The 20th Brainstorming Week on Membrane Computing
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西華大學
Xihua University

Applications of Membrane Computing in power systems

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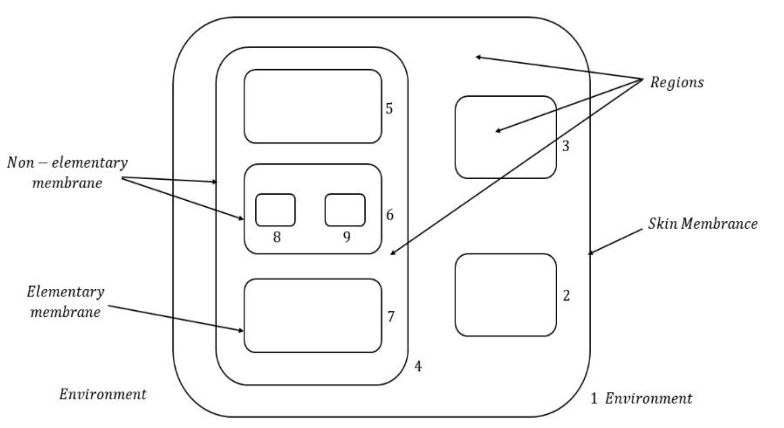
Outline:

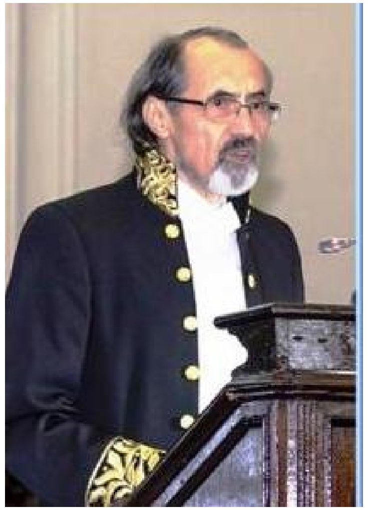
1. Background
2. Applications of membrane computing in fault diagnosis of transmission networks
3. Applications of membrane computing in fault diagnosis of distribution networks
4. Applications of membrane computing in optimal operation of integrated energy systems
5. Applications of virus machines in power systems

Background

Membrane Computing (P systems)

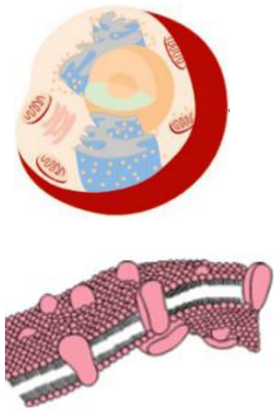


Membrane computing, formally introduced by Păun, aims at abstracting computing models from the structure and the functioning of living cells, as well as from the way that cells are organized in tissues or higher order structures.

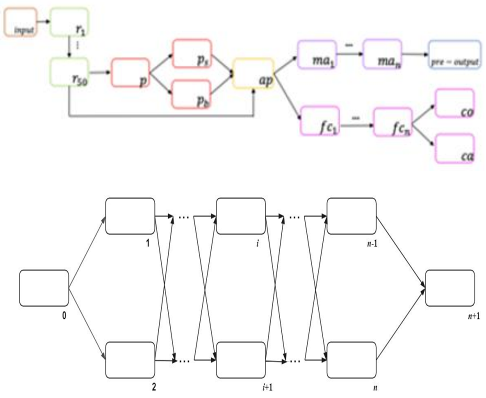


Gheorghe Păun

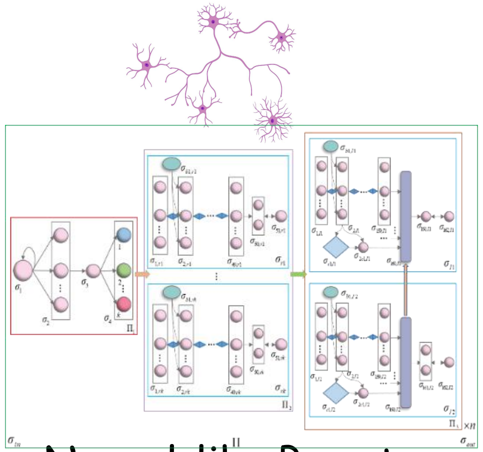
Member of Academia Europaea & Romanian Academy of Science, MC, 1998



Cell-like P system



Tissue-like P system



Neural-like P system

- Tao Wang, Gexiang Zhang*, Junbo Zhao, Zhengyou He, Jun Wang, Mario J. Pérez-Jiménez. Fault diagnosis of electric power systems based on fuzzy reasoning spiking neural P systems. IEEE Transactions on Power Systems, 2015, 30(3): 1182-1194.

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1. Background
2. Applications of membrane computing in fault diagnosis of transmission networks
3. Applications of membrane computing in fault diagnosis of distribution networks
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5. Applications of virus machines in power systems

Fault diagnosis of transmission networks

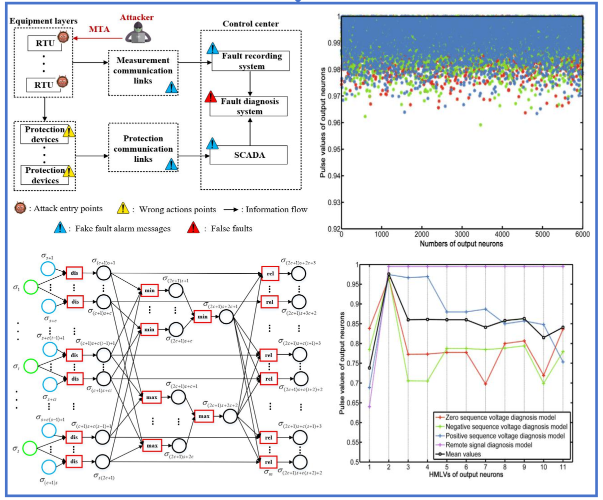
Applications of **membrane computing** in fault diagnosis of transmission networks

Applications of **spiking neural P systems** in fault diagnosis of transmission networks

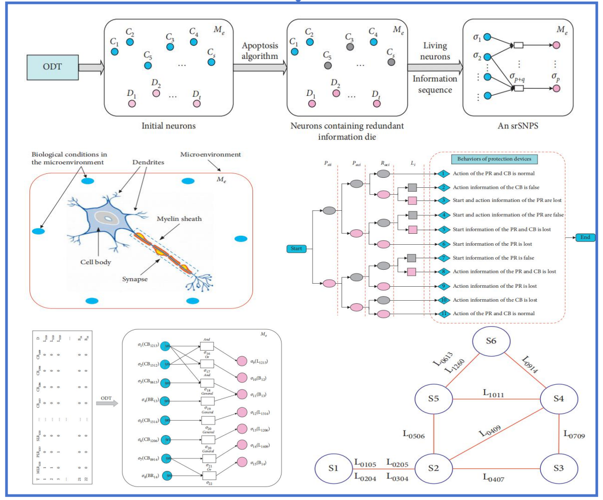
Considering attacks

Fault diagnosis

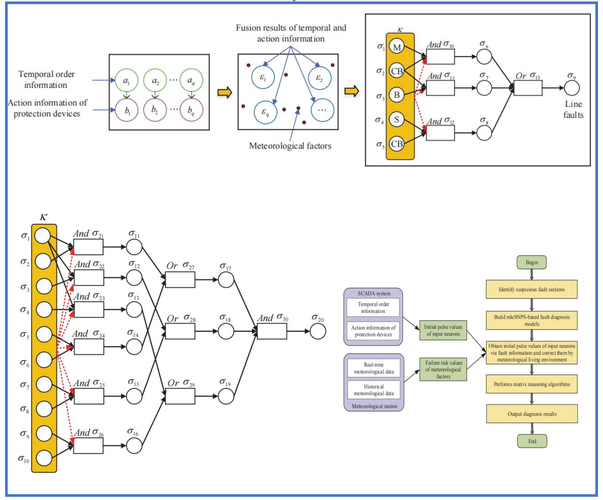
Considering meteorological factors



A novel fault diagnosis method of smart grids based on memory spiking neural P systems considering measurement tampering attacks



A fault diagnosis method for power transmission networks based on spiking neural P systems with self-updating rules considering biological apoptosis mechanism



A fault diagnosis method considering meteorological factors for transmission networks based on P systems

Fault diagnosis of transmission networks

Definition 1. A spiking neural P system with self-updating rules (srSNPS) is a tuple:

$$\Pi = (O, M_e, \sigma_1, \ldots, \sigma_m, \mathrm{syn}, \mathrm{in}, \mathrm{out}), \qquad (1)$$

where

(1) $O = \{a\}$ is a singleton alphabet (a is called a spike, O is a set of spikes).

(2) $M_e = (D_i, C_j)$ is called microenvironment, where

(a) $D_i = (\theta_{di/T}, T, f_i)$, $1 \le i \le s$, is the i-th decision-making neuron (DN) in M_e and represents suspicious faulty equipment in the targeted power network, where

(3) $\sigma_i = (\theta_i, r_i, e_i)$, $1 \le i \le p$, is the i-th proposition neuron (PN) corresponding to a protection device or the equipment, $\sigma_j = (\delta_j, r_j)$, $1 \le j \le q$, is the j-th rule neuron (RN) corresponding to a fault production rule, and $p + q = m$, where

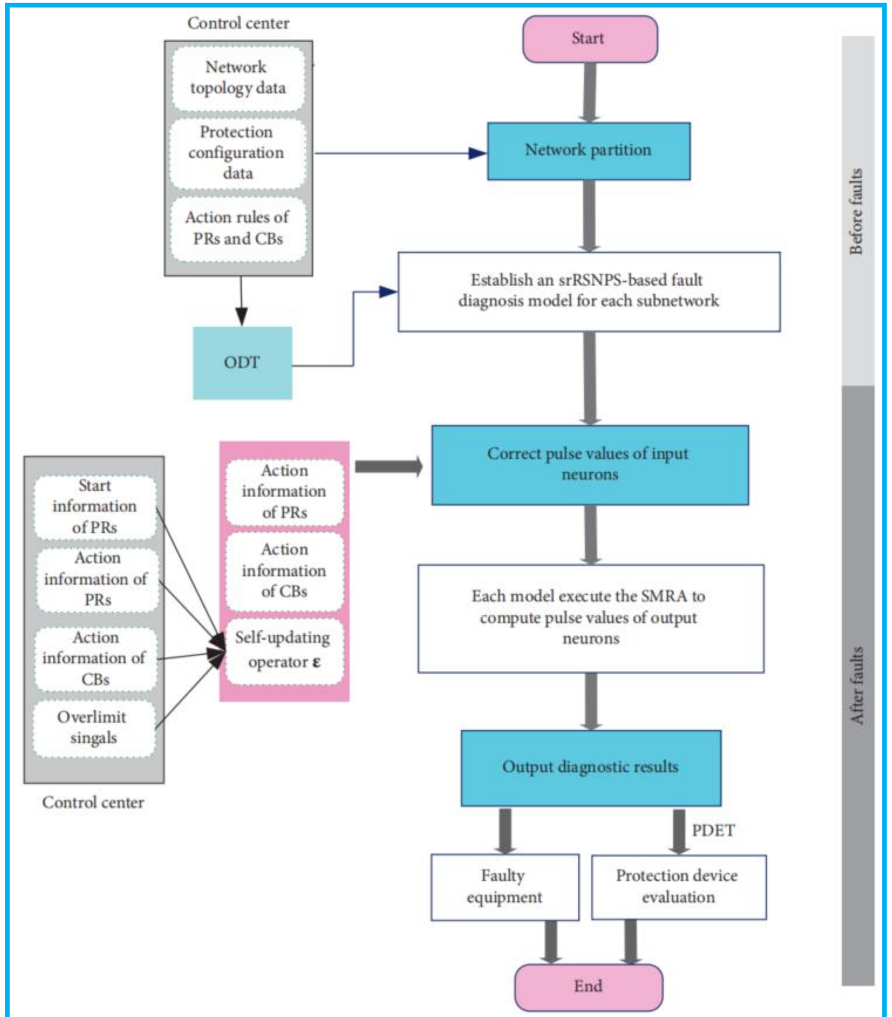
(a) θ_i and δ_j are pulse values (equal to 0 or 1) in proposition neuron σ_i and rule neuron σ_j, respectively.

(b) r_i represents a firing rule of σ_i with the form $E/a^{\theta} \longrightarrow a^{\theta}$, where $E = \{a\}$ is the firing condition, which means that once σ_i contains a spike, r_i can be applied. Then, σ_i will consume a spike with pulse value θ, produce a new spike with the same pulse value, and then transmit it to its postsynaptic neurons; r_j represents a firing rule of σ_j with the form $E/a^{\delta} \longrightarrow a^{\beta}$, where $E = \{a\}$ is the firing condition, which means that once σ_j contains a spike, r_j can be applied. Then, σ_j will consume a spike with pulse value δ, produce a new spike with pulse value β (equals to 0 or 1), and then transmit it to its postsynaptic neurons.

(c) e_i represents a self-updating rule of the form $E/a^{\theta} \longrightarrow a^{\bar{\theta}}$. The firing condition is $E = \{\varepsilon_i > 0\}$, which means that e_i can be applied if and only if the self-updating operator $\varepsilon_i > 0$. Then, σ_i will consume a spike with pulse value θ, produce a new spike with pulse value $\overline{\theta}$ (equals to 0 or 1, called the antispike of θ), and then $\varepsilon_i = \varepsilon_i - 1$. Note that only input proposition neurons contain self-updating rules.

4) $\mathrm{syn} \subseteq \{1, \ldots, m\} \times \{1, \ldots, m\}$ with $i \ne j$ for all $(i, j) \in \mathrm{syn}$ for $1 \le i, j \le m$ is a directed synaptic connection between linked neurons.

5) in, out indicate the input neuron set and output neuron set, respectively.



Flowchart of the proposed srSNPS-based fault diagnosis method

Research 1: A fault diagnosis method for power transmission networks based on spiking neural P systems with self-updating rules considering biological apoptosis mechanism

- Wei Liu, Tao Wang*, Tianlei. Zang, Zhu Huang, Jun Wang, Tao Huang, XiaoGuang Wei, Chuan Li. A fault diagnosis method for power transmission networks based on spiking neural P systems with self-updating rules considering biological apoptosis mechanism. Complexity, 2020, Article ID: 2462647.

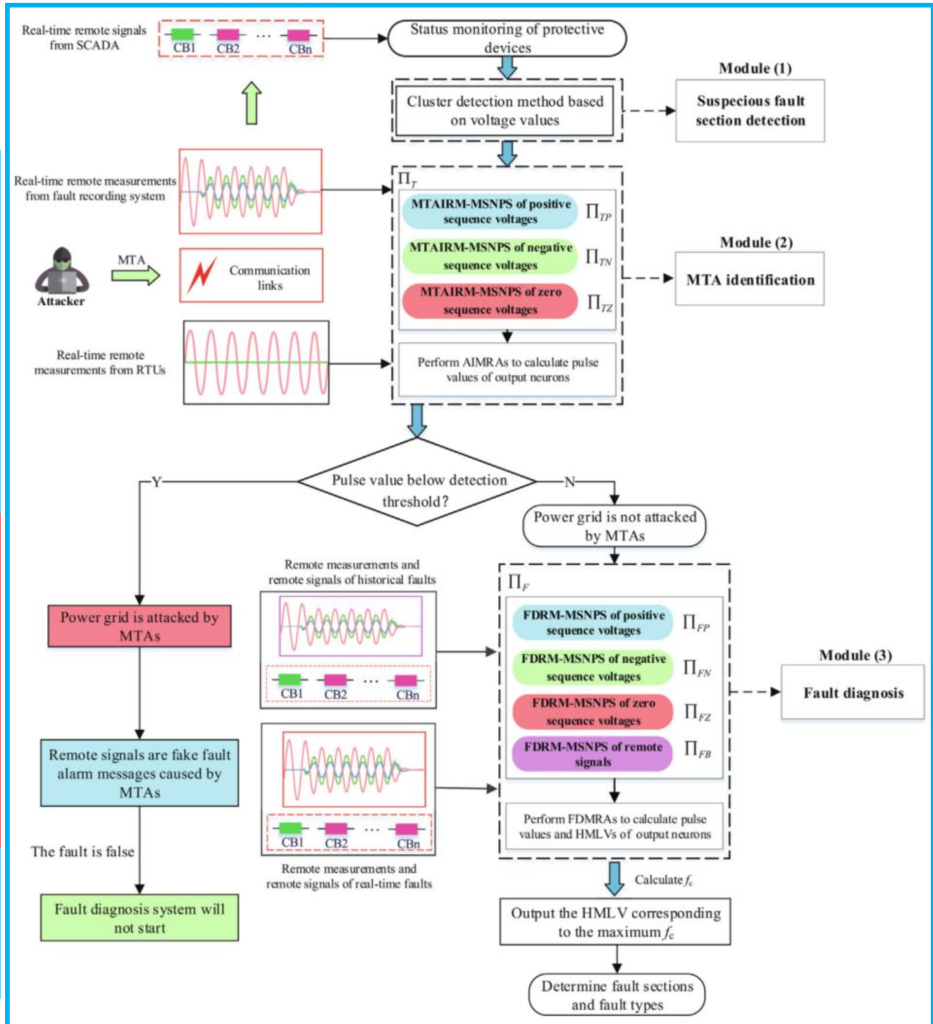
Fault diagnosis of transmission networks

Definition 1. A memory spiking neural P system (MSNPS) of degree $m \geqslant 1$ is a tuple $\Pi = (O, \sigma_1, \ldots, \sigma_m, syn, in, out)$, where:

(1) $O = \{a\}$ is a singleton alphabet (a is called a spike).
(2) $\sigma_1, \ldots, \sigma_m$ are m neurons. $\sigma_i = (\theta_i, \lambda_i, c, \tau_i, r_i), i = 1, \ldots, m$, represents the i-th neuron, where:

(a) θ_i is the real number in $[-1, 1]$, representing the pulse value in σ_i.
(b) λ_i represents the firing threshold of σ_i. According to the characteristics of fault diagnosis of smart grids, the thresholds of all neurons are set to 0.
(c) c is a natural number, indicating the number of historical memory events. Its value is determined by the types of historical events associated with the problem to be solved. For the MTA identificaiton and fault diagnosis problems in this paper, c is set to 0 and 11 according to the considered attack and fault types, respectively.
(d) τ_i is an integer in $[0, c]$, representing the historical memory label value (HMLV) in σ_i. If a neuron does not have an HMLV, then the value is 0.
(e) r_i represents the firing rule of σ_i with the form of $E/a^{(\theta,\tau)} \rightarrow a^{(\beta,\tau)}$. The firing condition is $E = \{a^n; |\theta| > \lambda_i\}$, which means that r_i can be applied if and only if σ_i receives at least n spikes with its pulse value $|\theta| > \lambda_i$. Then, σ_i will consume a spike with a pulse value θ and an HMLV τ, and will produce and emit a new spike with a pulse value β and an HMLV τ to its postsynaptic neurons.

(3) $syn \subseteq \{1,\ldots,m\} \times \{1,\ldots,m\}$ with $i \neq j$ for all $(i,j) \in syn$ $(1 \leqslant i,j \leqslant m)$ is a directed synaptic connection between linked neurons.
(4) $in, out \subseteq \{1, \ldots, m\}$ indicate input neuron and output neuron sets, respectively.



Schematic diagram of the proposed method

Research 2: A novel fault diagnosis method of smart grids based on memory spiking neural P systems considering measurement tampering attacks

- Tao Wang*, Wei Liu, Luis Valencia-Cabrera, Peng Wang, Xiaoguang Wei, Tianlei Zang. A novel fault diagnosis method of smart grids based on memory spiking neural P systems considering measurement tampering attacks, Information Sciences, 2022, 596: 520-536.

Fault diagnosis of transmission networks

Definition 1. *A spiking neural P system considering the meteorological living environment (mleSNPS) with a degree of $m \geq 1$ is a tuple*

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

where

(1) $O = \{a\}$ *is a set of singleton alphabets, and* a *denotes a spike.*

(2) $\sigma_1, \ldots, \sigma_m$ *are neurons, which consist of two classes, i.e., rule neurons and proposition neurons. A rule neuron corresponds to a fuzzy fault production rule, while a proposition neuron is associated with a proposition in the rule. Each neuron* σ_i $(i = 1, \ldots, m)$ *is of the form* $(\theta_i, c_i, \vec{\omega}_i, \lambda_i, r_i)$, *where*

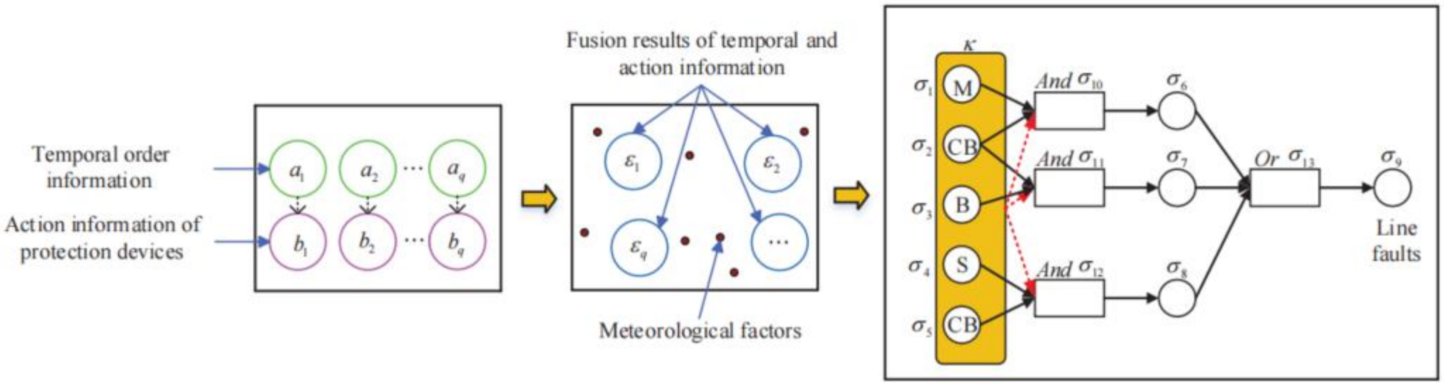
- (a) θ_i *is a real number in* $[0,1]$, *which denotes the pulse value of the neuron.*
- (b) c_i *is a real number in* $[0,1]$, *which represents the fuzzy truth value of the neuron. If* σ_i *is a proposition neuron, then* $c_i = 0$; *otherwise,* c_i *is equal to the certainty factor of the fuzzy production rule corresponding to* σ_i;
- (c) $\vec{\omega}_i = (\omega_{1\to i}, \ldots, \omega_{N_i \to i})$ *expresses the input weight vector of* σ_i, *where* $\omega_{k\to i}$ $(k = 1, \ldots, N_i$ *is set as 0.5 or 1, representing the weight value of* σ_i *from its k-th presynaptic neuron;* N_i *is a natural number, denoting the number of synapses that end at neuron* σ_i. *Specifically, input weights beginning from input neurons are set as 0.5, while the others are set as 1. This is because an input neuron corresponds to a protection device (i.e., a protective relay or a circuit breaker). Usually, the two kinds of protection devices play an equally important role in computation.*
- (d) λ_i *is a real number in* $[0,1]$, *which indicates the firing (spiking) threshold of the neuron. In this paper,* $\lambda_i = 0.2$ [13];
- (e) r_i *represents the firing rule of* σ_i, *which is in the form of* $E/a^{\theta} \to a^{\beta}$, *where both* θ *and* β *are real numbers in* $[0,1]$; $E = \{a^n, \theta \geq \lambda_i\}$ *denotes the firing condition of* r_i. *The fire rule can be applied if and only if it receives at least n spikes with potential value* $\theta \geq \lambda_i$. *When different types of neurons execute the firing rules, their pulse values are updated in different manners, which is explained in detail following Definition 1.*

(3) $syn \subseteq \{1, \ldots, m\} \times \{1, \ldots, m\}$ *denotes the directional-weighted synaptic connection between neurons in* Π, *where* $i \neq j$ *for all* $(i,j) \in syn$ $(1 \leq i, j \leq m)$.

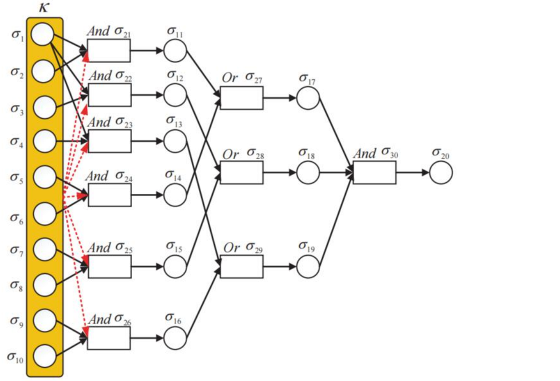
(4) $in, out \subseteq \{1, \ldots, m\}$ *represent the sets of input and output neurons, respectively. It is worth noting that an input neuron corresponds to a protection device (i.e., a protective relay or a circuit breaker) of a suspicious fault transmission line. Initial pulse values of input neurons represent the correction values of fusion results of action information of corresponding protection devices and temporal order information. An output neuron is associated with a suspicious fault transmission line, and its pulse value denotes the fault confidence level of the corresponding section.*

(5) $\kappa = (\gamma, \xi, f, \rho)$ *indicates the meteorological living environment of input neurons, where*

- (a) γ *is a real number in* $[0,1]$ *representing the failure risk value of a suspicious transmission line considering meteorological factors.*
- (b) ξ *is a real number in* $(0,1)$ *representing the weight of* γ *in input parameters of a fault diagnosis model. Its value is set according to the influence degree of a meteorological level on the communication system of a power grid.*
- (c) f *denotes the firing threshold of an eliminating rule of the meteorological living environment. In this paper,* f *is set as 0.5 according to expertise.*
- (d) ρ *expresses an eliminating rule, whose firing condition is* $E = \{\gamma < f\}$, *meaning that rule* ρ *can be applied if and only if* $\gamma < f$. *Afterwards, the influence of meteorological factors on the transmission line will not be considered in the diagnosis model; i.e., the influence of meteorological factors on a line fault will not be taken into account in the subsequent diagnosis process. Otherwise, the rule* ρ *cannot be executed. In this case, the influence of meteorological factors on the fault should be considered in the diagnosis process; that is, the fault risk value* γ *should be one of the input parameters of the diagnosis model.*



Sketch map of building process of mleSNPS-based diagnosis model



The mleSNPS-based fault diagnosis model of B03

Research 3: A fault diagnosis method considering meteorological factors for transmission networks based on P systems

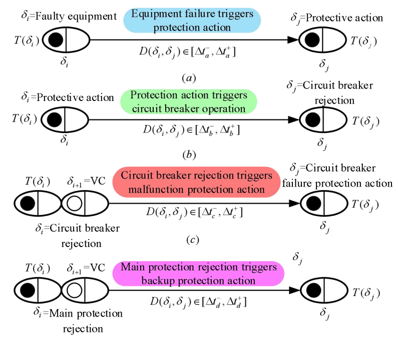
- Xiaotian Chen, Tao Wang*, Ruixuan Ying, Zhibo Cao. A fault diagnosis method considering meteorological factors for transmission networks based on P systems. Entropy, 2021, 23(8), Article ID: 1008.

Fault diagnosis of transmission networks

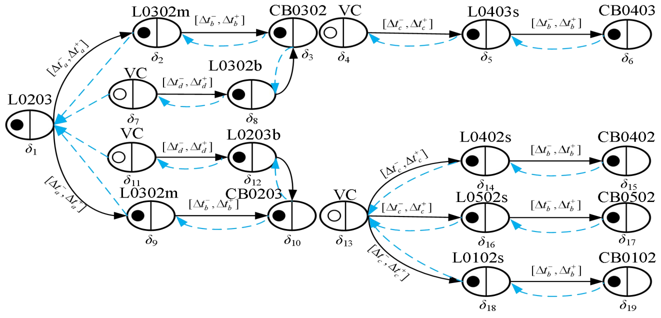
Applications of **membrane computing** in fault diagnosis of transmission networks

Applications of **Cell-like P systems** in fault diagnosis of transmission networks

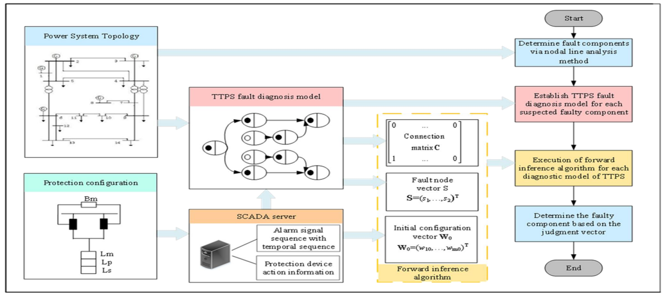
A fault diagnosis method for power systems based on temporal tissue-like P systems



Four types of correlations in TTPS

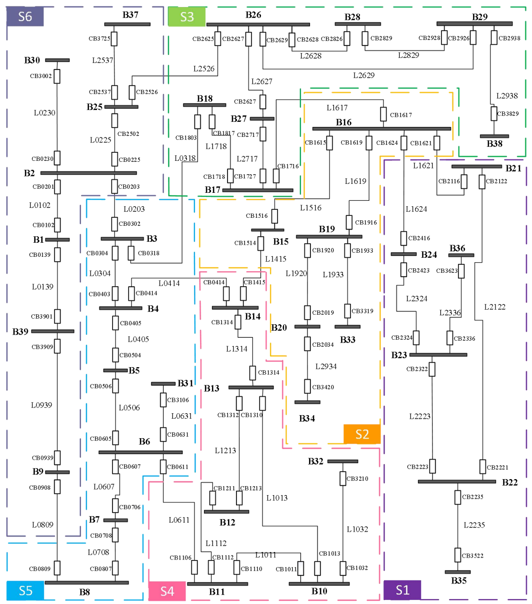


TTPS-based fault diagnosis model of L0203

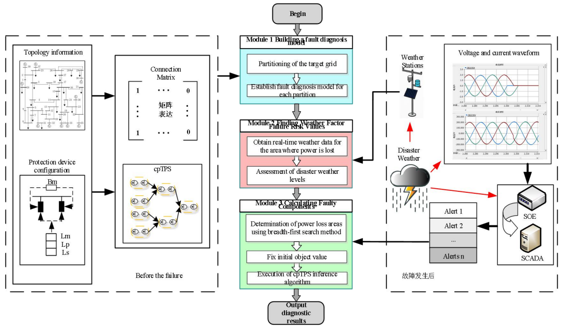


Framework of fault diagnosis of power system based on TTPS

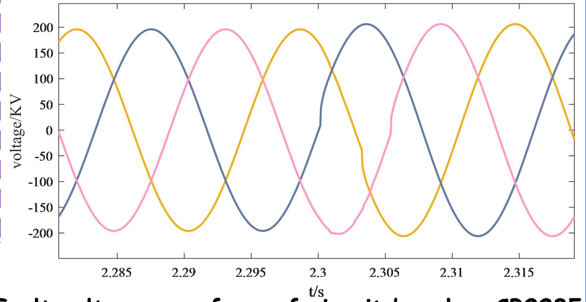
A fault diagnosis method considering weather factor for transmission networks based on tissue-like P system with cell populations



IEEE39 node partition results



Diagnostic flow chart



Fault voltage waveform of circuit breaker CB2235

Fault diagnosis of transmission networks

Definition 1: An TTPS of degree $m \geq 1$ is a tuple, i.e.:

$$\Pi = (O, \sigma_1, \ldots, \sigma_m, E, T, D, syn, i_0)$$

where:

(1) O is a non-empty alphabet whose element is called object;

(2) $\sigma_i = (w_{i0}, R_{i1})$ or $\sigma_i = (w_{i0}, R_{i2})$, $1 \leq i \leq m$, is the i^{th} tissue cell, and m is the number of tissue cells. The TTPS-based fault diagnosis model includes two types of tissue cells, namely, real cells and virtual cells (VC), whose forms are $\sigma_i = (w_{i0}, R_{i1})$ and $\sigma_i = (w_{i0}, R_{i2})$, respectively, where:

(a) w_{i0} denotes the initial object value on the alphabet O;

(b) $R_{i1} = (i, x / \lambda, j)$ is the transport rule of real cells, where x is the object in the cell i, λ is the object in the cell j and is an empty string. The object x in the cell i will be passed to the empty string λ in the cell j after the rule is executed;

(c) $R_{i2} = (E, e / \lambda, \mathrm{VC})$ is the transport rule of VC, indicating main protection rejection or circuit breaker rejection; e is the object in the tissue fluid environment E, and λ is the object in VC. The object e in the tissue fluid environment E will be passed to the empty string λ in VC after the rule is executed.

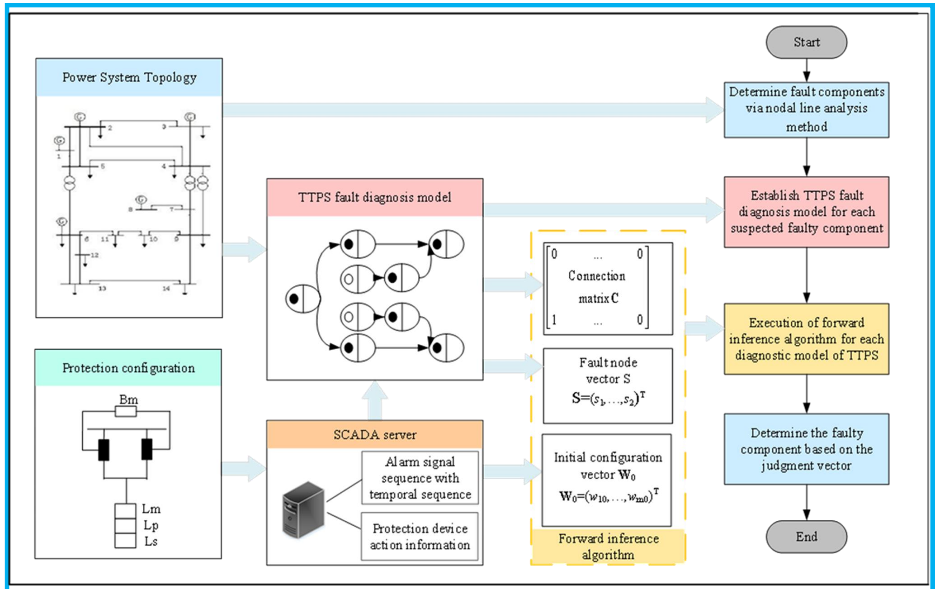
(3) $E = \{e_1, \ldots, e_n\}$ is the liquid environment of tissue cells (called tissue fluid environment), where $e_i \in O$ $(1 \leq i \leq n)$ indicates the objects in E, and n is the number of the objects. If there is no direct channel for exchanging information between two tissue cells, then the environment can be used as an indirect channel to exchange messages. Consequently, when a real tissue cell does not satisfy the transport rule R_{i1}, it will perform the transport rule $(i, x / \lambda, E)$, where x is the object in the cell i, λ is the object in E. The object x in the cell i will be passed to the empty string λ in E after the rule is executed;

(4) $T = \{T(t_{\sigma i}) | \sigma_i \in \sigma\}$ is the time-point constraint of tissue cells, where $T(t_{\sigma i}) = [t_i^-, t_i^+]$ represents the time-point occurrence of the cell σ_i in the interval $[\Delta t_{ij}^-, \Delta t_{ij}^+]$;

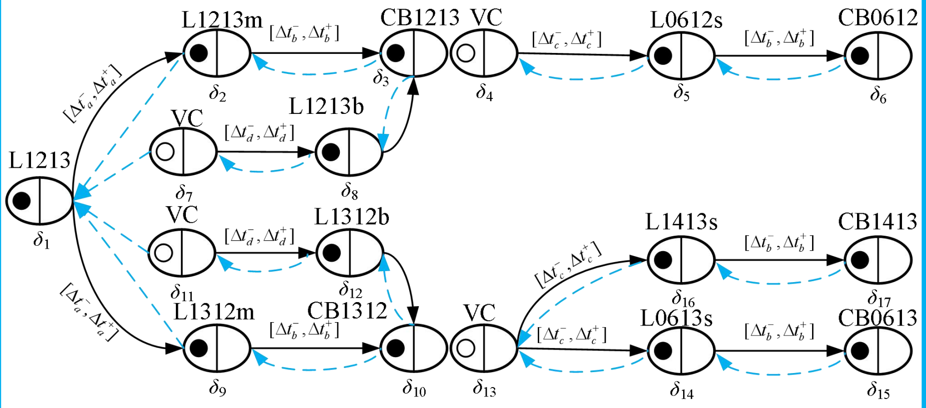
(5) $D = \{D(\sigma_i, \sigma_j) | \sigma_i, \sigma_j \in \sigma\}$ is the time-distance constraint of tissue cells, where $D(\sigma_i, \sigma_j) = [\Delta t_{ij}^-, \Delta t_{ij}^+]$ represents the time-distance between the occurrence of the cells σ_i and σ_j in the interval $[\Delta t_{ij}^-, \Delta t_{ij}^+]$;

(6) $syn \subseteq \{1, \ldots, m\} \times \{1, \ldots, m\}$ denotes the connection channel between tissues cells in Π, where $i \neq j$ for all $(i, j) \in syn (1 \leq i, j \leq m)$;

(7) $i_0 \in \{1, \ldots, n\}$ indicates the output cell set. It is worth noting that an output cell is marked as a suspected faulty component.



Framework of fault diagnosis of power system based on TTPS



TTPS-based fault diagnosis model of L1213

Research 1: A Fault Diagnosis Method for Power Systems Based on Temporal Tissue-like P Systems

- Kequan Zhou, Tao Wang*, Xiaotian Chen, Quanlin Leng. A Fault Diagnosis Method for Power Systems Based on Temporal Tissue-like P Systems, Protection and Control of Modern Power Systems, 2023, accept

Fault diagnosis of transmission networks

Research 2: A fault diagnosis method considering weather factor for transmission networks based on tissue-like P system with cell populations

Definition 1. Formal definition of cpTPS:

$$\Pi = (O, \theta, \aleph, syn, i_{in}, i_{out})$$

(1) O is a non-empty alphabet (its elements are called objects);

(2) $\theta=[\theta_1,\ldots,\theta_n]$ denotes the cell population in the system and n is the total number of cell populations. Cell population θ_k is denoted as $\theta_k = (w_{in}, R_1, R_2, \delta_{k/1},\ldots, \delta_{k/m}, scn)$, where:

(a) w_{in} denotes the initial object on O;

(b) R_1 represents a transit rule for a cell population of the form $(e, x/\lambda, f)$, where x and λ represent objects in cell population e and cell population f, respectively, and λ is an empty string. Upon execution of the rule, the object x in cell population e will be passed to the empty string λ in cell population f;

(c) R_2 denotes a lysis rule for a cell population of the form $[a]_e[b]_f \to [c]_k$, where a, b, c denotes an object in cell population e, cell population f and cell population k, respectively. Upon execution of the rule, object a in cell population e and object b in cell population f are jointly dissolved into object c in cell population k;

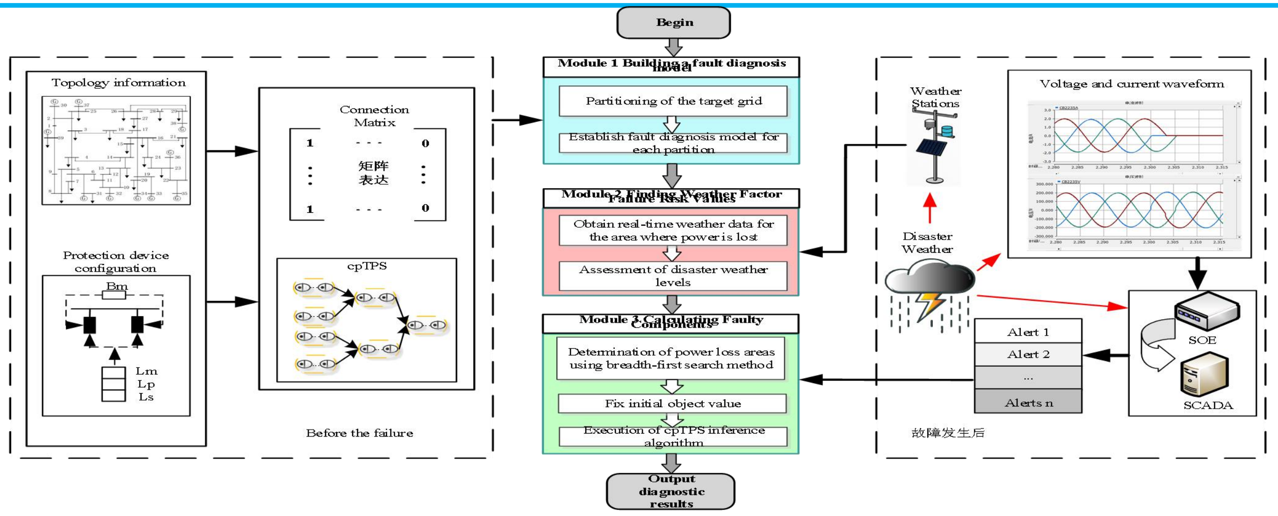
(d) $\delta_{k/j}$ denotes the j th cell in the k th cell population, $1 \le k \le n, 1 \le j \le m$, where n is the total number of cell populations, and m is the total number of cells in the k th cell population. In addition, when the k th cell population is the output cell population of a line, the total number of cells in this cell population is s, and each cell corresponds to a line in the target grid. cpTPS fault diagnosis model has a cell modulation rule of $[\delta^T_{k/j}\beta^T \to \delta^{T'}_{k/j}]$, where $\delta^T_{k/j}$ denotes the object value of the j th cell in the k th cell population at the moment T, β^T is the auxiliary object of the confidence level at the moment of action, $\delta^{T'}_{k/j}$ denotes the modulated object value of the j th cell in the k th cell population at the moment T;

(e) $scn \subseteq \{1,\ldots,m\}\times\{1,\ldots,m\}$ denotes the anchoring connection relationship of cells within the k th cell population, where cells form a stable, ordered cell population by anchoring connections between them;

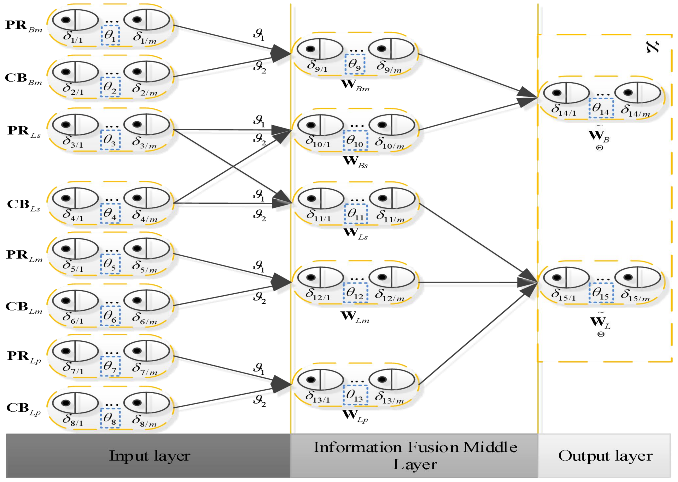
(3) $\aleph = (\tau, \bar{\lambda}, \hbar)$ denotes the weather survival microenvironment of the output cell population, i.e., tissue fluid, where τ is a real number on [0,1], which denotes the weather factor risk value of the transmission line; $\bar{\lambda}$ denotes the fault matching degree of the transmission line considering weather factor, and based on expert experience, $\bar{\lambda}$ takes the value of 0.2 or 0 in this paper; when the dispatch center only receives the protective relay action signal or circuit breaker action signal, $\bar{\lambda}$ takes the value of 0.2; otherwise, $\bar{\lambda} = 0$. $\hbar$ denotes the infiltration rule of the output cell group tissue fluid, and its trigger condition is $H \ge H_3$, indicating that the rule can be executed when and only when the weather risk level H is higher than the higher risk, i.e., the influence of weather factors on transmission grid line faults will be considered in the subsequent transmission grid fault diagnosis process. At this time, the weather factor risk value and the fault matching degree of the weather factor will be used as one of the input parameters of the diagnostic model;

(4) $syn \subseteq \{1,\ldots,n\}\times\{1,\ldots,n\}$ indicates the state of connection between cell populations, where interconnected cell populations can exchange information;

(5) $i_{in}, i_{out} \in \{1,\ldots,n\}$ denotes the set of input cell populations and output cell populations.



Diagnostic flow chart



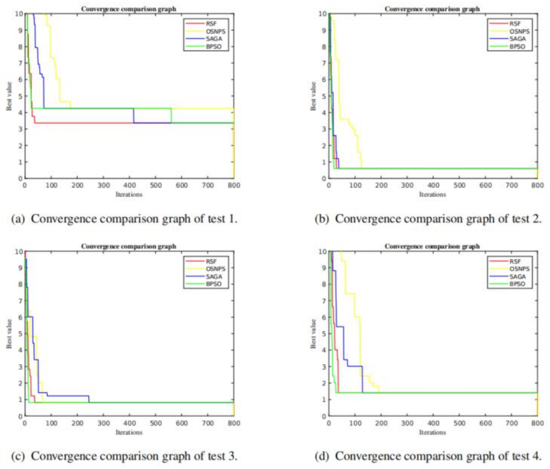
Fault diagnosis model based on cpTPS

Fault diagnosis of transmission networks

Applications of **membrane computing** in fault diagnosis of transmission networks

Applications of membrane optimization algorithms in fault diagnosis of transmission networks

Fault diagnosis for power grids under disaster weather based on a random self-regulating algorithm

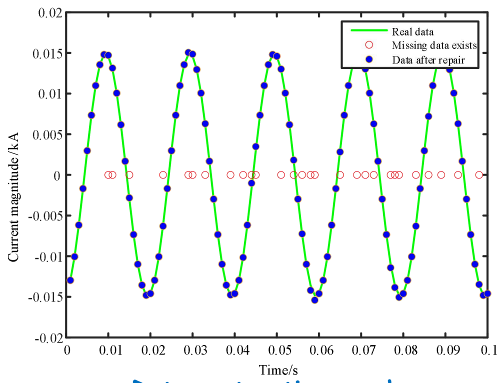


(a) Convergence comparison graph of test 1.
(b) Convergence comparison graph of test 2.
(c) Convergence comparison graph of test 3.
(d) Convergence comparison graph of test 4.

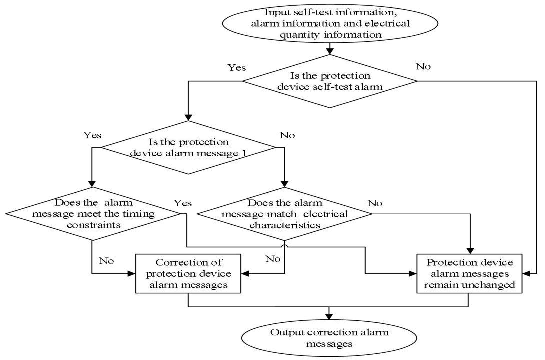
Convergence comparison graph

We propose a novel fault diagnosis method based on a random self-regulating algorithm. To comprehensively and efficiently use the fault alarm information, self-test information of protection devices and weather data, three types of self-regulating trust factors are designed to avoid the subjectivity of empirical weights and improve the fault tolerance and diagnostic accuracy of analytic models. Moreover, a bionic self-regulating function based on the solution and control matrices is proposed to establish the random self-regulating algorithm.

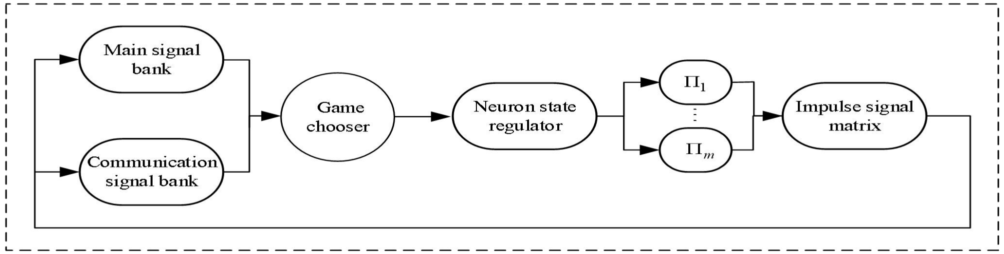
A multi-objective optimization fault diagnosis method for power grids based on multi-source information



Data restoration graph



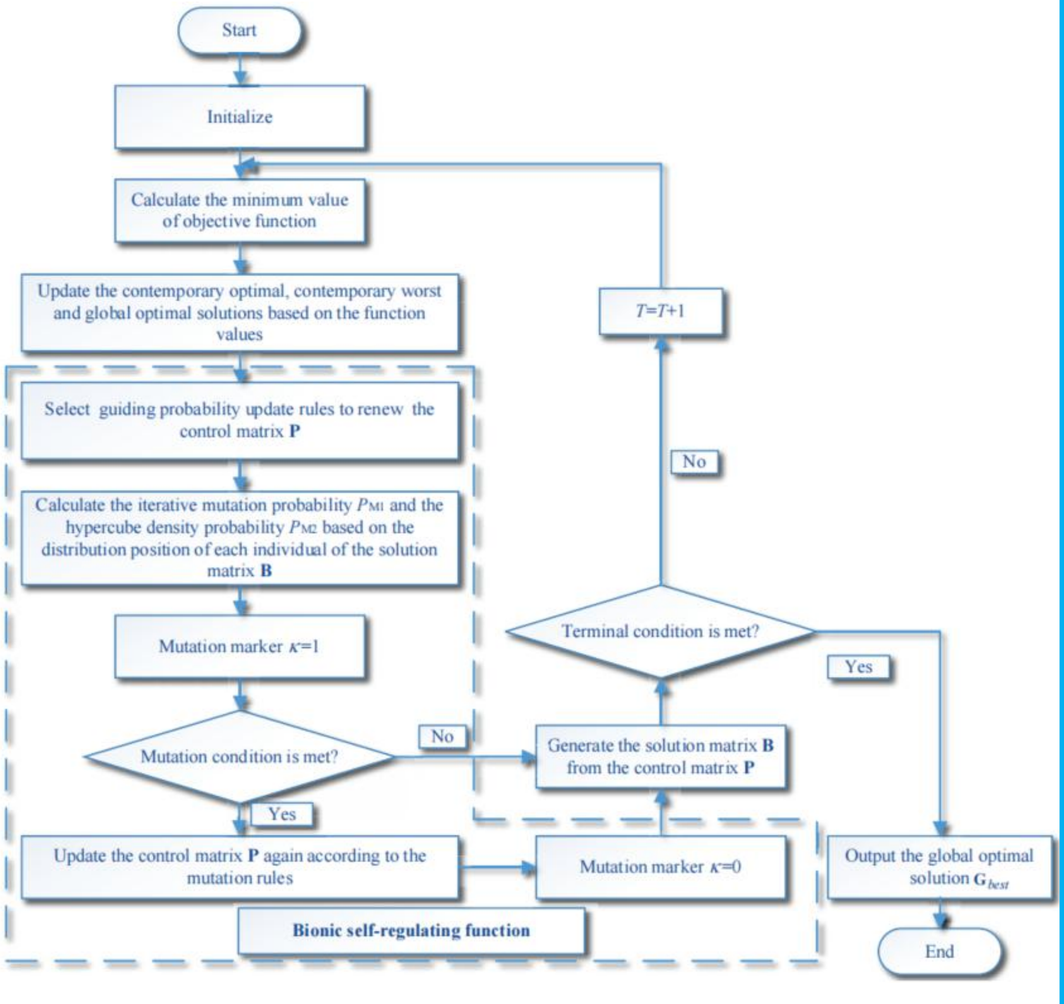
Alarm information correction module flow chart



Schematic diagram of the structure of multi-objective spiking neural P systems optimization algorithm

Fault diagnosis of transmission networks

Research 1: Fault diagnosis for power grids under disaster weather based on a random self-regulating algorithm

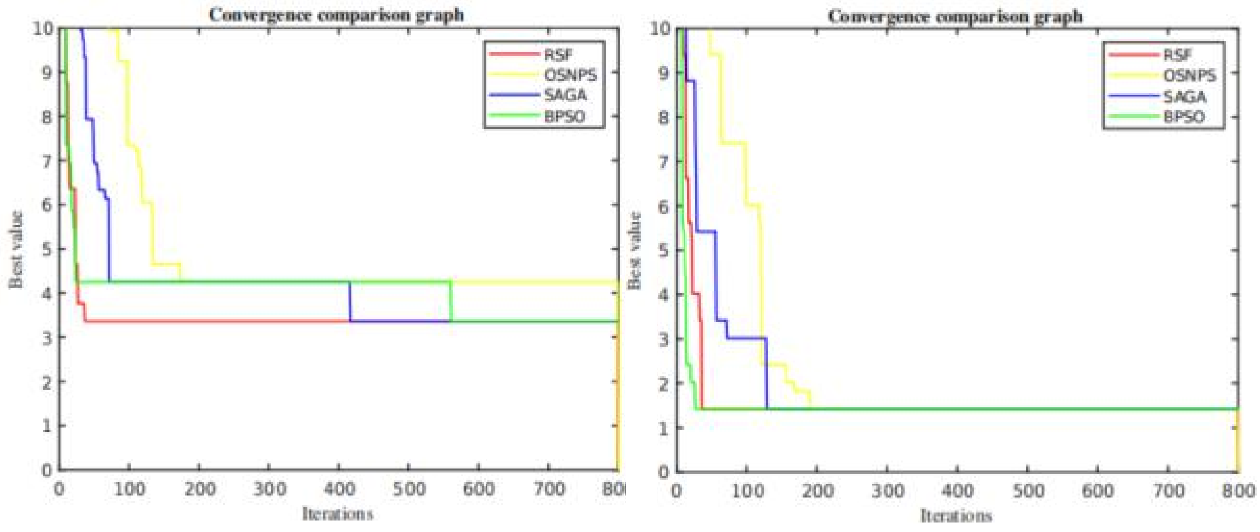


Flowchart of random self-regulating algorithm

Random Self-regulating Algorithm

Input parameters of the random self-regulating algorithm include H, m, p_j^a and T_{maxgen}, where p_j^a represents the selection probability of each element of the matrix $\mathbf{B}$, T_{maxgen} represents the maximum number of iterations of the algorithm.

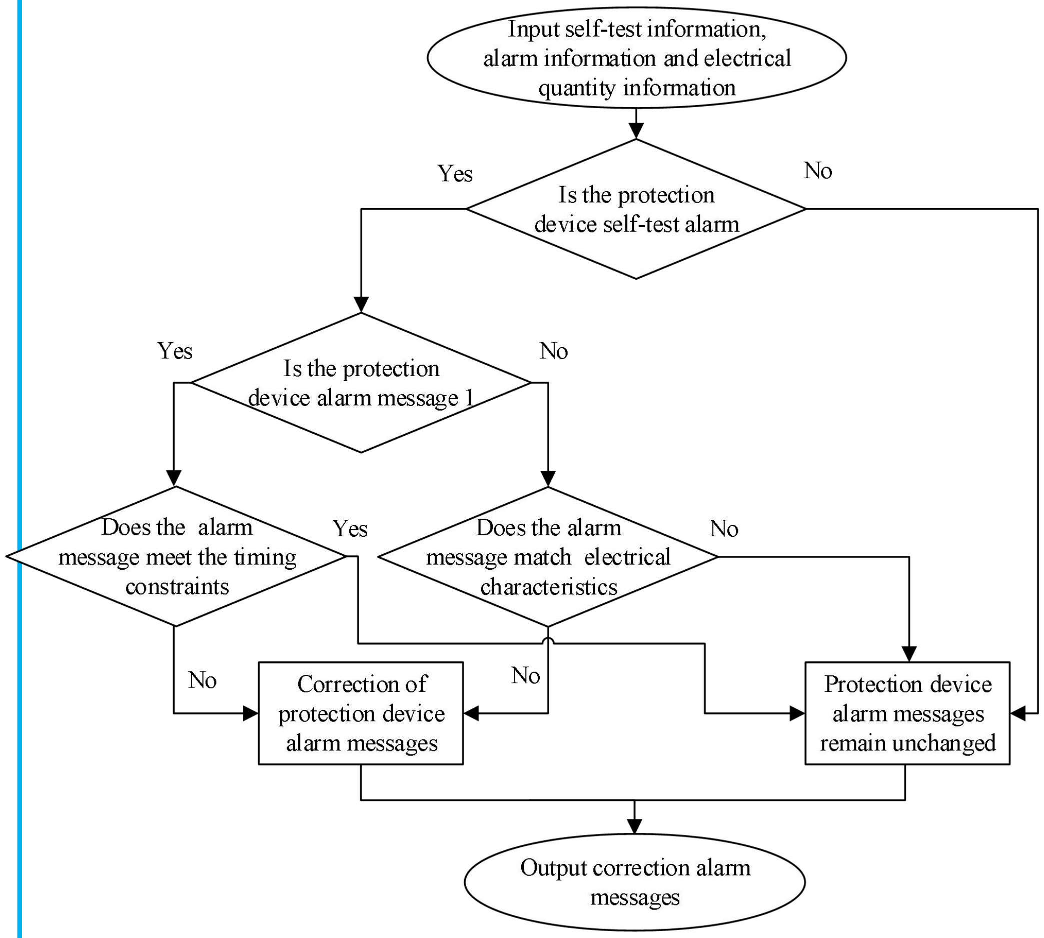
In this paper, p_j^a is set as 0.5. Besides, several important variables are involved in the algorithm, such as $\mathbf{B}_i$, $f_{\mathbf{B}_i}$, $\mathbf{B}_{best}$, $\mathbf{B}_{bad}$, $\mathbf{G}_{bad}$ and Δ, where $\mathbf{B}_i$ ($\mathbf{B}_i = (b_{i,1}, b_{i,2}, \ldots b_{i,m})$) represents the i-th solution vector in $\mathbf{B}$, $f_{\mathbf{B}_i}$ represents the function value of $\mathbf{B}_i$, $\mathbf{B}_{best}$ represents contemporary optimal solution, $\mathbf{B}_{bad}$ represents the contemporary worst solution and $\mathbf{G}_{bad}$ represents the global worst solution; Δ represents the increment operator of each element in $\mathbf{P}$, i.e., the increment operator of guiding probability. The output of random self-regulating algorithm is $\mathbf{G}_{best}$, which represent the global optimal solution. The steps of random self-regulating algorithm are described as follows, whose flowchart is shown in Fig. 2.



Convergence comparison graph

Fault diagnosis of transmission networks

Research 2: A multi-objective optimization fault diagnosis method for power grids based on multi-source information



Alarm information correction module flow chart

Multi-objective spiking neural P systems optimization algorithm

Firstly, the formal definition of subsystem Π in the multi-objective spiking neural P systems optimization algorithm (MOSNPSOA) is introduced, as shown below.

$$\Pi = (O, \delta_1, \ldots, \delta_{n+2}, syn, out)$$

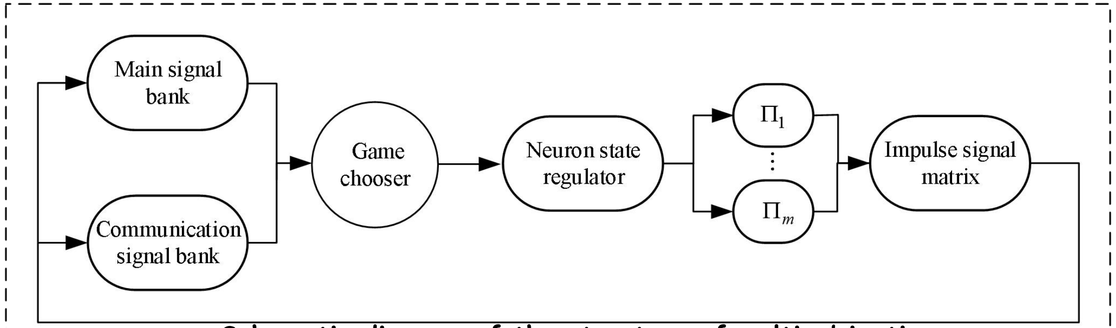
where:

(1) $O = \{a\}$ is a single-letter set, a is a pulse;

(2) $\sigma_1, \ldots, \sigma_{n+2}$ is neurons in system Π. Neurons σ_{n+1} and σ_{n+2} provide impulses to the system, and both have the same form and function, represented as $\sigma_{n+1}=\sigma_{n+2}=(1,\{a \to a\})$; Neuron σ_j ($1 \le j \le n$) is represented as $\sigma_j = (1, R_j^{\xi}, P_j)$, where $R_j^{\xi} = \{r_j^1, r_j^2\}$ is the set of rules, and r_j^1 and r_j^2 are the ignition and forgetting rules, respectively, represented as $r_j^1 = \{a \to a\}$ and $r_j^2 = \{a \to \lambda\}$; $P_j = \{p_j^1, p_j^2\}$ is a selection probability expression for the ignition rule and the forgetting rule, and satisfies $p_j^1 + p_j^2 = 1$;

(3) $syn = \{(u, v) | (1 \le u \le n+1) \wedge (v = n+2) \vee (u = n+2) \wedge (v = n+1)\}$ represents synapses between neurons.

(4) $out = \{\sigma_1, \ldots, \sigma_n\}$ is the set of output neurons, and subsystem Π outputs a binary pulse string consisting of "0" and "1" through neuron σ_i ($j = 1, \ldots, n$).



Schematic diagram of the structure of multi-objective spiking neural P systems optimization algorithm

Outline:

1. Background
2. Applications of membrane computing in fault diagnosis of transmission networks
3. Applications of membrane computing in fault diagnosis of distribution networks
4. Applications of membrane computing in optimal operation of integrated energy system
5. Applications of virus machines in power systems

Fault diagnosis of distribution networks

Research 1: A Hierarchical fault location method for distribution networks based on intuitionistic fuzzy spiking neural P systems

We propose a hierarchical fault location method for distribution networks based on intuitionistic fuzzy spiking neural P system. With the continuous expansion of the distribution network scale, the goal is to improve the fault tolerance and rapidity of fault location algorithm and simplify the fault location method of distribution networks with distributed power supply.

An intuitionistic fuzzy reasoning spiking neural P system is formally defined as follows

$$\Pi=(O,\sigma,\xi,\nu,syn,in,out) \tag{4}$$

where:

(1) $O=\{a\}$ is the set of single letters, a represents a neural pulse.

(2) $\sigma=\{\sigma_1,\ldots,\sigma_m\}$ is the set of m perceptual neurons in the system, denoted $\sigma_i=(\theta_i,r_i),1\le i\le m$, $\xi=\xi_1,\ldots,\xi_n$ is the set of n perceptual neurons in the system, denoted $\xi_j=(\delta_j,r_j,R_j),1\le j\le n$, where:

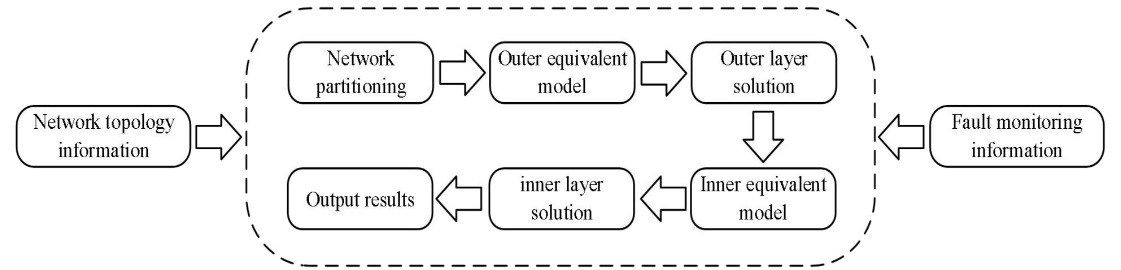
(i) θ_i indicates the impulse value, or potential value, within the perceptive neuron. It is of the form $\theta_i=(\mu_i,\gamma_i),\mu_i\ge 0,\gamma_i\ge 0$, which indicates the perceptive neuron's certainty and uncertainty, respectively, and $0\le\mu_i+\gamma_i\le 1$. r_i and r_j represent the firing rules of the perception and execution neurons, respectively, which are formally consistent as $E/a^{\theta}\to a^{\beta}$, where θ and β are the set of intuitionistic fuzzy numbers $(\mu_K,\gamma_K),\mu_K\ge 0,\gamma_K\ge 0$, $0\le\mu_K+\gamma_K\le 1$. $E=a^k$ indicates the ignition condition, meaning that the neuron can only execute this ignition rule if and only if it receives at least k pulses. Otherwise, this ignition rule cannot be executed.

(ii) δ_j indicates the impulse value inside the actuating neuron, which is of the form $\delta_j=(\mu_j,\gamma_j),\mu_j\ge 0,\gamma_j\ge 0$, and $0\le\mu_j+\gamma_j\le 1$. R_j indicates the set of optimization rules for executing neuron impulse values of the form $R_j\to\begin{cases}f_\psi(\mu)=e^{-3(\mu-1)^2}\\ f_\psi(\gamma)=\alpha\gamma\end{cases}$, where $f_\psi(\mu)$ indicates that the certainty of executing neuron impulse values is optimized by a Gaussian function to make the computation result more convergent to the ideal final value. $f_\psi(\gamma)$ indicates the uncertainty of the execution neuron, which is optimized according to the probability factor of the fault spreading direction α, where $\alpha=\frac{\gamma}{Num}$, Num indicates the number of actual fault spreading directions, so the optimization equation of the uncertainty can also be expressed as $f_\psi(\gamma)=\frac{\gamma^2}{Num}$.

(3) S_i is the set of synaptic activation thresholds, and $S_i=\{s_i^r,s_i^i\}$. s_i^r,s_i^i indicate the activation thresholds of real and imaginary synapses of a neuron, respectively. For both real and virtual synapses, a synapse is in an activated state when the value of the impulse transmitted at the synapse is greater than or equal to the activation threshold ($\eta^r=1,\eta^i=1$). Note that when no impulse is transmitted at the real synapse, the virtual synapse is in an inhibitory state ($\eta^i=0$), and the value of the impulse cannot be transmitted even if the presynaptic neuron of the virtual synapse satisfies the ignition rule.

(4) $syn\subseteq\{1,\ldots,m\}\times\{1,\ldots,m\}$ indicates a directed synaptic connectivity relation between neurons, for all $(i,j)\in syn,1\le i,j\le m$ having $i\ne j$.

(5) $in,out\subseteq\{1,\ldots,m\}$ indicate the set of input and output neurons, respectively.

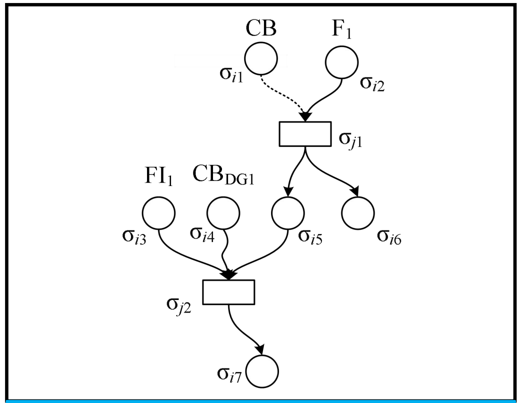


Solution flowchart

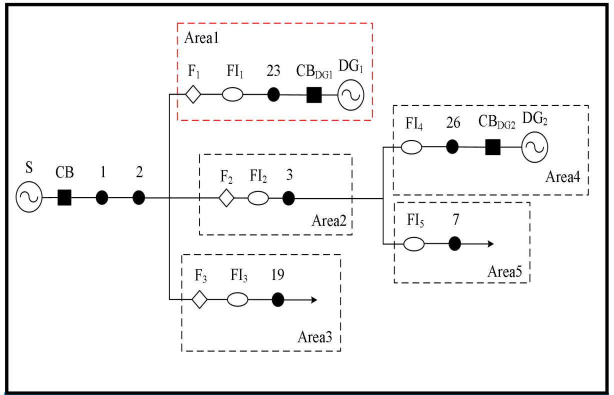
Fault diagnosis of distribution networks

Research 1: A Hierarchical fault location method for distribution networks based on intuitionistic fuzzy spiking neural P systems

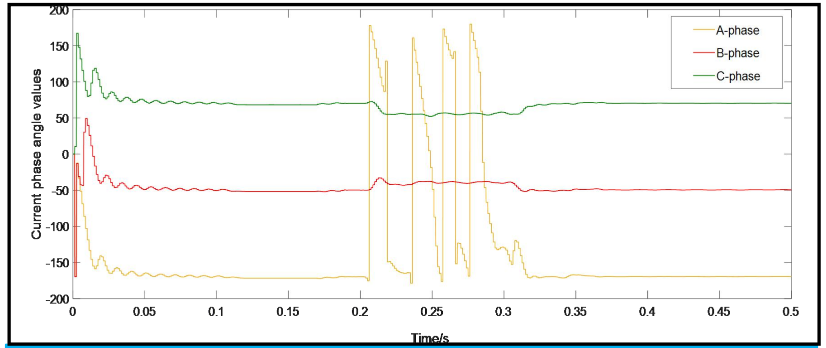
We propose a hierarchical fault location method for distribution networks based on intuitionistic fuzzy spiking neural P system. With the continuous expansion of the distribution network scale, the goal is to improve the fault tolerance and rapidity of fault location algorithm and simplify the fault location method of distribution networks with distributed power supply.



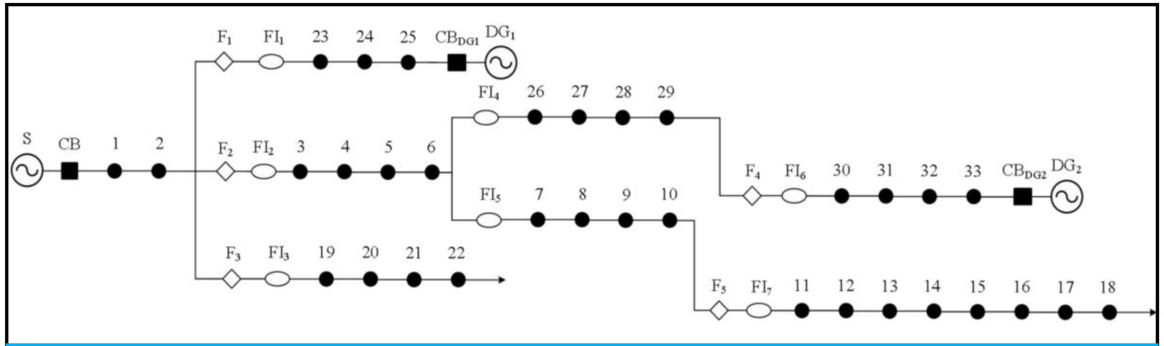
Fault location model



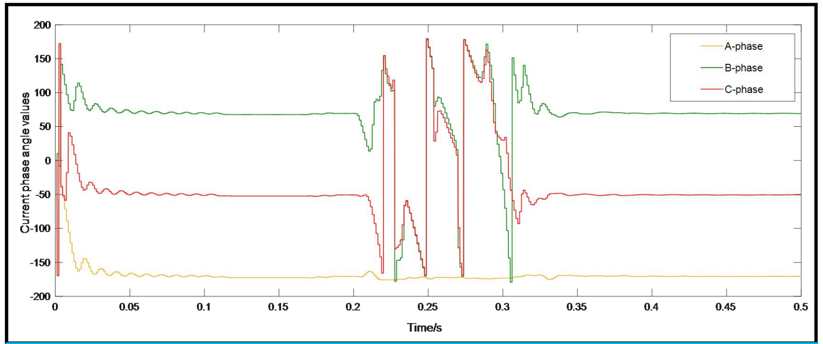
Outer equivalent structure



Phase angle variation before and after short circuit ground fault current in phase A at node 24



33-node distribution network structure



Phase angle variation before and after BC two-phase short-circuit fault current at node 24

Fault diagnosis of distribution networks

2.1 Spiking Neural P Systems with Excitatory and Inhibitory Synapses

An SNPS with excitatory and inhibitory synapses (SNPSEI) of degree $m \geq 1$ is a construct of:

$$\Pi = (O, \sigma_1, \sigma_2, ..., \sigma_m, syn, in, out)$$

where

(1) $O = \{a\}$ is a set of singleton alphabets, and a denotes a spike.

(2) $\sigma_1, \sigma_2, ..., \sigma_m$ are neurons in the system, and each neuron $\sigma_i (1 \leq i \leq m)$ is of the form $\sigma_i = (\alpha_i, \kappa_i, R_i)$, where:

(a) $\alpha_i \in \{-1, 0, 1\}$ is the quantity of electric charges carried by the spike in neuron σ_i;

(b) $\kappa_i \in \{0, 1\}$ is the firing threshold value of neuron σ_i; and

(c) $R_i = \{r_1, r_2, r_3\}$ is a finite set of rules in neuron σ_i, which are as follows:

- $r_1 : E = (\alpha_i \geq \kappa_i) / a^{\alpha_i} \rightarrow a^{\varepsilon}$ is a firing rule, where a^{α_i} denotes the spike that is consumed for executing the firing rule. $\varepsilon \in \{0, 1\}$ denotes the quantity of electric charges carried by the newly produced spike. It means that if and only if the quantity of the electric charges in neuron σ_i satisfies the firing condition $\alpha_i \geq \kappa_i$, then the firing rule can be executed. After that, the spike a^{α_i} is consumed and a new spike a^{ε} is produced and sent to all the synapses connected to neuron σ_i. It is worth noting that the transmission of quantity of electric charges does not consume time in the system, i.e., the spike immediately reaches the connected synapses.
- $r_2 : E = (\alpha_i < \kappa_i) / a^{\alpha_i} \rightarrow \lambda$ is a forgetting rule, where λ is a null character indicating that no new electric charge is generated. If the quantity of electric charge satisfies $\alpha_i < \kappa_i$, then the forgetting rule will be executed and no new electric charge is generated.
- $r_3 : t = \{t_1, \overline{t_1}\}$ denotes the set of synapses, where t_1 and $\overline{t_1}$ denote excitatory and inhibitory synapses, respectively. The neurons before and after the excitatory synapses are called pre-excitatory and post-excitatory neurons, respectively. If a pre-excitatory neuron meets its firing condition, then the corresponding excitatory synapses will work. Likewise, the neurons before and after the inhibitory synapses are called pre-inhibitory and post-inhibitory neurons, respectively. If and only if the quantity of electric charges carried by the spike in a pre-inhibitory neuron equals 0, then the corresponding inhibitory synapses will work.

(3) $syn \subseteq \{1, 2, ..., m\} \times \{1, 2, ..., m\}$ denotes the connection relation between neurons, where $(i, j) \in syn$, $1 \leq i, j \leq m$ with $i \neq j$.

(4) $in, out \subseteq \{1, 2, ..., m\}$ represent the sets of input and output neurons, respectively.

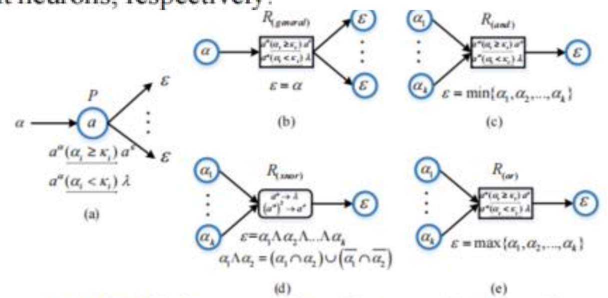
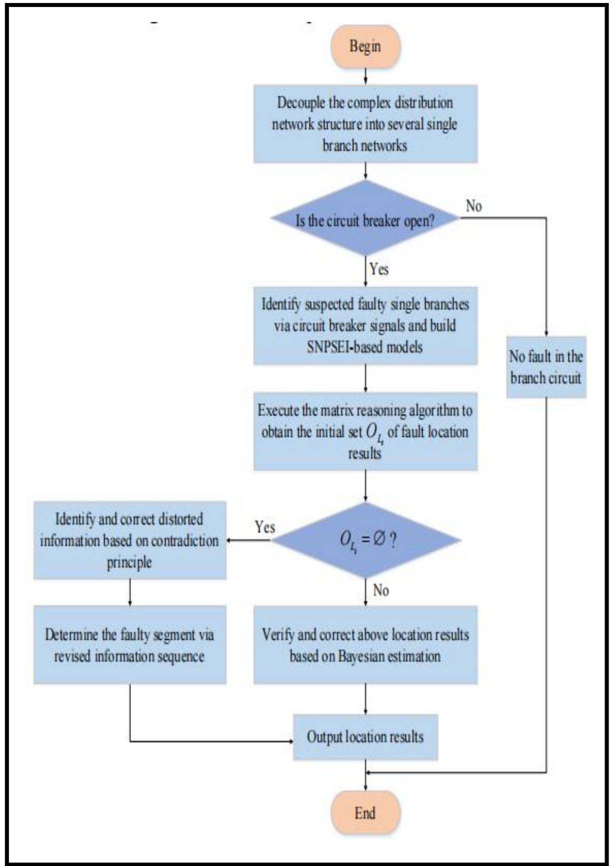


Fig. 1 Graphical representation of neurons. (a) Proposition neuron, (b) *general* rule neuron, (c) *and* rule neuron, (d) *xnor* rule neuron, and (e) *or* rule neuron.

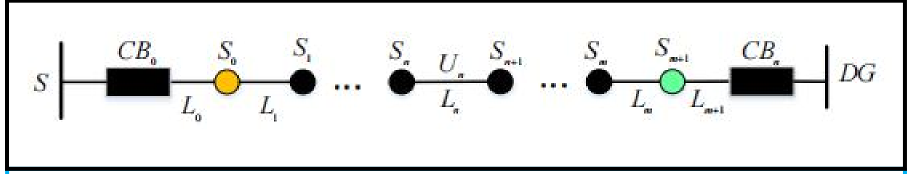
Research 2: A fault segment location method for distribution networks based on spiking neural P systems and bayesian estimation

- Yi Wang, Tao Wang*, Liyuan Liu. A fault segment location method for distribution networks based on spiking neural P systems and Bayesian estimation, Protection and Control of Modern Power Systems, 2023, 8(1), Article ID 47.

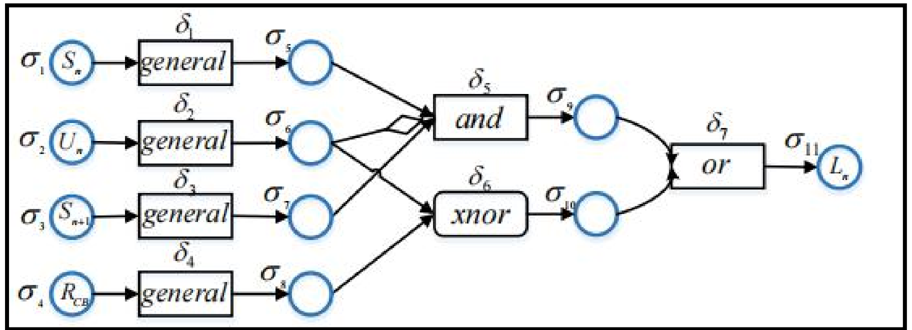
Fault diagnosis of distribution networks



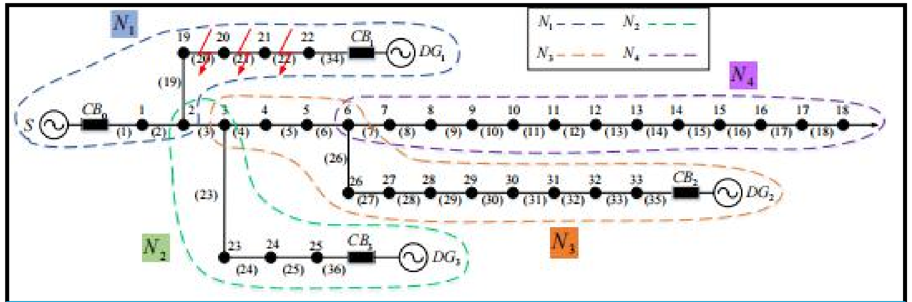
Flow chart of fault location method for distribution networks based on SNPSEI and Bayesian Estimation



Schematic diagram of single branch network



A universal fault location model of distribution network based on SNPSEI



Decoupling into four single branch network schematic

Accuracy simulation results under 100 failures of this method

Simulation requirements	Single fault accuracy	Single fault average solving time	Double fault accuracy	Double fault average solution time
Simulation results	100%	0.01248s	100%	0.01404s

We propose a fault segment location method based on spiking neural P systems and Bayesian estimation for distribution networks with distributed generation. First, the decoupled single-branch networks are modeled by SNPS with excitatory and inhibitory synapses (SNPSEIs) and then their matrix reasoning algorithms are employed for segment initial localization. After that, if the initial localization result set is not empty, Bayesian estimation will be used to verify and correct the initial localization result; otherwise, the contradiction principle will be used to identify and correct the distortion information and derive the final location results.

Research 2: A fault segment location method for distribution networks based on spiking neural P systems and bayesian estimation

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Outline:

Optimal operation of integrated energy systems

Research 1: A Low-carbon Operation Optimization Method of Electric-thermal-gas Regional Integrated Energy Systems Based on Adaptive Single-objective Continuous Optimization Spiking Neural P Systems

- ✓ We propose a novel low-carbon operation optimization method of electric-thermal-gas regional integrated energy systems. To enhance the low-carbon operation capacity of regional integrated energy systems, a coordinated operation framework is presented, which includes carbon capture devices, the power to gas equipment, the combined heat and power equipment, and a multi-energy storage system. To solve the high-dimensional constraint imbalance problem in the optimization process, an adaptive single-objective continuous optimization spiking neural P system is designed, based on which the low-carbon operation optimization method of regional integrated energy systems is proposed.

A. Adaptive Single-objective Continuous Optimization Spiking Neural P System

Definition 1: An adaptive single-objective continuous optimization spiking neural P system (ASCOSNPS) of degree $m > 1$ is a tuple

$$\Pi = (S_1, \dots, S_m, G)$$

where

(1) $S_l = (O, \sigma_1, \dots, \sigma_{n+2}, syn, I_{out}), 1 \le l \le m$ represents the i-th subsystem, where

(i) $O = \{a\}$ represents a singleton alphabet (a represents a spike, O represents a set of spikes);

(ii) $Q = Q_p \cup Q_s$ represents a neuron set, where $Q_p = \{\sigma_1, \dots, \sigma_n\}$ represents the set of pulse-generating neurons and $Q_s = \{\sigma_{n+1}, \sigma_{n+2}\}$ represents the set of pulse-supplying neurons. Each pulse-generating neuron σ_i is of the form $(\theta_i, R_i, P_i), 1 \le i \le n$, where

(a) θ_i represents the potential value of spikes contained in σ_i;

(b) $R_i' = \{a^\theta \to a^\beta\}$ represents the firing rule of σ_i, where its execution will consume a spike a^θ and generate a new pulse at the same time, denoted as a^β;

(c) P_i represents the rule excitation operator in σ_i;

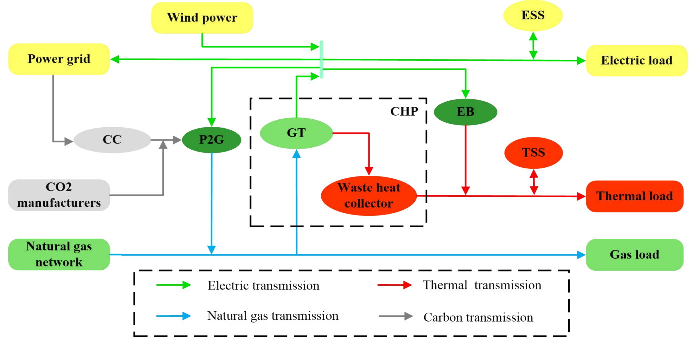
(iii) Both σ_{n+1} and σ_{n+2} work as the step-by-step supplier of spikes to $\sigma_1, \dots, \sigma_n$.

(iv) $syn = \{(i, j) \mid ((1 \le i \le n+1) \wedge (j = n+2)) \vee ((i = n+2) \wedge (j = n+1))\}$ represents the directional synaptic connection between neurons;

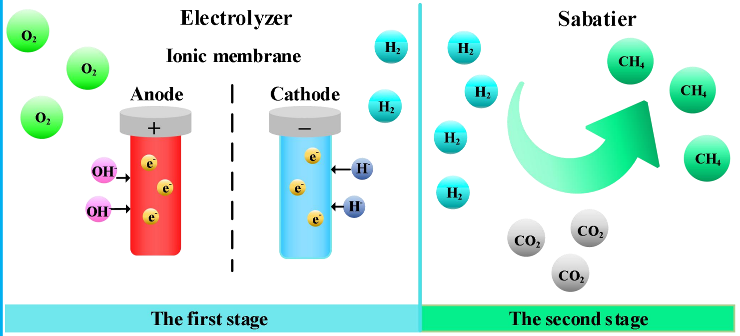
(v) $I_{out} = \{\sigma_1, \dots, \sigma_n\}$ represents a finite set of output neurons, i.e., the output is a spike train formed by concatenating the outputs of $\sigma_1, \dots, \sigma_n$;

(2) G represents an adaptive director, which is used to adaptively adjust the size of rule excitation operators in the neuron σ_i;

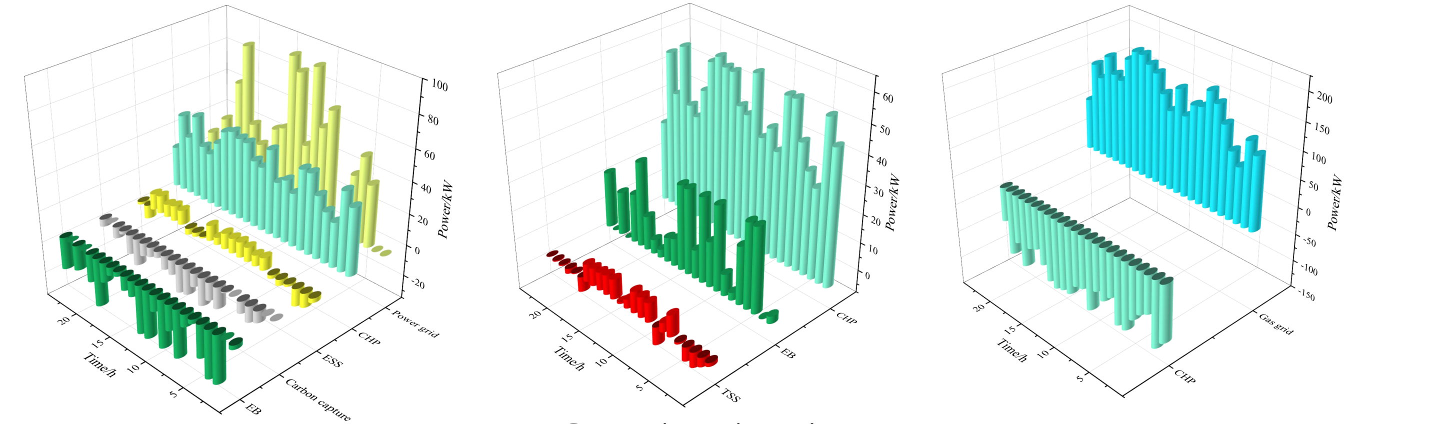
Optimal operation of integrated energy systems



Framework of electric-thermal-gas regional integrated energy system considering carbon capture devices



Chemical reaction process of P2G.



Energy dispatch results

Optimization results of ASCOSNPS, GA and QPSO

Algorithms	Natural gas purchased /kWh	CO_2captured/ kg	CO_2emissions /kg	Reutilizationrate of CO2 captured /%	Carbon reduction capacity ofETG-RIES/%	Consumption rate of wind power/%
ASCOSNPS	3754.98	969.80	933.75	4.50%	50.95%	100%
GA	3242.21	1205.13	1174.56	2.99%	50.64%	100%
QPSO	4129.76	548.95	810.77	0.05%	40.37%	87.76%

Optimal operation of integrated energy systems

Research 2: Multi guidance operational optimization of regional integrated energy systems considering fault effect propagation

- ✓ We propose a new energy framework and its corresponding optimization algorithm, in which the carbon storage device is added to the framework to consider the deep utilization of CO_2, and which considers a multi guidance optimization study of integrated regional energy sources in terms of reliability, economy and low carbon dimensions. Finally, the results of the analysis show that the proposed method can take into account the multiple characteristics of the target area.

A. Adaptive multi guidance spiking neural P system

Definition 1: Adaptive multi guidance spiking neural P system (AMGSNPS) is defined formally as follows.

$$\prod = (S_1, \dots, S_m, G)$$

where,

(1) $S_l = (O, \sigma_1, \dots, \sigma_{2n+2}, syn, I_{out}), 1 \le l \le m$ denoting the l-th subsystem, where

(i) $O = \{a\}$ represents a singleton alphabet (a represents a spike, O represents a set of spike).

(ii) $Q = \{Q_{p1}, Q_{p2}, Q_s\}$ represents a neuron set, where $Q_{p1} = \{\sigma_1, \dots, \sigma_n\}$ represents the set of 1-st class guided pulse-generating neurons, $Q_{p2} = \{\sigma_{n+1}, \dots, \sigma_{2n}\}$ represents the set of 2-st class guided pulse-generating neurons, $Q_s = \{\sigma_{2n+1}, \sigma_{2n+2}\}$ represents the set of pulse supply neurons.

(iii) $\sigma_i = (\theta_i, R_i, P_i), 1 \le i \le 2n$ represents the i-th pulse-generating neuron, where

(a) θ_i represents the potential value of spikes contained in σ_i.

(b) R_i represents the firing rule of σ_i, Firing rules shaped like $E / a^{\theta_i} \to a^{\beta_i}$, where $E = \{a, \theta_i \ge 0\}$ represents firing conditions, when neuron σ_i receives a pulse with pulse value θ_i, the neuron σ_i triggers the firing, generating a new pulse with pulse value β_i and sending it backwards.

(c) P_i represents the regular excitation operator in neuron σ_i.

(iv) $\sigma_{2n+1}, \sigma_{2n+2}$ work as a step by step supplier of spikes to σ_i.

(a) $\sigma_{2n+1}, \sigma_{2n+2}$ will simultaneously execute the firing rules and supply pulses to each other.

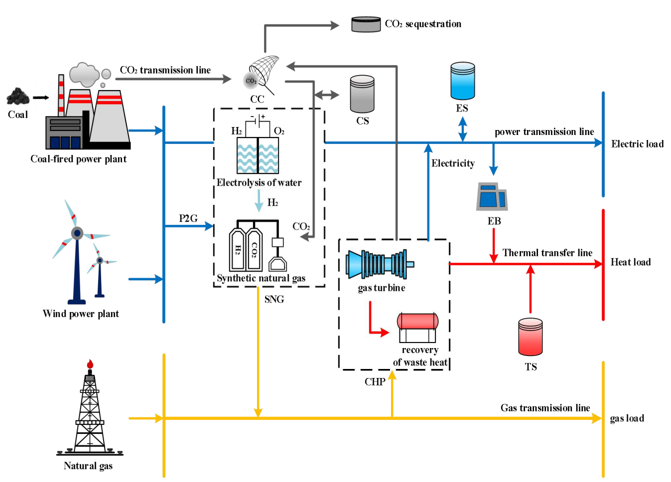
(b) σ_{2n+2} supplies pulses to σ_i.

(v) $syn = \{(i, j) \mid ((1 \le i \le 2n+1) \wedge (j = 2n+2)) \vee ((i = 2n+2) \wedge (j = 2n+1))\}$ represents the directional synaptic connection between neurons.

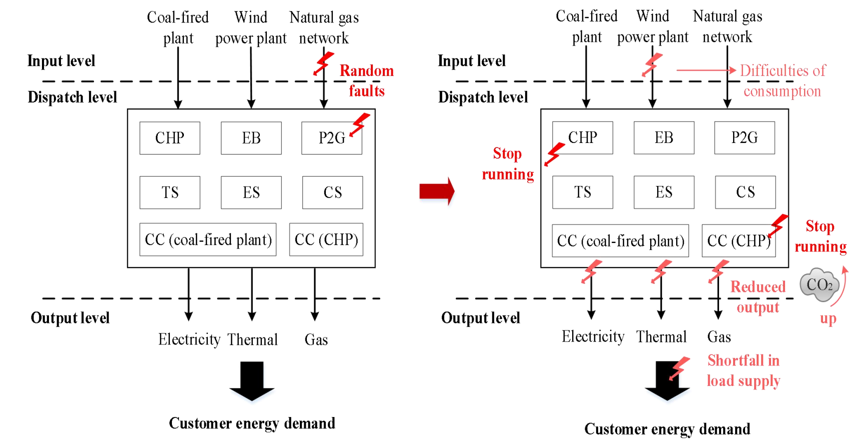
(vi) $I_{out} = \{\sigma_1, \dots, \sigma_n, \dots, \sigma_{2n}\}$ represents a finite set of output neurons, i.e., the output is a spike train formed by concatenating the outputs of $\sigma_1, \dots, \sigma_n$.

(2) $G = \{g_1, g_2\}$ represents adaptive multi-guides for adaptively regulating the size of regular excitation operators in neurons σ_i, where g_1 regulating P in Q_{p1}, g_2 regulating P in Q_{p2}.

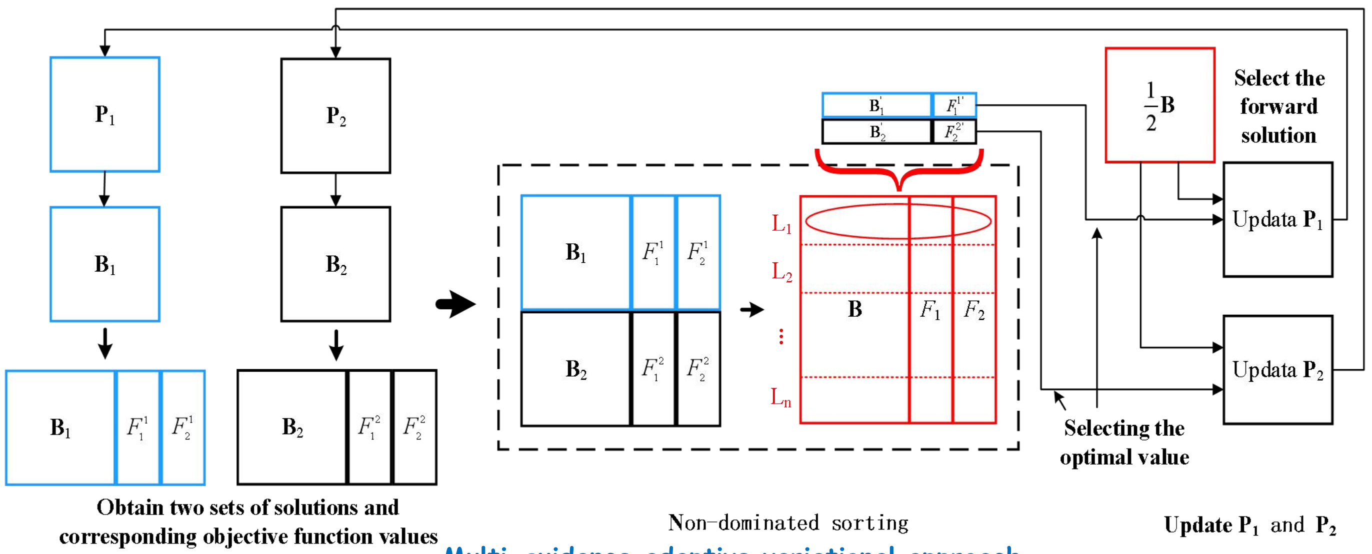
Optimal operation of integrated energy systems



DCU-RIES



An example diagram of fault effect propagation of the DCU-RIES



Multi-guidance adaptive variational approach

Outline:

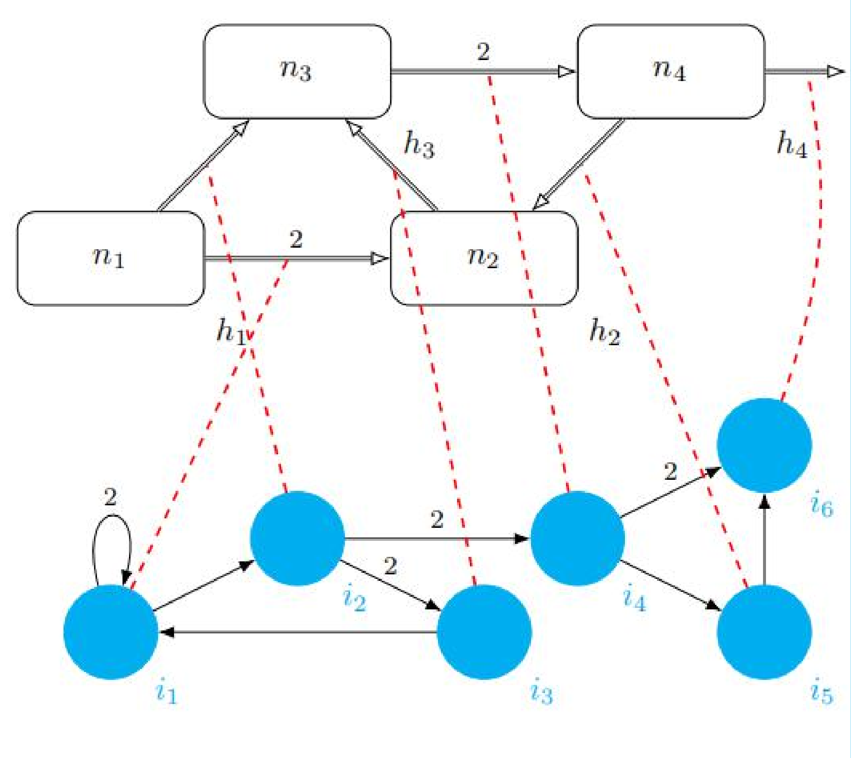
1. Background
2. Applications of membrane computing in fault diagnosis of transmission networks
3. Applications of membrane computing in fault diagnosis of distribution networks
4. Applications of membrane computing in optimal operation of integrated energy systems
5. Applications of virus machines in power systems

Virus machines in power systems

Definition of a basic Virus Machine

Definition 1 *A Virus Machine Π of degree (p, q), with $p \geq 1, q \geq 1$, is a tuple $(\Gamma, H, I, D_H, D_I, G_C, n_1, \ldots, n_p, i_1, h_{out})$, where:*

- *$\Gamma = \{v\}$ is the singleton alphabet;*
- *$H = \{h_1, \ldots, h_p\}$ and $I = \{i_1, \ldots, i_q\}$ are ordered sets such that $v \notin H \cup I$ and $H \cap I = \emptyset$;*
- *$D_H = (H \cup \{h_{out}\}, E_H, w_H)$ is a weighted directed graph, where $E_H \subseteq H \times (H \cup \{h_{out}\})$, $(h, h) \notin E_H$ for each $h \in H$, out-degree$(h_{out}) = 0$, and w_H is a mapping from E_H onto $\mathbb{N} \setminus \{0\}$ (the set of positive integer numbers);*
- *$D_I = (I, E_I, w_I)$ is a weighted directed graph, where $E_I \subseteq I \times I$, w_I is a mapping from E_I onto $\mathbb{N} \setminus \{0\}$ and, for each vertex $i_j \in I$, the out-degree of i_j is less than or equal to 2;*
- *$G_C = (V_C, E_C)$ is an undirected bipartite graph, where $V_C = I \cup E_H$, being $\{I, E_H\}$ the partition associated with it (i.e., all edges go between the two sets I and E_H). In addition, for each vertex $i_j \in I$, the degree of i_j in G_C is less than or equal to 1;*
- *$n_j \in \mathbb{N}$ $(1 \leq j \leq p)$ and $i_1 \in I$;*
- *$h_{out} \notin I \cup \{v\}$ and h_{out} is denoted by h_0 in the case that $h_{out} \notin H$.*



Structure of a Virus Machine

◆ **CMC16, Basic Virus Machines, 2015**

Virus machines in power systems

How to use the virus machine in power systems? **Just an idea ! ! !**

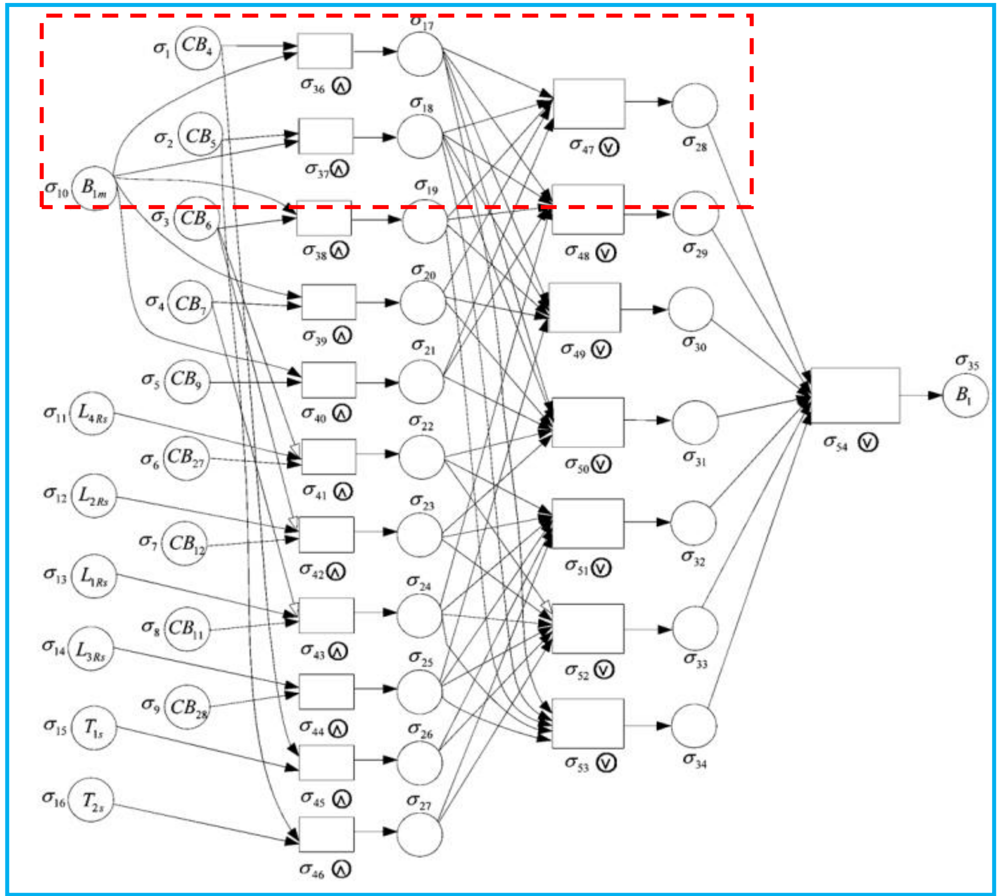
◆ Using virus machine to express fault production rules

Take a Bus for example:

$$R_1(c_1{=}AH){:}\ (p_1\ operates)\ \textcircled{\wedge}\ (all\ or\ partial\ CB_1\ trips)\ \rightarrow B\ fails$$

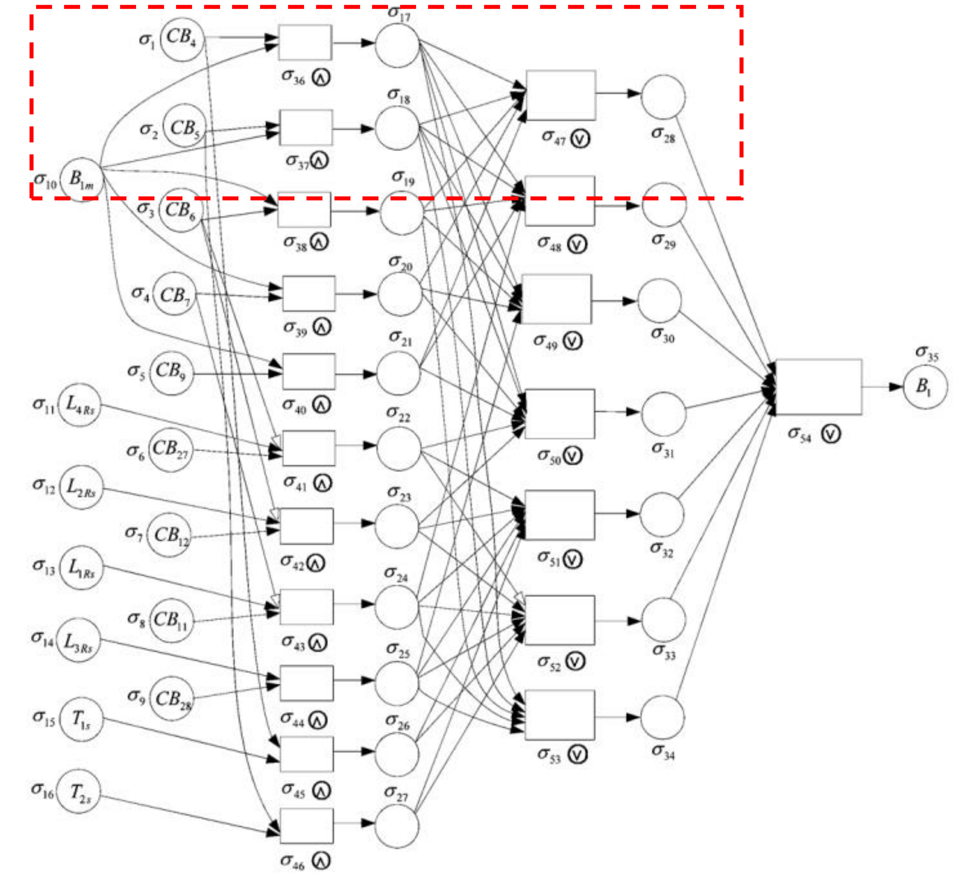
$$R_2(c_2 = VH):(p_2\ operates)\ \textcircled{\wedge}\ (CB_2\ trips) \rightarrow B\ fails.$$

Fault production rules of a Bus

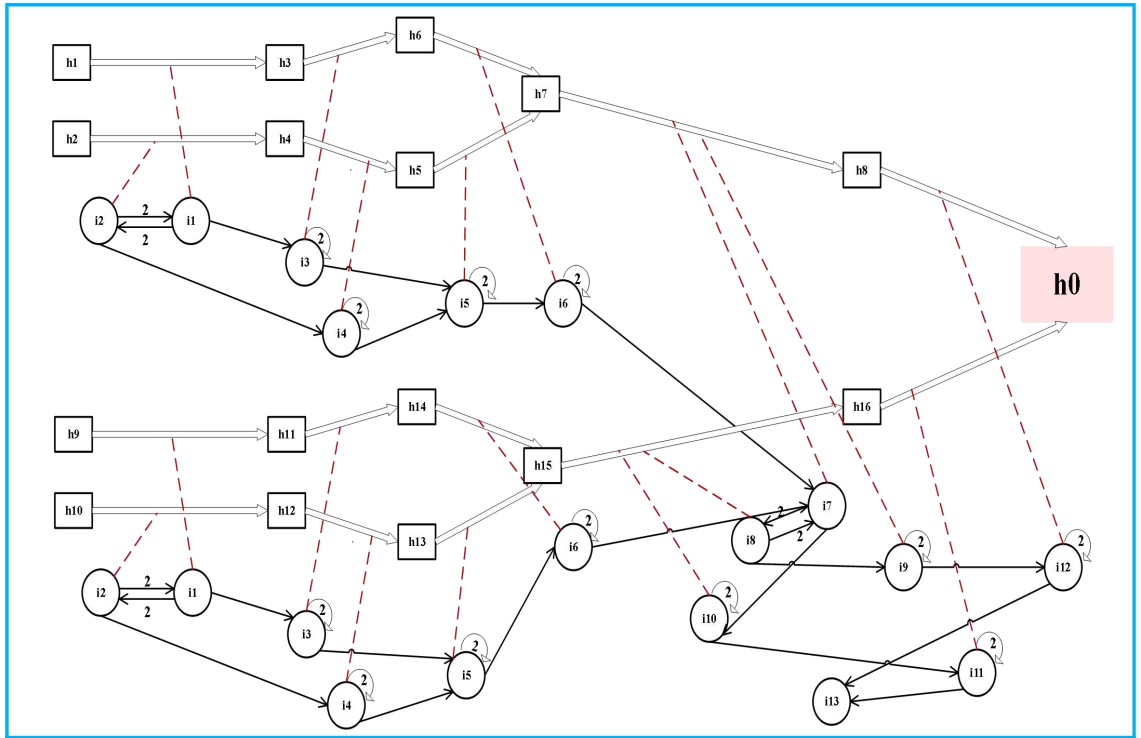


Fault diagnosis model of bus B1 based on an FRSN P system

Virus machines in power system



Fault diagnosis model of bus B1 based on an FRSN P system



Structure diagram of the power system fault production rule virus machine model

- Combine the modules of the virus machine: take the output value as the input to the host
- The input is 0 and 1, indicates the closing and opening of protection relays and circuit breakers
- Hosts represent protection relays and circuit breakers

Virus machines in power system

Questions:

- Is there the possibility of using directly a binary encoding of the input?
- Is there the possibility of one instruction connecting multiple channels?

↓

More applications: such as the intelligent operation and maintenance of distributed photovoltaic power stations

Thanks for your attention!

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