Fișa de evaluare

Subsemnatul Răzvan Valentin Florian declar că îndeplinesc standardele minimale naționale pentru abilitare corespunzătoare Comisiei de Informatică, aprobate prin Ordinul Ministrului Educației Naționale și Cercetării Științifice (OMENCȘ) nr. 6129/2016.

Anexez calculul punctajului corespunzător criteriilor din OMENCȘ nr. 6129/2016.

Perspectiva a):

Nu mi-am atribuit (implicit sau explicit) rezultate (teoretice sau empirice), texte sau imagini care nu-mi aparțin, și nici nu am inclus în publicațiile mele, fără citarea corespunzătoare, părți copiate din literatură sau din alte surse (inclusiv manuscrise nepublicate ale altor autori).

Perspectiva b):

Valori minime / praguri (CS I)	Valori realizate
56	66,93
A*+A ≥ 24	33,6
A*+A+B ≥ 40	62,93

Perspectiva c):

Valori minime / praguri (CS I)	Valori realizate
120	912
A*+A+B ≥ 40	912

Perspectiva d):

Valori minime (CS I)	Valori realizate
60	67
Minim un proiect, cu echipă de cel puțin 2 (doi) membri, obținut de candidat prin competiție la nivel național sau internațional	2

Anexa 1: Perspectiva b)

Publicația	**Tip forum**	**Scor asociat forumului**	**Număr autori**	**Punctaj al publicației**
Davody, A., Safari, M., & Florian, R. V. (2022). SuperCoder: Program learning under noisy conditions from superposition of states. *Neurocomputing*, 489, 323-332. doi:10.1016/j.neucom.2022.03.011	B	4	3	4
Tóth, I., Lázár, Z. I., Varga, L., Járai-Szabó, F., Papp, I., Florian, R. V., & Ercsey-Ravasz, M. (2021). Mitigating ageing bias in article level metrics using citation network analysis. Journal of Informetrics, 15(1), 101105. doi:10.1016/j.joi.2020.101105	A	8	7	1,6
Rusu, C. V., & Florian, R. V. (2014). A new class of metrics for spike trains. *Neural Computation*, 26(2), 306–348. doi:10.1162/NECO_a_00545	A	8	2	8
Florian, R. V. (2012). The chronotron: A neuron that learns to fire temporally precise spike patterns. *PLoS ONE*, 7(8), e40233. doi:10.1371/journal.pone.0040233	A	8	1	8
Florian, R. V. (2012). Aggregating post-publication peer reviews and ratings. *Frontiers in Computational Neuroscience*, 6, 31. doi:10.3389/fncom.2012.00031	B	4	1	4
Florian, R. V. (2010). Challenges for interactivist-constructivist robotics. *New Ideas in Psychology*, 28(3), 350–353. doi:10.1016/j.newideapsych.2009.09.009	B	4	1	4
Florian, R. V. (2008). Tempotron-like learning with ReSuMe. În Artificial Neural Networks - ICANN 2008 (Vol. Part II, p. 368-375). Prezentată la 18th *International Conference on Artificial Neural Networks*, Berlin / Heidelberg: Springer. doi:10.1007/978-3-540-87559-8_38	B	4	1	4
Florian, R. V. (2007). Irreproducibility of the results of the Shanghai academic ranking of world universities. *Scientometrics*, 72(1), 25–32. doi:10.1007/s11192-007-1712-1	B	4	1	4
Florian, R. V. (2007). Reinforcement learning through modulation of spike-timing-dependent synaptic plasticity. *Neural Computation*, 19(6), 1468–1502. doi:10.1162/neco.2007.19.6.1468	A	8	1	8
Néda, Z., Florian, R., Ravasz, M., Libál, A., & Györgyi, G. (2006). Phase transition in an optimal clusterization model. *Physica A: Statistical Mechanics and its Applications*, 362(2), 357–368. doi:10.1016/j.physa.2005.08.008	B	4	5	1,33

Florian, R. V., & Mureşan, R. C. (2006). Phase precession and recession with STDP and anti-STDP. În Artificial Neural Networks – ICANN 2006 (p. 718-727). Prezentată la 16th *International Conference on Artificial Neural Networks*, Berlin Heidelberg: Springer. doi:10.1007/11840817_75	B	4	2	4
Florian, R. V. (2006). Spiking neural controllers for pushing objects around. În From Animals to Animats 9 (p. 570-581). Prezentată la *9th International Conference on Simulation of Adaptive Behavior*, SAB 2006, Roma, Italia. *Lecture Notes in Computer Science*, vol. 4095. Berlin / Heidelberg: Springer. doi:10.1007/11840541_47. Print ISBN: 978-3-540-38608-7. Online ISBN: 978-3-540-38615-5.	C	2	1	2
Florian, R. V. (2005). A reinforcement learning algorithm for spiking neural networks. În D. Zaharie, D. Petcu, V. Negru, T. Jebelean, G. Ciobanu, A. Cicortaş, et al. (editori), *Seventh International Symposium on Symbolic and Numeric Algorithms for Scientific Computing* (SYNASC 2005), 25-29 September 2005, Timisoara, Romania (p. 299–306). IEEE Computer Society. doi:10.1109/SYNASC.2005.13	C	2	1	2
Florian, R., & Galam, S. (2000). Optimizing conflicts in the formation of strategic alliances. *The European Physical Journal B - Condensed Matter and Complex Systems*, 16(1), 189-194. doi:10.1007/s100510070264	B	4	2	4
Néda, Z., Florian, R., & Brechet, Y. (1999). Reconsideration of continuum percolation of isotropically oriented sticks in three dimensions. *Physical Review E*, 59(3), 3717–3719. doi:10.1103/PhysRevE.59.3717	A	8	3	8
Total				**66,93**

Anexa 2: Perspectiva c)

Publicația citată	**Citări**	**Tip forum**	**Punctaj**
Florian, R. V. (2007). Reinforcement learning through modulation of spike-timing-dependent synaptic plasticity. *Neural Computation*, 19(6), 1468–1502. doi:10.1162/neco.2007.19.6.1468	Gerstner, W., Sprekeler, H., & Deco, G. (2012). Theory and simulation in neuroscience. Science, 338(6103), 60-65.	A*	12
	Urbanczik, R., & Senn, W. (2009). Reinforcement learning in populations of spiking neurons. Nature Neuroscience, 12(3), 250.	A*	12
	Buonomano, D. V., & Maass, W. (2009). State-dependent computations: spatiotemporal processing in cortical networks. Nature Reviews Neuroscience, 10(2), 113-125.	A*	12
	Morrison, A., Diesmann, M., & Gerstner, W. (2008). Phenomenological models of synaptic plasticity based on spike timing. Biological Cybernetics, 98(6), 459-478.	B	4
	Legenstein, R., Pecevski, D., & Maass, W. (2008). A learning theory for reward-modulated spike-timing-dependent plasticity with application to biofeedback. PLoS Computational Biology, 4(10), e1000180.	A	8
	Ponulak, F., & Kasiński, A. (2010). Supervised learning in spiking neural networks with ReSuMe: sequence learning, classification, and spike shifting. Neural Computation, 22(2), 467-510.	A	8
	Mohemmed, A., Schliebs, S., Matsuda, S., & Kasabov, N. (2012). Span: Spike pattern association neuron for learning spatio-temporal spike patterns. International Journal of Neural Systems, 22(04), 1250012.	B	4
	Frémaux, N., Sprekeler, H., & Gerstner, W. (2010). Functional requirements for reward-modulated spike-timing-dependent plasticity. Journal of Neuroscience, 30(40), 13326-13337.	A	8
	Potjans, W., Morrison, A., & Diesmann, M. (2009). A spiking neural network model of an actor-critic learning agent. Neural Computation, 21(2), 301-339.	A	8
	Legenstein, R., Chase, S. M., Schwartz, A. B., & Maass, W. (2010). A reward-modulated hebbian learning rule can explain experimentally observed network reorganization in a brain control task. Journal of Neuroscience, 30(25), 8400-8410.	A	8
	Legenstein, R., Wilbert, N., & Wiskott, L. (2010). Reinforcement learning on slow features of high-dimensional input streams. PLoS Computational Biology, 6(8), e1000894.	A	8

	Vasilaki, E., Frémaux, N., Urbanczik, R., Senn, W., & Gerstner, W. (2009). Spike-based reinforcement learning in continuous state and action space: when policy gradient methods fail. PLoS Computational Biology, 5(12), e1000586.	A	8
	Rachmuth, G., Shouval, H. Z., Bear, M. F., & Poon, C. S. (2011). A biophysically-based neuromorphic model of spike rate-and timing-dependent plasticity. Proceedings of the National Academy of Sciences, 108(49), E1266-E1274.	A	8
	Fernando, C., Karishma, K. K., & Szathmáry, E. (2008). Copying and evolution of neuronal topology. PLoS ONE, 3(11), e3775.	A	8
	Frémaux, N., Sprekeler, H., & Gerstner, W. (2013). Reinforcement learning using a continuous time actor-critic framework with spiking neurons. PLoS Computational Biology, 9(4), e1003024.	A	8
	Xu, Y., Zeng, X., Han, L., & Yang, J. (2013). A supervised multi-spike learning algorithm based on gradient descent for spiking neural networks. Neural Networks, 43, 99-113.	A	8
	Friedrich, J., Urbanczik, R., & Senn, W. (2011). Spatio-temporal credit assignment in neuronal population learning. PLoS Computational Biology, 7(6), e1002092.	A	8
	Beyeler, M., Dutt, N. D., & Krichmar, J. L. (2013). Categorization and decision-making in a neurobiologically plausible spiking network using a STDP-like learning rule. Neural Networks, 48, 109-124.	A	8
	Xu, Y., Zeng, X., & Zhong, S. (2013). A new supervised learning algorithm for spiking neurons. Neural Computation, 25(6), 1472-1511.	A	8
	Potjans, W., Diesmann, M., & Morrison, A. (2011). An imperfect dopaminergic error signal can drive temporal-difference learning. PLoS Computational Biology, 7(5), e1001133.	A	8
	Soltoggio, A., & Stanley, K. O. (2012). From modulated Hebbian plasticity to simple behavior learning through noise and weight saturation. Neural Networks, 34, 28-41.	A	8
	Soltoggio, A., & Steil, J. J. (2013). Solving the distal reward problem with rare correlations. Neural Computation, 25(4), 940-978.	A	8
	Gütig, R. (2014). To spike, or when to spike?. Current Opinion in Neurobiology, 25, 134-139.	A*	12
	Kolodziejski, C., Porr, B., & Wörgötter, F. (2008). Mathematical properties of neuronal TD-rules and differential Hebbian learning: a comparison. Biological Cybernetics, 98(3), 259.	B	4

	Neymotin, S. A., Chadderdon, G. L., Kerr, C. C., Francis, J. T., & Lytton, W. W. (2013). Reinforcement learning of two-joint virtual arm reaching in a computer model of sensorimotor cortex. Neural Computation, 25(12), 3263-3293.	A	8
	Chadderdon, G. L., Neymotin, S. A., Kerr, C. C., & Lytton, W. W. (2012). Reinforcement learning of targeted movement in a spiking neuronal model of motor cortex. PLoS ONE, 7(10), e47251.	A	8
	Vassiliades, V., Cleanthous, A., & Christodoulou, C. (2011). Multiagent reinforcement learning: Spiking and nonspiking agents in the iterated prisoner's dilemma. IEEE Transactions on Neural Networks, 22(4), 639-653.	A	8
	O'Brien, M. J., & Srinivasa, N. (2013). A spiking neural model for stable reinforcement of synapses based on multiple distal rewards. Neural Computation, 25(1), 123-156.	A	8
	Friedrich, J., Urbanczik, R., & Senn, W. (2010). Learning spike-based population codes by reward and population feedback. Neural Computation, 22(7), 1698-1717.	A	8
	Fee, M. S. (2014). The role of efference copy in striatal learning. Current Opinion in Neurobiology, 25, 194-200.	A*	12
	Shrestha, S. B., & Song, Q. (2015). Adaptive learning rate of SpikeProp based on weight convergence analysis. Neural Networks, 63, 185-198.	A	8
	Castro, D. D., Volkinshtein, D., & Meir, R. (2009). Temporal difference based actor critic learning-convergence and neural implementation. In Advances in Neural Information Processing Systems (pp. 385-392).	A	8
	Richmond, P., Buesing, L., Giugliano, M., & Vasilaki, E. (2011). Democratic population decisions result in robust policy-gradient learning: a parametric study with GPU simulations. PLoS ONE, 6(5), e18539.	A	8
	Kolodziejski, C., Porr, B., & Wörgötter, F. (2009). On the asymptotic equivalence between differential Hebbian and temporal difference learning. Neural Computation, 21(4), 1173-1202.	A	8
	Legenstein, R. A., Pecevski, D., & Maass, W. (2007, December). Theoretical Analysis of Learning with Reward-Modulated Spike-Timing-Dependent Plasticity. In NIPS (pp. 881-888).	A	8
	Sprekeler, H., Hennequin, G., & Gerstner, W. (2009). Code-specific policy gradient rules for spiking neurons. In Advances in Neural Information Processing Systems (pp. 1741-1749).	A	8

	Gardner, B., & Grüning, A. (2013, September). Learning temporally precise spiking patterns through reward modulated spike-timing-dependent plasticity. In International Conference on Artificial Neural Networks (pp. 256-263). Springer Berlin Heidelberg.	B	4
	Soltoggio, A. (2015). Short-term plasticity as cause–effect hypothesis testing in distal reward learning. Biological Cybernetics, 109(1), 75-94.	B	4
	Christodoulou, C., & Cleanthous, A. (2011). Does high firing irregularity enhance learning?. Neural Computation, 23(3), 656-663.	A	8
	Vassiliades, V., Cleanthous, A., & Christodoulou, C. (2009). Multiagent reinforcement learning with spiking and non-spiking agents in the iterated prisoner's dilemma. Artificial Neural Networks–ICANN 2009, 737-746.	B	4
	Urbanczik, R., & Senn, W. (2009). A gradient learning rule for the tempotron. Neural Computation, 21(2), 340-352.	A	8
	Cohen, Y., & Schneidman, E. (2013). High-order feature-based mixture models of classification learning predict individual learning curves and enable personalized teaching. Proceedings of the National Academy of Sciences, 110(2), 684-689.	A	8
	Skorheim, S., Lonjers, P., & Bazhenov, M. (2014). A spiking network model of decision making employing rewarded STDP. PLoS ONE, 9(3), e90821.	A	8
	Vassiliades, V., & Christodoulou, C. (2010, July). Multiagent reinforcement learning in the iterated prisoner's dilemma: fast cooperation through evolved payoffs. In Neural Networks (IJCNN), The 2010 International Joint Conference on (pp. 1-8). IEEE.	A	8
	Friedrich, J., & Senn, W. (2012). Spike-based decision learning of Nash equilibria in two-player games. PLoS Computational Biology, 8(9), e1002691.	A	8
	Gardner, B., Sporea, I., & Grüning, A. (2015). Learning spatiotemporally encoded pattern transformations in structured spiking neural networks. Neural Computation 27 (12), 2548-2586.	A	8
	Huemer, A., Elizondo, D., & Gongora, M. (2008). A reward-value based constructive method for the autonomous creation of machine controllers. Artificial Neural Networks-ICANN 2008, 773-782.	B	4
	Katahira, K., Okanoya, K., & Okada, M. (2012). Statistical mechanics of reward-modulated learning in decision-making networks. Neural Computation, 24(5), 1230-1270.	A	8

	Leibfried, F., & Braun, D. A. (2015). A reward-maximizing spiking neuron as a bounded rational decision maker. Neural Computation 27(8):1686-720.	A	8
	Castro, D. D., & Meir, R. (2010). A convergent online single time scale actor critic algorithm. Journal of Machine Learning Research, 11(Jan), 367-410.	A*	12
	Nakano, T., Otsuka, M., Yoshimoto, J., & Doya, K. (2015). A Spiking Neural Network Model of Model-Free Reinforcement Learning with High-Dimensional Sensory Input and Perceptual Ambiguity. PLoS ONE, 10(3), e0115620.	A	8
	Kolodziejski, C., Porr, B., Tamosiunaite, M., & Wörgötter, F. (2009). On the asymptotic equivalence between differential Hebbian and temporal difference learning using a local third factor. In Advances in Neural Information Processing Systems (pp. 857-864).	A	8
	El-Laithy, K., & Bogdan, M. (2010, September). A hebbian-based reinforcement learning framework for spike-timing-dependent synapses. In International Conference on Artificial Neural Networks (pp. 160-169). Springer Berlin Heidelberg.	B	4
	Kerr, R. R., Grayden, D. B., Thomas, D. A., Gilson, M., & Burkitt, A. N. (2014). Coexistence of reward and unsupervised learning during the operant conditioning of neural firing rates. PLoS ONE, 9(1), e87123.	A	8
	Katahira, K., Okanoya, K., & Okada, M. (2010). Effects of synaptic weight diffusion on learning in decision making networks. In Advances in Neural Information Processing Systems (pp. 1081-1089).	A	8
	Lightheart, T., Grainger, S., & Lu, T. F. (2013). Spike-timing-dependent construction. Neural Computation, 25(10), 2611-2645.	A	8
	Gardner, B., Sporea, I., & Grüning, A. (2014, September). Classifying spike patterns by reward-modulated STDP. In International Conference on Artificial Neural Networks (pp. 749-756). Springer International Publishing.	B	4
	Zheng, N., & Mazumder, P. (2017). Hardware-Friendly Actor-Critic Reinforcement Learning Through Modulation of Spike-Timing-Dependent Plasticity. IEEE Transactions on Computers, 66(2), 299-311.	A	8
	Shrestha, S. B., & Song, Q. (2017). Robust learning in SpikeProp. Neural Networks, 86, 54-68.	A	8

Florian, R. V. (2012). The chronotron: A neuron that learns to fire temporally precise spike patterns. *PLoS ONE*, 7(8), e40233. doi:10.1371/journal.pone.0040233	Gütig, R. (2016). Spiking neurons can discover predictive features by aggregate-label learning. Science, 351(6277), aab4113.	A*	12
	Mohemmed, A., Schliebs, S., Matsuda, S., & Kasabov, N. (2012). Span: Spike pattern association neuron for learning spatio-temporal spike patterns. International Journal of Neural Systems, 22(04), 1250012.	B	4
	Yu, Q., Tang, H., Tan, K. C., & Li, H. (2013). Precise-spike-driven synaptic plasticity: Learning hetero-association of spatiotemporal spike patterns. PLoS ONE, 8(11), e78318.	A	8
	Mohemmed, A., Schliebs, S., Matsuda, S., & Kasabov, N. (2013). Training spiking neural networks to associate spatio-temporal input–output spike patterns. Neurocomputing, 107, 3-10.	B	4
	Xu, Y., Zeng, X., & Zhong, S. (2013). A new supervised learning algorithm for spiking neurons. Neural Computation, 25(6), 1472-1511.	A	8
	Memmesheimer, R. M., Rubin, R., Ölveczky, B. P., & Sompolinsky, H. (2014). Learning precisely timed spikes. Neuron, 82(4), 925-938.	A*	12
	Gütig, R. (2014). To spike, or when to spike?. Current Opinion in Neurobiology, 25, 134-139.	A*	12
	Yger, P., & Harris, K. D. (2013). The Convallis rule for unsupervised learning in cortical networks. PLoS Computational Biology, 9(10), e1003272.	A	8
	Abbott, L. F., DePasquale, B., & Memmesheimer, R. M. (2016). Building functional networks of spiking model neurons. Nature Neuroscience, 19(3), 350-355.	A*	12
	Zhang, Y., Li, P., Jin, Y., & Choe, Y. (2015). A digital liquid state machine with biologically inspired learning and its application to speech recognition. IEEE Transactions on Neural Networks and Learning Systems, 26(11), 2635-2649.	A	8
	Grüning, A., & Bohte, S. M. (2014, October). Spiking Neural Networks: Principles and Challenges. In ESANN.	B	4
	Shirin, D., Savitha, R., & Suresh, S. (2013, August). A basis coupled evolving spiking neural network with afferent input neurons. In Neural Networks (IJCNN), The 2013 International Joint Conference on (pp. 1-8). IEEE.	A	8
	Taherkhani, A., Belatreche, A., Li, Y., & Maguire, L. P. (2015). DL-ReSuMe: a delay learning-based remote supervised method for spiking neurons. IEEE Transactions on Neural Networks and Learning Systems, 26(12), 3137-3149.	A	8

	Dora, S., Subramanian, K., Suresh, S., & Sundararajan, N. (2016). Development of a self-regulating evolving spiking neural network for classification problem. Neurocomputing, 171, 1216-1229.	B	4
	Albers, C., Westkott, M., & Pawelzik, K. (2013). Perfect associative learning with spike-timing-dependent plasticity. In Advances in Neural Information Processing Systems (pp. 1709-1717).	A*	12
	Dora, S., Suresh, S., & Sundararajan, N. (2014, July). A sequential learning algorithm for a Minimal Spiking Neural Network (MSNN) classifier. In Neural Networks (IJCNN), 2014 International Joint Conference on (pp. 2415-2421). IEEE.	A	8
	Gardner, B., Sporea, I., & Grüning, A. (2015). Learning spatiotemporally encoded pattern transformations in structured spiking neural networks. Neural Computation 27(12):2548-86.	A	8
	Roy, S., San, P. P., Hussain, S., Wei, L. W., & Basu, A. (2016). Learning spike time codes through morphological learning with binary synapses. IEEE Transactions on Neural Networks and Learning Systems, 27(7), 1572-1577.	A	8
	Mohemmed, A., & Kasabov, N. (2012, June). Incremental learning algorithm for spatio-temporal spike pattern classification. In Neural Networks (IJCNN), The 2012 International Joint Conference on (pp. 1-6). IEEE.	A	8
	Hu, J., Tang, H., Tan, K. C., & Li, H. (2016). How the brain formulates memory: A spatio-temporal model research frontier. IEEE Computational Intelligence Magazine, 11(2), 56-68.	A	8
	Yu, Q., Yan, R., Tang, H., Tan, K. C., & Li, H. (2016). A spiking neural network system for robust sequence recognition. IEEE Transactions on Neural Networks and Learning Systems, 27(3), 621-635.	A	8
	Albers, C., Westkott, M., & Pawelzik, K. (2016). Learning of Precise Spike Times with Homeostatic Membrane Potential Dependent Synaptic Plasticity. PLoS ONE, 11(2), e0148948.	A	8
	Dora, S., Sundaram, S., & Sundararajan, N. (2015, July). A two stage learning algorithm for a Growing-Pruning Spiking Neural Network for pattern classification problems. In Neural Networks (IJCNN), 2015 International Joint Conference on (pp. 1-7). IEEE.	A	8
	Taherkhani, A., Belatreche, A., Li, Y., & Maguire, L. P. (2015, July). Multi-DL-ReSuMe: multiple neurons delay learning remote supervised method. In Neural Networks (IJCNN), 2015 International Joint Conference on (pp. 1-7). IEEE.	A	8

	Anwani, N., & Rajendran, B. (2015, July). Normad-normalized approximate descent based supervised learning rule for spiking neurons. In Neural Networks (IJCNN), 2015 International Joint Conference on (pp. 1-8). IEEE.	A	8
	Wang, J., Belatreche, A., Maguire, L., & McGinnity, T. M. (2015, July). Dynamically Evolving Spiking Neural network for pattern recognition. In Neural Networks (IJCNN), 2015 International Joint Conference on (pp. 1-8). IEEE.	A	8
	Matsuda, S. (2016, July). BPSpike: a backpropagation learning for all parameters in spiking neural networks with multiple layers and multiple spikes. In Neural Networks (IJCNN), 2016 International Joint Conference on (pp. 293-298). IEEE.	A	8
	Lin, X., Wang, X., & Hao, Z. (2017). Supervised learning in multilayer spiking neural networks with inner products of spike trains. Neurocomputing, 237, 59-70.	B	4
	Gardner, B., Sporea, I., & Grüning, A. (2014, September). Classifying spike patterns by reward-modulated STDP. In International Conference on Artificial Neural Networks (pp. 749-756). Springer International Publishing.	B	4
	Xu, Y., Yang, J., & Zhong, S. (2017). An online supervised learning method based on gradient descent for spiking neurons. Neural Networks 93:7-20.	A	8
	Guo, L., Wang, Z., Cabrerizo, M., & Adjouadi, M. (2016). A Cross-Correlated Delay Shift Supervised Learning Method for Spiking Neurons with Application to Interictal Spike Detection in Epilepsy. International Journal of Neural Systems, 1750002.	B	4
	Banerjee, A. (2016). Learning Precise Spike Train–to–Spike Train Transformations in Multilayer Feedforward Neuronal Networks. Neural Computation 28 (5), pp. 826-848.	A	8
	Xie, X., Qu, H., Liu, G., Zhang, M., & Kurths, J. (2016). An Efficient Supervised Training Algorithm for Multilayer Spiking Neural Networks. PLoS ONE, 11(4), e0150329.	A	8
	Roy, S., & Basu, A. (2016). An online structural plasticity rule for generating better reservoirs. Neural Computation 14: 1-28.	A	8
	Xie, X., Qu, H., Liu, G., & Zhang, M. (2017). Efficient training of supervised spiking neural networks via the normalized perceptron based learning rule. Neurocomputing, 241, 152-163.	B	4

	Yu, Q., Tang, H., & Tan, K. C. (2014, July). A new learning rule for classification of spatiotemporal spike patterns. In Neural Networks (IJCNN), 2014 International Joint Conference on (pp. 3853-3858). IEEE.	A	8
	Lee, W. W., Kukreja, S. L., & Thakor, N. V. (2017). CONE: Convex-Optimized-Synaptic Efficacies for Temporally Precise Spike Mapping. IEEE Transactions on Neural Networks and Learning Systems, 28(4), 849-861.	A	8
	Jin, Y., & Li, P. (2017). Performance and robustness of bio-inspired digital liquid state machines: A case study of speech recognition. Neurocomputing, 226, 145-160.	B	4
	Zhang, M., Qu, H., Xie, X., & Kurths, J. (2017). Supervised learning in spiking neural networks with noise-threshold. Neurocomputing, 219, 333-349.	B	4
	Gardner, B., & Grüning, A. (2016). Supervised Learning in Spiking Neural Networks for Precise Temporal Encoding. PLoS ONE, 11(8), e0161335.	A	8
Rusu, C. V., & Florian, R. V. (2014). A new class of metrics for spike trains. *Neural Computation*, 26(2), 306–348. doi:10.1162/NECO_a_00545	Norton, D., & Ventura, D. (2010). Improving liquid state machines through iterative refinement of the reservoir. Neurocomputing, 73(16), 2893-2904.	B	4
	Huemer, A., Gongora, M., & Elizondo, D. (2008, June). Evolving a neural network using dyadic connections. In Neural Networks, 2008. IJCNN 2008.(IEEE World Congress on Computational Intelligence). IEEE International Joint Conference on (pp. 1019-1025). IEEE.	A	8
Florian, R. V. (2005). A reinforcement learning algorithm for spiking neural networks. In D. Zaharie, D. Petcu, V. Negru, T. Jebelean, G. Ciobanu, A. Cicortas, et al. (Eds.), *Seventh International Symposium on Symbolic and Numeric Algorithms for Scientific Computing* (SYNASC 2005), 25-29 September 2005, Timisoara, Romania (p. 299–306). IEEE Computer Society. doi:10.1109/SYNASC.2005.13	Howard, D., & Elfes, A. (2014). Evolving spiking networks for turbulence-tolerant quadrotor control. ALIFE14 (pp. 431-438).	A	8
	Daucé, E. (2009). A Model of Neuronal Specialization Using Hebbian Policy-Gradient with "Slow" Noise. Artificial Neural Networks–ICANN 2009, 218-228.	B	4
	Norton, D., & Ventura, D. (2010). Improving liquid state machines through iterative refinement of the reservoir. Neurocomputing, 73(16), 2893-2904.	B	4
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	Wiles, J., Ball, D., Heath, S., Nolan, C., & Stratton, P. (2010, January). Spike-time robotics: a rapid response circuit for a robot that seeks temporally varying stimuli. In 17th International Conference on Neural Information Processing (ICONIP).	A	8
Florian, R. V. (2008). Tempotron-like learning with ReSuMe. În *Artificial Neural Networks - ICANN 2008* (Vol. Part II, p. 368-375). Prezentată la 18th International Conference on Artificial Neural Networks, Praga, Cehia. Lecture Notes in Computer Science, vol. 5164. Berlin / Heidelberg: Springer. doi:10.1007/978-3-540-87559-8_38. Print ISBN: 978-3-540-87558-1. Online ISBN: 978-3-540-87559-8.	Ponulak, F., & Kasiński, A. (2010). Supervised learning in spiking neural networks with ReSuMe: sequence learning, classification, and spike shifting. Neural Computation, 22(2), 467-510.	A	8
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	Wang, J., Belatreche, A., Maguire, L. P., & McGinnity, T. M. (2017). SpikeTemp: An Enhanced Rank-Order-Based Learning Approach for Spiking Neural Networks With Adaptive Structure. IEEE Transactions on Neural Networks and Learning Systems, 28(1), 30-43.	A	8
Florian, R. V. (2007). Irreproducibility of the results of the Shanghai academic ranking of world universities. *Scientometrics*, 72(1), 25–32. doi:10.1007/s11192-007-1712-1	Fanelli, D. (2010). Do pressures to publish increase scientists' bias? An empirical support from US States Data. PLoS ONE, 5(4), e10271.	A	8
	Billaut, J. C., Bouyssou, D., & Vincke, P. (2010). Should you believe in the Shanghai ranking?. Scientometrics, 84(1), 237-263.	B	4
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	Dehon, C., McCathie, A., & Verardi, V. (2010). Uncovering excellence in academic rankings: A closer look at the Shanghai ranking. Scientometrics, 83(2), 515-524.	B	4
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	Daraio, C., Bonaccorsi, A., & Simar, L. (2015). Rankings and university performance: A conditional multidimensional approach. European Journal of Operational Research, 244(3), 918-930.	A	8
	Mryglod, O., Kenna, R., Holovatch, Y., & Berche, B. (2013). Comparison of a citation-based indicator and peer review for absolute and specific measures of research-group excellence. Scientometrics, 97(3), 767-777.	B	4
	Skilton, P. (2008). Does the human capital of teams of natural science authors predict citation frequency?. Scientometrics, 78(3), 525-542.	B	4
	Matthews, A. P. (2012). South African universities in world rankings. Scientometrics, 92(3), 675-695.	B	4
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	Kivinen, O., Hedman, J., & Kaipainen, P. (2013). Productivity analysis of research in Natural Sciences, Technology and Clinical Medicine: an input–output model applied in comparison of Top 300 ranked universities of 4 North European and 4 East Asian countries. Scientometrics, 94(2), 683-699.	B	4
	Freyer, L. (2014). Robust rankings. Scientometrics, 100(2), 391-406.	B	4
	Docampo, D., Egret, D., & Cram, L. (2015). The effect of university mergers on the Shanghai ranking. Scientometrics, 104(1), 175-191.	B	4
	An, M. C. D. M. (2010). Should you believe in the Shanghai ranking?. Scientometrics, 84, 237-263.	B	4
	Schmoch, U., Fardoun, H. M., & Mashat, A. S. (2016). Establishing a World-Class University in Saudi Arabia: intended and unintended effects. Scientometrics, 109(2), 1191-1207.	B	4
Total			**912**

Lista publicațiilor care citează publicațiile proprii a fost extrasă din Google Scholar. Au fost contorizate doar o parte din citările identificate, respectiv citări din forumuri de categoria A*, A și B, fără includerea citărilor tuturor publicațiilor proprii.

Anexa 3: Perspectiva d)

	Punctaj
i). Cărți de autor/editate şi capitole publicate în edituri de categoria B (conform clasamentului SENSE)	
Florian, R. V. (2012). Supervised Learning in Spiking Neural Networks. În N. M. Seel (ed.), Encyclopedia of the Sciences of Learning (p. 3245–3247). Boston, MA: Springer US. doi:10.1007/978-1-4419-1428-6_1714. Print ISBN: 978-1-4419-1427-9. Online ISBN: 978-1-4419-1428-6. - capitol, categoria B	4
Florian, R. V. (2012). Reinforcement learning in spiking neural networks. În N. M. Seel (ed.), Encyclopedia of the Sciences of Learning (p. 2802–2803). Boston, MA: Springer US. doi:10.1007/978-1-4419-1428-6_1713. Print ISBN: 978-1-4419-1427-9. Online ISBN: 978-1-4419-1428-6. - capitol, categoria B	4
v). Director (coordonator/responsabil) | membru al unui grant/proiect/contract/program de cercetare național/internațional	
Proiectul național „Object PErception and Reconstruction with deep neural Architectures", finanțat de Guvernul României / UEFISCDI (PN-III-P4-ID-PCE-2020-0788); membru (Institutul Român de Știință și Tehnologie); valoare intrată: 1.198.032 lei (~242.000 €)	4
Proiectul național „Metode de optimizare riemanniene pentru învățare profundă", finanțat prin Programul Operațional Competitivitate; membru (Institutul Român de Știință și Tehnologie); valoare intrată: 8.617.500 lei (~1.873.000 €)	5
Proiectul național „Dezvoltare automată de software prin abstractizare în modele computaționale profunde, distribuite" (P_37_679, finanțat de Fondul European pentru Dezvoltare Regională și Guvernul României prin Programul Operațional Competitivitate); membru (Institutul Român de Știință și Tehnologie); valoare intrată: 8.615.200 lei (~1.872.000 €); 2016-2020;	5
Proiectul național „Improving scientific evaluation through analysis of scientific networks" (PN-II-PT-PCCA-2011-3.2-0895, programul Parteneriate, finanțat de Guvernul României / UEFISCDI); responsabil proiect (Epistemio Systems SRL, partener); valoare intrată: 1.216.250 lei (~276.000 €); 2012-2016;	8
Proiectul internațional „Transfer tehnologic prin vizibilitate și mentorat" (finanțat de Guvernul Elvețian prin Programul de Cooperare Elvețiano-Român / FDSC; în parteneriat cu Ecole Polytechnique Fédérale de Lausanne, Elveția); membru (Institutul Român de Știință și Tehnologie); valoare intrată: 1.153.240 lei (~260.000 €); 2013-2015;	4
Grantul internațional „Grupul Partener Coneural – Max Planck" (finanțat de Societatea Max Planck, Germania; în parteneriat cu Institutul Max Planck de Cercetare a Creierului, Germania); membru (Coneural); valoare intrată: 100.000 €; 2008-2013;	3
Proiectul național „Metode de control al roboților autonomi folosind rețele neuronale cu pulsuri" (11039, programul Parteneriate, finanțat de Guvernul României / CNMP); director proiect (Coneural); valoare intrată: 1.142.338 lei (~272.000 €); 2007-2010;	8
Proiectul național „Metode de învățare probabilistică și de inspirație biologică: aplicații pentru controlul roboților" (CEEX/1473, finanțat de Guvernul României); membru (Universitatea Babeș-Bolyai); valoare intrată: 144.000 lei (~40.000 €); 2006-2008.	1
vii) Organizare evenimente ştiinţifice/şcoli de vară	
Transylvanian Machine Learning Summer School, 2018, https://tmlss.ro/ - membru al comitetului de organizare	1
viii). Keynote/invited speaker/profesor la evenimente/universități	
Bernstein Center for Computational Neuroscience, Albert-Ludwigs-Universitaet Freiburg, Germania (2004) - locul 189 cf. https://www.topuniversities.com/university-rankings/world-university-rankings/2023	4

ix). Profesor/cercetător asociat/visiting la o universitate din top 500	
Università degli Studi di Genova - locul 401-500 cf. http://www.shanghairanking.com/rankings/arwu/2021 – 2 pct. * 3 luni (2004-2005)	6
xiv). Dezvoltarea de pachete şi instrumente software	
Thyrix - http://www.thyrix.com/	2
Training highly effective connectivities within neural networks with randomly initialized, fixed weights - https://github.com/rist-ro/training-neural-connectivities	2
Spike train metrics - https://github.com/rist-ro/spike-train-metrics	2
Byte serving from PHP - https://github.com/rvflorian/byte-serving-php	2
xv). Poziții de conducere în organizații profesionale naționale	
Asociația Ad Astra a cercetătorilor români – membru al consiliului director, director executiv	2
Total	**67**

Proiecte, cu echipă de cel puțin 2 (doi) membri, obținute de candidat prin competiție la nivel național sau internațional:

1. Proiectul național „Improving scientific evaluation through analysis of scientific networks” (PN-II-PT-PCCA-2011-3.2-0895, programul Parteneriate, finanțat de Guvernul României / UEFISCDI); responsabil proiect (Epistemio Systems SRL, partener); valoare intrată: 1.216.250 lei (~276.000 €); 2012-2016;
2. Proiectul național „Metode de control al roboților autonomi folosind rețele neuronale cu pulsuri” (11039, programul Parteneriate, finanțat de Guvernul României / CNMP); director proiect (Coneural); valoare intrată: 1.142.338 lei (~272.000 €); 2007-2010;

Anexa 4: Precizări privind încadrarea în categorii a publicațiilor

Pentru reviste

Am pornit de la URL-ul indicat în OMENCȘ nr. 6129/2016, respectiv http://uefiscdi.gov.ro/articole/4386/Premierea-rezultatelor-cercetarii--articole.html , după care am urmat link-ul „Pachet de informații", care duce la pagina cu URL-ul https://uefiscdi.gov.ro/articole/4515/Premierea-rezultatelor-cercetarii--articole--Competitie-2016.html. Pentru revistele din Science Citation Index Expanded & Social Sciences Citation Index, sunt link-ate la această adresă 3 liste, una corespunzătoare anului 2016 și două corespunzătoare anului 2015. Din listele corespunzătoare anului 2015, una este ordonată în funcție de factorul de impact al revistelor (IF), iar alta este ordonată în funcție de scorul de influență al revistelor (AIS).

OMENCȘ nr. 6129/2016 precizează că „candidatul va utiliza lista corespunzătoare forumului pentru anul apariției publicației sau, în caz că acest lucru nu este posibil, a listelor cele mai apropiate de anul apariției publicației. În cazul existenței a două liste cele mai apropiate, se va utiliza lista cea mai favorabilă candidatului". Deoarece, cu excepția a două publicații (în Neurocomputing și în Journal of Informetrics), publicațiile analizate sunt anterioare anului 2015, iar toate publicațiile pentru care am contorizat citările sunt de asemenea anterioare anului 2015, pentru acestea am utilizat o listă corespunzătoare anului 2015. Deoarece AIS reflectă mai bine calitatea unei reviste decât IF, am utilizat lista corespunzătoare anului 2015 ordonată în funcție de scorul de influență al revistelor (AIS), având URL-ul https://uefiscdi.gov.ro/userfiles/file/PREMIERE_ARTICOLE/ARTICOLE%202016/Clasament%20AIS%202015.pdf. În cazul încadrării unei reviste în mai multe domenii în această listă, am luat în considerare încadrarea cea mai favorabilă. Categoriile folosite sunt indicate în tabelul de mai jos.

Nume revistă	**Categoria**	**Motivarea categorizării**	**Domeniu**
Biological Cybernetics	B	Zona galbenă	Computer science, cybernetics
Current Opinion in Neurobiology	A*	Primele 20% reviste din zona roșie (locul 12/62<20%)	Neurosciences
European Journal of Operational Research	A	Zona roșie	Operations research & management science
Frontiers in Computational Neuroscience	B	Zona galbenă	Mathematical & computational biology
IEEE Computational Intelligence Magazine	A	Zona roșie	Computer science, artificial intelligence
IEEE Transactions on Computers	A	Zona roșie	Computer science, hardware & architecture
IEEE Transactions on Neural Networks and Learning Systems	A	Zona roșie	Computer science, artificial intelligence; Computer science, hardware & architecture; Computer science, theory & methods; Engineering, electrical & electronic
International Journal of Neural Systems	B	Zona galbenă	Computer science, artificial intelligence
Journal of Machine Learning Research	A*	Primele 20% reviste din zona roșie (locul 2/30<7%)	Computer science, artificial intelligence
Journal of Neurophysiology	A	Zona roșie	Physiology
Journal of Neuroscience	A	Zona roșie	Neurosciences
Nature Neuroscience	A*	Primele 20% reviste din zona roșie (locul 5/62<9%)	Neurosciences
Nature Reviews Neuroscience	A*	Primele 20% reviste din zona roșie (locul 1/62<2%)	Neurosciences

Neural Computation	A	Zona roșie	Computer science, artificial intelligence
Neural Networks	A	Primele 6 reviste din zona galbenă (respectiv locul 1 din zona galbenă), deoarece 30 × 20%=6	Computer science, artificial intelligence
Neurocomputing	B	Primele 6 reviste din zona albă (respectiv locul 3 din zona albă), deoarece 30 × 20%=6	Computer science, artificial intelligence
Neuron	A*	Primele 20% reviste din zona roșie (locul 6/62<10%)	Neurosciences
New Ideas in Psychology	B	Zona galbenă	Psychology, multidisciplinary
Physica A - Statistical Mechanics and its Applications	B	Zona galbenă	Physics, multidisciplinary
Physical Review E	A	Zona roșie	Physics, fluids & plasmas
PLoS Computational Biology	A	Zona roșie	Mathematical & computational biology; Biochemical research methods
PLoS ONE	A	Zona roșie	Multidisciplinary sciences
Proceedings of the National Academy of Sciences of the United States of America	A	Zona roșie	Multidisciplinary sciences
Science	A*	Primele 20% reviste din zona roșie (locul 2/14<15%)	Multidisciplinary sciences
Scientometrics	B	Zona galbenă	Information science & library science
The European Physical Journal B - Condensed Matter and Complex Systems	B	Zona galbenă	Physics, condensed matter

Pentru cele două articole publicate în 2021 și 2022 în revistele Neurocomputing și Journal of Informetrics, am folosit încadrarea cea mai puțin favorabilă dintre opțiunile: a) folosirea listei corespunzătoare anului 2016 de la https://uefiscdi.gov.ro/articole/4515/Premierea-rezultatelor-cercetarii--articole--Competitie-2016.html; b) cea mai recentă listă disponibilă pentru 2022 conform pachetului de informații pentru cea mai recentă competiție, respectiv lista pentru AIS pentru 2021 de la https://uefiscdi.gov.ro/premierea-rezultatelor-cercetarii-articole, în lista bazată pe AIS.

Nume revistă	**Categorie 2016**	**Motivarea categorizării, 2016**	**Categorie 2021**	**Motivarea categorizării, 2021**	**Domeniu**
Neurocomputing	B	Zona galbenă	A	Zona roșie	Computer science, artificial intelligence
Journal of Informetrics	A	Zona roșie	A	Zona roșie	Computer science, interdisciplinary applications; Information science & library science

Pentru conferințe

Am pornit de la URL-ul indicat în OMENCȘ nr. 6129/2016, http://www.core.edu.au/ , după care am accesat link-urile „CORE Rankings Portal”, respectiv „ACCESS THE CORE CONFERENCE DB HERE”, ajungând la URL-ul http://portal.core.edu.au/conf-ranks/ pornind de la care au fost făcute căutările. Categoriile folosite sunt indicate în tabelul de mai jos.

Nume conferință	**Abreviere**	**Categoria**	**Liste corespunzătoare**	**URL conferință**
Advances in Neural Information Processing Systems	NIPS	A*	CORE2008, CORE2013, CORE2014, CORE2017	http://portal.core.edu.au/conf-ranks/98/
Advances in Neural Information Processing Systems	NIPS	A	ERA2010	http://portal.core.edu.au/conf-ranks/98/
European Symposium on Artificial Neural Networks	ESANN	B	ERA2010, CORE2013, CORE2014, CORE2017	http://portal.core.edu.au/conf-ranks/512/
IEEE International Joint Conference on Neural Networks	IJCNN	A	CORE2008, ERA2010, CORE2013, CORE2014, CORE2017	http://portal.core.edu.au/conf-ranks/685/
International Conference on Artificial Neural Networks	ICANN	B	CORE2008, ERA2010, CORE2013, CORE2014, CORE2017	http://portal.core.edu.au/conf-ranks/915/
International Conference on Neural Information Processing	ICONIP	A	CORE2008, ERA2010, CORE2013, CORE2014, CORE2017	http://portal.core.edu.au/conf-ranks/1152/
International Conference on the Simulation and Synthesis of Living Systems	ALIFE	A	CORE2008, ERA2010, CORE2013, CORE2014, CORE2017	http://portal.core.edu.au/conf-ranks/1240/
International Symposium on Symbolic and Numeric Algorithms for Scientific Computing	SYNASC	C	ERA2010, CORE2013, CORE2014, CORE2017	http://portal.core.edu.au/conf-ranks/1421/