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Modeling Fault Propagation Paths in Power Systems: A New Framework Based on Event SNP Systems With Neurotransmitter Concentration / Wang, T.; Wei, X.; Huang, T.; Wang, J.; Peng, H.; Perez-Jimenez, M. J.; Valencia-Cabrera, L.. - In: IEEE ACCESS. - ISSN 2169-3536. - 7:(2019), pp. 12798-12808. [10.1109/ACCESS.2019.2892797]

Availability:

This version is available at: 11583/2765738 since: 2019-11-08T00:17:11Z

Publisher:

Institute of Electrical and Electronics Engineers Inc.

Published

DOI:10.1109/ACCESS.2019.2892797

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Received December 29, 2018, accepted January 7, 2019, date of publication January 14, 2019, date of current version February 6, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2892797

Modeling Fault Propagation Paths in Power Systems: A New Framework Based on Event SNP Systems With Neurotransmitter Concentration

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This work was supported in part by the National Natural Science Foundation of China under Grant 61703345, Grant 51877181, and Grant 51607146, in part by the Key Fund Project of the Sichuan Provincial Education Department under Grant 18ZA0459, in part by the Key Scientific Research Fund Project of Xihua University under Grant Z17108, and in part by the Young Scholars Reserve Talents Support Project of Xihua University.

ABSTRACT To reveal fault propagation paths is one of the most critical studies for the analysis of power system security; however, it is rather difficult. This paper proposes a new framework for the fault propagation path modeling method of power systems based on membrane computing. We first model the fault propagation paths by proposing the event spiking neural P systems (Ev-SNP systems) with neurotransmitter concentration, which can intuitively reveal the fault propagation path due to the ability of its graphics models and parallel knowledge reasoning. The neurotransmitter concentration is used to represent the probability and gravity degree of fault propagation among synapses. Then, to reduce the dimension of the Ev-SNP system and make them suitable for large-scale power systems, we propose a model reduction method for the Ev-SNP system and devise its simplified model by constructing single-input and single-output neurons, called reduction-SNP system (RSNP system). Moreover, we apply the RSNP system to the IEEE 14- and 118-bus systems to study their fault propagation paths. The proposed approach first extends the SNP systems to a large-scaled application in critical infrastructures from a single element to a system-wise investigation as well as from the post-ante fault diagnosis to a new ex-ante fault propagation path prediction, and the simulation results show a new success and promising approach to the engineering domain.

INDEX TERMS Spiking neural P system, membrane computing, fault propagation path, fault propagation relationship, power system.

I. INTRODUCTION

Membrane computing (P systems) [1]–[3] is one of the important lines of artificial intelligence (AI) and aims at taking ideas for computing from the structures and the functioning of living cells as well as tissues or higher order structures organized by the cells. There are, basically, three main types of P systems: cell-like P systems [4], [5], tissue-like P systems [6]–[8] and neural-like P systems [9]. In the past decades, the research on neural-like P systems, in the framework of membrane computing, mainly focused on spiking

neural P systems (SNP systems) [10]–[12], where the specific type of cells from which we took inspiration were the spiking neurons. Generally speaking, the SNP systems are a kind of distributed and parallel neural computing devices motivated by the behavior of neurons transferring information with each other by identical electric impulse (spikes) [12], [13].

The SNP system aims at incorporating specific ideas from spiking neurons into membrane computing and are considered as a combination of spiking neural networks (SNNs) and P systems. Thus, the SNP systems have the characteristics of

spiking neurons, P systems and SNNs, which makes the SNP systems suitable for dealing with practical engineering problems with desirable performance [14], such as combinatorial optimization problems [15], image processing [16], intrusion detection [17], knowledge representation and reasoning [18]–[21], fault diagnosis [22]–[28], etc. Among them, the research about fault diagnosis has been the hottest topic with increasing fruitful results, and many variants of the SNP systems were proposed for designing the SNP system-based fault diagnosis methods of different power systems, including the modeling method for electric locomotive systems [23], the fault section estimation method for traction power supply systems of high-speed railways [24], the fault equipment diagnosis method for metro traction power systems [25] and the fault diagnosis methods for electrical power systems [26]–[28], especially from a fuzzy perspective [29].

Although these research works advanced the development of the SNP system-based fault diagnosis methods for power systems, weak points w.r.t. both the SNP system models and the related applications have been observed after intensive studies:

1) Even the models can diagnose faults, but they *cannot reveal the mechanism of the fault propagation and can only focus on a single element after a failure*. The SNP system-based model is built for each suspicious element, which cannot macroscopically reveal the failure propagation mechanism of the whole power network before a fault.

2) The solution is still derived by *manual reasoning procedure and is difficult to be computerized* due to the drastically increased complexity of the logic relationships among all power elements and the associated protections with the growth of the system size.

3) The models have very *limited topological flexibility* thus cannot easily be applied to emerging power systems, characterized by high penetration of renewable and distributed generation, a large number of connected micro-grids, highly integrated multi-energy systems, etc., which require demanding topological flexibility of the models for fault diagnosis.

Therefore, it is essential to have a new framework that can take full advantages of the SNP system while extending its flexibility and applications to a larger and more complex system.

On the other hand, modeling fault propagation paths is a vital application which forms the fundamental basis for all security related analysis and guarantees the secure operation of the power system, including revealing fault propagation mechanism, analyzing weaknesses of the system, applying suitable countermeasures, etc. Methods for analyzing the dynamic characteristics of power systems, such as oscillations and transients, angular stability, frequency stability, via some real-time simulation platforms, have been focused in [30]–[33]. The dynamic methods mainly study the transient propagation process of fault propagation paths and focus on the fault features of electronic or rotating devices over time. Therefore, the dynamic methods can accurately reveal the

operational characteristics of components under contingency within short time, especially under a couple of minutes.

However, the dynamic methods are not suitable for studying the fault propagation paths of complex large-scaled systems over long time due to the high complexity of calculation. Therefore, static methods are widely employed to analyze the fault propagation paths due to its efficiency, simplicity and scalability [34]–[37]. In general, the static methods use the power flow results to study the overload in lines of the system with statistical/probabilistic methods to model the fault propagation paths. The ideas are that the fault characteristics of components, such as, lines, protections, etc., are regarded as satisfying some certain distributions and thus the statistical/probabilistic models such as, Markov chain [38], [39], Monte Carlo [40], can be adopted to analyze the fault propagation characteristics.

Besides the pure power system analysis methods, the complex network theory, especially suitable for large-scaled grids, is also one of the popular static methods. For instance, the OPA [41]–[43] and CASCADE [44], [45] models are proposed to analyze the self-organized criticality of grids. In addition, by analyzing some statistical indices of complex network from the perspective of topological structures of electrical networks, many electrical networks are proved to be small-world networks [46], [47]. It indicates that when one or more components fail, the faults can fast spread to other components due to the features of high clustering coefficient and short characteristic path of small-world networks. Further, many studies demonstrate that the electrical networks also have scale-free features [48], [49], which indicates that the networks are vulnerable under deliberate attacks but robust under random attacks.

Although complex network theory has an advantage to model large-scale grids, the theory mainly focuses on the topological structure of grids and many studies neglect the operational and physical features to some extent. To reveal features in different fault operations, propagation graphs, such as, cascading fault graph [49]–[51], risk graph [52], influence graph [53], [54] and interaction graph [55], [56], are employed to analyze the fault propagation relationships among lines and propagation paths of fault. These approaches investigate the occurrences of different paths involved in the fault propagations by simulating several cascading events. Particularly, the propagation graphs not only consider topological features but also the physical and operational features, thus provide a valuable research prospect.

However, all of the above-mentioned approaches are deriving the fault propagation paths from the entire system point of view without considering many detailed aspects of the element; therefore, sometimes it cannot reflect the real reactions of each element in the network, especially their response against the propagated fault. Furthermore, the traditional methods are based on the reductionism, thus the non-linear reactions, i.e. the complexity and the self-organizational features of the entire system have been lost in the modeling procedure. In addition, the majority of the methods is lack of

the visualization of the fault propagation, even though some give holistic system-wise information with graphs. Therefore, a more sophisticated framework for identifying the propagation paths is needed to better the analysis per se as well as the final representation of the results with a more intuitive and vivid fashion.

Among many different modern methods, the SNP systems, inspired by the neurophysiological behavior of neurons sending electrical impulses (spikes) along axons, is an apt option to model the behaviors of the study objects at both the system and element levels. It conceptualizes and computerizes the real world problem from a holistic way. As each single component can be model as a proposition neuron with dedicated features and functions, the non-linear and complex response with its peer and the entire system can be captured.

Inspired by the propagation graphs, the SNP systems are employed to model fault propagation paths in transmission electrical networks. In the SNP systems, connective relationships among neurons can reflect temporal adjacent information; therefore, we can reveal the fault temporal features among lines by the aid of neurons. The spike can dynamically imitate the information transfer process; therefore, we can employ the spike to draw the fault propagation process among lines of a transmission network. In addition, the SNP systems have a strong ability of graphical modeling, knowledge reasoning and parallel computing, which can reveal the propagation mechanism among lines intuitively and vividly.

To reformulate a new framework based on the SNP system for studying the fault propagation paths, we propose the event-spiking neural P systems with neurotransmitter concentration (Ev-SNP systems) from the perspective of overload mechanism in electric networks. After improving the Ev-SNP systems to RSNP systems to reduce the computational burden, two standard benchmarks are used to verify the effectiveness of the proposed models. This paper mainly focuses on how to employ the SNP system to model fault propagation paths; therefore, we adopt a general simplified way to study the propagation mechanism from the perspective of overload mechanism. The main contributions of this paper are:

(1) Due to the similarity between the *spike* transmission among different neurons through synapses and the fault propagation in the power systems, we innovatively model the fault propagation in the transmission network through the *spike* transmission in the SNP system. The Ev-SNP systems with neurotransmitter concentration are proposed to achieve such a goal, where the neurotransmitter concentration is employed to describe the probability and gravity degree of fault propagation among synapses. The higher the concentration is, the higher the probability is.

(2) Targeted to the untraceable calculation burden of the Ev-SNP systems, we devise a reduction-SNP system (RSNP system) to combat the dimension disaster of such system by constructing single-input and single-output neurons.

(3) We first extend the application of the SNP systems from a locality to a holism, from a single element to a system-wise investigation, from the post-ante application to a new

ex-ante framework. This new framework not only can take full advantages of the SNP system, but also can model large and complex system with good topological flexibility.

The remainder of this paper is organized as follows. Section II introduces the definition and computation configurations of the Ev-SNP systems. The RSNP systems are proposed to model the fault propagation paths in Section III. In Section IV, the RSNP system is applied to the IEEE 14- and 118- bus systems with the analysis of their effectiveness. Conclusions are finally drawn in Section V.

II. EVENT-SPIKING NEURAL P SYSTEMS

The SNP system [18] can be viewed as directed graphs composed of neurons and synapses, where the neurons are the vehicle for knowledge (information) representation, storage, and calculation while the synapses are used for knowledge (information) transmission. Three important ingredients including objects, spiking (firing) rules and forgetting rules are contained in the neurons which can be viewed as vertexes of the directed graphs. By contrast, the synapses can be regarded as edges of the directed graphs.

To make the SNP system suitable for modeling fault propagation of power systems, we propose a new variation of the SNP system based on the works in [27] and [28], called event spiking neural P systems with neurotransmitter concentration (Ev-SNP systems).

Definition 1: An event-spiking neural P system with neurotransmitter concentration (Ev-SNP system, for short) of degree (s, k) with $s, k \geq 1$ is a tuple

$$\Pi = (A, Q, \text{syn}, I, O) \quad (1)$$

where

(1) $A = \{a\}$ is a singleton alphabet (a is called *spike* and represents *a fault*);

(2) $Q = \{\sigma_1, \dots, \sigma_s, \sigma_{s+1}, \dots, \sigma_{s+k}\}$ is a set whose elements are called *neurons*.

$Q_p = \{\sigma_1, \dots, \sigma_s\}$ is the *proposition neuron* set. Each proposition neuron σ_i ($1 \leq i \leq s$) represents a transmission line (the i -th line) and is denoted by σ_{pi} (the i -th proposition neuron). It is of the form (ε_i, r_i) , where

(a) ε_i represents an *event* that the i -th transmission line corresponding to σ_{pi} faults;

(b) r_i denotes its spiking (firing) rule of the form $E/a \rightarrow a^{\varepsilon_i}$, being E a regular expression over $\{a\}$. The firing rule r_i can be applied if and only if it receives one spike. For the fault propagation path modeling, it means that if a proposition neuron receives one spike, then the r_i can be applied and will produce a new spike. This new spike a indicates that the *event* associated with the neuron σ_{pi} (i.e., ε_i) happens, i.e., the i -th transmission line faults.

$Q_r = \{\sigma_{s+1}, \dots, \sigma_{s+k}\}$ is the *rule neuron* set. Each rule neuron σ_{s+j} ($1 \leq j \leq k$) is denoted by σ_{rj} (the j -th rule neuron) and it can be of two different types: *AND-rule neuron* (denoted by \otimes -neuron) and *OR-rule neuron* (denoted by \oplus -neuron). The rule neuron σ_{rj} is of the form (c_j, η_j, r_j) , where

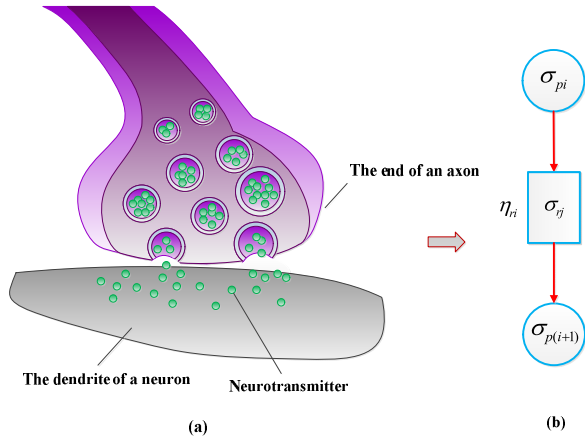


FIGURE 1. Neurotransmitter concentration. (a) Illustration of neurotransmitter in a biosystem. (b) The neurotransmitter concentration in a simple Ev-SNP system.

(a) c_j is a natural number expressing the number of the presynaptic neurons of σ_{rj} ;

(b) η_j is a real number in $[0, 1]$ representing the neurotransmitter concentration of σ_{rj} . For the fault propagation path modeling, the η_j is used to express the fault propagation probability among the synapses that connect to the postsynaptic neurons of σ_{rj} , as shown in Figure 1;

(c) r_i denotes its spiking (firing) rule of the form $E/a^{(\varepsilon_1, \dots, \varepsilon_{c_j})} \rightarrow a^{\varepsilon_{c_j+1}}$, where $\varepsilon_1, \dots, \varepsilon_{c_j}$ represent the c_j presynaptic neurons of σ_{rj} , respectively, ε_{c_j+1} represents the postsynaptic neuron of σ_{rj} and E is a regular expression over $\{a\}$.

For an *AND-rule neuron* σ_{rj} , its firing condition is $E = a^{c_j}$. It means that the firing rule r_i can be applied if and only if it receives c_j spikes from its presynaptic neurons at a same time. For the fault propagation path modeling, it means that if a \otimes -neuron receives c_j spikes, then the r_i can be applied and will produce a new spike. If this new spike a is transmitted to a postsynaptic proposition neuron, then the new spike indicates that the *event* associated with the neuron $\sigma_{p(c_j+1)}$ (i.e., ε_{c_j+1}) will happen with a probability η_j , i.e., the $(c_j + 1)$ -th transmission line will fault with a probability η_j . If the new spike a is transmitted to a postsynaptic \oplus -neuron, then the new spike indicates that the *event* ε_{c_j+1} can be easily effected by spikes transmitted from different synapses with different probabilities.

For an *OR-rule neuron* σ_{rj} , the firing rule r_i can be applied if and only if it receives at least one spike from its presynaptic neurons. For the fault propagation path modeling, it means that if a \oplus -neuron receives at least one spike, then the r_i can be applied and will produce a new spike. This new spike a indicates that the *event* associated with the neuron $\sigma_{p(c_j+1)}$ (i.e., ε_{c_j+1}) happens, i.e., the $(c_j + 1)$ -th transmission line faults. It is noted that the neurotransmitter concentration η_j of an *OR-rule neuron* σ_{rj} is always equal to 1, which demonstrates that a fault must be propagated to other lines once the OR-rule neuron is active.

(3) $\text{syn} = \{1, \dots, s + k\} \times \{1, \dots, s + k\}$ provides the arcs of a directed synapse graph such that $(l, l) \notin \text{syn}$,

for $1 \leq l \leq s + k$, and if $(s + j, s + j') \in \text{syn}$ then $(s + j', s + j) \notin \text{syn}$ for any $1 \leq j, j' \leq k$, that is, there is no cycle only formed by two rule neurons. If $(l, l') \in \text{syn}$ then we say that neuron σ_l is a *presynaptic neuron* of $\sigma_{l'}$ and we also say that neuron $\sigma_{l'}$ is a *postsynaptic neuron* of σ_l ;

(4) $I \subseteq Q_p$ and $O \subseteq Q_p$ are the input (proposition) neuron set and the output (proposition) neuron set, respectively.

In the Ev-SNP system, the proposition neurons characterize the propositions whose knowledge information is carried by the spikes in the associated proposition neurons. The rule neurons are employed to reason the proposition neuron information and then generate a new spike transferred to one or more postsynaptic neurons. Each rule neuron has associated a presynaptic neuron set (whose elements can be proposition neurons or rule neurons) and a postsynaptic neuron set (whose elements can be proposition neurons or rule neurons). At any instant, a proposition neuron contains one spike and a rule neuron can have two different states: active or inactive.

A *configuration* C_t of an Ev-SNP system at an instant t is a $s + t$ -tuple, i.e., $n_{1,t}, \dots, n_{s,t}, m_1, \dots, m_k$, describing the number of spikes $n_{i,t}$ associated with proposition neuron σ_{pi} at that moment together with the state $m_j \in \{0, 1\}$ (active/inactive) of each rule neuron σ_{rj} at instant t . The *initial configuration* C_0 is given by the number of spikes initially associated with each proposition neuron encoding the input information, and all rule neurons are initially inactive.

Let us consider an *AND-rule neuron* σ_{rj} with α presynaptic neurons and β postsynaptic neurons. If the neuron σ_{rj} receives exactly α spikes from its presynaptic neurons at an instant t , and all presynaptic neurons are active at that moment t , then the state of σ_{rj} becomes active. If the state of σ_{rj} is active at the instant t , then it will produce one spike into each postsynaptic neuron at the instant $t + 1$ and the state of σ_{rj} becomes inactive at that moment.

Let us consider an *OR-rule neuron* σ_{rj} with α presynaptic neurons and β postsynaptic neurons. If the neuron σ_{rj} receives at least one spike from its presynaptic neurons at an instant t , then the state of σ_{rj} becomes active. If the state of rule neuron σ_{rj} is active at the instant t then it will produce one spike into each postsynaptic proposition neuron at the instant $t + 1$ and the state of σ_{rj} becomes inactive at that moment.

Given an Ev-SNP system Π , we denote $C \Rightarrow_{\Pi} C'$ meaning that configuration C yields to configuration C' in *one transition step* by applying the rules in the proposition neurons and the active rule neurons in C . A configuration is a *halting configuration* if no rule of the system is applicable and all rule neurons are inactive. A *computation* is a (finite or infinite) sequence of configurations such that: (1) the first term of the sequence is the initial configuration of the system; (2) each non-first term of the sequence is obtained from the previous configuration by applying spiking rules of the system in a maximally parallel manner with the restrictions previously mentioned; and (3) if the sequence is finite (called *halting computation*), then the last term of the sequence is a halting configuration.

All the computations start from an initial configuration and proceed as stated above; and only halting computations give a result, which is encoded by the spikes present in the output neurons from O associated with the halting configuration.

III. ANALYSIS OF FAULT PROPAGATION PATHS USING THE SNP SYSTEMS

A. GENERATION OF FAULT PROPAGATION PATHS

In electric transmission networks, the trip of one or more lines will cause load redistribution in the entire network, which may lead to other lines overloaded, i.e. the flow over a line exceeds its capacity. Therefore, a fault propagation path can be described from the perspective of the overload mechanism as a set of overloaded lines that are tripped in turn due to the load redistribution. It should be noted that although the power flow over the network is complex power; however, the main transmitted power is the active part and the reactive is more related with a local problem. Therefore, in this paper, we use DC model to simplify the over load procedure.

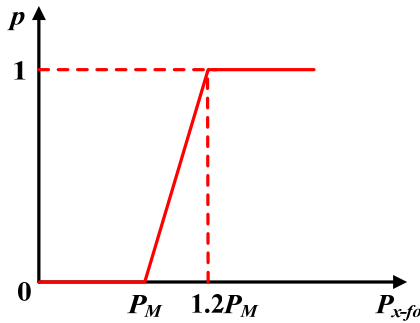


FIGURE 2. Distribution function of an element tripping probability.

1) CANDIDATE LINES

we employ a probabilistic model to represent the tripping probability of a single element. The selected candidate lines, according to the tripping probability, are listed into the next contingency set (failure events), and all the lines inside the set will be tripped in the next step. The distribution function of the probabilistic model of a single element is shown in Figure 2.

(1) If the power flow over the line i under the x -th contingency P_{x-fo}^i is less than or equal to its limit P_M^i , then

$$p(P_{x-fo}^i \leq P_M^i) = 0 \quad (2)$$

(2) If P_{x-fo}^i is more than or equal to 1.2 times of P_M^i , then

$$p(P_{x-fo}^i \geq 1.2P_M^i) = 1 \quad (3)$$

(3) If P_{x-fo}^i is in between the aforementioned (1) and (2), then

$$p(P_M^i < P_{x-fo}^i < 1.2P_M^i) = 5\left(\frac{P_{x-fo}^i}{P_M^i} - 1\right) \quad (4)$$

2) POWER REGULATION

when a network component fails, it may cause a power imbalance; therefore, some measures need to be taken to adjust the outputs of generators and loads to re-establish a new power balance of the system. In this paper, we adjust both generators' outputs and loads. We use the minimal load curtailment as the objective (5) and employ the DC-OPF in every step to adjust the power injection and withdrawal at each node in the transmission network, if needed:

$$f_x = \min \Delta_x \quad (5)$$

$$s.t. \mathbf{P}_x = \mathbf{B}_x \boldsymbol{\theta}_x \quad (6)$$

$$P_h^{\min} \leq P_{hx} \leq P_h^{\max}, \quad h = 1, 2, \dots, N_G \quad (7)$$

where Δ_x represents the load shedding percentage in the contingency x ; \mathbf{P}_x is the net active power injection; \mathbf{B}_x is the susceptance matrix; $\boldsymbol{\theta}_x$ is the phase angle of bus voltages; P_h^{\min} and P_h^{\max} represent the lower and upper bound of the output of generator h , respectively; P_{hx} represents the output of generator h during contingency x ; N_G represents the total number of generators.

Based on the above models, the generation of fault propagation paths can be described as algorithm 1.

Algorithm 1 Simulation Process of Fault Propagation Paths

Input: Electrical network information

Output: Load shedding, propagation step, the number of tripped lines.

Begin

Step 1: Initialization: Choose initial fault lines based on Monte Carlo method.

Step 2: WHILE

Step 3: Power flow calculation: Calculate the power flow using DC power flow.

Step 4: Overload line detection: Form a set of overloaded lines. If exists, go to **Step 5**; otherwise **BREAK**.

Step 5: Contingency set generation: Apply equations 3 and 4 to the set in Step 4 to define the next contingency set.

Step 6: Load shedding calculation: Calculate the minimum load shedding by DC-OPF.

Step 7: Candidate line tripping: Cut off the candidate lines in the next contingency set.

Step 8: END WHILE

End

B. THE SNP SYSTEM-BASED FAULT PROPAGATION

1) FAULT CHAIN

We employ fault chain theory to describe the fault propagation paths. A fault propagation can be represented as a fault chain

$$\vec{F}_y = \{L_1 \rightarrow L_2 \rightarrow \dots \rightarrow L_{M_y}\} \quad (8)$$

where L_x ($x = 1, 2, \dots, M_y$) represents the set of tripped lines in the contingency x . Therefore, the set of contingency

events can be represented as

$$\mathbf{F} = \{\vec{F}_1, \vec{F}_2, \dots, \vec{F}_Y\} \quad (9)$$

2) THE Ev-SNP SYSTEM-BASED FAULT CHAINS

For a temporal fault relationship $L_x \rightarrow L_{x+1}$ ($x = 1, 2, \dots, M_y - 1$) in \vec{F}_y , take L_x and L_{x+1} as the input proposition neuron set and output proposition neuron set, respectively. Denote the temporal fault relationship as r_x .

Definition 2: The knowledge representation of the aforementioned relationship can be represented as

$$L_{x+1} = L_x \otimes r_x \quad (10)$$

Define the neurotransmitter concentration w_x of the \otimes -neuron as

$$w_x = |L_{x+1}| / \left(|\vec{F}_y| |L_x| |L_1| \right) \quad (11)$$

where $|L_x|$ is the quantity of tripped lines in the contingency x . $|L_1|$ is the quantity of initial fault lines. $|\vec{F}_y|$ is the length of the fault chain y . In equation (11), the less of both $|\vec{F}_y|$ and $|L_1|$ demonstrates the fault chain can be trigger with higher possibility. Meanwhile, the less $|L_x|$ with more $|L_{x+1}|$ demonstrates fault propagation is more gravity from the contingency x to $x+1$. The neurotransmitter concentration w_x can reveal the gravity degree that the tripped lines in the contingency x propagate faults to candidate lines in the contingency $x+1$.

Therefore \vec{F}_y is described as

$$L_{M_y} = L_1 \otimes r_1 \otimes r_2 \cdots \otimes r_{M_y-1} \quad (12)$$

Definition 3: If $L_{x'} \in \vec{F}_1 \cap \vec{F}_2 \cap \cdots \cap \vec{F}_{Y'}$ ($Y' \leq Y$) and $L_{x'} = L_{x_i}^i \otimes r_{x'}^i$ ($i = 1, 2, \dots, Y'$), \oplus -neurons are employed to describe as

$$L_{x'} = [L_{x_1}^1 \otimes r_{x_1}^1, L_{x_2}^2 \otimes r_{x_2}^2, \dots, L_{x_{Y'}}^{Y'} \otimes r_{x_{Y'}}^{Y'}] \oplus r_{x'} \quad (13)$$

According to the definitions 2 and 3, the \mathbf{F} can be described as an Ev-SNP system consisted of proposition neurons and rule neurons.

Definition 4: If there exist two knowledge representations $L_{x+1} = L_x \otimes r_x$ in $|\vec{F}_y|$, $L_{x'+1} = L_{x'} \otimes r_{x'}$ in $|\vec{F}_{y'}|$ ($\vec{F}_y \neq \vec{F}_{y'}$), and $L' = L_{x+1} - L_{x'+1}$ ($L_{x'+1} \subset L_{x+1}$), the two knowledge representations are merged as

$$L_{x+1} \cap L_{x'+1} = L_x \otimes r_x \quad (14)$$

In addition, we employ $|\vec{F}_y|$ and $|L'_1|$ to define the neurotransmitter concentration w'_x of the \otimes -neuron as

$$w'_x = |L_{x'+1}| / \left(|\vec{F}_y| |L_x| |L'_1| \right) \quad (15)$$

where $L_x \in \vec{F}_y$ and $L'_1 \in \vec{F}_{y'}$. Equation (15) is the same meaning with equation (11).

Definition 5 If there exist two knowledge representations $L_{x+1} = L_x \otimes r_x$ in $|\vec{F}_y|$, $L_{x'+1} = L_{x'} \otimes r_{x'}$ in $|\vec{F}_{y'}|$ ($\vec{F}_y \neq \vec{F}_{y'}$), and $L' = L_x - L_{x'}$ ($L_{x'} \subset L_x$), the spikes of the L' cannot fire the \otimes -neuron; therefore the two knowledge representations are merged as $L_{x+1} = L_x \otimes r_x$.

C. REDUCTION OF THE Ev-SNP SYSTEMS

Although the Ev-SNP system can properly describe fault propagation paths, the dimension will become very large, leading to a difficulty in describing large-scaled power systems with increasing faults. To reduce the dimension of the Ev-SNP systems, a reduction-SNP system (RSNP system) is proposed by using single-input and single-output *AND-rule neuron* (\otimes -neuron). Thus, equation 10 can be expressed as:

$$L_i = L_j \otimes r_x^{ij} \quad (16)$$

where $L_i \in L_{x+1}$ ($i = 1, 2, \dots, |L_{x+1}|$), $L_j \in L_x$ ($j = 1, 2, \dots, |L_x|$).

The neurotransmitter concentration w_x of the \otimes -neuron remains as equation 11.

Definition 5: If there exist $L_{i_1} = L_{j_1} \otimes r_{x_1}^{i_1 j_1}$ in \vec{F}_1 , $L_{i_2} = L_{j_2} \otimes r_{x_2}^{i_2 j_2}$ in \vec{F}_2 , \dots , $L_{i_{Y'}} = L_{j_{Y'}} \otimes r_{x_{Y'}}^{i_{Y'} j_{Y'}}$ in $\vec{F}_{Y'}$ ($Y' \leq Y$, $\vec{F}_1 \neq \vec{F}_2 \neq \cdots \neq \vec{F}_{Y'}$) and $L_{i_1} = L_{i_2} = \cdots = L_{i_{Y'}}$ and $L_{j_1} = L_{j_2} = \cdots = L_{j_{Y'}}$, the knowledge representations are merged as

$$L_i = L_j \otimes r^{ij} \quad (17)$$

where $L_i = L_{i_1}$ and $L_j = L_{j_1}$. The neurotransmitter concentration w^{ij} of the \otimes -neuron is

$$w^{ij} = w_{x_1}^{i_1 j_1} + w_{x_2}^{i_2 j_2} + \cdots + w_{x_{Y'}}^{i_{Y'} j_{Y'}} \quad (18)$$

According to the above simplification, the RSNP system has advantageous characteristics as follows.

(1) The RSNP system avoids employing the *OR-rule neuron* (\oplus -neurons) and its dimension can effectively be reduced, which enhances the ability of visual modeling and reduces neurons of the system.

(2) By representing the Ev-SNP system by single-input and single-output rule neurons, the fault propagation relationship between single lines in an RSNP system can be highlighted, which helps to reveal the fault propagation mechanism of power systems.

(3) Through the simplified yet neat graph generated by the RSNP system, the modeling process can be more straightforward.

IV. CASE STUDY

In this section, the proposed model is applied to the IEEE 14-bus and 118-bus systems. The computational work is conducted in MATLAB, running on a laptop. The laptop (Compaq, v3646TU) is with Intel® Core™ 2 Duo CPU T7250 @ 2.00GHz CPU, 2.00G RAM, and 64bit windows 7 operating system. We employ the Monte Carlo method to generate the set of initial contingent events. For each fault propagation path, no more than three lines are randomly selected as the initial triggering lines.

A. IEEE 14-BUS SYSTEM

We first employ the Ev-SNP system \prod_1 to model the fault propagation paths of 20 chains to show modeling mechanism of the proposed method, as shown in Figure 3. It is noted

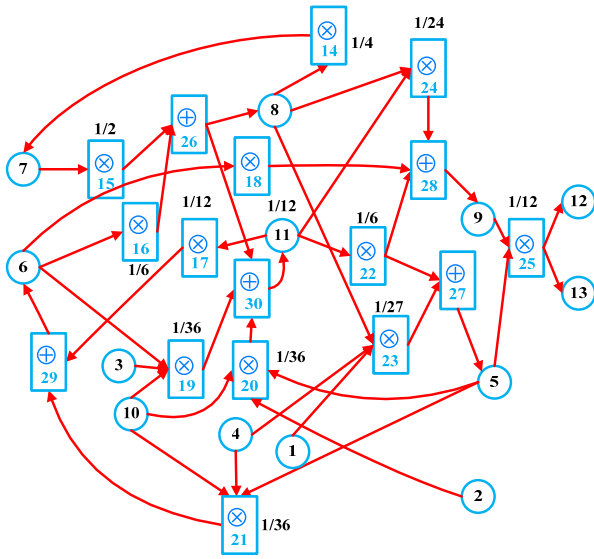


FIGURE 3. Ev-SNP system of 20 fault propagation chains.

that Figure 3 is used to simply show how the Ev-SNP system would look like in detail with a lower number of simulation, i.e. Figure 3 is not a “converged” graph with stable propagation paths.

$$\prod = (\mathbb{A}, \mathbb{Q}, \text{syn}, \mathbb{I}, \mathbb{O})$$

where

(1) $\mathbb{A} = \{a\}$ is a singleton alphabet (a is called spike and represent a fault);

(2) $\mathbb{Q} = \{\mathbb{Q}_1, \mathbb{Q}_2\}$ is a neuron set, where proposition neuron set is $\mathbb{Q}_1 = \{\sigma_1, \dots, \sigma_{13}\} = \{\sigma_{p1}, \dots, \sigma_{p13}\}$ and rule neuron set is $\mathbb{Q}_2 = \{\sigma_{14}, \dots, \sigma_{30}\} = \{\sigma_{r1}, \dots, \sigma_{r17}\}$, where $\sigma_{14}, \dots, \sigma_{25}$ are \otimes -neurons and $\sigma_{26}, \dots, \sigma_{30}$ are \oplus -neuron; i.e. $s = 13, t = 17, m = 30$;

(3) $\text{syn} = \{(1,23), (2,20), (3,19), (4,21), (4,23), (5,20), (5,21), (5,25), (6,16), (6,18), (6,19), (7,15), (8,14), (8,23), (8,24), (9,25), (10,19), (10,20), (10,21), (11,17), (11,22), (11,24), (14,7), (15,26), (16,26), (17,29), (18,28), (19,30), (20,30), (21,29), (22,27), (22,28), (23,27), (24,28), (25,12), (25,13), (26,8), (26,130), (27,5), (28,9), (29,6), (30,11)\}$;

(4) $\mathbb{I} = \{\sigma_{p1}, \sigma_{p2}, \sigma_{p3}, \sigma_{p10}\}$, $\mathbb{O} = \{\sigma_{p12}, \sigma_{p13}\}$.

It is manifest that the Ev-SNP system can reveal the fault propagation paths and the \otimes -neuron can indicate the condition of triggering line faults in the next contingency. For instance, when lines 5 and 9 (i.e., proposition neurons σ_5 and σ_9) are tripped, they emit a spike individually to the \otimes -neuron σ_{25} , leading to the triggering of lines 12 and 13 (i.e., proposition neurons σ_{12} and σ_{13}). Therefore the temporal fault propagation relationship among lines can be simply traced by the Ev-SNP system. In addition, the neurotransmitter concentrations of \otimes -neurons can reflect the possibility of activating \otimes -neurons. The propagation path $\sigma_7 \rightarrow \sigma_{15} \rightarrow \sigma_{26} \rightarrow \sigma_8$ can be triggered more easily and seriously than others due to the higher neurotransmitter concentration in \otimes -neuron σ_{15} . Meanwhile, line 11 (i.e., proposition neuron σ_{11}) is more easily affected by a fault because it can

receive spikes from more \otimes - or \oplus -neurons than others. In addition, it is noted that when a \oplus -neuron has multiple presynaptic \otimes -neurons, it demonstrates that the *event* associated with the postsynaptic neurons of the \oplus -neuron can be effected by the faults from different propagated paths. For example, the line 6 (i.e., proposition neuron σ_6) has a presynaptic \oplus -neuron (i.e., rule neuron σ_{16}), which demonstrates the line 6 can be affected by a propagated fault from two different combinations: a) line 11 (i.e., proposition neuron σ_{11}) and b) lines 4, 5 and 10 (i.e., proposition neuron $\sigma_4, \sigma_5, \sigma_{10}$).

Although the Ev-SNP system can reveal the fault propagation paths, the dimension of the Ev-SNP system becomes very high with the increasing of simulated events (i.e. fault chains); therefore, the modeling of the Ev-SNP system is very difficult for large-scaled networks. On the other hand, if we reduce the number of triggering contingent events, the model cannot comprehensively investigate fault propagation paths and reveal fault propagation relationships among lines. Therefore, we further proposed the RSNP system to analyze the fault propagation paths.

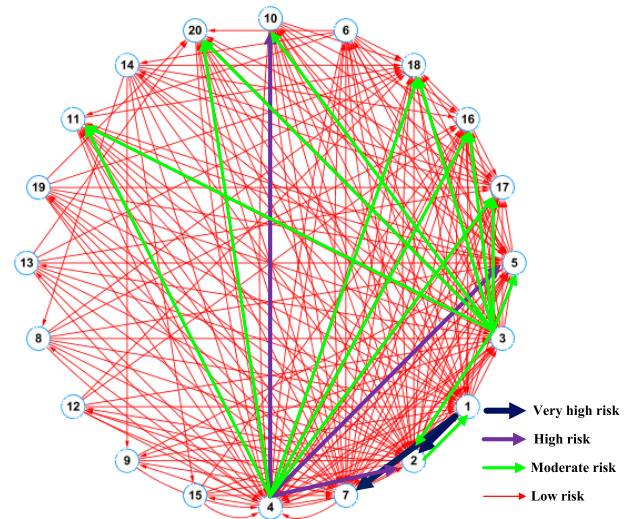


FIGURE 4. RSNP system with 1000 cascading chains.

Figures 4 and 5 give the results of the RSNP system with 1000 and 2000 fault chains, respectively, with \otimes -neurons omitted for the sake of space. Based on the neurotransmitter concentration w of \otimes -neurons, the fault propagation relationships among lines can be divided into four levels: very high risk ($w \geq 0.5$), high risk ($0.3 \leq w < 0.5$), moderate risk ($0.1 \leq w < 0.3$) and low risk ($w < 0.1$). The fault propagation relationships for the very high risk, high risk and moderate risk, except 4-5 and 4-10, are the same with 1000 and 2000 fault chains. Therefore, we can assert that when the simulation reaches 1000 cascading fault chains, the main fault propagation paths are credibly discovered.

In addition, the fault propagation paths 1-2 and 1-7 are very high risk, which indicates lines 2 and 7 will fail with high probability once line 1 fails; therefore line 1 is very high vulnerable line that needs prioritized protection. Similarly, line 4

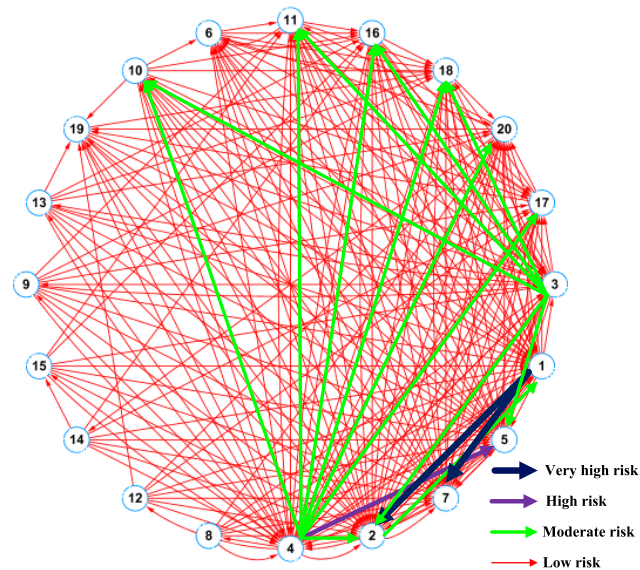


FIGURE 5. RSNP system with 2000 fault chains.

TABLE 1. Vulnerable lines and fault propagation path in 2000 contingency events.

Risk Level	Vulnerable line	Fault propagation
Very high risk	1	1-7, 1-2
High risk	4	4-5
	2	2-1
Moderate risk	3	3-2, 3-5, 3-10, 3-11, 3-16, 3-17, 3-18, 3-20
	4	4-2, 4-10, 4-11, 4-16, 4-17, 4-18, 4-20

is also a vulnerable line due to the propagation relationships among line 4 and other lines. Line 3 is a moderate vulnerable line, compared with lines 1 and 4. Although its risk level is not very high, it appears in many moderate risk propagation path, which makes it difficult to forecast the propagation in the next contingency; therefore line 3 should also be closely monitored during the normal operation. In summary, the results are shown in Table 1.

B. IEEE 118-BUS SYSTEM

To demonstrate the ability of the RSNP system on a large system, we employ the IEEE 118-bus system to simulate 2000 fault propagation paths, as shown in Figure 6. For the sake of clarity, only the paths over high risk are given.

There are mainly two groups of paths: small group with line 71 as the origin of faults and a large group with lines 3, 8, 36, 54, 96, 104, 107 and 108 as the sources of faults. In the small group, lines 70, 75, 76 and 81 fail with high probability once line 71 trips. In the large group, lines 36, 54 and 96 can only spread fault but are not easily affected by a propagated fault. By contrast, lines 3, 8, 104, 107 and 108 can spread faults as well as be affected by a fault. In addition, there are two main propagation paths in the large group: 36-3 and 36-8-(104, 107, 108). Therefore, strengthening the protection of the lines in the main propagation paths can effectively reduce or even avoid the fault propagation paths.

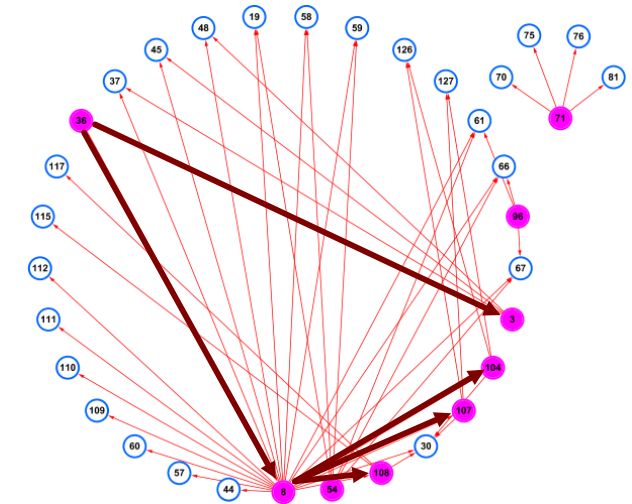


FIGURE 6. Fault propagation relationship over moderate risk with 2000 fault chains.

In summary, the Ev-SNP system and its simplified one (i.e., RSNP system) can reveal the fault propagation mechanism and fault temporal relationships among lines efficiently and intuitively due to the advantages of the SNP in terms of graphical modeling and parallel knowledge representations and logic reasoning.

V. CONCLUSIONS

The fault propagation path identification is fundamental to the power system analysis and secure operation of it as it forms the basis of all following countermeasures. To make the SNP system suitable for modeling fault propagation paths of power systems, this paper proposes an Ev-SNP system with neurotransmitter concentration representing the firing possibility of rule neurons. The Ev-SNP systems can reveal the fault propagation mechanism of fault propagation paths and temporal relationship among lines. In addition, the neurotransmitter concentrations of \otimes -neurons are introduced to reflect the possibility and gravity degree of fault propagation among lines. Moreover, the RSNP system is proposed because the original Ev-SNP systems is only suitable for the set of less contingency events. The proposed RSNP system can intuitively and effectively identify fault propagation paths and vulnerable lines.

In this paper, we extended the membrane computing application in power systems from a static single local element fault diagnosis to the dynamic relationship among multiple elements in a system wide scale. The proposed method has been successfully applied the SNP system to a large power system application in terms of investigating the fault propagation paths through a reasonable abstraction of the protection scheme of the element in the power systems.

The proposed method has the following advantages over the previous tools: 1) modeling the problem in such a holistic and systematic way that the complexity and non-linear feature can be captured, i.e. the self-organizational and butterfly effects can be naturally considered in the model; 2) modeling

the fault propagation through a visualization fashion and an analogy between the fault propagation in the electricity grid and the spike transmission in the neuron networks. This analogy allows us to use the synaptic connections among neurons to describe the logical and temporal relationship among power equipment, thus the fault propagation can be modeled as the natural response of a biological system. So, the proposed method has an intuitive illustration based on a strictly mathematical expression, a good description for the adjacent fault relationships between branches, and an understandable graphical model-building process.

In the future, our work is further to develop the software of SNP systems to analyze the fault propagation characteristics online of real power networks. In addition, SNP systems can be improved to model fault propagation paths of large complex power systems, such as smart grids with distributed generations, microgrids, etc.

REFERENCES

- [1] G. Păun, "Computing with membranes," *J. Comput., Syst. Sci.*, vol. 61, no. 1, pp. 108–143, 2000. [Online]. Available: <http://www.tucs.fi>
- [2] G. Păun and M. J. Pérez-Jiménez, "Membrane computing: Brief introduction, recent results and applications," *Biosystems*, vol. 85, no. 1, pp. 11–22, Jul. 2006.
- [3] T. Wang, G. X. Zhang, and M. J. Pérez-Jiménez, "Fuzzy membrane computing: Theory and applications," *Int. J. Comput. Commun.*, vol. 10, no. 6, pp. 861–892, Oct. 2015.
- [4] G. Păun, G. Rozenberg, and A. Salomaa, *The Oxford Handbook of Membrane Computing*. New York, NY, USA: Oxford Univ. Press, 2010.
- [5] G. Zhang, M. Gheorghe, L. Pan, and M. J. Pérez-Jiménez, "Evolutionary membrane computing: A comprehensive survey and new results," *Inf. Sci.*, vol. 279, pp. 528–551, Sep. 2014.
- [6] C. Martín-Vide, G. Păun, J. Pazos, and A. Rodríguez-Patón, "Tissue P systems," *Theor. Comput. Sci.*, vol. 296, no. 2, pp. 295–326, 2003.
- [7] B. Song, C. Zhang, and L. Pan, "Tissue-like P systems with evolutionary symport/antiport rules," *Inf. Sci.*, vol. 378, pp. 177–193, Feb. 2017.
- [8] H. Peng, J. Wang, P. Shi, M. J. Pérez-Jiménez, and A. Riscos-Núñez, "Fault diagnosis of power systems using fuzzy tissue-like P systems," *Integr. Comput.-Aided Eng.*, vol. 24, pp. 401–411, Jan. 2017.
- [9] T. Wang et al., "Application of neural-like P systems with state values for power coordination of photovoltaic/battery microgrids," *IEEE Access*, vol. 6, pp. 46630–46642, 2018.
- [10] T. Wu, A. Păun, Z. Zhang, and L. Pan, "Spiking neural P systems with polarizations," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 29, no. 8, pp. 3349–3360, Aug. 2018.
- [11] L. Pan, G. Păun, G. Zhang, and F. Neri, "Spiking neural P systems with communication on request," *Int. J. Neural Syst.*, vol. 27, no. 8, p. 1750042, 2017.
- [12] D. Díaz-Pernil and M. A. Gutiérrez-Naranjo, "Semantics of deductive databases with spiking neural P systems," *Neurocomputing*, vol. 272, pp. 365–373, Jan. 2018.
- [13] H. Peng et al., "Competitive spiking neural P systems with rules on synapses," *IEEE Trans. NanoBiosci.*, vol. 16, no. 8, pp. 888–895, Dec. 2017.
- [14] T. Pan, X. Shi, Z. Zhang, and F. Xu, "A small universal spiking neural P system with communication on request," *Neurocomputing*, vol. 275, pp. 1622–1628, Jan. 2018.
- [15] G. Zhang, H. Rong, F. Neri, and M. J. Pérez-Jiménez, "An optimization spiking neural P system for approximately solving combinatorial optimization problems," *Int. J. Neural Syst.*, vol. 24, no. 5, p. 1440006, 2014.
- [16] D. Díaz-Pernil, F. P. Cantillana, and M. A. Gutiérrez-Naranjo, "A parallel algorithm for skeletonizing images by using spiking neural P systems," *Neurocomputing*, vol. 115, pp. 81–91, Sep. 2013.
- [17] R. K. Idowu, R. C. Muniyandi, and Z. A. Othman, "The prospects of using spiking neural P system for intrusion detection," *Int. J. Inf. Netw. Secur.*, vol. 2, no. 6, pp. 492–498, 2013.
- [18] J. Wang, P. Shi, H. Peng, M. J. Pérez-Jiménez, and T. Wang, "Weighted fuzzy spiking neural P systems," *IEEE Trans. Fuzzy Syst.*, vol. 21, no. 2, pp. 209–220, Apr. 2013.
- [19] J. Wang and H. Peng, "Adaptive fuzzy spiking neural P systems for fuzzy inference and learning," *Int. J. Comput. Math.*, vol. 90, no. 4, pp. 857–868, Apr. 2013.
- [20] T. Wang, J. Wang, H. Peng, and H. Wang, "Knowledge representation and reasoning based on FRSN P systems," in *Proc. WCICA*, Beijing, China, 2011, pp. 849–854.
- [21] T. Wang, J. Wang, H. Peng, and Y. Deng, "Knowledge representation using fuzzy spiking neural P system," in *Proc. BIC-TA*, Beijing, China, 2010, pp. 586–590.
- [22] T. Wang, S. Zeng, G. Zhang, M. J. Pérez-Jiménez, and J. Wang, "Fault section estimation of power systems with optimization spiking neural P systems," *Sci. Technol.*, vol. 18, no. 3, pp. 240–255, 2015.
- [23] T. Wang, G. Zhang, and M. J. Pérez-Jiménez, "Fault diagnosis models for electric locomotive systems based on fuzzy reasoning spiking neural P systems," in *Membrane Computing* (Lecture Notes in Computer Science), vol. 8961. Cham, Switzerland: Springer, 2014, pp. 361–374.
- [24] T. Wang, G. Zhang, M. J. Pérez-Jiménez, and J. Cheng, "Weighted fuzzy reasoning spiking neural P systems: Application to fault diagnosis in traction power supply systems of high-speed railways," *J. Comput. Theor. Nanos.*, vol. 12, no. 7, pp. 1103–1114, Jul. 2015.
- [25] Y. Y. He, T. Wang, K. Huang, G. Zhang, and M. J. Pérez-Jiménez, "Fault diagnosis of metro traction power systems using a modified fuzzy reasoning spiking neural P system," *Romanian J. Inf. Sci. Technol.*, vol. 18, no. 3, pp. 256–272, Jan. 2015.
- [26] G. Xiong, D. Shi, L. Zhu, and X. Duan, "A new approach to fault diagnosis of power systems using fuzzy reasoning spiking neural P systems," *Math. Problems Eng.*, vol. 2013, May 2013, Art. no. 815352.
- [27] T. Wang, G. Zhang, J. Zhao, Z. He, J. Wang, and M. J. Pérez-Jiménez, "Fault diagnosis of electric power systems based on fuzzy reasoning spiking neural P systems," *IEEE Trans. Power Syst.*, vol. 30, no. 3, pp. 1182–1194, May 2015.
- [28] H. Peng et al., "Fault diagnosis of power systems using intuitionistic fuzzy spiking neural P systems," *IEEE Trans. Smart Grid*, vol. 9, no. 5, pp. 4777–4784, Sep. 2018.
- [29] X. Xie, D. Yue, H. Zhang, and Y. Xue, "Fault estimation observer design for discrete-time Takagi–Sugeno fuzzy systems based on homogenous polynomially parameter-dependent Lyapunov functions," *IEEE Trans. Cybern.*, vol. 47, no. 9, pp. 2504–2513, Sep. 2017.
- [30] J. Yan, Y. Tang, H. He, and Y. Sun, "Cascading failure analysis with DC power flow model and transient stability analysis," *IEEE Trans. Power Syst.*, vol. 30, no. 1, pp. 285–297, Jan. 2015.
- [31] H. T. Ma and B. H. Chowdhury, "Dynamic simulations of cascading failures," in *Proc. 38th North Amer. Power Symp. (NAPS)*, Carbondale, IL, USA, Sep. 2006, pp. 619–623.
- [32] S. Poudel, Z. Ni, T. M. Hansen, and R. Tonkoski, "Cascading failures and transient stability experiment analysis in power grid security," in *Proc. IEEE Power Energy Soc. Innov. Smart Grid Technol. Conf. (ISGT)*, Minneapolis, MN, USA, Sep. 2016, pp. 1–5.
- [33] C. Luo, J. Yang, Y. Sun, J. Yan, H. He, and M. Liu, "A cascading failure simulation model considering frequency dynamics and power flow distribution," in *Proc. North Amer. Power Symp. (NAPS)*, Charlotte, NC, USA, Oct. 2015, pp. 1–6.
- [34] S. Mei, Y. Ni, G. Wang, and S. Wu, "A study of self-organized criticality of power system under cascading failures based on AC-OPF with voltage stability margin," *IEEE Trans. Power Syst.*, vol. 23, no. 4, pp. 1719–1726, Nov. 2008.
- [35] B. A. Carreras, V. E. Lynch, I. Dobson, and D. E. Newman, "Complex dynamics of blackouts in power transmission systems," *Chaos, Interdiscipl. J. Nonlinear Sci.*, vol. 14, no. 3, pp. 643–652, Sep. 2004.
- [36] R. Kinney, P. Crucitti, R. Albert, and V. Latora, "Modeling cascading failures in the North American power grid," *Eur. Phys. J. B-Condensed Matter Complex Syst.*, vol. 46, no. 1, pp. 101–107, 2005.
- [37] J. Bialek et al., "Benchmarking and validation of cascading failure analysis tools," *IEEE Trans. Power Syst.*, vol. 31, no. 6, pp. 4887–4900, Nov. 2016.
- [38] M. Rahnamay-Naeini, Z. Wang, N. Ghani, A. Mammoli, and M. M. Hayat, "Stochastic analysis of cascading-failure dynamics in power grids," *IEEE Trans. Power Syst.*, vol. 29, no. 4, pp. 1767–1779, Jul. 2014.

- [39] X. Zou, L. Cheng, and Y. Sun, "Evaluation of cascading failure in power system based on the operational reliability theory," in *Proc. IEEE 11th Int. Conf. Probabilistic Methods Appl. Power Syst. (PMAPS)*, Singapore, Jun. 2010, pp. 184–189.
- [40] P. Rezaei, P. D. H. Hines, and M. J. Eppstein, "Estimating cascading failure risk with random chemistry," *IEEE Trans. Power Syst.*, vol. 30, no. 5, pp. 2726–2735, Sep. 2014.
- [41] S. Mei, F. He, X. Zhang, S. Wu, and G. Wang, "An improved OPA model and blackout risk assessment," *IEEE Trans. Power Syst.*, vol. 24, no. 2, pp. 814–823, May 2004.
- [42] X. Liu and Z. Li, "Revealing the impact of multiple solutions in DCOPF on the risk assessment of line cascading failure in OPA model," *IEEE Trans. Power Syst.*, vol. 31, no. 5, pp. 4159–4160, Sep. 2016.
- [43] I. Dobson, B. A. Carreras, V. E. Lynch, and D. E. Newman, "An initial model FO complex dynamics in electric power system blackouts," in *Proc. Hawaii Int. Conf. Syst. Sci.*, Maui, HI, USA, Jan. 2001, pp. 710–718.
- [44] I. Dobson, B. A. Carreras, and D. E. Newman, "A probabilistic loading-dependent model of cascading failure and possible implications for blackouts," in *Proc. 36th Annu. Hawaii Int. Conf. Syst. Sci.*, 2003, vol. 19, no. 1, pp. 15–32.
- [45] I. Dobson, B. A. Carreras, V. Lynch, and D. E. Newman, "Complex systems analysis of series of blackouts: Cascading failure, criticality, and self-organization," in *Proc. Bulk Power Syst. Dyn. Control-VI*, Italy, Aug. 2004, pp. 438–451.
- [46] Å. J. Holmgren, "Using graph models to analyze the vulnerability of electric power networks," *Risk Anal.*, vol. 26, no. 4, pp. 955–969, 2006.
- [47] V. Rosato, S. Bologna, and F. Tiriticco, "Topological properties of high-voltage electrical transmission networks," *Electr. Power Syst. Res.*, vol. 77, no. 2, pp. 99–105, 2007.
- [48] M. Rosas-Casals, S. Valverde, and R. V. Solé, "Topological vulnerability of the European power grid under errors and attacks," *Int. J. Bifurcation Chaos*, vol. 17, no. 7, pp. 2465–2475, 2007.
- [49] X. Wei, J. Zhao, T. Huang, and E. Bompard, "A novel cascading faults graph based transmission network vulnerability assessment method," *IEEE Trans. Power Syst.*, vol. 33, no. 3, pp. 2995–3000, May 2018.
- [50] X. Wei, S. Gao, T. Huang, E. Bompard, R. Pi, and T. Wang, "Complex network based cascading faults graph for the analysis of transmission network vulnerability," *IEEE Trans. Ind. Informat.*, to be published, doi: [10.1109/TII.2018.2840429](https://doi.org/10.1109/TII.2018.2840429).
- [51] X. Wei et al., "Cascading fault graph for the analysis of transmission network vulnerability under different attacks," in *Proc. CSEE*, Jan. 2018, vol. 38, no. 2, pp. 465–474.
- [52] Y. Zhu, J. Yan, Y. Sun, and H. He, "Revealing cascading failure vulnerability in power grids using risk-graph," *IEEE Trans. Parallel Distrib. Syst.*, vol. 25, no. 12, pp. 3274–3284, Dec. 2014.
- [53] P. D. H. Hines, I. Dobson, and P. Rezaei, "Cascading power outages propagate locally in an influence graph that is not the actual grid topology," *IEEE Trans. Power Syst.*, vol. 32, no. 2, pp. 958–967, Mar. 2016.
- [54] Z.-N. Fan et al., "Effect of damper winding and stator slot skewing structure on no-load voltage waveform distortion and damper bar heat in large tubular hydro generator," *IEEE Access*, vol. 6, pp. 22281–22291, 2018.
- [55] J. Qi, K. Sun, and S. Mei, "An interaction model for simulation and mitigation of cascading failures," *IEEE Trans. Power Syst.*, vol. 30, no. 2, pp. 804–819, Mar. 2015.
- [56] W. Ju, K. Sun, and J. Qi, "Multi-layer interaction graph for analysis and mitigation of cascading outages," *IEEE J. Emerg. Sel. Topics Circuits Syst.*, vol. 7, no. 2, pp. 239–249, Jun. 2017.



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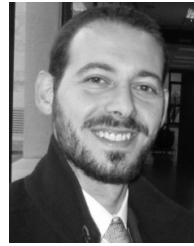
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