Ongoing work on Spiking Neural P Systems

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OUTLINE

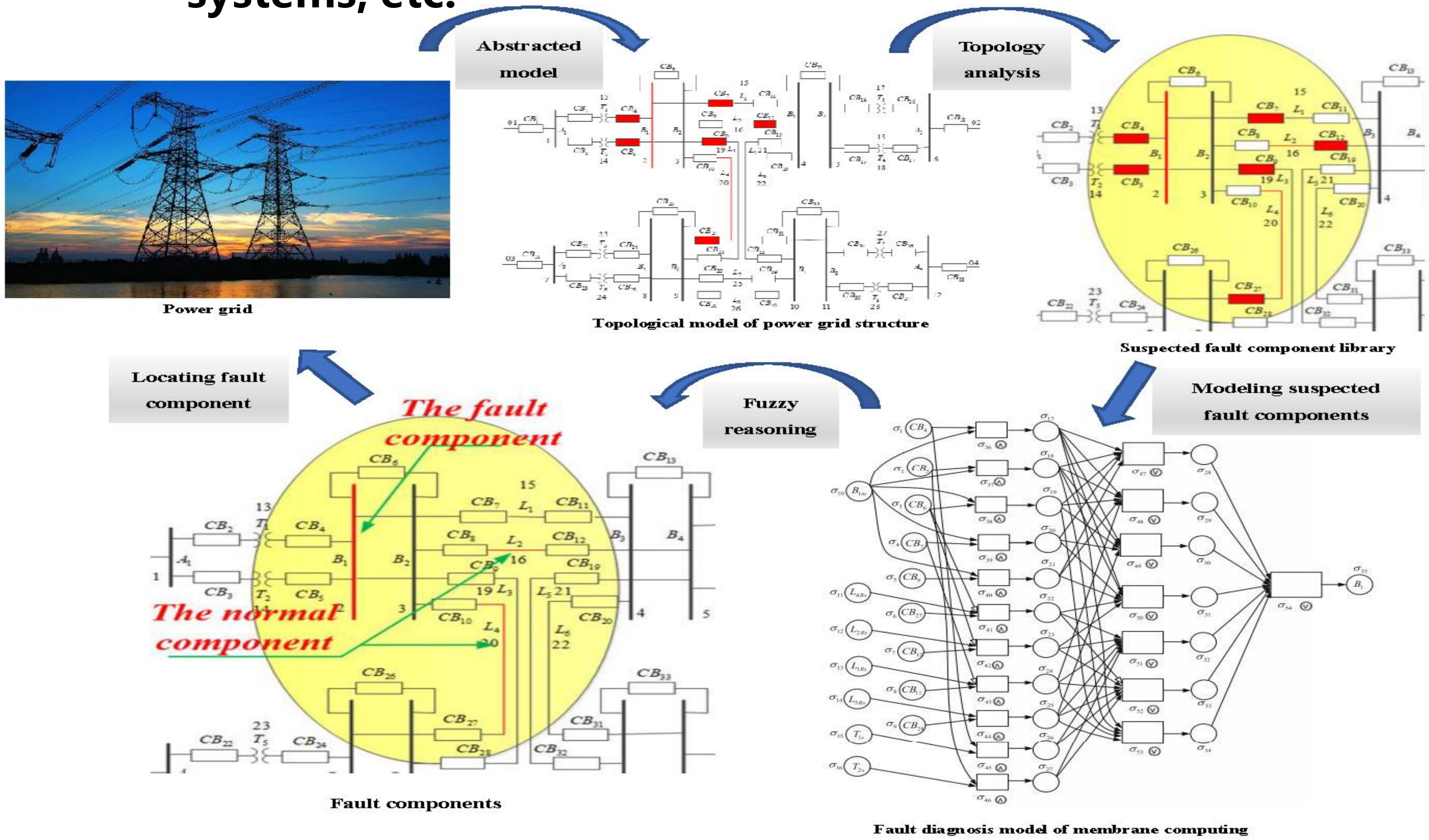
1

SN P systems for diagnosing faults of aircraft engines

1. SN P systems for diagnosing faults of aircraft engines

■ Motivation:

- Lots of work on the use of fuzzy reasoning SN P systems for fault diagnosis of electrical systems, such as power transmission networks, metro traction power systems, etc.



T. Wang, G. Zhang*, Mario J. Pérez-Jiménez, et al. Fault diagnosis of electric power systems based on fuzzy reasoning spiking neural P systems, IEEE Trans. Power Systems, 2015, 30(3): 1182-1194. (ESI 1% Hi-Ci)

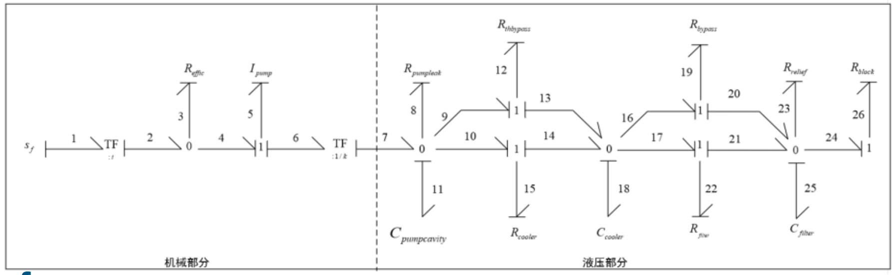
1. SN P systems for diagnosing faults of aircraft engines

■ Motivation:

➢ **Extending this methodology from electrical systems to electromechanical systems, aircraft engines, with fuzzy reasoning numerical SN P systems (FRNSNPS)**

Aircraft engine

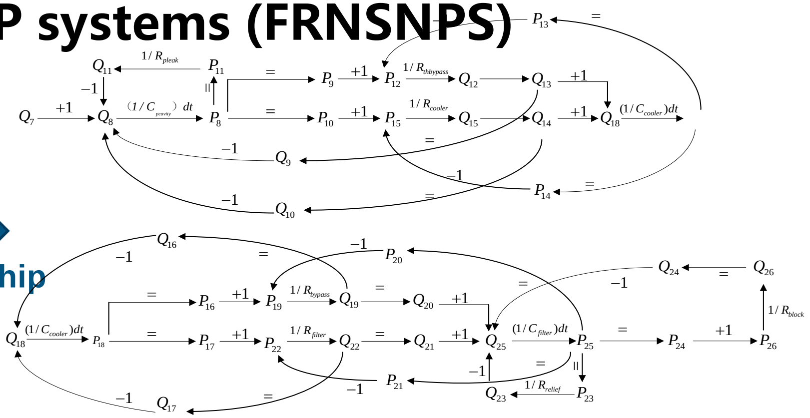
System bonding diagram



Bonding diagram of lubricating oil system

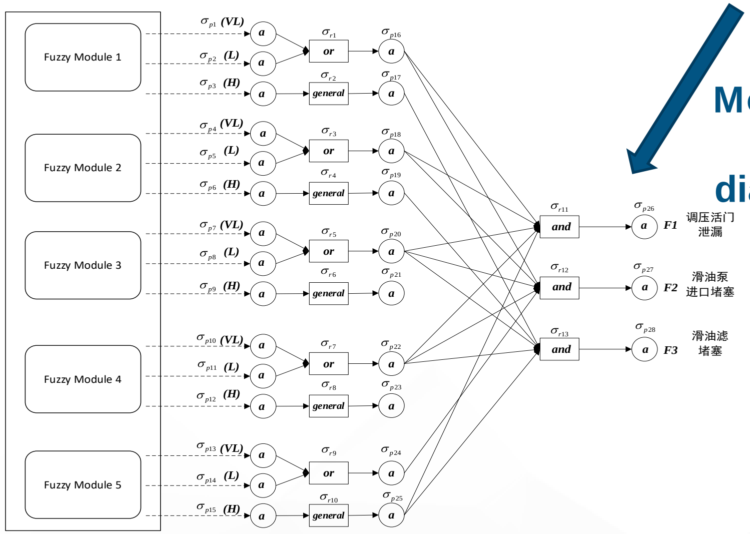
Failure cause & effect

Relationship analysis



Temporal causal diagram

Modelling fault diagnosis



FRNSNPS

Fuzzy reasoning

故障类型（负载，转速）	故障类型置信度			
	F1	F2	F3	诊断结果
（100%，2080r/min）调压活门泄露	0.753	0.309	0.600	F1
（75%，2080r/min）调压活门泄露	0.869	0.308	0.599	F1
（50%，2080r/min）调压活门泄露	0.871	0.308	0.597	F1
（100%，2080r/min）滑油泵进口堵塞	0.231	0.720	0.231	F2
（75%，2080r/min）滑油泵进口堵塞	0.231	0.720	0.231	F2
（50%，2080r/min）滑油泵进口堵塞	0.230	0.720	0.230	F2
（100%，2080r/min）滑油滤堵塞	0	0	0.717	F3
（75%，2080r/min）滑油滤堵塞	0.002	0	0.717	F3
（50%，2080r/min）滑油滤堵塞	0.011	0	0.716	F3

Cause of failure

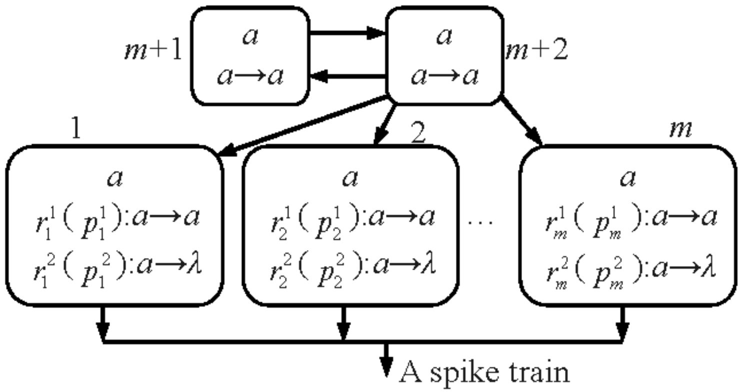
Confidence levels of fault types

2

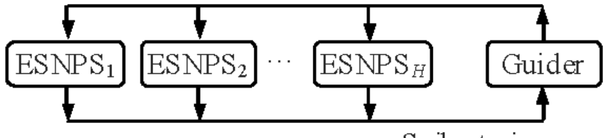
SN P systems for constructing heuristic search algorithms

2. SN P systems for constructing heuristic search algorithms

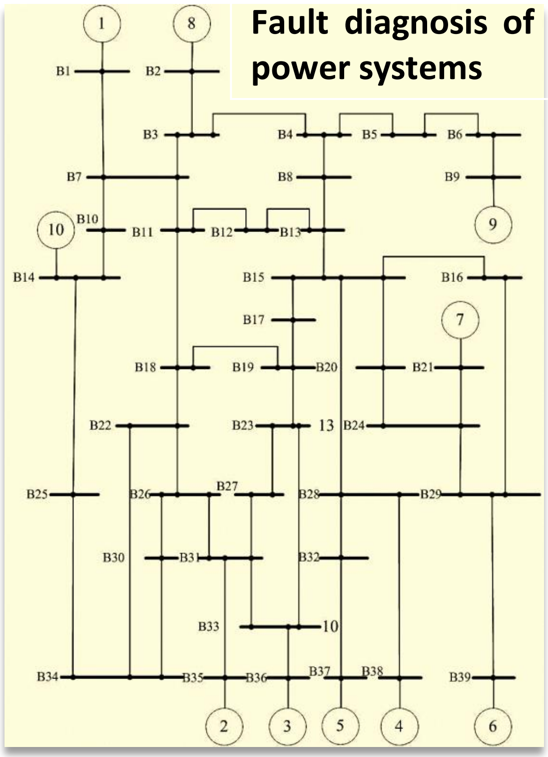
Optimization spiking neural P systems



An extended spiking neural P system

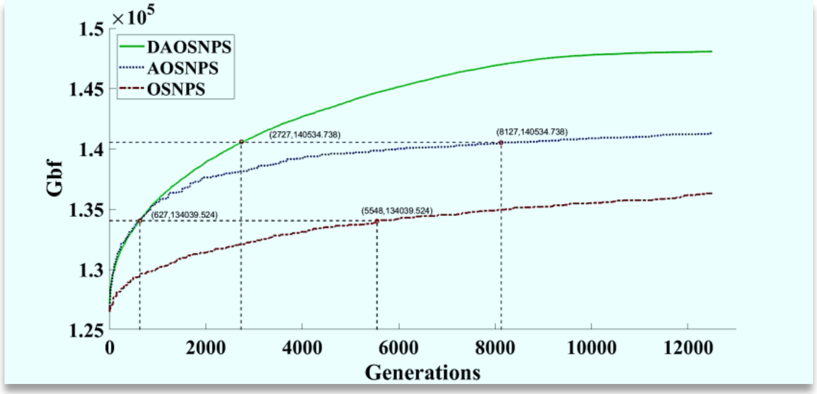


G. Zhang, et al. OSNPS. Int. J. Neural Systems, 2014. (Most cited articles in IJNS, IF=6.325, Category Quartile: Q1)

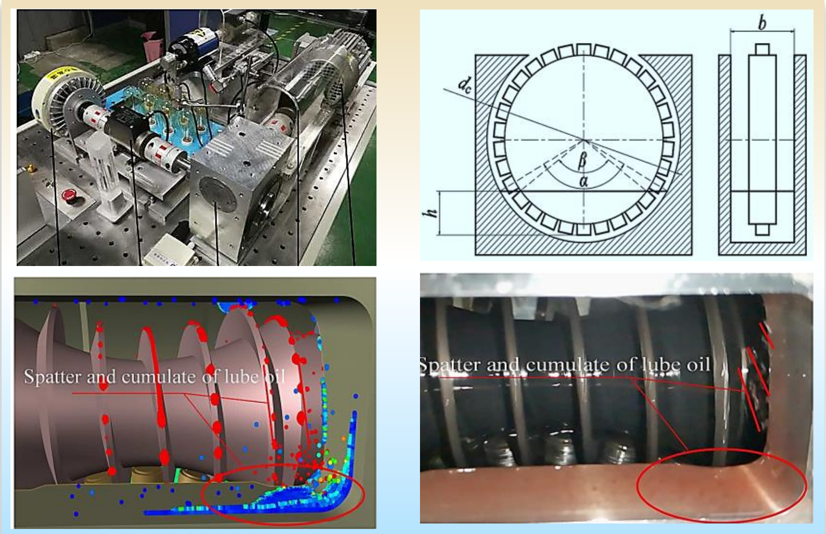


IEEE 39 bus power system

M. Zhu, G. Zhang, et al. Adaptive OSNPS. Int. J. Neural Systems, 2021. (Most cited articles in IJNS)



J. Dong, G. Zhang, et al. Distributed adaptive OSNPS. Inform. Sci., 2022. (IF=8.233, Category Quartile: Q1)



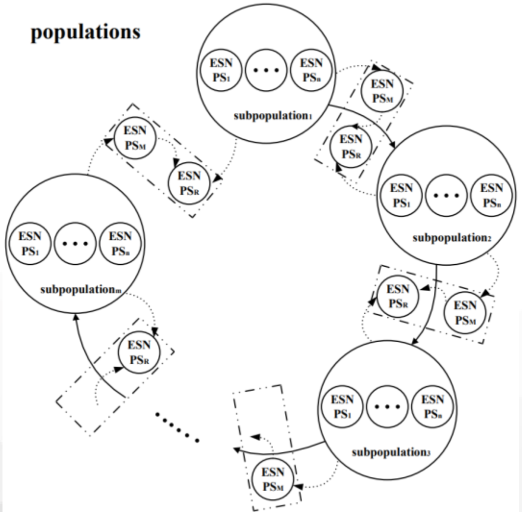
X. Deng, G. Zhang*, et al. Reducer lubrication optimization with OSNPS. Inform. Sci., 2022.

2. SN P systems for constructing heuristic search algorithms

Optimization spiking neural P systems

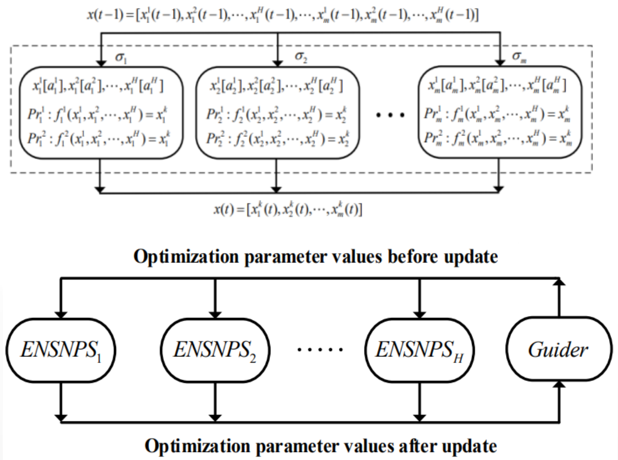
DAOSNPS

DAOSNPS with the distributed structure and the adaptive learning rate can better handle combinatorial optimization problems comparing to OSNPS and AOSNPS



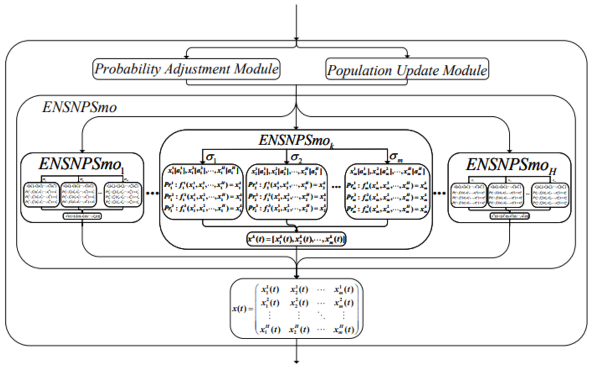
ONSNPS

ONSNPS with multiple parallel ENSN P systems and Guider algorithm are designed to solve continuous constrained optimization problems.



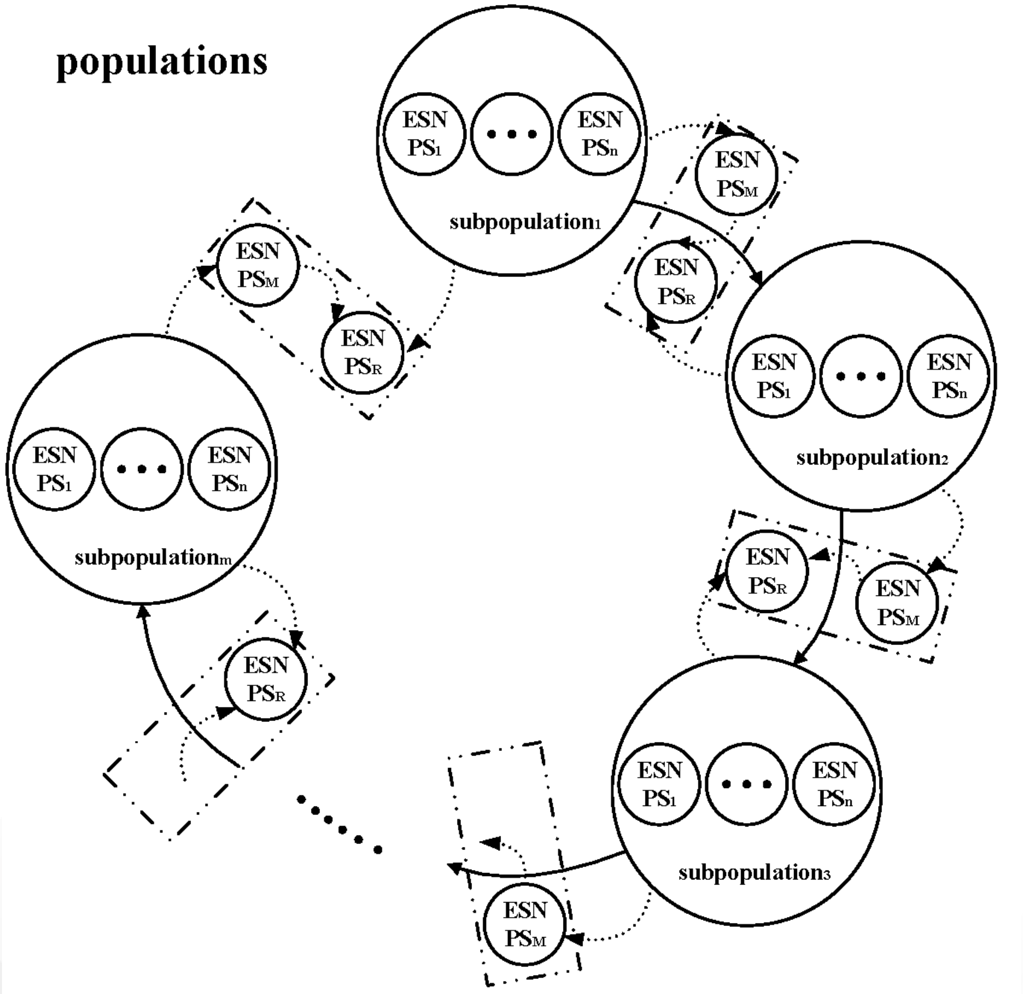
AONSNPS

AONSNPS with adaptive multi-mutation operators and population update strategy are proposed to balance the exploration and exploitation ability.



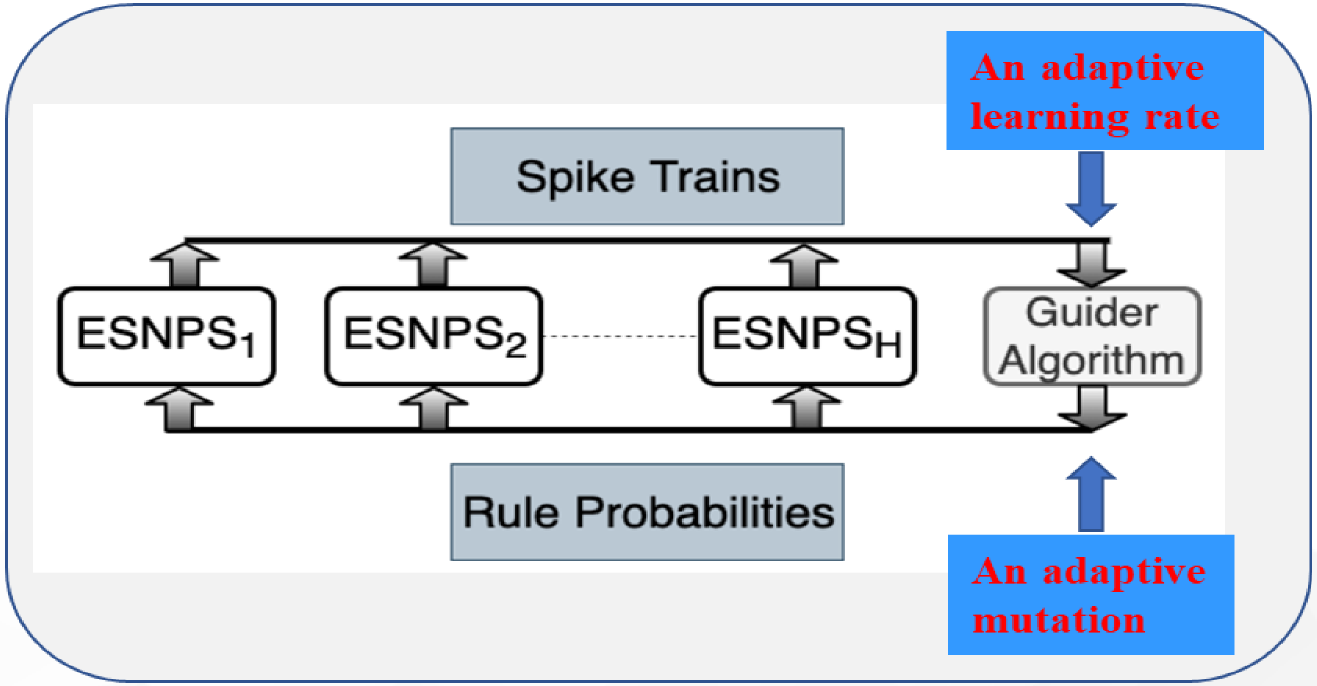
2. SN P systems for constructing heuristic search algorithms

DAOSNPS



DAOSNPS enhances OSNPS by introducing three novel elements:

1) **A distributed population structure**
2) **An adaptive learning rate**
3) **An adaptive mutation**



Experimental Results of DAOSNPS

Mean values (μ), standard deviations (σ) and Wilcoxon rank (w) of experimental results ("*items*" is the number of items. "+", "–" and "=" represent that DAOSNPS achieves better performance, worse performance and no difference than other algorithms, respectively.).

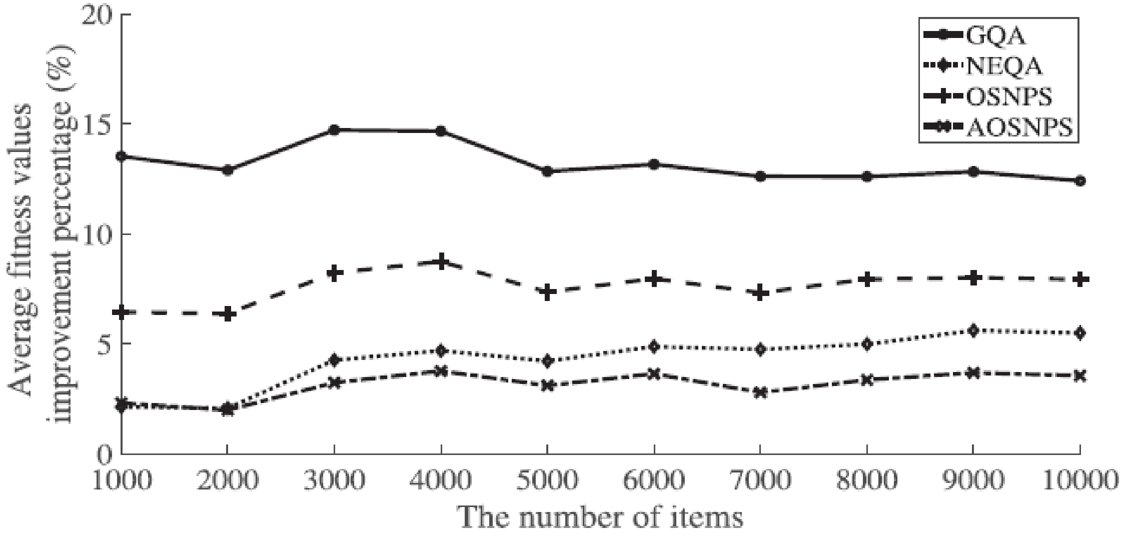
items	GQA			NQEA			OSNPS			AOSNPS			DAOSNPS	
	μ	σ	w	μ	σ	w	μ	σ	w	μ	σ	w	μ	σ
1000	26341	163	+	29274	131	+	28090	311	+	29225	187	+	**29901**	**49**
2000	52908	209	+	58516	293	+	56150	536	+	58562	389	+	**59729**	**99**
3000	78060	276	+	85887	503	+	82745	693	+	86738	587	+	**89548**	**221**
4000	103801	423	+	113691	667	+	109459	724	+	114707	832	+	**119022**	**174**
5000	131224	342	+	142078	714	+	137928	835	+	143602	1328	+	**148068**	**256**
6000	157119	415	+	169517	578	+	164674	730	+	171544	1516	+	**177784**	**490**
7000	182670	441	+	196377	873	+	191659	849	+	200107	1219	+	**205699**	**755**
8000	208561	322	+	223674	953	+	217578	1128	+	227194	1532	+	**234831**	**691**
9000	233946	570	+	249931	917	+	244398	1129	+	254552	1163	+	**263943**	**775**
10000	259881	541	+	276903	1160	+	270663	**769**	+	282101	1774	+	**292116**	907

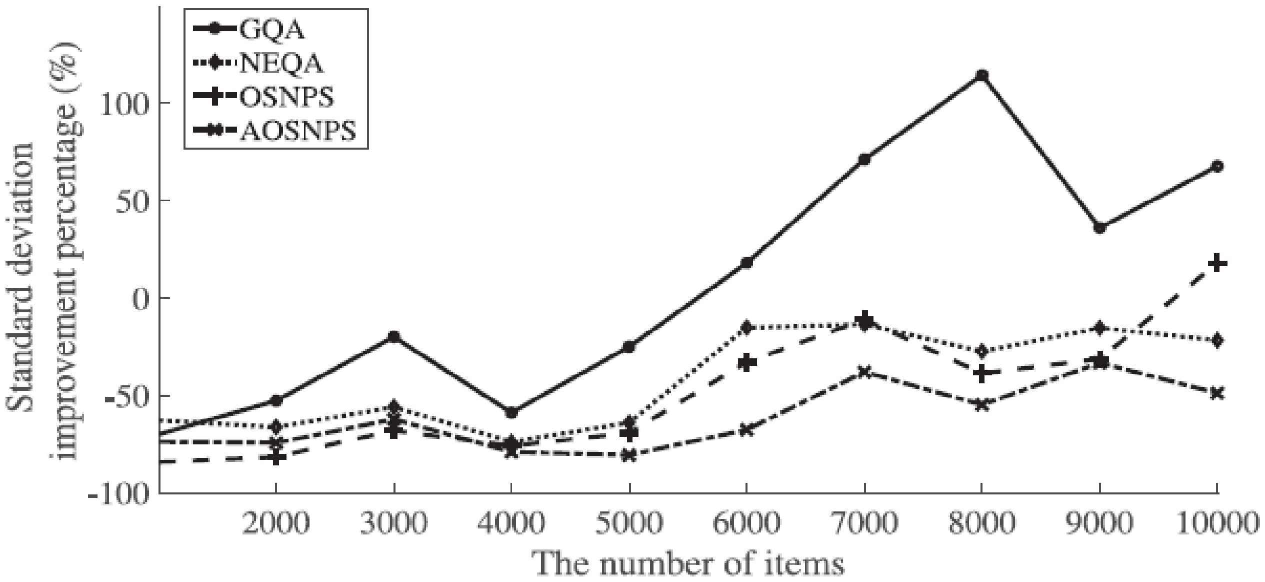
2. SN P systems for constructing heuristic search algorithms

Experimental Results of DAOSNPS

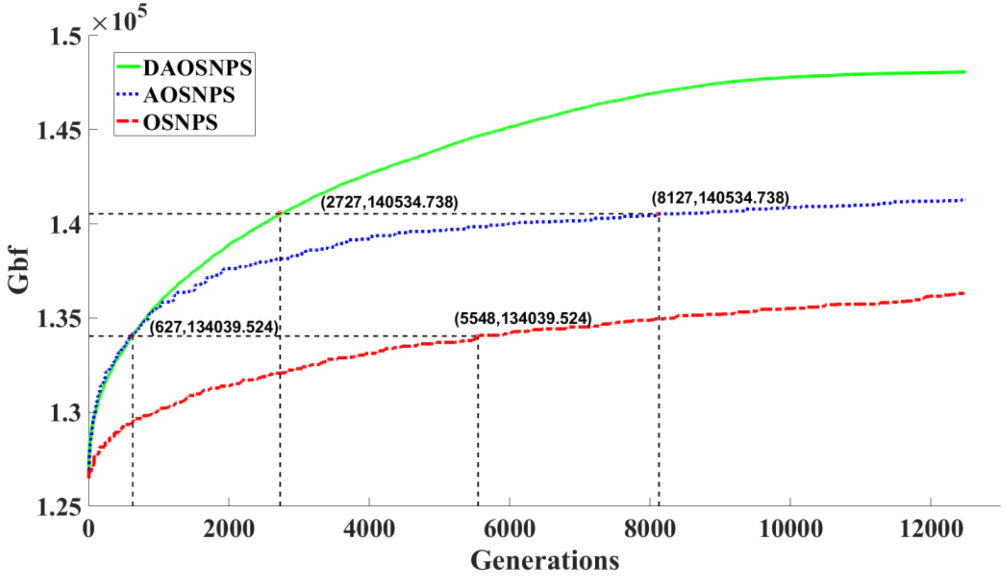
Holm-Bonferroni Procedure with DAOSNPS as reference ($R_0 = 5.0e+00$).

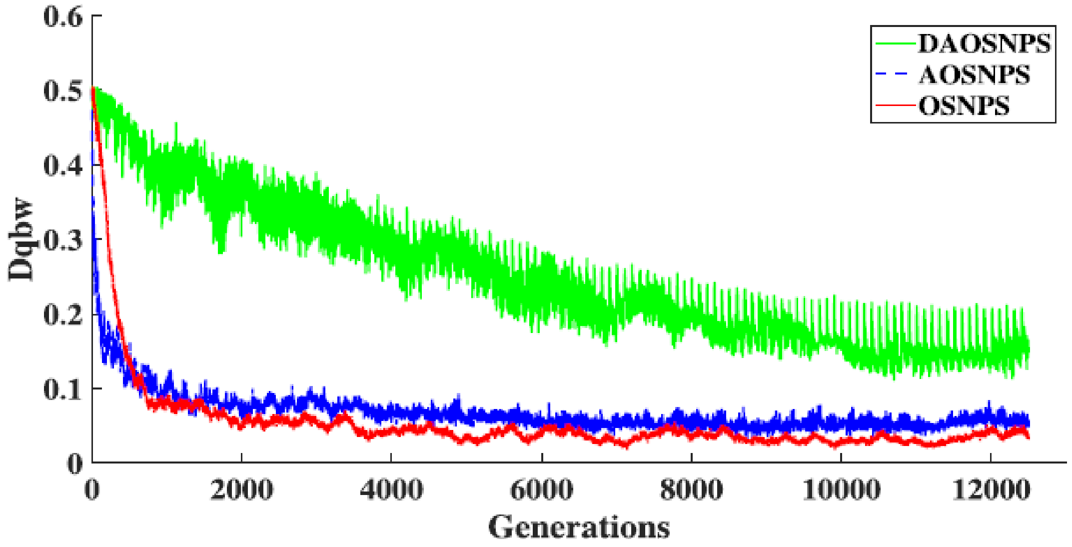
	R_k	z_k	p_k	δ/k	Test
AOSNPS	3.9e+00	−1.5556e+00	1.0617e−01	5.00e−02	Accepted
NQEA	3.1e+00	−2.6870e+00	6.3893e−03	2.50e−02	Rejected
OSNPS	2.0e+00	−4.2426e+00	1.9577e−05	1.67e−02	Rejected
GQA	1.0e+00	−5.6569e+00	1.3663e−08	1.25e−02	Rejected

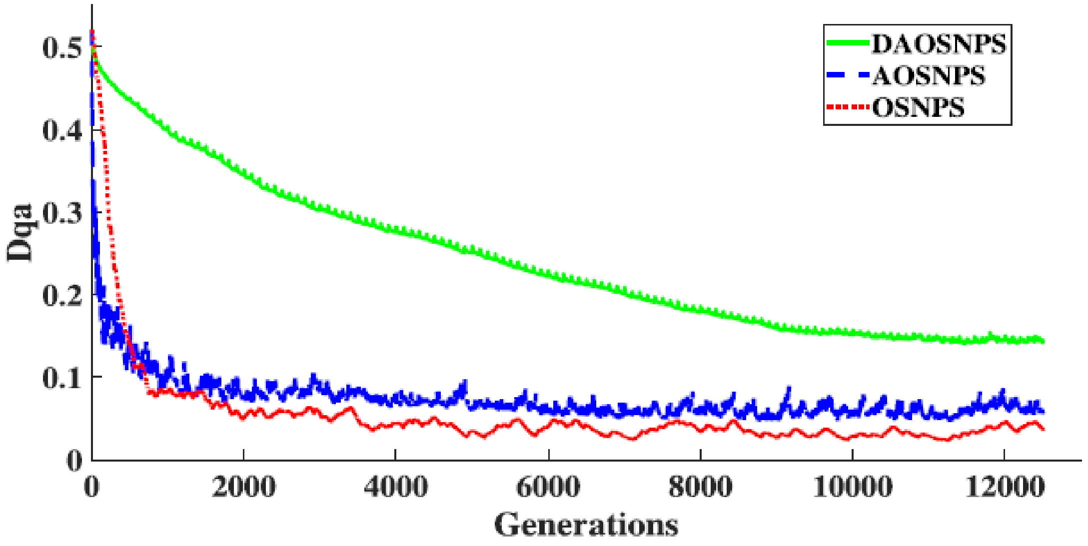


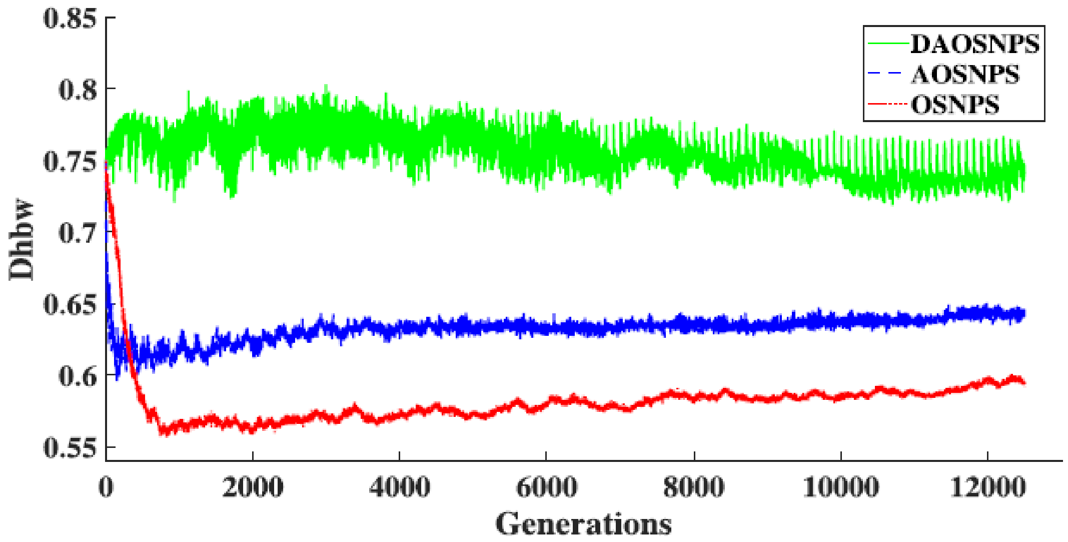


2. SN P systems for constructing heuristic search algorithms









2. SN P systems for constructing heuristic search algorithms

Optimization numerical SN P systems

The values of numerical variables are used to encode and process information.

Numerical Spiking Neural P Systems[1]
(NSN P systems)

[1] Wu, T., Pan, L., Yu, Q., Tan, K.: Numerical spiking neural P systems. IEEE Transactions on Neural Networks and Learning Systems, 32(6),1-15(2020).

The probability selection of evolution rules is designed to choose which rule to perform.

Multiple neurons process information in parallel.

Optimization Spiking Neural P Systems[2]
(OSN P systems)

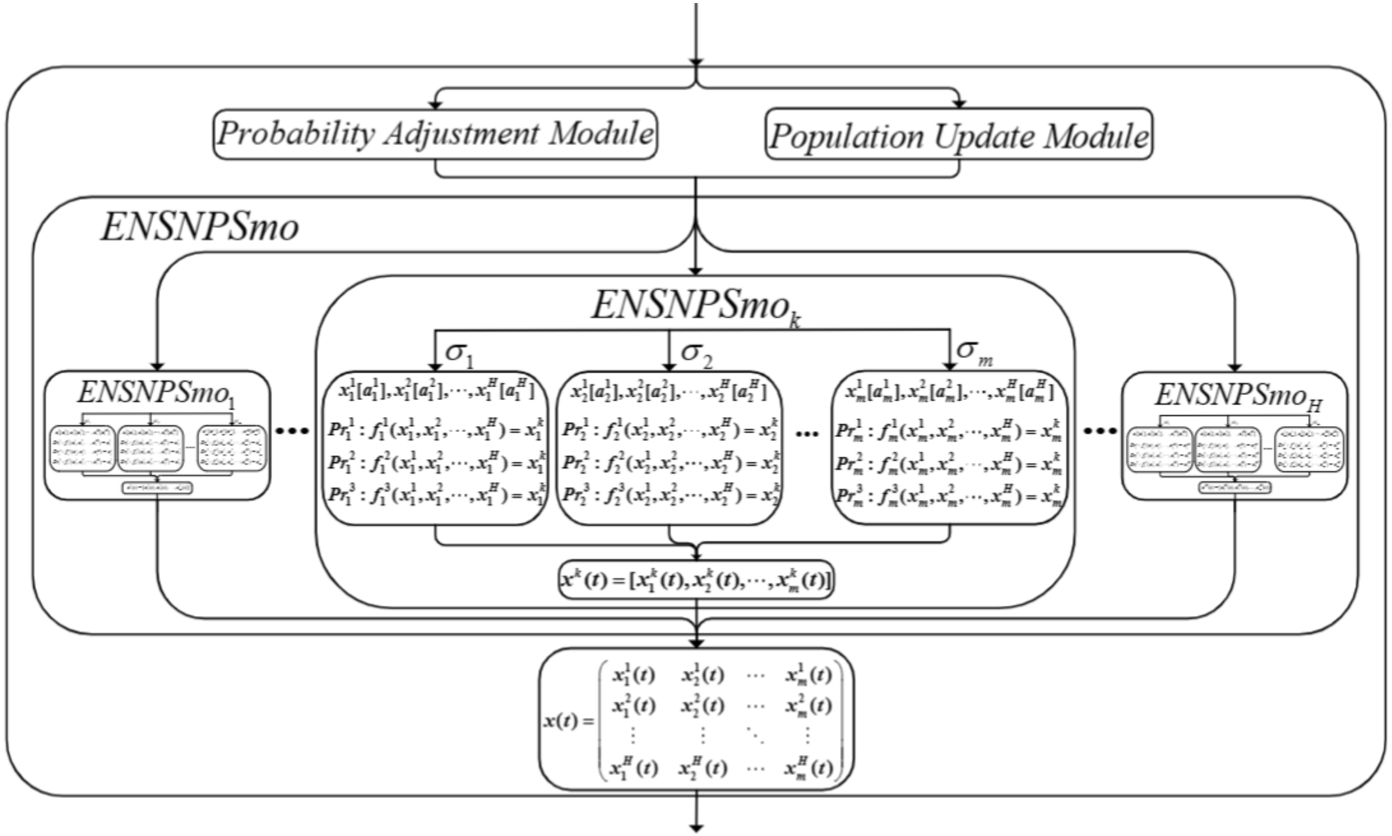
[2] Gexiang Zhang, Haina Rong, Ferrante Neri, Mario J. Pérez-Jiménez.An optimization spiking neural P system for approximately solving combinatorial optimization problems. International Journal of Neural Systems, 2014, 24(5).

Optimization Numerical Spiking Neural P Systems?
(ONSN P systems)

- The values of numerical variables are used to encode and process information.
- Introduce the probability selection of production functions.
- Multiple parameters are processed in parallel.

2. SN P systems for constructing heuristic search algorithms

AONSNPS



1. AONSNPS is composed of multiple parallel ENSNPSmos and two guider modules. Each of ENSNPSmos is employed to generated the candidate population. Comparing to the ONSNPS, every basic neuron in the ENSNPSmos has three different mutation operators where each operator has a different effect.

2. Two guider modules (probability adjustment module and population update module) are used to adjust the mutation probability and achieve crossover and selection among individuals.

3. Multiple parallel ENSNPSmos can generate multiple candidate population according to the initial values and the generation functions. The candidate population is input to probability adjustment module and population update module after mutation.

2. SN P systems for constructing heuristic search algorithms

Optimization SN P systems for segmenting brain tumor images

Problems:

1) In multi-threshold segmentation of brain tumor magnetic resonance imaging (MRI) images, due to the low contrast between the tumor area and normal tissue, as well as between normal tissue and normal tissue, it is necessary to increase the number of threshold segmentation to improve segmentation accuracy. The increase in the number of thresholds leads to a sharp increase in computational complexity.

2) In multi-threshold segmentation of brain tumor MRI images, the initialization threshold setting directly determines the convergence speed of finding the optimal threshold. Therefore, exploring and mining the optimal threshold from different optimization directions will be beneficial for finding the optimal threshold.

3) MRI brain tumor images include four modalities: T1 weighted (T1), enhanced T1 weighted (T1ce), T2 weighted (T2), and fluid attenuation reversal recovery (Flair), and each modality has different imaging characteristics. Based on the characteristics of MRI brain tumors, the multi-area segmentation problem of brain tumors can be transformed into a single region segmentation problem.

2. SN P systems for constructing heuristic search algorithms

Model Construction

$$max(\sigma_W^2)=max(\sum_{i=0}^{q-1} w_i.\sigma_i^2)$$

$$\Downarrow$$

$$T_{best}=(T_1,T_2,\cdots,T_{q-1})$$

$$\Downarrow$$

$$g_{Flair}(x,y)=\begin{cases}0 & if\ \ f(x,y)<T_1\\ G_i & if\ \ T_i+1\le f(x,y)<T_{i+1}\\ G_{\max} & if\ \ f(x,y)<T_{q-1}\end{cases}$$

$$C_{Li}=\sum_{x=1}^{240}\sum_{y=1}^{240}P_{Li}^{(x,y)}\quad 0\le i\le q\text{-}1$$

$$\Downarrow$$

$$C_{\max}=\max\{C_{L1},C_{L2},\cdots,C_{Lq-1}\}$$

$$\Downarrow$$

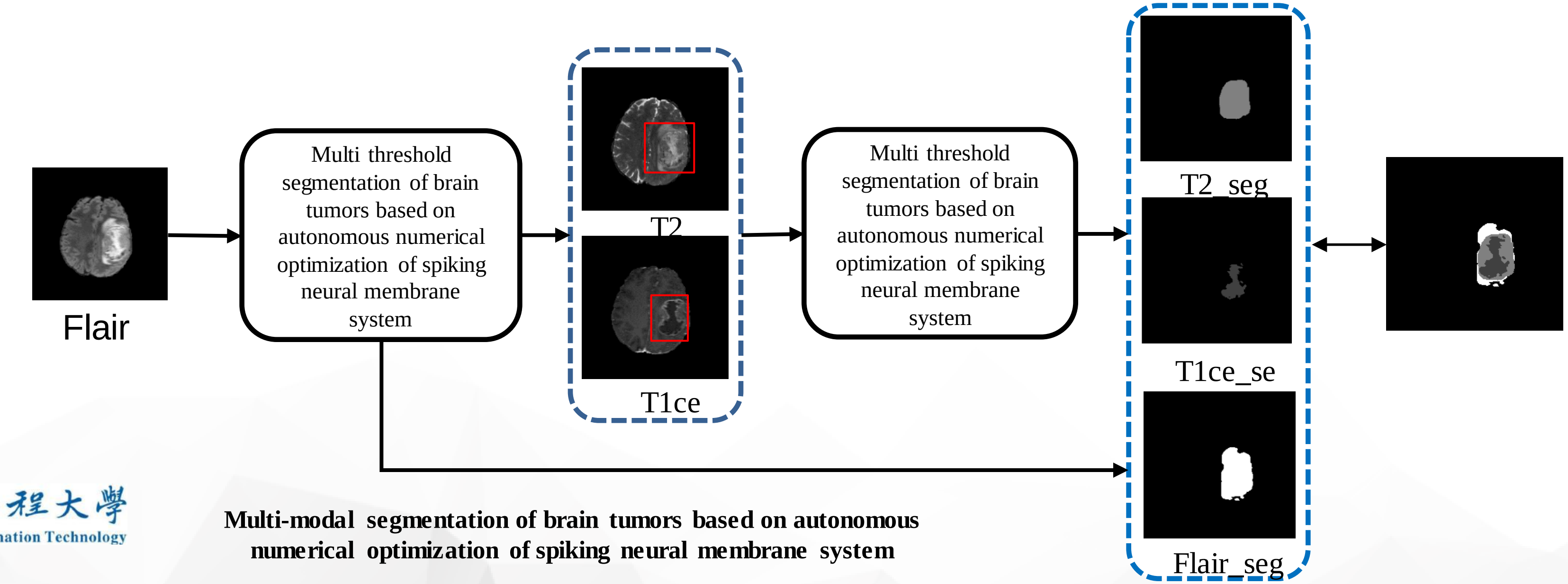
$$g_{Flair\_Seg}(x,y)=\begin{cases}0 & if\ \ (x,y)\notin C_{\max}\\ G_{\max} & if\ \ (x,y)\in C_{\max}\end{cases}$$

$$g_{T1ce}(x,y)=\begin{cases}0 & if\ \ g_{Flair}(x,y)=0\\ g_{T1ce}(x,y) & if\ \ g_{Flair}(x,y)=G_{\max}\end{cases}$$

$$g_{T1ce\_Seg}(x,y)=\begin{cases}0 & if\ \ (x,y)\notin C_{\max}\\ G_{\max} & if\ \ (x,y)\in C_{\max}\end{cases}$$

$$g_{T2}(x,y)=\begin{cases}0 & if\ \ g_{Flair}(x,y)=0\\ g_{T1ce}(x,y) & if\ \ g_{Flair}(x,y)=G_{\max}\end{cases}$$

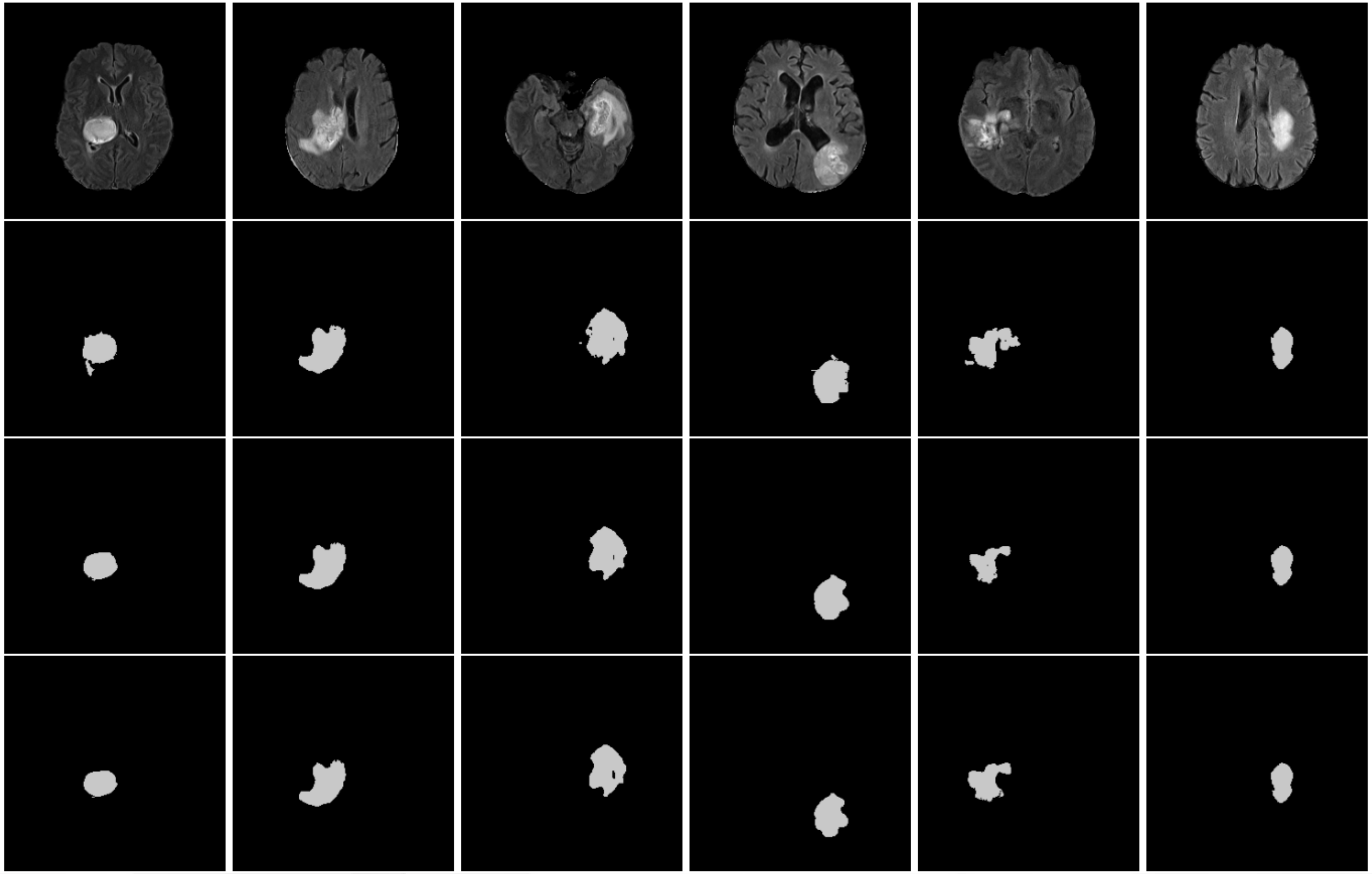
$$g_{T2\_Seg}(x,y)=\begin{cases}0 & if\ \ (x,y)\notin C_{\max}\\ G_{\max} & if\ \ (x,y)\in C_{\max}\end{cases}$$



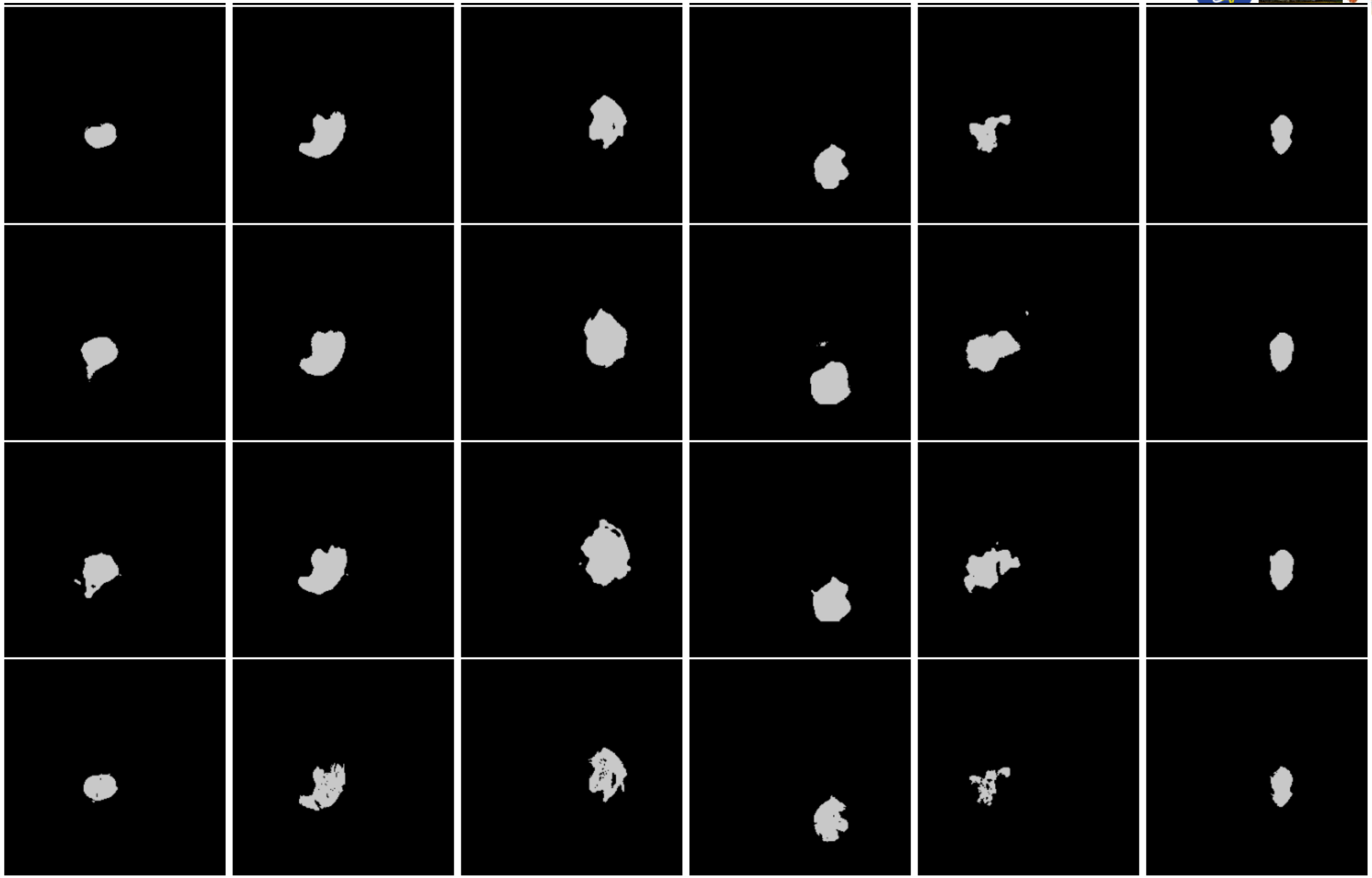
Multi-modal segmentation of brain tumors based on autonomous numerical optimization of spiking neural membrane system

2. SN P systems for constructing heuristic search algorithms

Experimental results

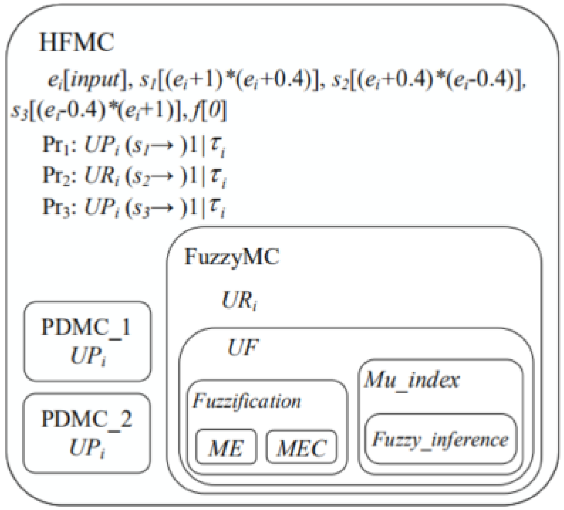


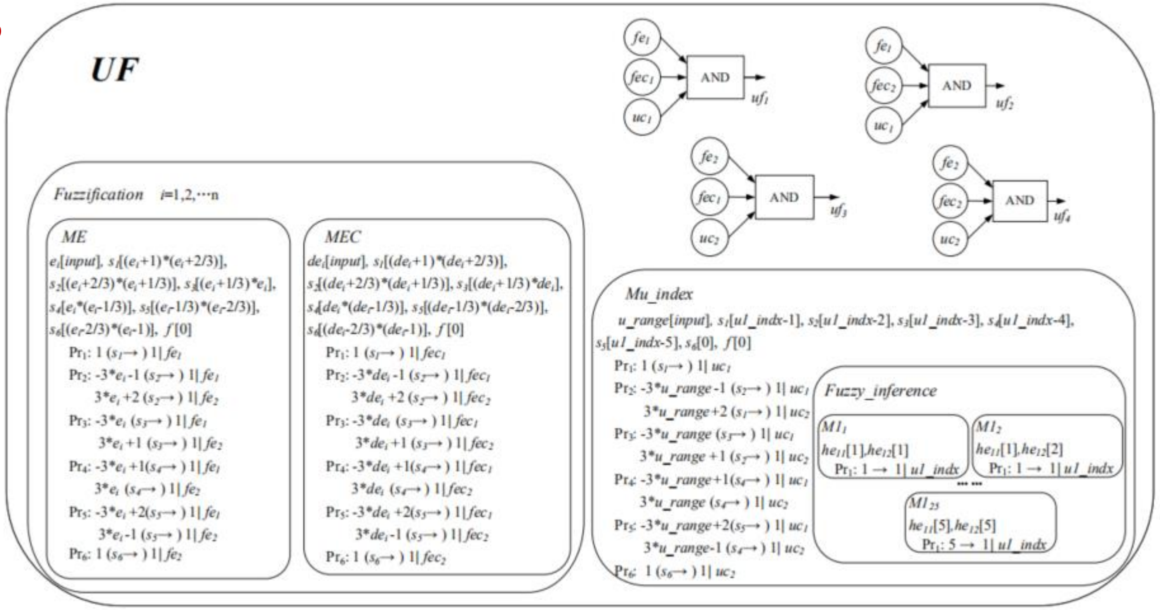
2. SN P systems for constructing heuristic search algorithms

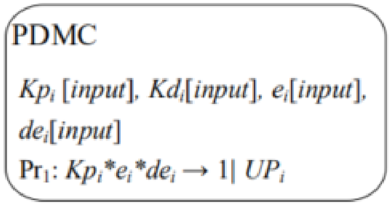


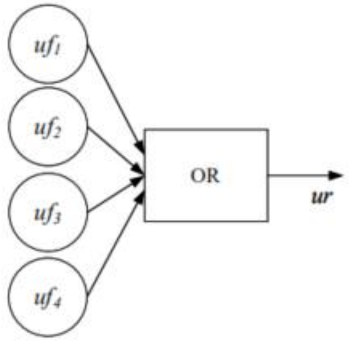
Multi-threshold segmentation of brain tumors MRI-Flair based on autonomous numerical optimization of spiking neural membrane system (The MRI image segmentation results of brain tumors based on ABC, CMA-ES, SHADE, CSO, RMSProp, and ONSNPSamos. The first to second rows of six images represent the original MRI images and the standard segmentation images of brain tumors, ranging from 1 to 6. The third to eighth rows represent the segmentation results of brain tumor MRI images ranging from 1 to 6 based on ONSNPSamos, ABC, SHADE, FCN16s, HybridUnet, and ONSNPS, respectively.).

Optimization SN P systems for optimizing the parameters of controllers for Biped robots

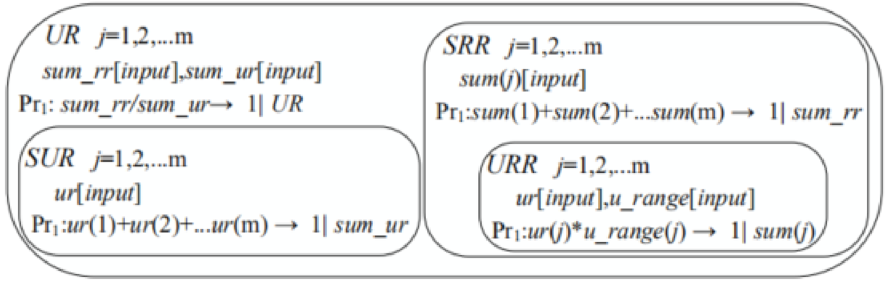








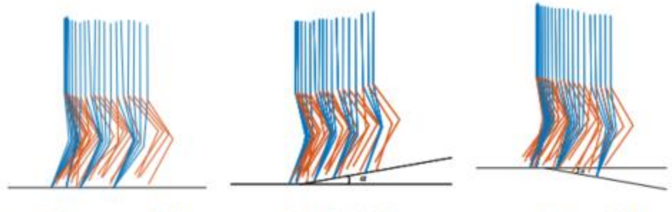
(a) The membrane structure of *ur*.



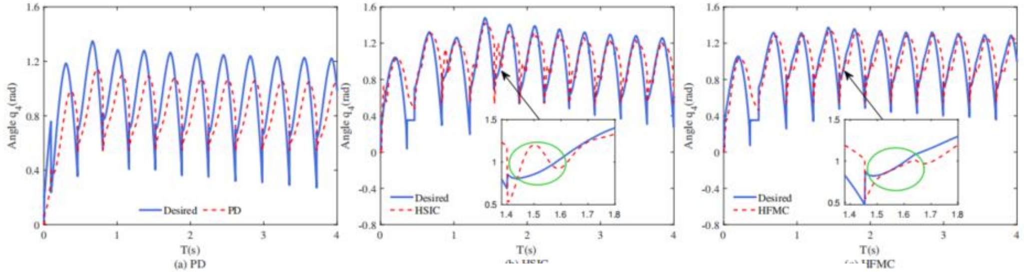
(b) The membrane structure of *UR*.

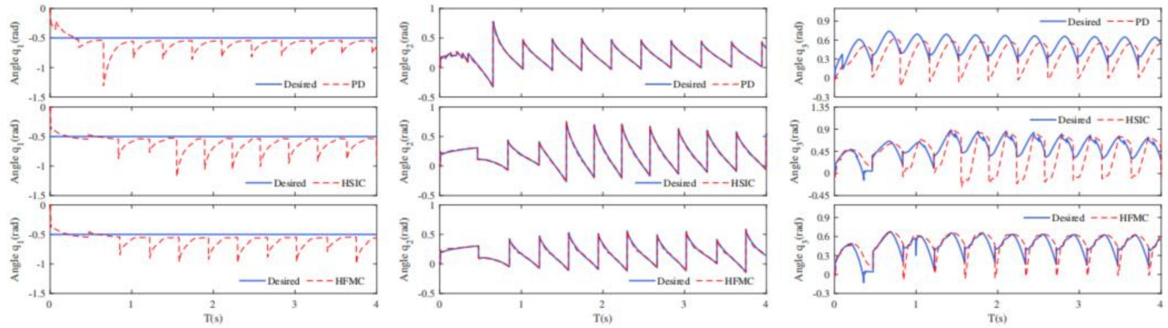
2. SN P systems for constructing heuristic search algorithms

Optimization SN P systems for optimizing the parameters of controllers for Biped robots

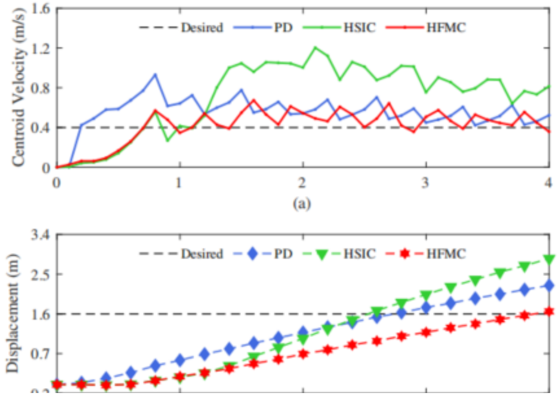


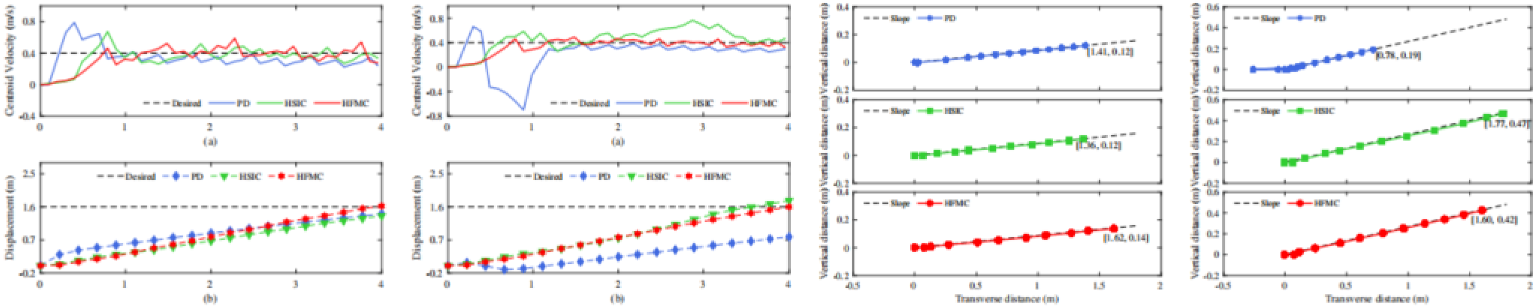
(a) Planar walking. (b) Uphill. (c) Downhill.





(a) Angle tracking performance of joint q_1 under PD, HSIC and HFMC. (b) Angle tracking performance of joint q_2 under PD, HSIC and HFMC. (c) Angle tracking performance of joint q_3 under PD, HS

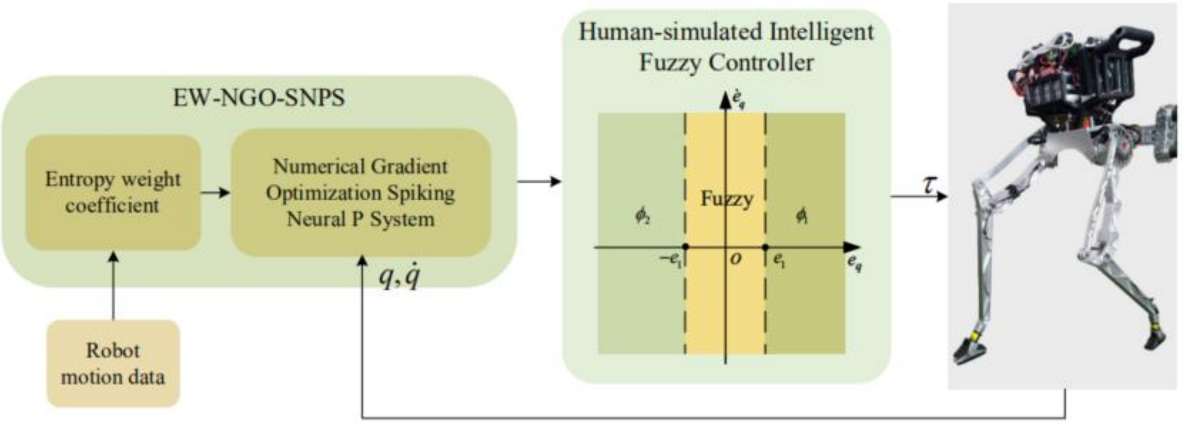


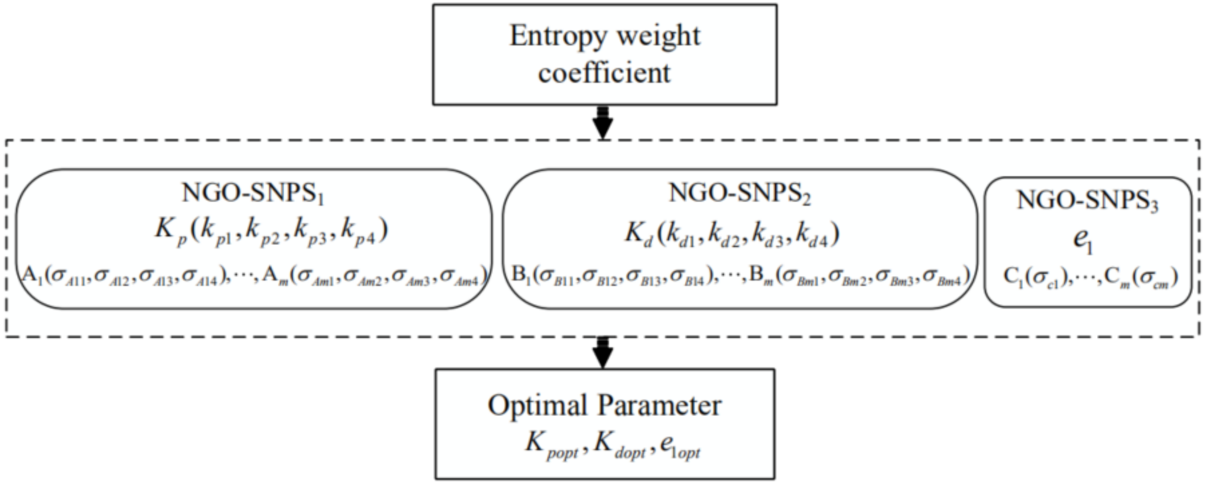


(a) Centroid velocity and displacement at a slope angle of $\alpha = 5°$. (b) Centroid velocity and displacement at a slope angle of $\alpha = 15°$. (c) Foot placement at a slope angle of $\alpha = 5°$. (d) Foot placement at a slope angle of $\alpha = 15°$.

2. SN P systems for constructing heuristic search algorithms

Optimization SN P systems for optimizing the parameters of controllers for Biped robots





3

SN P systems for machines learning methods

3. SN P systems for machines learning methods

Learning Numerical Spiking Neural P Systems

LSNPS converts nonlinear separable data into linear separable data and automatically adjusts weights through dimensionality enhancement techniques and Widrow-Off learning rules, respectively.

Spiking neural networks (SNNs)

Membrane systems (P Systems)

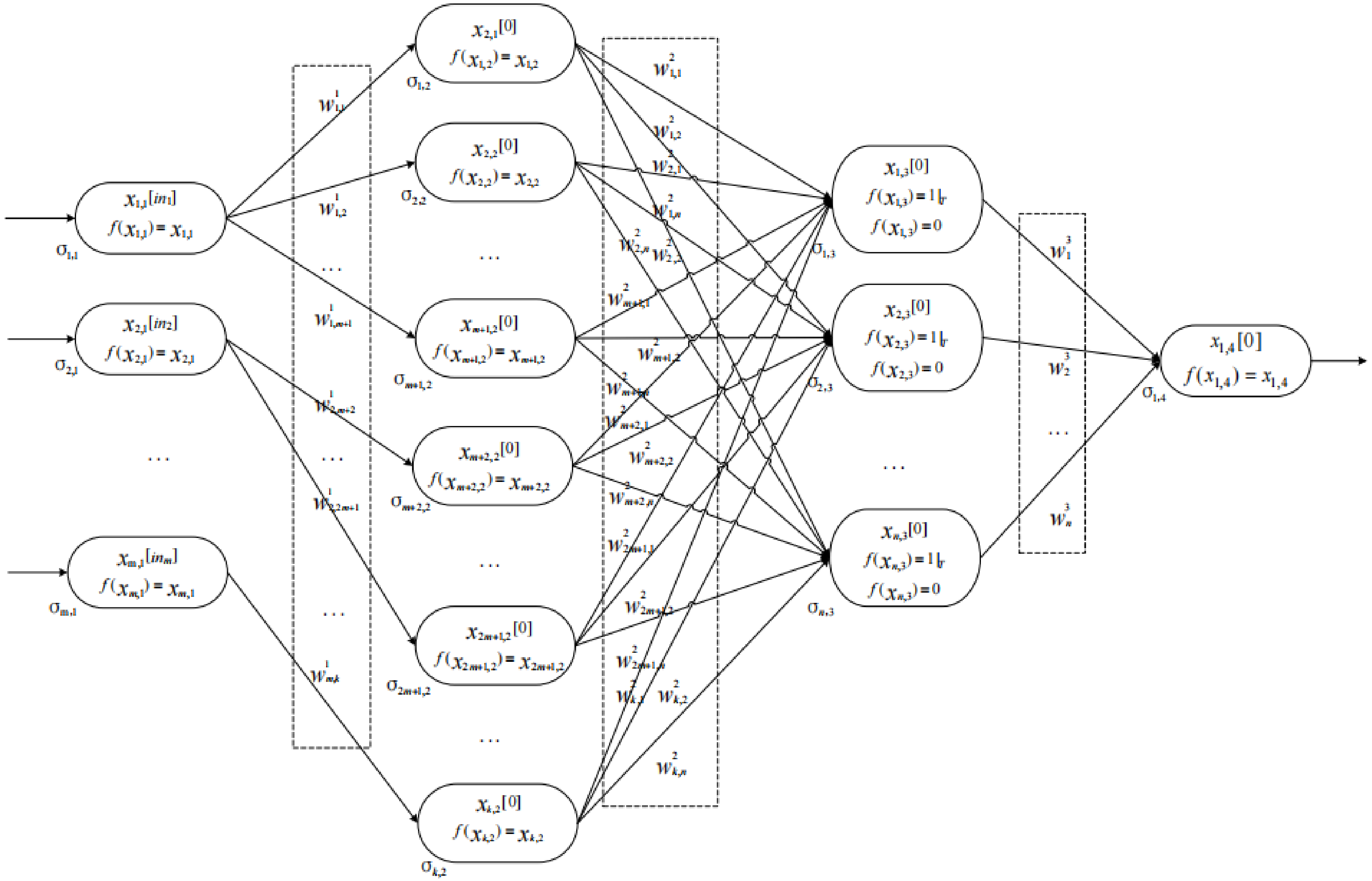
→ Spiking neural P systems (SN P Systems) → Layer Spiking neural P systems (LSN P Systems) → Learning Spiking neural P systems (LNSN P Systems)

Comparing to SNN, SNP can only operate on integers and cannot operate on floating-point numbers.

Better convergence performance and lower loss value?

3. SN P systems for machines learning methods

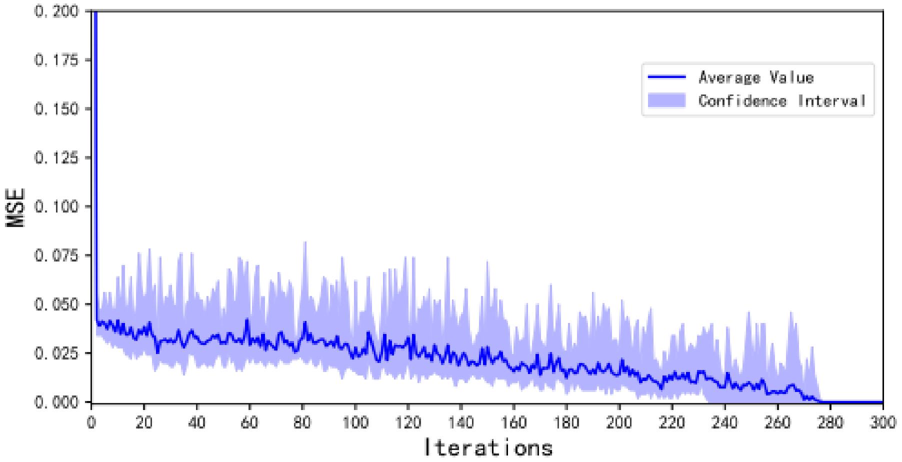
The structure of an LNSN P system is constructed by the input layer, the pre-processing layer, the classification layer, and the output layer. Data is imported from the environment to the input layer.



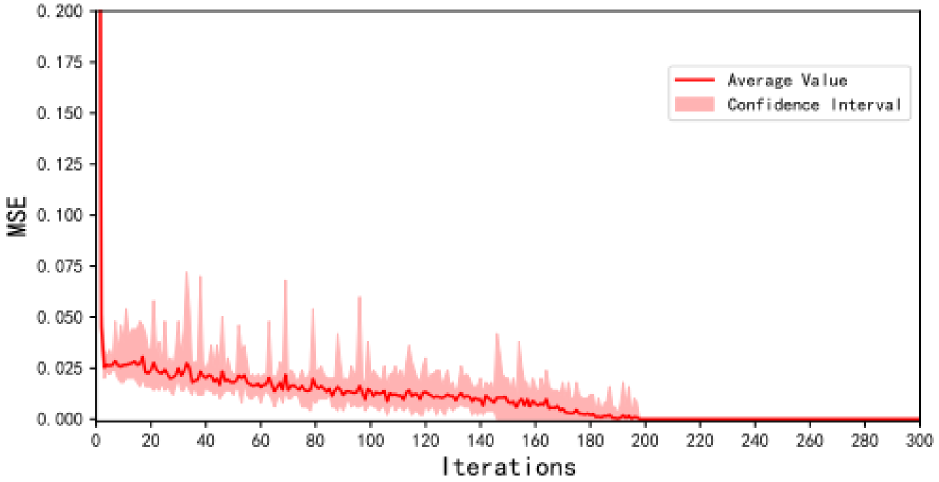
Framework of LNSN P systems

3. SN P systems for machines learning methods

Experimental results

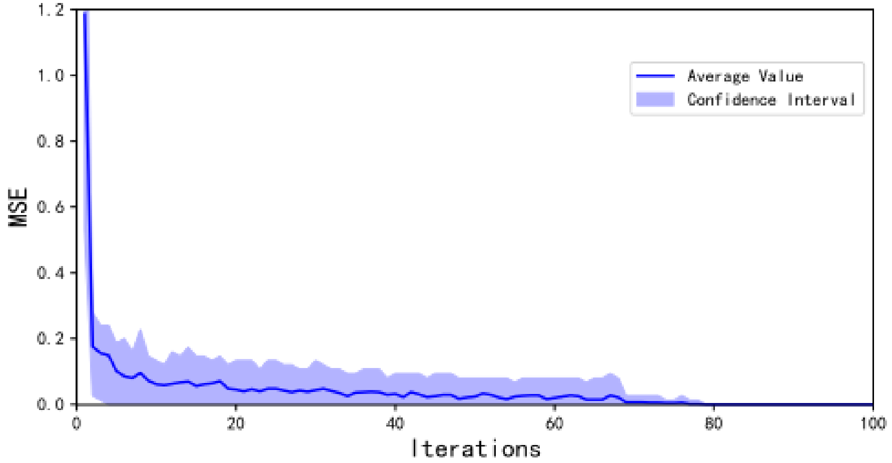


(a) The mean square value (blue line) of the average of 20 independent runs and associated confidence interval (blue band) based on LSNPS.

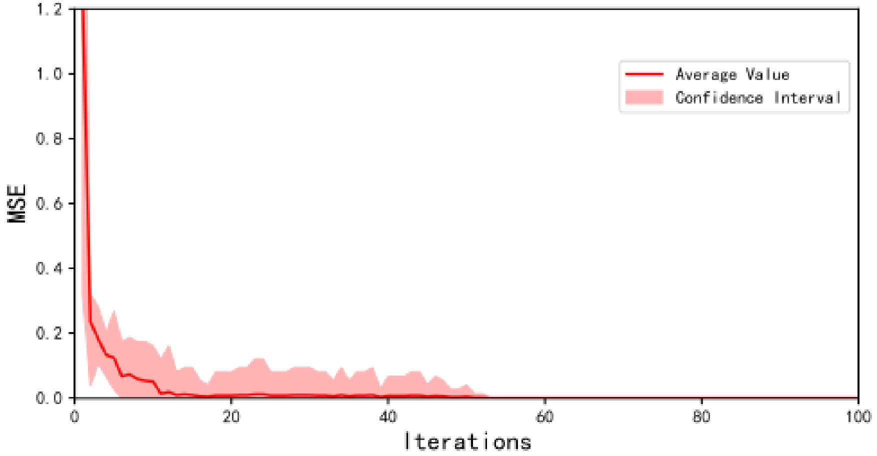


(b) The mean square value (red line) of the average of 20 independent runs and associated confidence interval (red band) based on LNSNPSla.

Breast Cancer Wisconsin (original)



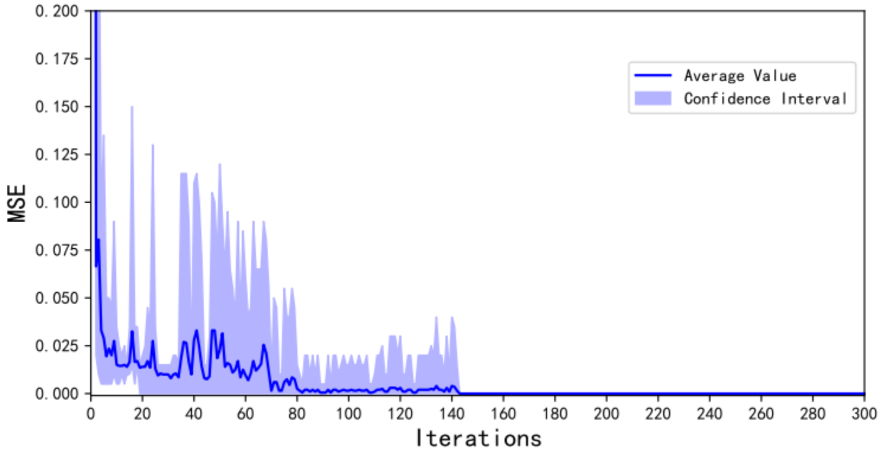
(a) The mean square value (blue line) of the average of 20 independent runs and associated confidence interval (blue band) based on LSNPS.



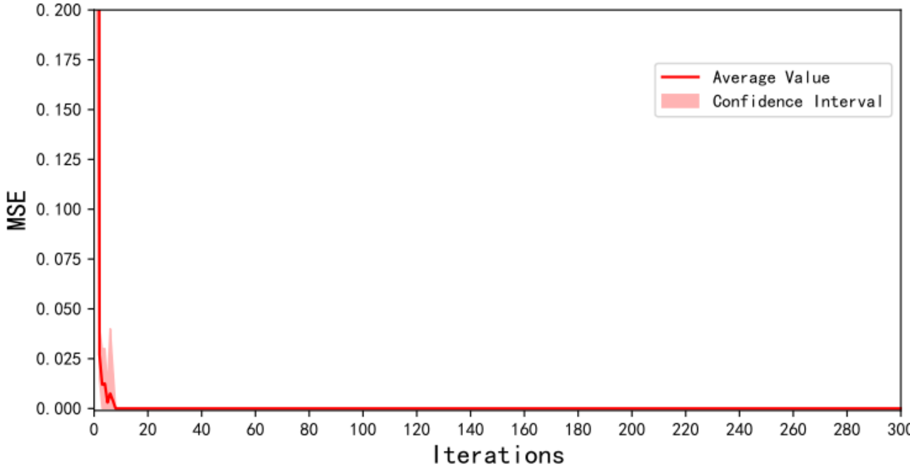
(b) The mean square value (red line) of the average of 20 independent runs and associated confidence interval (red band) based on LNSNPSla.

Iris Flower

3. SN P systems for machines learning methods

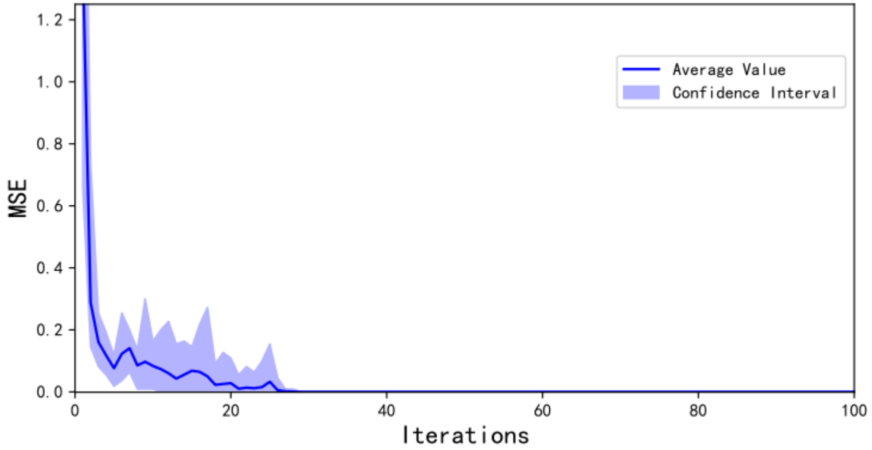


(a) The mean square value (blue line) of the average of 20 independent runs and associated confidence interval (blue band) based on LSNPS.

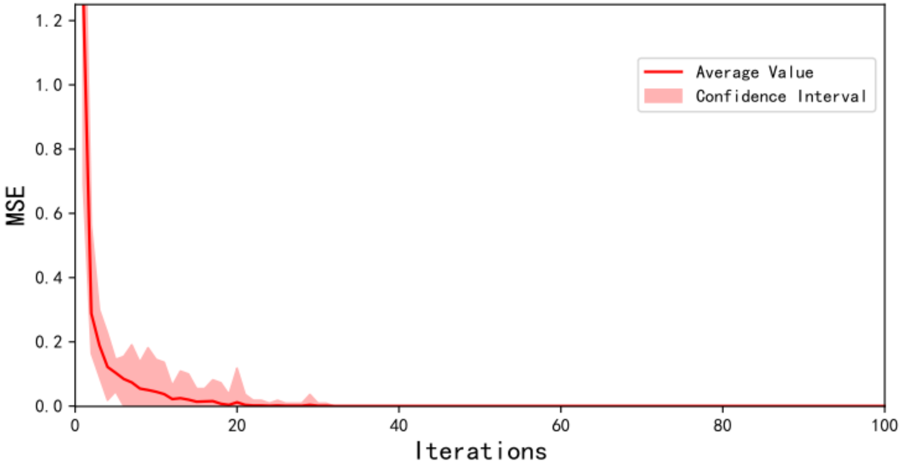


(b) The mean square value (red line) of the average of 20 independent runs and associated confidence interval (red band) based on LNSNPSla.

Palmer Penguins



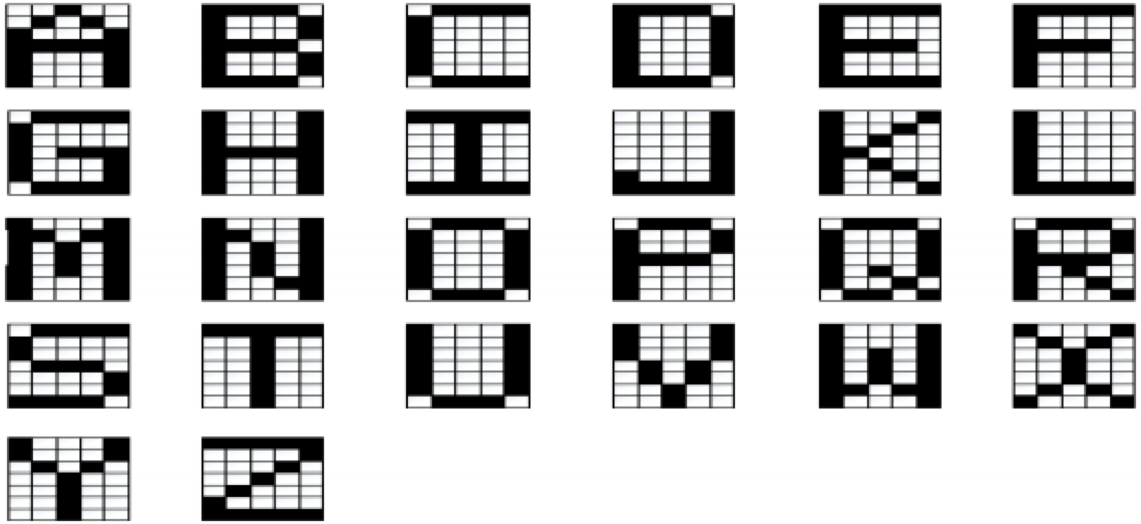
(a) The mean square value (blue line) of the average of 20 independent runs and associated confidence interval (blue band) based on LSNPS.



(b) The mean square value (red line) of the average of 20 independent runs and associated confidence interval (red band) based on LNSNPSla.

Seeds

3. SN P systems for machines learning methods



English letters

Accuracy evaluation of English letters with 0-7 bits flipping between LNSNPS, LSNPS , BPNN , SNN, and HLSNPS.

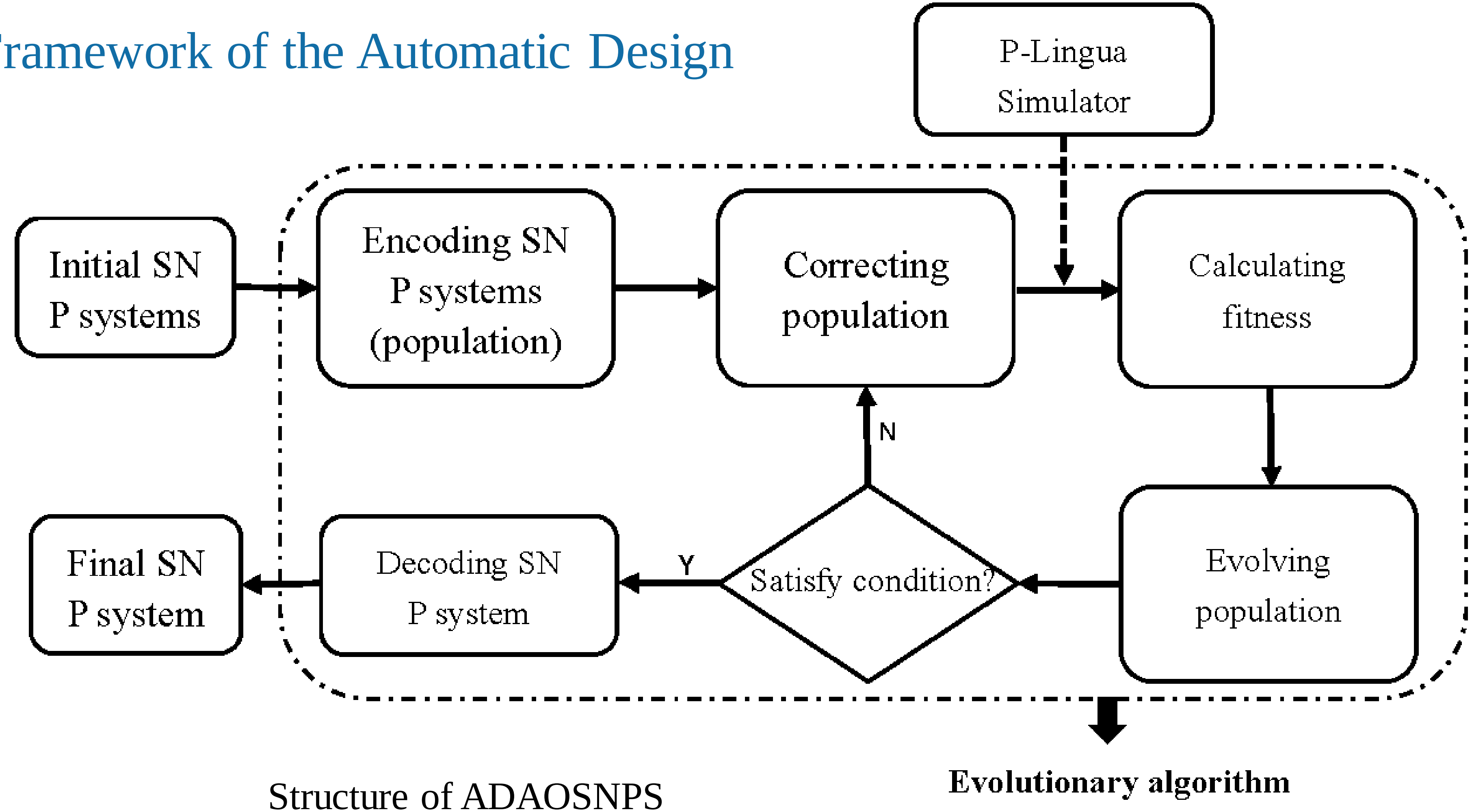
Methods	d=0		d=1		d=2		d=3		d=4		d=5		d=6		d=7	
	A_{te}	W	A_{te}	W	A_{te}	W	A_{te}	W	A_{te}	W	A_{te}	W	A_{te}	W	A_{te}	W
BPNN	94.23%	+	90.81%	+	84.94%	+	79.14%	+	72.93%	+	62.54%	+	55.94%	+	49.22%	+
SNN	93.85%	+	92.70%	+	92.24%	+	89.41%	+	**96.45%**	-	81.60%	+	74.52%	+	66.22%	+
HLSNPS	98.77%	+	98.15%	+	97.12%	+	**95.96%**	-	87.69%	+	83.81%	+	80.38%	+	77.77%	+
LSNPS	100%	+	98.87%	+	97.26%	+	93.56%	+	91.57%	+	88.83%	+	84.03%	+	77.43%	+
LNSNPS	**100%**		**99.31%**		**97.63%**		93.40%		92.37%		**88.97%**		**85.30%**		**78.04%**	
+/≈/-	4/0/0		4/0/0		4/0/0		3/0/1		3/0/1		4/0/0		4/0/0		4/0/0	
Score	d=0		4		4		4		2		2		4		4	

4

Automatic design of SN P systems

4. Automatic design of SN P systems for arithmetic operations

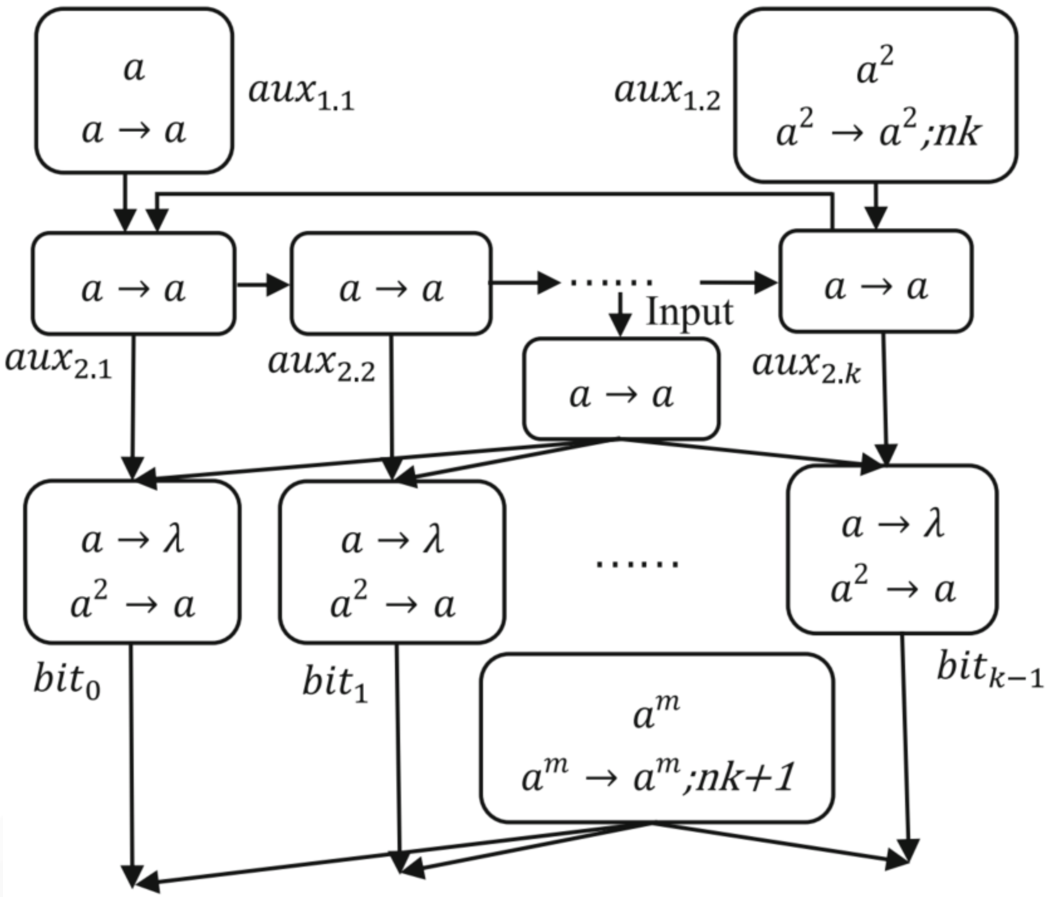
Framework of the Automatic Design



Structure of ADAOSNPS

4. Automatic design of SN P systems

Experimental Results



The structure of the input

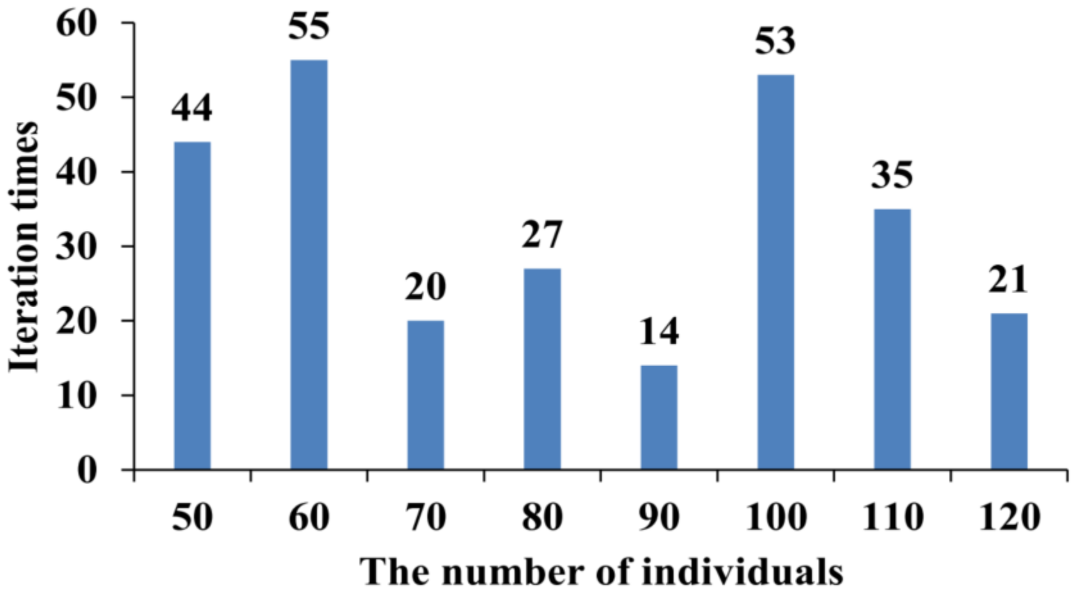
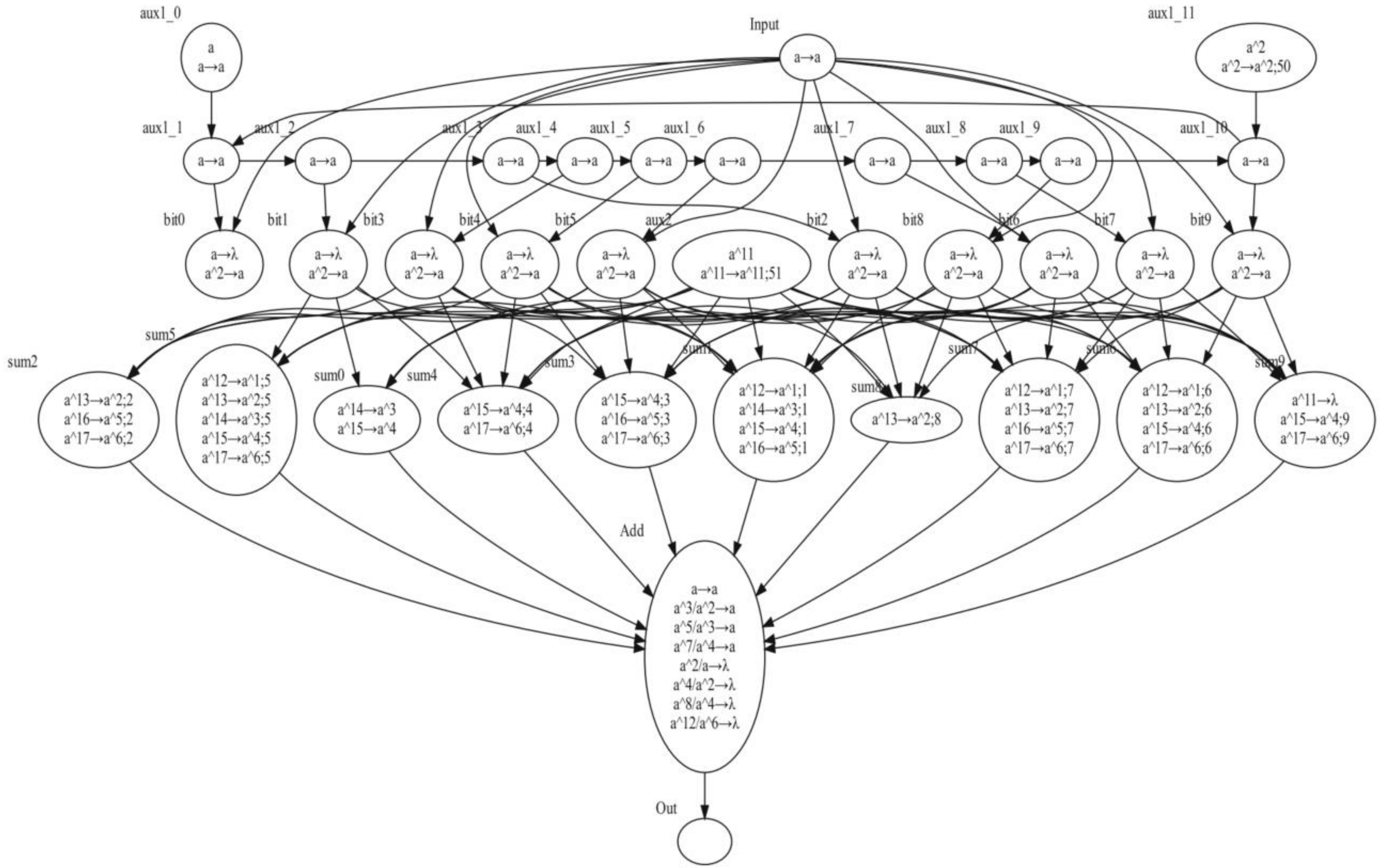


Fig. 6 The number of iterations corresponding to different population sizes

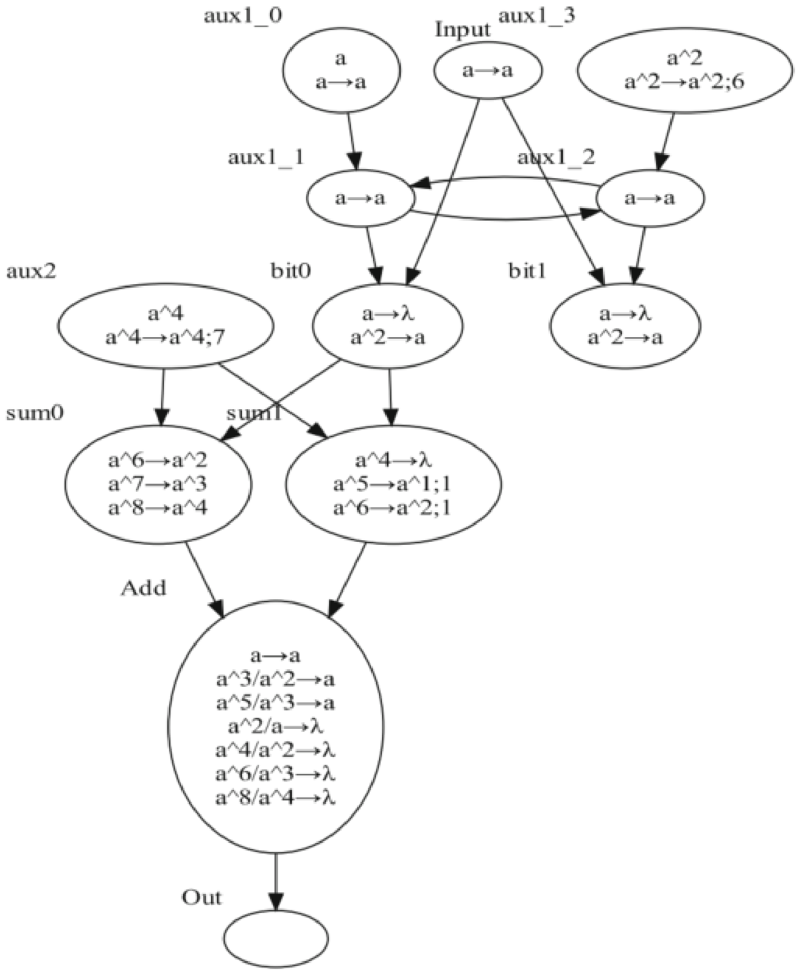
In the experiments, the parameter H is set to $H = \{50, 60, 70, 80, 90, 100, 110, 120\}$. Experimental results for the discussion of the four parameters are shown in Fig. 6. where the horizontal axis represents the number of different populations. The vertical axis represents the number of iterations.

4. Automatic design of SN P systems

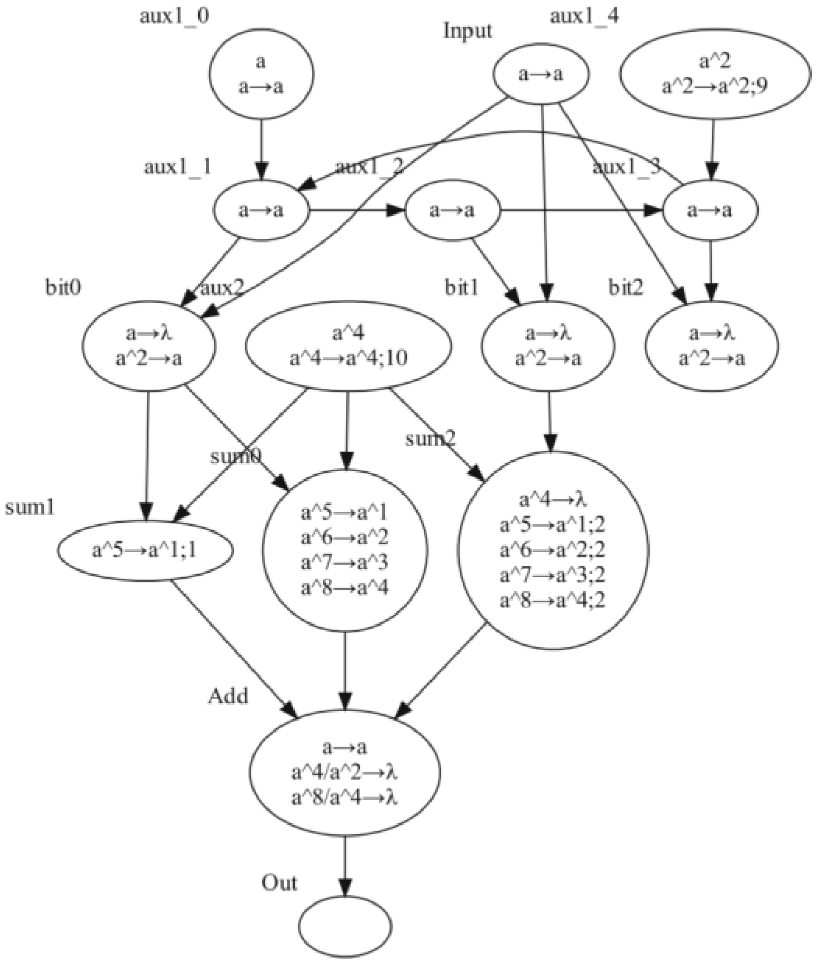


The SN P system corresponding to 513 + 6 +54+98 + 12

4. Automatic design of SN P systems

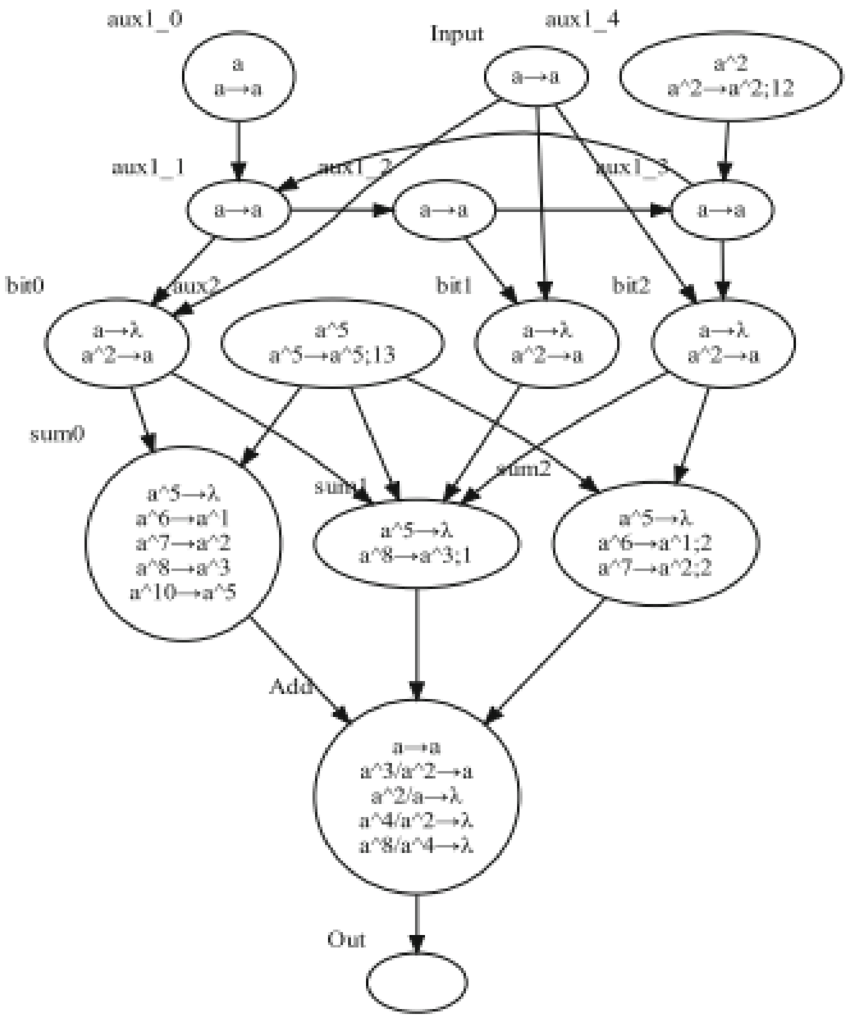


The SN P system corresponding to 1+2+3

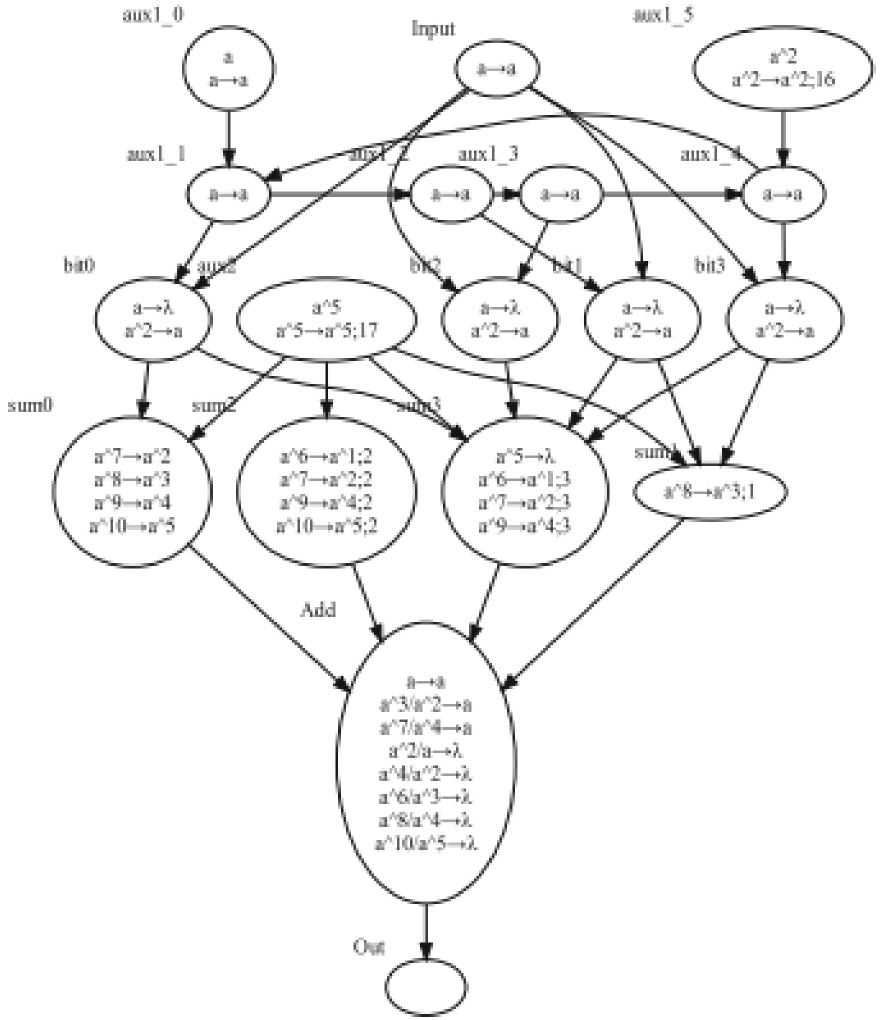


The SN P system corresponding to 2+1+4

4. Automatic design of SN P systems

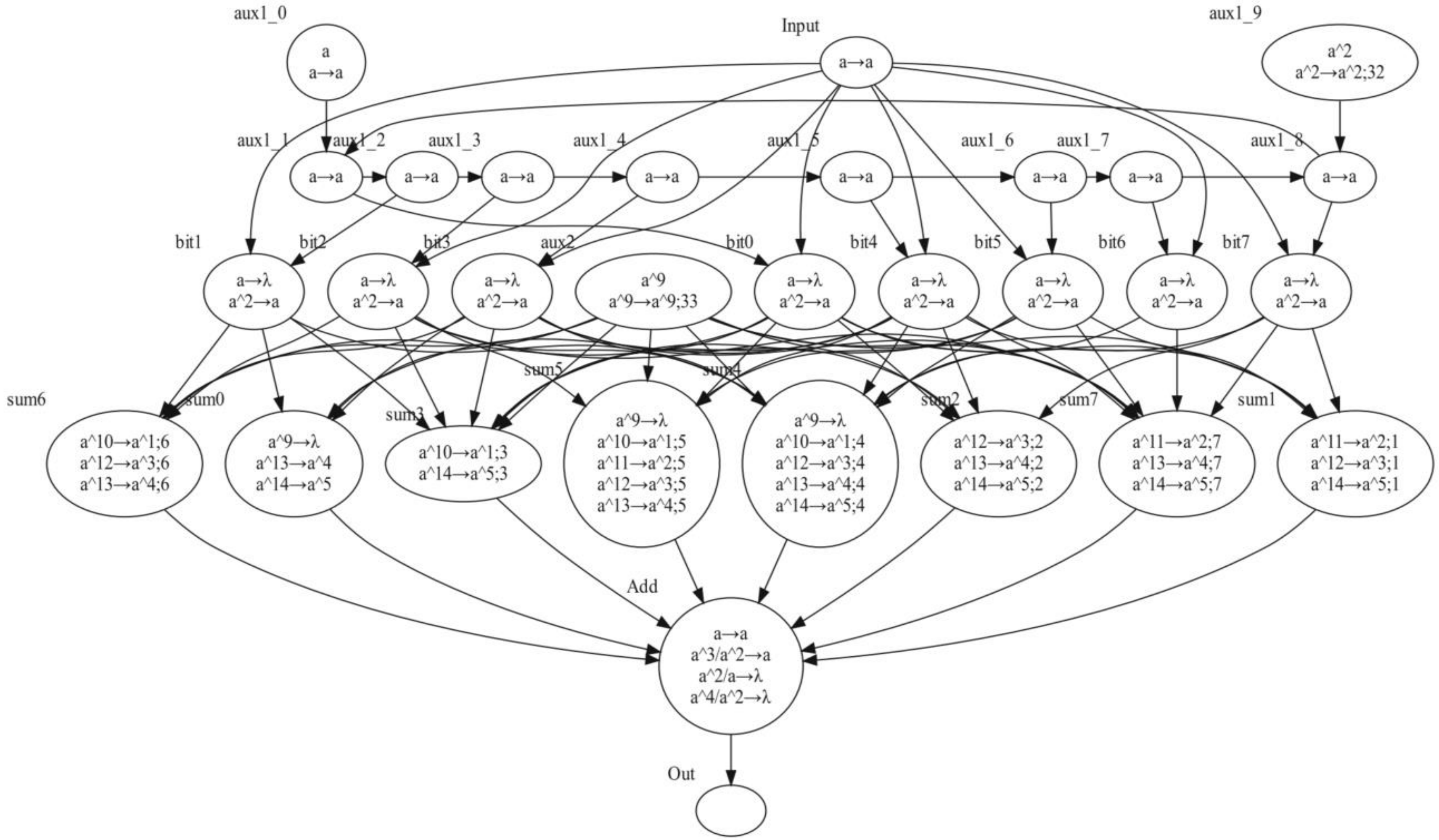


The SN P system corresponding to 7+5+2+3



The SN P system corresponding to 15+8+9+3

4. Automatic design of SN P systems



The SN P system corresponding to 128+56+7+89

5

Several issues on SN P systems

ACMC 2024

- ✓ Asian Conference on Membrane Computing (ACMC 2024)
- ✓ Location: Singapore
- ✓ Time: Early August, 2024

A book under consideration

- ✓ Spiking neural P systems: theory, applications & implementations
- ✓ Call for co-authors

Thanks for your attention