections of L	CB_4	CB_s related to P_4
P_5	sending end second backup protections of L	CB_5	CB_s related to P_5
P_6	receiving end second backup protections of L	CB_6	CB_s related to P_6

TABLE III
MEANING OF EACH PROPOSITION IN RULE SET OF B

P_1	main protections of B	CB_1	CB_s related to P_1
P_2	backup protections of B	CB_2	CB_s related to P_2

TABLE IV
MEANING OF EACH PROPOSITION IN RULE SET OF T

P_1	main protections of T	CB_1	CB_s related to P_1
P_2	first backup protections of T	CB_2	CB_s related to P_2
P_3	second backup protections of T	CB_3	CB_s related to P_3

TABLE V
CONFIDENCE LEVELS OF THE OPERATED PROTECTIVE DEVICES

Sections	Protective devices					
	Main		First backup		Second backup	
	Relays	CBs	Relays	CBs	Relays	CBs
L	VH	VH	H	H	MH	MH
B	VH	VH	-	-	MH	MH
T	VH	VH	H	H	MH	MH

Table III:

$$R_1(c_1 = AH): (p_1\ operates) \bigwedge (all\ or\ partial\ CB_1\ trips)$$
$$\rightarrow B\ fails$$
$$R_2(c_2 = VH): (p_2\ operates) \bigwedge (CB_2\ trips) \rightarrow B\ fails.$$

The fault fuzzy production rule set for transformers contains three rules, in which the meaning for each proposition is shown in Table IV:

$$R_1(c_1 = AH): (p_1\ operates) \bigwedge (all\ or\ partial\ CB_1\ trips)$$
$$\rightarrow T\ fails$$
$$R_2(c_2 = AH): (p_2\ operates) \bigwedge (all\ or\ partial\ CB_2\ trips)$$
$$\rightarrow T\ fails$$
$$R_3(c_3 = VH): (p_3\ operates) \bigwedge (CB_3\ trips) \rightarrow T\ fails.$$

The information obtained from the SCADA system may include operation failure, maloperation and misinformation; it is necessary to use a confidence level to describe the operation accuracy of each section. Thus, we assign an empirical confidence level to each protective device including the protective relay of each line, bus or transformer, or each of its corresponding CBs. Tables V and VI show the confidence levels of the operated protective devices and the non-operate protective devices, respectively.

TABLE VI
CONFIDENCE LEVELS OF THE NON-OPERATE PROTECTIVE DEVICES

Sections	Protective devices					
	Main		First backup		Second backup	
	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

D. Algorithmic Elaboration of FDSNP

This subsection summarizes the FDSNP method, whose flow-chart is shown in Fig. 4, as follows.

Step 1) Read operation messages about protective relays and/or CBs in a power transmission network from the SCADA system.

Step 2) Search for outage areas. We suggest network topology analysis because it decreases the number of candidate diagnosing areas and reduce the subsequent computational workload [10]. The search process is described as follows:

  i) Let the search iteration $t = 1$;
  ii) Construct a set Q_t of section numbers: assign a number to each section in the power transmission network. The numbers of all sections constitute the set Q_t;
  iii) Construct a subset M_t of section numbers: put the number of a randomly chosen section from Q_t into the subset M_t. If there is a closed CB connecting this chosen section, find all the closed CBs connecting it, otherwise, go to vi). Find all the other sections linking with each of the closed CBs and put their numbers from Q_t into M_t. Continue to find the closed CBs and sections according to those in M_t;
  iv) t is increased by one;
  v) *Construct the set Q_t*: remove the numbers of the sections in M_t from Q_{t-1} and obtain Q_t. If Q_t is not empty, the search process goes to (iii);
  vi) Find passive networks, i.e., outage areas, from $M_1, M_2, \ldots, M_{N_s}$, where N_s is the maximum number of all numbers referring to section subsets. The search process stops.

Step 3) If there is only one section in the passive networks found in *Step 2*, this section is the faulty one and the algorithm stops, otherwise, a fault diagnosis model based on an FRSN P system is built for each section. The model-building process is described as follows. A section in the passive network is chosen randomly. According to the relay protections of the section, we design fault fuzzy production rules and then determine proposition and rule neurons and create their linking relationship to obtain the FRSN P system. The certainty factor of each rule is empirically set. According to Tables V and VI, we set confidence levels for main protections, first backup pro-

TABLE VII
Status Information About Protective Relays and CBs

Cases	Status information	
	Operated relays	Tripped CBs
1	B_{1m}, L_{2Rs}, L_{4Rs}	CB_4, CB_5, CB_7 CB_9, CB_{12}, CB_{27}
2*	L_{2Rs}, L_{4Rs}	CB_4, CB_5, CB_7 CB_9, CB_{12}, CB_{27}
3	B_{1m}, L_{1Sp}, L_{1Rm}	CB_4, CB_5, CB_6 CB_7, CB_9, CB_{11}
4	B_{1m}, L_{1Sm}, L_{1Rp} B_{2m}, L_{2Sp}, L_{2Rm}	CB_4, CB_5, CB_6 CB_7, CB_8, CB_9 $CB_{10}, CB_{11}, CB_{12}$
5	T_{3p}, L_{7Sp}, L_{7Rp}	$CB_{14}, CB_{16}, CB_{29}, CB_{39}$
6	$L_{1Sm}, L_{1Rp}, L_{2Sp}$ $L_{2Rp}, L_{7Sp}, L_{7Rm}$ L_{8Sm}, L_{8Rm}	CB_7, CB_8, CB_{11} $CB_{12}, CB_{29}, CB_{30}$ CB_{39}, CB_{40}
7*	T_{7m}, T_{8P}, B_{7m} B_{8m}, L_{5Sm}, L_{5Rp} $L_{6Ss}, L_{7Sp}, L_{7Rm}, L_{8Ss}$	$CB_{19}, CB_{20}, CB_{29}, CB_{30}$ $CB_{32}, CB_{33}, CB_{34}, CB_{35}$ $CB_{36}, CB_{37}, CB_{39}$

TABLE VIII
Fault Sections and Their Fault Confidence Levels Obtained by Using FDSNP

Cases	Diagnosis results of FDSNP		
	Fault sections	Fault confidence levels	
		Trapezoidal fuzzy numbers	Linguistic terms
1	B_1	(0.975, 0.98, 1, 1)	VH
2	B_1	(0.5655, 0.6174, 0.80, 0.86)	[M, MH]
3	B_1	(0.975, 0.98, 1, 1)	VH
	L_1	(0.9506, 0.9604, 1, 1)	[H, VH]
4	B_1	(0.975, 0.98, 1, 1)	VH
	B_2	(0.975, 0.98, 1, 1)	VH
	L_1	(0.9506, 0.9604, 1, 1)	[H, VH]
	L_2	(0.9506, 0.9604, 1, 1)	[H, VH]
5	T_3	(0.72, 0.78, 0.92, 0.97)	H
	L_7	(0.9506, 0.9604, 1, 1)	[H, VH]
6	L_1	(0.702, 0.7644, 0.92, 0.97)	[H, VH]
	L_2	(0.702, 0.7644, 0.92, 0.97)	[H, VH]
	L_7	(0.702, 0.7644, 0.92, 0.97)	[H, VH]
	L_8	(0.9506, 0.9604, 1, 1)	[H, VH]
7	L_5	(0.702, 0.7644, 0.92, 0.97)	[H, VH]
	L_7	(0.702, 0.7644, 0.92, 0.97)	[H, VH]
	B_7	(0.975, 0.98, 1, 1)	[H, VH]
	B_8	(0.975, 0.98, 1, 1)	[H, VH]
	T_7	(0.975, 0.98, 1, 1)	[H, VH]
	T_8	(0.72, 0.78, 0.92, 0.97)	H

tections, second backup protections and their CBs. Then a one-to-one relationship between the fuzzy truth value of each input neuron and the confidence level of each protection is established to obtain the initial values of the model.

Step 4) The algebraic fuzzy reasoning algorithm is used to acquire the fault confidence level of each section.

Step 5) If the confidence level θ of a section satisfies the condition $\theta \geq (0.58, 0.63, 0.80, 0.86)$, the section is faulty, otherwise, if θ satisfies the condition $\theta \leq (0.17, 0.22, 0.36, 0.42)$, the section is not faulty, otherwise, the section may be faulty.

IV. CASE STUDIES

In this section, seven cases of the local system in an EPS shown in Fig. 3 are considered as examples to test the effectiveness and superiority of FDSNP. These cases include single and multiple fault situations. The status information (with/without incompleteness and uncertainty) about protective relays and CBs is shown in Table VII, where "∗" means that this case includes incomplete or uncertain status information from the SCADA system.

FDSNP is used to diagnose faults for the seven cases, and the diagnosis results are shown in Table VIII, which contains the faulty sections and their fault confidence levels. Table VIII lists the fault confidence levels of only faulty sections. In fact, FDSNP provides fault confidence levels of all diagnosed sections. Four diagnosis methods, fuzzy logic (FL) [3], fuzzy Petri nets (FPN) [4], genetic algorithm-tabu search (GATS) [15], and genetic algorithm (GA) [17], are used as benchmarks to perform comparative experiments. The reason that we choose the four methods is that they considered the same local electrical power system as FDSNP as well as the same cases. The diagnosis results of the five methods are shown in Table IX, where "-" means that this case was not considered in the corresponding reference. It is worth pointing out that FL in [3] used only the information about CBs and the diagnosis results of GA in [17] may contain multiple solutions, such as *Cases 5–7*.

From Table VIII, we can see that the fault confidence levels represented by trapezoidal fuzzy numbers provide a quantitative description for the faulty sections which makes these results more reliable. The linguistic terms corresponding to these trapezoidal fuzzy numbers provide a more intuitive and flexible way for experts and dispatchers than probability values, since their knowledge usually contain linguistic terms with a certain degree of uncertainty.

From Table IX, we can see that the diagnosis results of FDSNP, in *Case 1* and *Cases 3–6*, are the same as those in [3] and [4], in other words, FDSNP is effective in fault diagnosis of power transmission networks in power systems. Table IX also shows that, in some cases, FDSNP is superior to FL, FPN, and GA on correctly identifying fault sections. For instance, in *Case 7*, the fault diagnosis result of FDSNP is different from those in [3], [4], and [17]. In this case, for section L_8, only its second backup protective relay S_{L8Ss} operated and actually, S_{L8Ss} operated as the second backup protective relay of section B_8. So in fact, L_8 is not a faulty section. For section B_7, its main protective relay B_{7m} operated and tripped its corresponding CBs, CB_{33}, CB_{34}, and CB_{35}. So B_7 is a faulty section. Thus, for *Case 7*, the diagnosis result of FDSNP and GATS is better than those in [3], [4], and [17]. In *Cases 5–7*, comparisons of diagnosis results between FDSNP and the methods in [17]

TABLE IX
COMPARISONS BETWEEN FDSNP AND FOUR FAULT DIAGNOSIS METHODS

Cases	Diagnosis results				
	FDSNP	FL [3]	FPN [4]	GATS [15]	GA [17]
1	B_1	B_1	B_1	-	B_1
2	B_1	-	-	-	-
3	B_1	B_1	B_1	-	B_1
	L_1	L_1	L_1		L_1
4	B_1	B_1	B_1	-	B_1
	B_2	B_2	B_2		B_2
	L_1	L_1	L_1		L_1
	L_2	L_2	L_2		L_2
5	T_3	T_3	T_3	T_3	(1)T_3, L_7
	L_7	L_7	L_7	L_7	(2) T_3
					(3) L_7
					(4) No
6	L_1	L_1	L_1	L_1	(1)L_1, L_2
	L_2	L_2	L_2	L_2	L_7, L_8
	L_7	L_7	L_7	L_7	(2)L_1, L_7
	L_8	L_8	L_8	L_8	L_8
7	L_5	L_5	L_5	L_5	
	L_7	L_7	L_7	L_7	(1)L_5, L_7
	B_7	B_8	B_7	B_7	B_7, B_8
	B_8	T_7	B_8	B_8	T_7, T_8
	T_7	T_8	T_7	T_7	(2)L_5, L_7
	T_8		T_8	T_8	T_7, B_8
			L_8		

Fig. 12. Fault diagnosis model of bus B_1 based on an FRSN P system.

show that FDSNP can solve the nonuniqueness problem of the diagnosis solution, which proves the correctness of FDSNP in diagnosing faulty sections. Besides, the diagnosis results in *Cases 2* and *7* show that FDSNP can obtain satisfying results in the situations with incomplete or uncertain alarm information. Therefore, from the seven typical cases, FDSNP is effective with a good accuracy in fault diagnosis of power transmission networks.

In what follows, we use *Case 1* and *Case 2* as examples to illustrate the steps of FDSNP.

Case 1: complete information is obtained from the SCADA system. Operated relays: B_{1m}, L_{2Rs}, and L_{4Rs}. Tripped CBs: CB_4, CB_5, CB_7, CB_9, CB_{12}, and CB_{27}.

The search process of outage areas is described as follows.

1) *Construct the set Q_1 of section numbers*: $Q_1 = \{01, 02, 03, 04, 1, 2, , 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28\}$, where numbers $01 \sim 04$ represent four joint nodes, which are considered as active nodes, between the local power system in Fig. 3 and other parts of the power system.

2) *Construct the subset M_1 of section numbers*: add number *1* into M_1 and find all the closed CBs, i.e., CB_1, CB_2, and CB_3, connecting the section *1*. Find all the other sections,
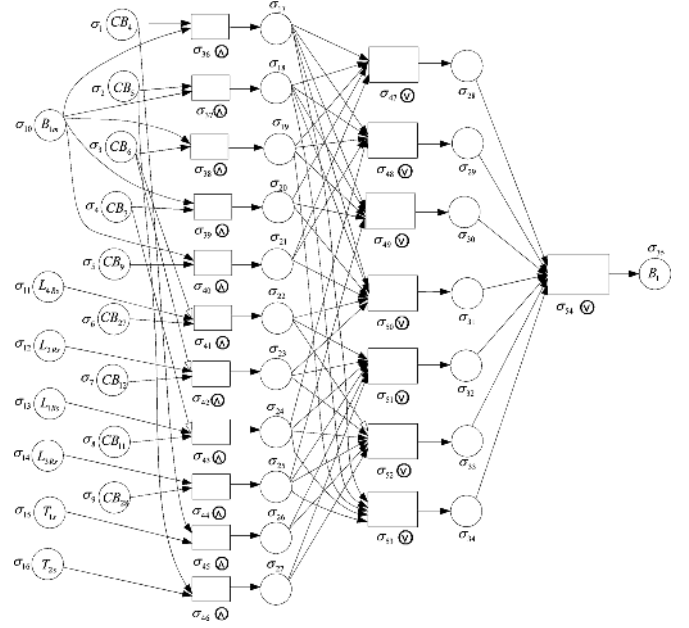
i.e., *01*, *13*, and *14*, linking with CB_1, CB_2, and CB_3 and add them into M_1. No other closed CB is found according to the sections in M_1. Thus, $M_1 = \{01, 1, 13, 14\}$.

3) *Construct the set Q_2*: remove the numbers of the sections in M_1 from Q_1 and obtain $Q_2 = \{02, 03, 04, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28\}$.

4) *Construct the subset M_2*: add number *2* into M_2 and execute the step *3)* in *Step 2* in Section III-D. We get $M_2 = \{2, 3, 16, 20\}$.

5) *Construct the set Q_3*: remove the numbers of the sections in M_2 from Q_2 and obtain $Q_3 = \{02, 03, 04, 4, 5, 6, 7, 8, 9, 10, 11, 12, 15, 17, 18, 19, 21, 22, 23, 24, 25, 26, 27, 28\}$.

6) *Construct the subset M_3*: add number *4* into M_3 and execute step *(iii)* in *Step 2* in Section III-D. We get $M_3 = \{02, 03, 04, 4, 5, 6, 7, 8, 9, 10, 11, 12, 15, 17, 18, 19, 21, 22, 23, 24, 25, 26, 27, 28\}$.

7) *Construct the set Q_4*: remove the numbers of the sections in M_3 from Q_3 and obtain $Q_4 = \emptyset$.

8) Find one passive network $M_2 = \{2, 3, 16, 20\}$ in M_1, M_2, M_3, where the numbers 2, 3, 16, 20 represent bus B_1, bus B_2, line L_2 and line L_4, respectively. The search process stops.

In what follows we take bus B_1 as an example to show how to use *Steps 3–5* in Section III-D. The fault diagnosis model of B_1 based on an FRSN P system is constructed and shown in Fig. 12, where there are 35 proposition neurons and 19 rule neurons. In this figure, there are four assistant arcs (synapses), i.e., (3,41), (3,42), (4,43), and (22,52), marked by hollow tips. We take the arc, from σ_3 to σ_{41}, as an example to illustrate the meaning of these assistant arcs. The arc (3,41) means that if CB_6 opens, the operation of L_{4Rs} and CB_{27} is invalid and then the values of L_{4Rs} and CB_{27} are set as (0,0,0,0); otherwise, the operation

of them is valid. The fuzzy reasoning process is described as follows.

According to the alarm information in *Case 1* and Tables I, V, and VI, we obtain the trapezoidal fuzzy numbers $\boldsymbol{\theta_0}$ and $\boldsymbol{\delta_0}$. In our case studies, numbers $\boldsymbol{\theta}$ are vectors of dimension 35 and numbers $\boldsymbol{\delta}$ are vectors of dimension 19:

$$\boldsymbol{\theta_0} = \begin{bmatrix} (0.975, 0.98, 1, 1) \\ (0.975, 0.98, 1, 1) \\ (0.04, 0.1, 0.18, 0.23) \\ (0.975, 0.98, 1, 1) \\ (0.975, 0.98, 1, 1) \\ (0.58, 0.63, 0.80, 0.86) \\ (0.58, 0.63, 0.80, 0.86) \\ (0.04, 0.1, 0.18, 0.23) \\ (0.04, 0.1, 0.18, 0.23) \\ (0.975, 0.98, 1, 1) \\ (0.58, 0.63, 0.80, 0.86) \\ (0.58, 0.63, 0.80, 0.86) \\ (0.17, 0.22, 0.36, 0.42) \\ (0.17, 0.22, 0.36, 0.42) \\ (0.17, 0.22, 0.36, 0.42) \\ (0.17, 0.22, 0.36, 0.42) \\ \mathbf{O} \end{bmatrix}, \quad \boldsymbol{\delta_0} = [\mathbf{O}].$$

When $g = 1$, we get the results

$$\boldsymbol{\delta_1} = \begin{bmatrix} (0.975, 0.98, 1, 1) \\ (0.975, 0.98, 1, 1) \\ (0.04, 0.1, 0.18, 0.23) \\ (0.975, 0.98, 1, 1) \\ (0.975, 0.98, 1, 1) \\ (0.58, 0.63, 0.80, 0.86) \\ (0.58, 0.63, 0.80, 0.86) \\ (0.04, 0.1, 0.18, 0.23) \\ (0.04, 0.1, 0.18, 0.23) \\ (0.17, 0.22, 0.36, 0.42) \\ (0.17, 0.22, 0.36, 0.42) \\ \mathbf{O} \end{bmatrix},$$

$$\boldsymbol{\theta_1} = \begin{bmatrix} \mathbf{O} \\ (0.975, 0.98, 1, 1)_{i=17} \\ (0.975, 0.98, 1, 1) \\ (0.04, 0.1, 0.18, 0.23) \\ (0.975, 0.98, 1, 1) \\ (0.975, 0.98, 1, 1) \\ (0.5655, 0.6174, 0.80, 0.86) \\ (0.5655, 0.6174, 0.80, 0.86) \\ (0.039, 0.098, 0.18, 0.23) \\ (0.039, 0.098, 0.18, 0.23) \\ (0.0156, 0.2156, 0.36, 0.42) \\ (0.0156, 0.2156, 0.36, 0.42) \\ \mathbf{O} \end{bmatrix}.$$

When $g = 2$, we get the results

$$\boldsymbol{\delta_2} = \begin{bmatrix} \mathbf{O} \\ (0.975, 0.98, 1, 1)_{j=12} \\ (0.975, 0.98, 1, 1) \\ (0.975, 0.98, 1, 1) \\ (0.975, 0.98, 1, 1) \\ (0.5655, 0.6174, 0.80, 0.86) \\ (0.5655, 0.6174, 0.80, 0.86) \\ (0.975, 0.98, 1, 1) \\ (0, 0, 0, 0) \end{bmatrix},$$

$$\boldsymbol{\theta_2} = \begin{bmatrix} \mathbf{O} \\ (0.975, 0.98, 1, 1)_{i=28} \\ (0.975, 0.98, 1, 1) \\ (0.975, 0.98, 1, 1) \\ (0.975, 0.98, 1, 1) \\ (0.5514, 0.6051, 0.80, 0.86) \\ (0.5514, 0.6051, 0.80, 0.86) \\ (0.975, 0.98, 1, 1) \\ (0, 0, 0, 0) \end{bmatrix}.$$

When $g = 3$, we get the results.

$$\boldsymbol{\delta_3} = \begin{bmatrix} \mathbf{O} \\ (0.975, 0.98, 1, 1) \end{bmatrix}, \quad \boldsymbol{\theta_3} = \begin{bmatrix} \mathbf{O} \\ (0.975, 0.98, 1, 1) \end{bmatrix}.$$

When $g = 4$, we get the results

$$\boldsymbol{\delta_4} = [\mathbf{O}].$$

Thus, the termination condition is satisfied and the reasoning process ends. We obtain the reasoning results, i.e., the fuzzy truth values $(0.975, 0.98, 1, 1)$ from output neuron σ_{35}.

According to the condition in *Step 5* in Section III-D, B_1 is a faulty section with a confidence level AH.

Similarly, we obtain that B_2, L_2 and L_4 have the same confidence level $(0.04, 0.1, 0.18, 0.23)$. According to the condition in *Step 5* in Section III-D, B_2, line L_2, and line L_4 are not faulty sections.

Case 2: incomplete information is obtained from the SCADA system. Operated relays: L_{2Rs} and L_{4Rs}. Tripped CBs: CB_4, CB_5, CB_7, CB_9, CB_{12}, and CB_{27}. In other words, the status information about B_{1m} is missing in this case.

We use the same method as in *case 1* and obtain one passive network $\{2, 3, 16, 20\}$. In what follows we also take bus B_1 as an example to show how to use *Steps 3–5* in Section III-D.

According to the alarm information in *Case 2* and Tables I, V, VI, we obtain the trapezoidal fuzzy numbers $\boldsymbol{\theta_0}$ and $\boldsymbol{\delta_0}$:

$$\boldsymbol{\theta_0} = \begin{bmatrix} (0.975, 0.98, 1, 1) \\ (0.975, 0.98, 1, 1) \\ (0.04, 0.1, 0.18, 0.23) \\ (0.975, 0.98, 1, 1) \\ (0.975, 0.98, 1, 1) \\ (0.58, 0.63, 0.80, 0.86) \\ (0.58, 0.63, 0.80, 0.86) \\ (0.04, 0.1, 0.18, 0.23) \\ (0.04, 0.1, 0.18, 0.23) \\ (0.17, 0.22, 0.36, 0.42) \\ (0.58, 0.63, 0.80, 0.86) \\ (0.58, 0.63, 0.80, 0.86) \\ (0.17, 0.22, 0.36, 0.42) \\ (0.17, 0.22, 0.36, 0.42) \\ (0.17, 0.22, 0.36, 0.42) \\ (0.17, 0.22, 0.36, 0.42) \\ \mathbf{O} \end{bmatrix}, \quad \boldsymbol{\delta_0} = [\mathbf{O}].$$

Due to limited space, only the final result of *Case 2* is given. We obtain the reasoning results, i.e., the fuzzy truth values $(0.5655, 0.6174, 0.80, 0.86)$ of the output neuron σ_{35}.

According to the condition in *Step 5* in Section III-D, B_1 may be a faulty section with a confidence level $(0.5655, 0.6174, 0.80, 0.86)$. Similarly, we obtain that B_2, L_2, and L_4 have the same confidence level $(0.04, 0.1, 0.18, 0.23)$. According to the condition in *Step 5* in Section III-D, bus B_2, line L_2, and line L_4 are not faulty sections. Therefore, we get a result that B_1 is the faulty section with a confidence level $(0.5655, 0.6174, 0.80, 0.86)$ $(M \leq (0.5655, 0.6174, 0.80, 0.86) \leq MH)$. Although *Case 2* has incomplete alarm information, the diagnostic result is the same as that in *Case 1*.

Since the analysis and fuzzy reasoning processes of other cases are similar to *Cases 1* and *2*, we omit them here.

V. CONCLUSIONS

In this study, a graphic modeling approach, FDSNP, based on FRSN P systems with trapezoidal fuzzy numbers is presented for fault diagnosis of power transmission networks. This approach provides a good accuracy of diagnosis solutions and a rather understandable fault diagnosis process because of its intuitive illustration of graphical models and understandability of diagnosis model-building process. In addition, FDSNP can handle incomplete and uncertain messages from a SCADA system by using trapezoidal fuzzy numbers and fuzzy production rules.

Furthermore, this method can be used for large-scale power transmission networks because the complexity of the fault diagnosis models based on FRSN P systems does not increase sharply and quickly with the scale of networks. When a fault occurs, outage areas are firstly identified according to SCADA data and then fault diagnosis models for suspicious sections in each outage area are constructed [10], [15]. Thus, FDSNP avoids the construction of a large diagnosis model for an entire power transmission network by sequentially and simply constructing one for each suspicious section. This makes the computation of matrix dimensions in this fuzzy reasoning algorithm for each used fault diagnosis model is independent of the scale of the entire network. In other words, in FDSNP the complexity of the FRSN P systems used does not have a direct relationship with the scale of the network, and therefore, the complexity of the FRSN P systems does not increase sharply with the scale of the power transmission network, so it can be used in a large system.

This study proposes FDSNP and tests its validity and feasibility in diagnosing faults in power transmission networks. In this method, the set of linguistic terms and their corresponding trapezoidal fuzzy numbers are decided in an empirical way. So the following work about the choice of the set of linguistic terms and their corresponding trapezoidal fuzzy numbers, FDSNP based on software, P-Lingua [33] and MeCoSim [34], in JAVA language is now in progress. Future work will focus on verifying the performance superiority of FDSNP, compared with other diagnosis methods, by using performance metrics including diagnosis time, fault section misinformation rate, fault section missing rate and computational complexity.
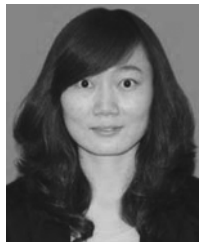
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