Spiking Neural P Systems

Subjects: Engineering, Electrical & Electronic
Contributor: Gexiang Zhang

Spiking neural P system (SNPS) is a popular parallel distributed computing model. It is inspired by the structure and functioning of spiking neurons. It belongs to the category of neural-like P systems and is well-known as a branch of the third generation neural networks. SNPS and its variants can perform the task of fault diagnosis in power systems efficiently.

Keywords: membrane computing ; spiking neural P system ; power systems ; fault diagnosis

1. Introduction

In the 21st century, electrical power systems are associated with the daily necessities of human beings. A network of electrical components is called an electrical power system and such systems help in the supply, transfer, and use of electrical power. However, any accident inside the power systems interrupts the supply of power. In order to perform the task of secure and stable supply of power, it is necessary for the electric devices to have efficient fault diagnosis methods which can identify the faults quickly as well as efficiently. Furthermore, whenever there is a fault in power system, the consoles in the dispatchers receive huge number of messages in a very short span of time from the SCADA (supervisor control and data control) systems. Very often the messages received from SCADA systems are incomplete and uncertain. Power systems are composed of a large number of generators, transmission lines, bus bars, and transformers. These aspects of power systems make very difficult the task of fault diagnosis in power systems. In recent years, the techniques from artificial intelligence have been used to perform the task of fault diagnosis in electric power systems. More specifically, many methods based on Bayesian networks [1][2], artificial neural networks [3][4], genetic algorithms [5], Petri nets [6][7][8][9], expert systems [10][11], fuzzy logic [7][8][12], multi-agent systems [13][14], optimization methods [5][15][16], information theory [17][18], cause-effect networks [19][20] have been introduced. P systems or membrane computing models are popular natural computing model. In recent years, many researchers have used different variants of P systems for fault diagnosis in power systems.

P system was introduced in 1998 by Gh. Păun [21]. P system is an abstract mathematical computing model which is inspired by the structure and functioning of the biological cells. The area of study of P systems is well-known as *Membrane Computing*. In P systems, the objects present inside the cells or membranes are represented by multiset of objects and the evolution processes happening inside these cells are represented by the rules which are applied in maximal parallel manner. P systems models are generally divided into three categories based on their structure, i.e., cell-like, tissue-like and neural-like.

Along with finding the analytic solutions for computationally hard problems using the concept of space-time trade-off, in recent years the study of constructing evolutionary algorithms by combining the structure and operations of membrane systems and capabilities of optimization algorithms has gained prominence [22]. Furthermore, approximate solutions of these problems are obtained by using the algorithms which are popularly known as “membrane algorithms”. In [23], the solution of an well-known NP -complete problem, i.e., Graph coloring problem (GCP) is obtained by using OLMS (one level membrane structure (OLMS) [24][25][26]) membrane algorithm with dynamic operators. Automatic design of P systems is also an attractive work and promising research direction [27][28][29][30].

2. Membrane computing models

Membrane computing models have a wide range of real-life applications [22][31][32][33][34][35] and the investigation more problems from different areas of real-life applications which can be solved by these models has drawn huge interest amongst many researchers around the global. One of the most interesting application of membrane computing models has been in the area of “Robotics”. In particular, the use of membrane computing models for designing of membrane controllers for single and multi-robot systems which further helps in navigation of the robot in unknown environments [31][36][37][38]. In recent years, many variants of P systems such as enzymatic numerical P systems, XP-colonies, etc. have been used in single and multiple-robot applications. The membrane controllers based on the membrane computing models are efficient and have comparable performance with respect to traditional robot controllers [31]. Image processing is another area where membrane computing models have been used extensively. Parallel distributed architecture along with the multisets present in the membranes which is useful for encoding of the information, make P systems a suitable model for dealing with digital images. Furthermore, these models can be used in image segmentation, skeletonization, etc. [32]. Moreover, SNPS models can perform binary operations and these models are also suitable to be used in cryptographic applications [39]. Array rewriting P systems can be used as a tool for generation of Peano curve, the Hilbert curve, etc. In [40], a state-of-the-art based on the P systems with parallel rewriting was introduced for generation of the space-filling curves, and related curves.

Membrane computing models also have been used for modelling and simulation of many phenomena existing in Biochemistry, Ecology, Robotics or Engineering [34]. These models also can model communities of very simple reactive agents living and acting in a joint shared environment. These types of membrane computing models are known as "P colonies" [41]. P colonies can simulate the interactive processes in other mechanisms such as reaction system which is inspired from the different chemical reactions happening in the environment [42]. P systems are also useful in modeling many biological phenomena such as swarming and aggregating behaviour in Myxobacteria bacterial populations [43][44].

Neural-like P systems/Spiking neural P systems (SNPS) [45] have gained popularity amongst the researchers because of its similarities with third-generation neural networks, i.e., spiking neural networks (SNNs) [46]. In recent years, the research in SNPS also has gained huge momentum and many variants of SNPS have been introduced inspired by the properties present in the biological neurons. Many variants of it already have been introduced along with investigations regarding their computational power [47][48], efficiency in solving computationally hard problems [49] and real-life applications [50][51][52]. A new variant of SNPS is introduced in [53] where the firing and forgetting rules are applied in generalized manner. In these models, if a rule is applied at any step of the computation, then it will be applicable any number of times. These models are also computational complete. Matrix representation and simulation algorithm of different variants of SNPS are investigated in [54]. Another novel variant of SNPS is recently introduced in [55] and it is called as dynamic threshold neural P systems. These models are inspired from the spiking and dynamic threshold mechanisms of neurons. Moreover, it has been proved that the sequential variant of this model is capable of generating/accepting Turing universal numbers. Some of the well-known variants of SNPS are SNPS with asynchronous systems [56], astrocytes [57], rule on synapses [58], communication on request [59], synapses with schedules [60], structural plasticity [61][62], weighted synapses [63], inhibitory synapses [64], anti-spikes [65], etc. Furthermore, SNPS have been used extensively in solving many real-world problems in many areas such as fault diagnosis of power systems [66][67][68][69][70][71][72][73][74][75], pattern recognition [76][77][78], computational biology [79], performing arithmetic and logical operations and hardware implementation [80][81][82][83][84][85][86][87], biochip design [88], programming for logic controllers [89][90], etc. In [91], SNPS models have been used for computing finite-state functions.

In the last few decades, although significant progress has been made in obtaining many theoretical results as well as real-life applications of membrane computing models, very little progress has been made towards in vivo implementation of these models. In [33], a mechanism was introduced where multivesicular liposomes can be experimentally produced through electroformation of dipalmitoylphosphatidylcholine films. It can be further used in 'real' P-systems.

Over the years one of the most interesting direction of research in membrane computing has been constructing simulation tools for different variants of P systems and their applications [92]. Many researchers have focused on developing softwares [93] based on P-Lingua which can simulate different variants of membrane systems efficiently such as (1) Cell-like P systems [94]; (2) P-Systems with String Replication [95]; (3) Tissue P systems [96] (4) Cell-like SNPS [97]; (5) Spiking Neural P Systems [98]; (6) Asynchronous Spiking Neural P Systems [99]. P-Lingua is an efficient tool. Recently, there has been significant progress towards constructing P-Lingua language, pLinguaCore library and MeCoSim environment. These tools also have been used for experimentally validate solutions of computationally hard problems [100]. Furthermore, many simulators have been proposed which are based on different programming languages other than P-Lingua and following is the list of some simulators: (1) CuSNP [101]; (2) UPSimulator [102]; (3) Psim [103]; (4) SNUPS [104]; (5) GPUPeP [105]. The P systems simulators work as an important tool for formally creating a framework for real-life applications. The simulators based on the requirements of the users and specific application abstract the concepts of different variants of P systems. The researchers in membrane computing community have constructed many types of simulators [106] and used it for simulation of the simple kernel P systems solution to the graph 3-colouring problem [107]. Moreover, testing methods for membrane computing models such as kernel P systems have been introduced [108].

The process of fault diagnosis in power systems is based on processing of uncertain and incomplete information. General SNPS models are not capable of handling these type of information. So a new variant of SNPS was introduced in order to serve this purpose. In [68], a new variant of SNPS, i.e., FRSNPS (fuzzy reasoning spiking neural P systems) was introduced, aiming to handle fuzzy diagnosis knowledge and reasoning. Furthermore, a methodology for fault diagnosis in transformers was presented. There has been only a few investigations regarding incorporating the idea of machine learning in SNPS. It is also difficult to introduce machine learning mechanisms in SNPS because of its formal language theory framework. Recently, a new method based on learning Spiking Neural P System with Belief AdaBoost [75] is introduced for fault diagnosis in transformers. Moreover, SNPS models and their variants have been introduced for identification of faults in power transmission networks [109], traction power supply systems of high-speed railways [72], metro traction power systems [66], electric locomotive systems [71]. Moreover, these models have been used for fault location estimation of power systems [110] and fault line detection [69].

References

1. Chien, C.F.; Chen, S.L.; Lin, Y.S. Using Bayesian network for fault location on distribution feeder. IEEE Trans. Power Deliv. 2002, 17, 785–793.
2. Zhu, Y.L.; Huo, L.M.; Liu, J.L. Bayesian networks based approach for power systems fault diagnosis. IEEE Trans. Power Deliv. 2006, 21, 634–639.
3. Cardoso, G.; Rolim, J.G.; Zurn, H.H. Identifying the primary fault section after contingencies in bulk power systems. IEEE Trans. Power Deliv. 2008, 23, 1335–1342.
4. Thukaram, D.; Khincha, H.P.; Vijaynarasimha, H.P. Artificial neural network and support vector machine approach for locating faults in radial distribution systems. IEEE Trans. Power Deliv. 2005, 20, 710–721.
5. Wen, F.S.; Han, Z.X. Fault section estimation in power systems using a genetic algorithm. Electr. Power Syst. Res. 1995, 34, 165–172.
6. Jiang, Z.; Li, Z.; Wu, N.; Zhou, M. A Petri net approach to fault diagnosis and restoration for power transmission systems to avoid the output interruption of substations. IEEE Syst. J. 2018, 12, 2566–2576.
7. Luo, X.; Kezunovic, M. Implementing fuzzy reasoning Petri-nets for fault section estimation. IEEE Trans. Power Syst. 2008, 23, 676–685.
8. Sun, J.; Qin, S.Y.; Song, Y.H. Fault diagnosis of electric power systems based on fuzzy Petri nets. IEEE Trans. Power Syst. 2004, 19, 2053–2059.
9. Yang, J.W.; He, Z.Y.; Zang, T.L. Power system fault-diagnosis method based on directional weighted fuzzy Petri nets. Proc. CSEE 2010, 30, 42–49.
10. Lee, H.J.; Ahn, B.S.; Park, Y.M. A fault diagnosis expert system for distribution substations. IEEE Trans. Power Deliv. 2008, 15, 92–97.
11. Ma, D.Y.; Liang, Y.C.; Zhao, X.S.; Guan, R.C.; Shi, X.H. Multi-BP expert system for fault diagnosis of power system. Eng. Appl. Artif. Intell. 2013, 26, 937–944.
12. Chang, C.S.; Chen, J.M.; Srinivasan, D.; Wen, F.S.; Liew, A.C. Fuzzy logic approach in power system fault section identification. IEE Proc. Gener. Transm. Distrib. 1997, 144, 406–414.
13. Davidson, E.M.; McArthur, S.D.J.; McDonald, J.R.; Watt, I. Applying multi-agent system technology in practice: Automated management and analysis of SCADA and digital fault recorder data. IEEE Trans. Power Syst. 2006, 21, 559–567.
14. Hossack, J.A.; Menal, J.; McArthur, S.D.J.; McDonald, J.R. A multiagent architecture for protection engineering diagnostic assistance. IEEE Trans. Power Syst. 2003, 18, 639–647.
15. He, Z.Y.; Chiang, H.D.; Li, C.W.; Zeng, Q.F. Fault-section estimation in power systems based on improved optimization model and binary pswarm optimization. In Proceedings of the 2009 IEEE Power & Energy Society General Meeting, Calgary, AB, Canada, 26–30 July 2009; pp. 1–8.
16. Lin, X.N.; Ke, S.H.; Li, Z.T.; Weng, H.L.; Han, X.H. A fault diagnosis method of power systems based on improved objective function and genetic algorithm-tabu search. IEEE Trans. Power Deliv. 2010, 25, 1268–1274.
17. Lin, S.; He, Z.Y.; Qian, Q.Q. Review and development on fault diagnosis in power grid. Power Syst. Protect. Control 2010, 38, 140–150.
18. Tang, L.; Sun, H.B.; Zhang, B.M.; Gao, F. Online fault diagnosis for power system based on information theory. Proc. CSEE 2003, 23, 5–11.
19. Chen, W.H. Fault section estimation using fuzzy matrix-based reasoning methods. IEEE Trans. Power Deliv. 2011, 26, 205–213.

20. Chen, W.H. Online fault diagnosis for power transmission networks using fuzzy digraph models. IEEE Trans. Power Del iv. 2012, 27, 688–698.
21. Păun, G. Computing with Membranes. J. Comput. Syst. Sci. 2000, 61, 108–143.
22. Zhang, G.; Pérez-Jiménez, M.J.; Gheorghe, M. Real-Life Applications with Membrane Computing, Emergence, Comple xity and Computation Book Series (ECC); Springer: New York, NY, USA, 2017; Volume 25.
23. Andreu-Guzmán, J.A.; Valencia-Cabrera, L. A novel solution for GCP based on an OLMS membrane algorithm with dyn amic operators. J. Membr. Comput. 2020, 2, 1–13.
24. Zhang, G.; Gheorghe, M.; Pan, L.; Pérez-Jiménez, M.J. Evolutionary membrane computing: A comprehensive survey a nd new results. Inf. Sci. 2014, 279, 528–551.
25. Zhang, G.; Cheng, J.; Gheorghe, M.; Meng, Q. A hybrid approach based on differential evolution and tissue membrane systems for solving constrained manufacturing parameter optimization problems. Appl. Soft Comput. 2013, 13, 1528–1 542.
26. Zhang, G.X.; Gheorghe, M.; Wu, C.Z. A quantum-inspired evolutionary algorithm based on P systems for knapsack pro blem. Fundam. Inform. 2008, 87, 93–116.
27. Ou, Z.; Zhang, G.; Wang, T.; Huang, X. Automatic design of cell-like P systems through tuning membrane structures, ini tial objects and evolution rules. Int. J. Unconv. Comput. 2013, 9, 425–443.
28. Yuan, W.; Zhang, G.; Pérez-Jiménez, M.J.; Wang, T.; Huang, Z. P systems based computing polynomials: Design and f ormal verification. Nat. Comput. 2016, 15, 591–596.
29. Zhang, G.; Rong, H.; Ou, Z.; Pérez-Jiménez, M.J.; Gheorghe, M. Automatic design of deterministic and non-halting me mbrane systems by tuning syntactical ingredient. IEEE Trans. NanoBiosci. 2014, 13, 363–371.
30. Zhu, M.; Zhang, G.; Yang, Q.; Rong, H.; Yuan, W.; Pérez-Jiménez, M.J. P systems based computing polynomials with i nteger coefficients: Design and formal verification. IEEE Trans. NanoBiosci. 2018, 17, 272–280.
31. Buiu, C.; Florea, A.G. Membrane computing models and robot controller design, current results and challenges. J. Mem br. Comput. 2019, 1, 262–269.
32. Díaz-Pernil, D.; Gutiérrez-Naranjo, M.A.; Peng, H. Membrane computing and image processing: A short survey. J. Mem br. Comput. 2019, 1, 58–73.
33. Mayne, R.; Phillips, N.; Adamatzky, A. Towards experimental P-systems using multivesicular liposomes. J. Membr. Com put. 2019, 1, 20–28.
34. Sánchez-Karhunen, E.; Valencia-Cabrera, L. Modelling complex market interactions using PDP systems. J. Membr. Co mput. 2019, 1, 40–51.
35. Zhu, M.; Yang, Q.; Dong, J.; Zhang, G.; Gou, X.; Rong, H.; Paul, P.; Neri, F. An adaptive optimization spiking neural P s ystem for binary problems. Int. J. Neural Syst. 2021, 31, 2050054.
36. Perez-Hurtado, I.; Martınez-del-Amor, M.A.; Zhang, G.; Neri, F.; Pérez-Jiménez, M.J. A membrane parallel rapidly-explo ring random tree algorithm for robotic motion planning. Integr. Comput. Aided Eng. 2020, 27, 121–138.
37. Wang, X.; Zhang, G.; Gou, X.; Paul, P.; Neri, F.; Rong, H.; Yang, Q.; Zhang, H. Multi-behaviors coordination controller d esign with enzymatic numerical P systems for robots. Integr. Comput. Aided Eng. 2021, 28, 119–140.
38. Wang, X.; Zhang, G.; Neri, F.; Jiang, T.; Zhao, J.; Gheorghe, M.; Ipate, F.; Lefticaru, R. Design and implementation of m embrane controllers for trajectory tracking of nonholonomic wheeled mobile robots. Integr. Comput. Aided Eng. 2016, 2 3, 15–30.
39. Ochirbat, O.; Ishdorj, T.-O.; Cichon, G. An error-tolerant serial binary full-adder via a spiking neural P system using HP/ LP basic neurons. J. Membr. Comput. 2020, 2, 42–48.
40. Ceterchi, R.; Subramanian, K.G. Generating pictures in string representation with P systems: The case of space-filling curves. J. Membr. Comput. 2020, 2, 369–379.
41. Ciencialová, L.; Csuhaj-Varjú, E.; Cienciala, L.; Sosík, P. P colonies. J. Membr. Comput. 2019, 1, 178–197.
42. Ciencialová, L.; Cienciala, L.; Csuhaj-Varjú, E. P colonies and reaction systems. J. Membr. Comput. 2020, 2, 269–280.
43. García-Quismondo, M.; Hintz, W.D.; Schuler, M.S.; Relyea, R.A. Modeling diel vertical migration with membrane compu ting. J. Membr. Comput. 2021, 3, 35–50.
44. Nash, A.; Kalvala, S. A P system model of swarming and aggregation in a Myxobacterial colony. J. Membr. Comput. 20 19, 1, 103–111.
45. Ionescu, M.; Păun, G.; Yokomori, T. Spiking neural P systems. Fundam. Inform. 2006, 71, 279–308.

46. Maass, W. Networks of spiking neurons: The third generation of neural network models. Neural Netw. 1997, 10, 1659–1671.

47. De la Cruz, R.T.A.; Cabarle, F.G.C.; Adorna, H.N. Generating context-free languages using spiking neural P systems with structural plasticity. J. Membr. Comput. 2019, 1, 161–177.

48. Song, T.; Pan, L. Spiking neural P systems with request rules. Neurocomputing 2016, 193, 193–200.

49. Liu, X.; Li, Z.; Suo, J.; Liu, J.; Min, X. A uniform solution to integer factorization using time-free spiking neural P system. Neural Comput. Appl. 2015, 26, 1241–1247.

50. Sun, Z.; Wang, Q.; Wei, Z. Fault location of distribution network with distributed generations using electrical synaptic transmission-based spiking neural P systems. Int. J. Parallel Emergent Distrib. Syst. 2021, 36, 11–27.

51. Chen, K.; Wang, J.; Sun, Z.; Luo, J.; Liu, T. Programmable Logic Controller Stage Programming Using Spiking Neural P Systems. J. Comput. Theor. Nanosci. 2015, 12, 1292–1299.

52. Huang, K.; Wang, T.; He, Y.; Zhang, G.; Peréz-Jiménez, M.J. Temporal fuzzy reasoning spiking neural P systems with real numbers for power system fault diagnosis. J. Comput. Theor. Nanosci. 2016, 13, 3804–3814.

53. Jiang, Y.; Su, Y.; Luo, F. An improved universal spiking neural P system with generalized use of rules. J. Membr. Comput. 2019, 1, 270–278.

54. Jimenez, Z.B.; Cabarle, F.G.C.; de la Cruz, R.T.A.; Buño, K.C.; Adorna, H.N.; Hernandez, N.H.S.; Zeng, X. Matrix representation and simulation algorithm of spiking neural P systems with structural plasticity. J. Membr. Comput. 2019, 1, 145–160.

55. Bao, T.; Zhou, N.; Lv, Z.; Peng, H.; Wang, J. Sequential dynamic threshold neural P systems. J. Membr. Comput. 2020, 2, 255–268.

56. Cavaliere, M.; Egecioglu, O.; Ibarra, O.H.; Woodworth, S.; Ionescu, M.; Păun, G. Asynchronous Spiking Neural P Systems: Decidability and Undecidability; Garzon, M.H., Yan, H., Eds.; Springer: Berlin, Germany, 2008; pp. 246–255.

57. Pan, L.; Wang, J.; Hoogeboom, H. Spiking neural P systems with astrocytes. Neural Comput. 2012, 24, 805–825.

58. Su, Y.; Wu, T.; Xu, F.; Păun, A. Spiking Neural P Systems with Rules on Synapses Working in Sum Spikes Consumption Strategy. Fundam. Inform. 2017, 156, 187–208.

59. Pan, L.; Păun, G.; Zhang, G.; Neri, F. Spiking neural P systems with communication on request. Int. J. Neural Syst. 2017, 27, 1750042.

60. Cabarle, F.G.C.; Adorna, H.N.; Jiang, M.; Zeng, X. Spiking Neural P Systems With Scheduled Synapses. IEEE Trans. Nanobiosci. 2017, 16, 792–801.

61. Cabarle, F.G.C.; Adorna, H.N.; Pérez-Jiménez, M.J.; Song, T. Spiking neural P systems with structural plasticity. Neural Comput. Appl. 2015, 26, 1905–1917.

62. De la Cruz, R.T.A.; Cabarle, F.G.; Macababayao, I.C.H.; Adorna, H.N.; Zeng, X. Homogeneous spiking neural P systems with structural plasticity. J. Membr. Comput. 2021, 3, 10–21.

63. Pan, L.; Zeng, X.; Zhang, X.; Jiang, Y. Spiking Neural P Systems with Weighted Synapses. Neural Process. Lett. 2012, 35, 13–27.

64. Song, T.; Wang, X. Homogenous Spiking Neural P Systems with Inhibitory Synapses. Neural Process. Lett. 2015, 42, 199–214.

65. Pan, L.; Păun, G. Spiking neural P systems with anti-spikes. Int. J. Comput. Commun. Control. 2009, 4, 273–282.

66. He, Y.; Wang, T.; Huang, K.; Zhang, G.; Pérez-Jiménez, M.J. Fault diagnosis of metro traction power systems using a modified fuzzy reasoning spiking neural P system. Rom. J. Inf. Sci. Technol. 2015, 18, 256–272.

67. Huang, Y.; Wang, T.; Wang, J.; Peng, H. Reliability evaluation of distribution network based on fuzzy spiking neural P system with self-synapse. J. Membr. Comput. 2021, 3, 51–62.

68. Peng, H.; Wang, J.; Peréz-Jimenéz, M.J.; Wang, H.; Shao, J.; Wang, T. Fuzzy reasoning spiking neural P system for fault diagnosis. Inf. Sci. 2013, 235, 106–116.

69. Rong, H.; Ge, M.; Zhang, G.; Zhu, M. An Approach for Detecting Fault Lines in a Small Current Grounding System using Fuzzy Reasoning Spiking Neural P Systems. Int. J. Comput. Commun. Control. 2018, 13, 521–536.

70. Tao, C.; Wang, J.; Wang, T.; Yang, Y. An Improved Spiking Neural P Systems with Anti-Spikes for Fault Location of Distribution Networks with Distributed Generation. In Bio-Inspired Computing: Theories and Applications. BIC-TA 2017. Communications in Computer and Information Science; He, C., Mo, H., Pan, L., Zhao, Y., Eds.; Springer: Singapore, 2017; Volume 791.

71. Wang, T.; Zhang, G.; Pérez-Jiménez, M.J. Fault Diagnosis Models for Electric Locomotive Systems Based on Fuzzy Re asoning Spiking Neural P Systems. In Membrane Computing; Gheorghe, M., Rozenberg, G., Salomaa, A., Sosík, P., Za ndron, C., Eds.; CMC 2014, LNCS 8961; Springer: New York, NY, USA, 2014.

72. Wang, T.; Zhang, G.; Pérez-Jiménez, J.M.; Cheng, J. Weighted fuzzy reasoning spiking neural P systems: Application t o fault diagnosis in traction power supply systems of high-speed railways. J. Comput. Theor. Nanosci. 2015, 12, 1103–1114.

73. Wang, T.; Zhang, G.; Zhao, J.; He, Z.; Wang, J.; Pérez- Jiménez, M.J. Fault diagnosis of electric power systems based on fuzzy reasoning spiking neural P systems. IEEE Trans. Power Syst. 2015, 30, 1182–1194.

74. Wang, T.; Zhang, G.; Pérez-Jiménez, M.J. Fuzzy membrane computing: Theory and Applications. Int. J. Comput. Com m. Contr. 2015, 10, 904–935.

75. Zhang, X.; Zhang, G.; Paul, P.; Zhang, J.; Wu, T.; Fan, S.; Xiong, X. Dissolved Gas Analysis for Transformer Fault Base d on Learning Spiking Neural P System with Belief AdaBoost. Int. J. Unconv. Comput. 2021, 16, 239–258.

76. Ma, T.; Hao, S.; Wang, X.; Rodríguez-Patón, A.; Wang, S.; Song, T. Double Layers Self-Organized Spiking Neural P Sy stems with Anti-spikes for Fingerprint Recognition. IEEE Access 2017, 7, 177562–177570.

77. Song, T.; Pan, L.; Wu, T.; Zheng, P.; Wong, M.L.D.; Rodríguez-Patón, A. Spiking Neural P Systems With Learning Funct ions. IEEE Trans. Nanobiosci. 2019, 18, 176–190.

78. Song, T.; Pang, S.; Hao, S.; Rodríguez-Paton, A.; Zheng, P. A Parallel Image Skeletonizing Method Using Spiking Neur al P Systems with Weights. Neural Process. Lett. 2019, 50, 1485–1502.

79. Chen, Z.; Zhang, P.; Wang, X.; Shi, X.; Wu, T.; Zheng, P. A computational approach for nuclear export signals identificat ion using spiking neural P systems. Neural Comput. Appl. 2018, 29, 695–705.

80. Díaz, C.; Sanchez, G.; Duchen, G.; Nakano, M.; Perez, H. An efficient hardware implementation of a novel unary Spikin g Neural Network multiplier with variable dendritic delays. Neurocomputing 2016, 189, 130–134.

81. Duchen, G.; Diaz, C.; Sanchez, G.; Perez, H. First steps toward memory processor unit architecture based on SN P sy stems. Electron. Lett. 2017, 53, 384–385.

82. Ganbaatar, G.; Nyamdorj, D.; Cichon, G.; Ishdorj, T. Implementation of RSA cryptographic algorithm using SN P system s based on HP/LP neurons. J. Membr. Comput. 2021, 3, 22–34.

83. Gutíerrez-Naranjo, M.A.; Leporati, A. Performing arithmetic operations with spiking neural P systems. In Proceedings of the 7th Brainstorming Week Membrane Computing, Sevilla, Spain, 27 February–2 April 2009; pp. 181–198.

84. Liu, X.; Li, Z.; Liu, J.; Liu, L.; Zeng, X. Implementation of arithmetic operations with time-free spiking neural P systems. I EEE Trans. Nanobiosci. 2015, 14, 617–624.

85. Zeng, X.; Song, T.; Zhang, X.; Pan, L. Performing four basic arithmetic operations with spiking neural P systems. IEEE Trans. Nanobiosci. 2012, 11, 366–374.

86. Zhang, G.; Rong, H.; Paul, P.; He, Y.; Neri, F.; Pérez-Jiménez, M.J. A Complete Arithmetic Calculator Constructed from Spiking Neural P Systems and its Application to Information Fusion. Int. J. Neural Syst. 2021, 31, 2050055.

87. Zhang, G.; Shang, Z.; Verlan, S.; Martínez-Del-Amor, M.A.; Yuan, C.; Valencia-Cabrera, L.; Pérez-Jiménez, M.J. An ov erview of hardware implementation of membrane computing models. ACM Comput. Surv. 2020, 53, 90.

88. Ishdorj, T.O.; Ochirbat, O.; Naimannaran, C. A μ-fluidic Biochip Design for Spiking Neural P Systems. Int. J. Unconv. Co mput. 2020, 15, 59–82.

89. Li, J.; Huang, Y.; Xu, J. Decoder Design Based on SpikingNeural P Systems. IEEE Trans. Nanobiosci. 2016, 15, 639–6 44.

90. Song, T.; Zheng, P.; Wong, M.L.D.; Wang, X. Design of logic gates using spiking neural P systems with homogeneous n eurons and astrocytes-like control. Inf. Sci. 2016, 372, 380–391.

91. Adorna, H.N. Computing with SN P systems with I/O mode. J. Membr. Comput. 2020, 2, 230–245.

92. Valencia-Cabrera, L.; Orellana-Martín, D.; Martínez-del-Amor, M.A.; Pérez-Jiménez, M.J. An interactive timeline of simu lators in membrane computing. J. Membr. Comput. 2019, 1, 209–222.

93. Pérez-Hurtado, I.; Orellana-Martín, D.; Zhang, G.; Pérez-Jiménez, M.J. P-Lingua in two steps: Flexibility and efficiency. J. Membr. Comput. 2019, 1, 93–102.

94. García-Quismondo, M.; Gutiérrez-Escudero, R.; Pérez-Hurtado, I.; Pérez-Jiménez, M.J.; Riscos-Núnez, A. An Overvie w of P-Lingua 2.0. In Membrane Computing; Păun, G., Pérez-Jiménez, M.J., Riscos-Núñez, A., Rozenberg, G., Saloma a, A., Eds.; WMC 2009, Lecture Notes in Computer Science; Springer: Berlin/Heidelberg, Germany, 2010; Volume 595 7.

95. Macari, V.; Magariu, G.; Verlan, T. Simulator of P-Systems with String Replication Developed in Framework of P-Lingua 2.1. Comput. Sci. J. Moldova 2010, 18, 246–268.

96. Martńez-del-Amor, M.A.; Pérez-Hurtado, I.; Pérez-Jiménez, M.J.; Riscos-Núñez, A. A P-Lingua based simulator for tissue P systems. J. Logic Algebraic Program. 2010, 79, 374–382.

97. Valencia-Cabrera, L.; Wu, T.; Zhang, Z.; Pan, L.; Pérez-Jiménez, M.J. A Simulation Software Tool for Cell-like Spiking Neural P Systems. Rom. J. Inf. Sci. Technol. 2016, 20, 71–84.

98. Macías-Ramos, L.F.; Pérez-Hurtado, I.; García-Quismondo, M.; Valencia-Cabrera, L.; Pérez-Jiménez, M.J.; Riscos-Núñez, A. A P-Lingua Based Simulator for Spiking Neural P Systems. In Membrane Computing; Gheorghe, M., Păun, G., Rozenberg, G., Salomaa, A., Verlan, S., Eds.; CMC 2011, Lecture Notes in Computer Science; Springer: Berlin/Heidelberg, Germany, 2012; Volume 7184.

99. Macías-Ramos, L.F.; Pérez-Jiménez, M.J.; Song, T.; Pan, L. Extending Simulation of Asynchronous Spiking Neural P Systems in P-Lingua. Fundam. Inform. 2015, 136, 253–267.

100. Valencia-Cabrera, L.; Song, B. Tissue P systems with promoter simulation with MeCoSim and P-Lingua framework. J. Membr. Comput. 2020, 2, 95–107.

101. Paul, J.; Carandang, A.; Villaflores, J.M.B.; Cabarle, F.G.C.; Adorna, H.N.; Martinez-del-Amor, M.A. CuSNP: Spiking Neural P Systems Simulators in CUDA. Rom. J. Inf. Sci. Technol. 2017, 20, 57–70.

102. Guo, P.; Quana, C.; Yea, L. UPSimulator: A general P system simulator. Knowl. Based Syst. 2019, 170, 20–25.

103. Bianco, L.; Manca, V.; Marchetti, L.; Petterlini, M. Psim: A simulator for biomolecular dynamics based on P systems. In Proceedings of the 2007 IEEE Congress on Evolutionary Computation, Singapore, 25–28 September 2007; pp. 883–887.

104. Arsene1, O.; Buiu, C.; Popescu, N. SNUPS: A Simulator for Numerical Membrane Computing. Int. J. Innov. Comput. Inf. Control 2011, 7, 3509–3522.

105. Raghavan, S.; Rai, S.S.; Rohit, M.P.; Chandrasekaran, K. GPUPeP: Parallel Enzymatic Numerical P System simulator with a Python-based interface. Biosystems 2020, 196, 104186.

106. Valencia-Cabrera, L.; Pérez-Hurtado, I.; Martínez-del-Amor, M.A. Simulation challenges in membrane computing. J. Membr. Comput. 2020, 2, 392–402.

107. Cooper, J.; Nicolescu, R. Alternative representations of P systems solutions to the graph colouring problem. J. Membr. Comput. 2019, 1, 112–126.

108. Turlea, A.; Gheorghe, M.; Ipate, F.; Konur, S. Search- based testing in membrane computing. J. Membr. Comput. 2019, 1, 241–250.

109. Liu, W.; Wang, T.; Zang, T.; Huang, Z.; Wang, J.; Huang, T.; Wei, X.; Li, C. A Fault Diagnosis Method for Power Transmission Networks Based on Spiking Neural P Systems with Self-Updating Rules considering Biological Apoptosis Mechanism. Complexity 2020, 2020, 2462647.

110. Wang, T.; Zeng, S.; Zhang, G.; Pérez-Jiménez, M.J.; Wang, J. Fault Section Estimation of Power Systems with Optimization Spiking Neural P Systems. Rom. J. Inf. Sci. Technol. 2015, 18, 240–255.