ARTIFICIAL NEURAL NETWORKS: FROM MATHEMATICAL MODELS TO BIOLOGICALLY INSPIRED SELF-ORGANIZING SYSTEMS

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DOI: 10.17973/MMSJ.2025_10_2025081

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This paper provides a comprehensive analysis of the evolutionary development of artificial neural networks (ANNs) through the lens of three key generations: from simple perceptrons to modern spiking neural networks (SNNs) and prospective biophysical models. Particular attention is paid to a critical comparison of artificial systems with their biological prototypes, identifying the fundamental limitations of existing approaches, and justifying the need for a new paradigmatic direction - self-organizing networks of uniform elements (SNUE). The proposed SNUE concept integrates key principles of biological neuroplasticity with the requirements of computational efficiency, offering an innovative framework for the development of the next generation of neuromorphic systems. The paper provides a detailed analysis of the theoretical foundations, potential architectural solutions, and promising directions for the practical implementation of this approach.

KEYWORDS

Artificial neural networks, Spiking neural networks, Biological neuroplasticity, Dendritic computations, Self-organizing systems, Neuromorphic computing

1 INTRODUCTION

Since the first mathematical models of neurons by McCulloch & Pitts [McCulloch 1943], artificial neural networks have come a long way in development, becoming the foundation of artificial intelligence. Modern ANNs demonstrate exceptional efficiency in highly specialized tasks (pattern recognition, natural language processing). However, despite impressive practical successes, a fundamental gap remains between biological reality and its computational models. The successes of ANNs are based on statistical patterns, not on the reproduction of the principles of biological brain operation. The gap between ANNs and biological neural networks (BNNs) manifests itself in three key aspects: a simplified view of neural signal transmission and processing; ignoring the spatio-temporal organization of neural ensembles; and the lack of genuine mechanisms of self-organization and adaptation. In this paper, we formulate an alternative approach to modeling neural-like networks.

We conduct a systematic analysis of the limitations of existing generations of ANNs, justify the necessity of considering biological principles, propose a new architecture based on self-organizing networks of uniform elements (SNUE), and define promising research directions.

2 ANALYSIS OF THREE GENERATIONS OF ANNS

The idea of a mathematical description of a neuron as a computational unit was formulated back in 1943 by McCulloch and Pitts [McCulloch 1943]. The features of this model are that the output value is a binary variable. This simplest neural model can be described as

$$y = f\Big(\sum_{i=1}^{N_i} w_i x_i - \Theta\Big) = \begin{cases} 1 & \text{if } \sum_{i=1}^{N_l} w_i x_i - \Theta \geq 0, \\ 0 & \text{if } \sum_{i=1}^{N_l} w_i x_i - \Theta < 0, \end{cases} \quad (1)$$

where y ∈ {0,1} is the neuron output, f(·) is the activation function, Ni is the number of input neurons, x_i is the input neuron i, w_i is the synaptic weights between input neuron i and the output neuron, θ ∈ ℜ is the neuron activation threshold. This representation was used in the computational model of the first-generation ANN - the perceptron [2, 3]. The perceptron is the simplest type of neural network. It is based on a mathematical model of information perception by the brain, consisting of sensors, associative and responding elements. Three key characteristics of the perceptron can be highlighted: first - binary inputs and outputs, second - a threshold activation function, and third - a single-layer network architecture. At the same time, there are fundamental limitations: the inability to solve non-linearly separable problems, the lack of learning mechanisms, and excessive simplification of biological processes. Despite its simplicity, perceptrons solve classification problems very well.

The further evolution of ANNs is associated with the emergence of deep neural networks, the development of error backpropagation algorithms, and the advancement of regularization methods. A feature of the second generation of artificial neural networks is the transition from a binary representation of input and output data to the use of real numbers. The activation function is a continuous function. An artificial neuron in this case can be described as

$$y = f\Big(\sum_{i=1}^{N_i} w_i x_i + b\Big) \quad (2)$$

where b ∈ R is the bias vector. The computational model of an artificial neural network based on this representation of a neuron is a feedforward and feedback signal propagation neural network. The ability to differentiate continuous functions allows for efficient network training using the error backpropagation method. This form of representing an artificial neuron is used today in most neural network-based applications. Second-generation neural networks have come a long way from multilayer perceptrons to modern transformers. Key achievements of second-generation networks include the ability to approximate complex nonlinear functions, successes in computer vision and NLP, and the development of specialized hardware (GPU, TPU).

Despite the huge successes in the application of second-generation networks, significant drawbacks must be noted. These include high energy consumption associated with the need to store and process a huge number of weight coefficients. Problems of interpretability - the inability to determine why the network made a particular decision. Catastrophic forgetting, due to the fact that training an artificial neural network inevitably leads to the loss of information (previously acquired knowledge about the environment), which is distributed throughout the network. By changing the weight coefficients, which essentially store all the "knowledge" of the network, we do not add new "knowledge" but overwrite all accumulated ones. The artificial neuron has no information storage mechanisms. At the same time, it should be noted that short-term memory can be organized using specially built configurations of artificial neural networks such as recurrent neural networks (RNN, Long short-term memory - LSTM).

The attempt to more accurately mimic biological neurons, especially in terms of temporal characteristics, led to the creation of third-generation neural networks - spiking neural networks (SNNs) [4-7]. A neuron in an SNN can be described as a hybrid system formalism [4]:

$$\begin{cases} \frac{d\mathbf{x}}{dt} = f(\mathbf{X}) \dots \\ \mathbf{X} \leftarrow g_i(\mathbf{X}) \dots \end{cases} \tag{3}$$

where **X** is a vector consisting of the neuron's state variables, f(·) represents differential equations describing the evolution of state variables, and $g_i(\cdot)$ represents the change in state variables caused by signal events at synapse *i*. A spiking neural network, based on a temporal coding scheme, initially contains a parameter such as time, so information memorization processes naturally enter the model. The connection between neurons in such a network is modeled through spikes - short pulses that are transmitted between neurons. Synaptic transmission in such networks is modeled through time delays and connection strengths that determine how quickly and strongly one neuron activates another. SNNs use models of synaptic plasticity [8 - 11], such as the STDP rule (Spike-Timing-Dependent Plasticity), which is based on temporal correlation between spikes, and Hebb's rule [12]. This rule regulates the synaptic weight depending on the time between the spike in the presynaptic and postsynaptic neurons, similar to how the strength of the synaptic connection changes in a biological system based on experience and learning. A detailed description of approaches for training SNNs can be found in the review [13].

The main advantage of spiking neural networks is that they can be implemented in "hardware" in neuromorphic computers that have significantly higher computation speeds and orders of magnitude lower energy consumption [9,14]. Table 1 shows the main differences between 2nd and 3rd generation ANNs.

Table 1. Comparative table of characteristics of ANNs and SNNs

Parameter	2nd generation ANN	Spiking Networks
Signal type	Analog	Impulse
Temporary resolution	No	High
Energy efficiency	Low	Tall
Biological adequacy	Moderate	Tall

Promising directions for the use of SNNs, in particular, are the development and creation of neuromorphic processors, resistive memory devices, and hybrid digital-analog systems.

3 COMPARISON WITH BIOLOGICAL SYSTEMS

Despite the huge successes in the use of ANNs based on representation (1), it must be noted that the representation of a neuron in this form is simply a mathematical trick and has practically nothing in common with biological neurons. Three main structural components of a biological neuron can be distinguished: dendrites, which are responsible for spatial signal integration, nonlinear processing of inputs, and have local computational nodes; the soma (body) of the neuron performs the functions of integrating dendritic signals, generating action potentials, and metabolic regulation; axons are necessary for transmitting signals over long distances, providing modulation of synaptic transmission and temporal synchronization.

In artificial neural networks, there are no analogues of dendrites and axons, and accordingly, there is no possibility of simply implementing the functions they perform in the process of receiving, processing, and transmitting excitation. The soma has a complex structure and performs the function of not only collecting information from dendrites (like a summator in an ANN) but also forming conditions for generating a response signal. Furthermore, there are other critical differences between biological and artificial neural networks. Biological neural networks are neural ensembles located in three-dimensional space with a 3D structure. The structure of these ensembles, as well as their topology, determine various properties, including the specialization of neurons and the functions they perform. Neither SNNs nor ANNs reflect the spatial arrangement of neurons and their parts. At the same time, taking into account the spatial location of the neurons themselves, as well as their structural parts - dendrites and axons, is extremely important. For example, Fig. 1 shows how the potential changes depending on the location of synaptic inputs (stimuli 1 and 2) co-activated within the same dendrite. Inputs located on the same dendritic branch will integrate in a nonlinear sigmoidal manner [15], while the same inputs distributed across different branches will linearly summate in the soma. This prediction has been confirmed experimentally on the basal dendrites of neocortical neurons [16].

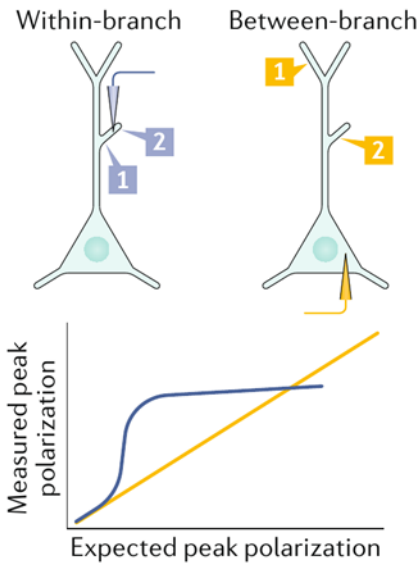

Figure 1. Schematic representation of a neuron with a dendrite. The numbers indicate co-activated input points. The lower graph shows membrane polarization depending on the input points of two signals. (from work [17])

Biological networks are characterized by dynamic reconfiguration of connections during signal transmission and learning, which is absent in ANN and SNN models.

It should be noted that there are biophysical models of neurons that take into account the morphology of living cells in detail. These models are ideally suited for studying how dendritic information processing influences neural computations at the single-cell level [17]. Such models include hundreds of compartments (dendritic branches), each equipped with numerous ionic mechanisms to accurately reproduce the electrophysiological profile of the simulated neurons. However, achieving high model accuracy is usually accompanied by an increase in computational complexity, leading to higher CPU/GPU requirements and a significant increase in execution time [17]. Therefore, this category of models is not suitable for modeling large networks where computational efficiency is a key priority.

In general, while dendrites provide biological networks with significant computational power, and these advantages are likely to extend to machine learning systems, in real SNN models, dendrites are usually not used. The reason is that detailed modeling of dendritic properties consists of overly complex equations with numerous free parameters, making it mathematically difficult to solve, and the equation describing dendrite dynamics

$$C^d \frac{dE_m^d}{dt} = -g_L^d(E_m^d - E_L^d) + \sum_{i \in C^d} I_a^{i,d} + \sum_{j \in S^d} I_{syn}^{j,d} \quad (4)$$

where, the parameter C^d characterizes capacitance; E_m - dendrite energy; E_L - dendrite closure energy; g_L- parameter characterizing leakage current conductance; I_a^i- current from the *i*- th dendritic branch attached to the dendrite; I^j_{syn} - current from the j-th synapse; C^d- includes all branches connected to this branch; S^d - all synapses of this branch. Similar equations are used to describe the dynamics of axons, cells, and the entire neural network. As a result, a complex system of differential equations arises, describing signal propagation, represented as a set of currents using Kirchhoff's laws. A number of other features inherent in biological neural networks can be highlighted. These are temporal characteristics: signal propagation delays, temporal integration windows, time-dependent plasticity. Synaptic dynamics: the chemical nature of signal transmission, modulation by neurotransmitters, long-term potentiation/depression.

SELF-ORGANIZING NETWORKS OF UNIFORM ELEMENTS

One of the possible directions for the further development of neural networks is the development of a fundamentally new class of computational systems that combine the advantages of biological information processing with the capabilities of modern digital technologies [18,19]. The main property of these systems should be the ability to self-organize during operation depending on the tasks performed. Below are the main principles of self-organizing networks of uniform elements.

First of all, this is heterogeneity of elements. The basic objects of the network do not necessarily have to be represented by neurons. They can be of a completely different nature depending on the task. These could be, for example, social network users or a swarm of unmanned vehicles. At the same time, the objects and principles of network organization must satisfy a set of requirements to ensure the possibility of self-organization and maintaining the network in working condition for a given time. Although we are generally talking about self-organization of uniform elements, structurally each element can itself consist of a set of sub-objects interacting with each other and the external environment. It is clear that to describe the interaction processes of such a composite system, it is necessary to use hybrid processing models, depending on the type, nature, and character of the interaction, for example, chemical interaction with the external environment or spike transmission within the network. A multi-level and multi-object structure leads to the need for a hierarchical organization of the network according to the principle from simple to complex.

Another main principle that the network must possess is the condition of dynamic self-organization: first of all, this is the requirement for emergent structure formation. Emergence is a phenomenon where new properties or behavior arise in a system that are not characteristic of its individual components. For example, in physics, as a result of quantum-mechanical interaction of particles, parameters characteristic of macroscopic systems appear, such as material resistance or boiling point. Another fundamental property of self-organizing systems is adaptation to input data. This property is necessary for the emergence of evolutionary mechanisms for optimizing the entire system. Evolutionary mechanisms are necessary to ensure the stability of the entire system and its properties regardless of changing external conditions. Moreover, these mechanisms should not be artificially introduced into the system in the form of rules, but should arise as a result of the emergent nature of system formation.

The next property that SNUE should possess is spatial embeddedness. In fact, the concept of space is absent in artificial neural networks. Existing SNNs and ANNs do not reflect the spatial arrangement of neurons and their parts. It was shown above that taking into account the spatial location of the neurons themselves, as well as their structural parts - dendrites and axons, is extremely important in biological systems. Introducing the concept of space into SNUE will naturally take into account physical limitations, for example, signal propagation in the intercellular environment, and also separate local and global interactions acting at different levels of the model. This will lead to the emergence of the property of architectural scalability.

Architecturally, the solution of the multi-level SNUE model can be represented in the form of three main parts:

1. Microlevel. At this level, individual elements of the system are simulated. These can be, for example, neurons, social network users, atoms, robots with primitive functionality. At this level, their state and internal variables are determined, as well as the rules of local interactions and associated input-output interfaces. Actually, this level is basic and directly tied to the type of network.

2. Mesolevel (ensembles): At this level, functional clusters that arise during the network's life are defined. Activation patterns directly related to input data, their interaction, and changes in the connectivity dynamics of both individual elements and ensembles of elements.

3. Macrolevel, at which the entire system is considered as a whole. Its global characteristics and emergent properties are determined, and adaptive behavior is formed. Table 2 shows the main characteristics of different generations of neural networks.

Table 2. Comparison of characteristics of neural network architectures

Parameter	Perceptrons (1st Gen)	Deep Networks (2nd Gen)	Spiking Networks (3rd Gen)	Biological Neural Networks	SNUE (Proposed Model)
Signal Type	Binary	Real-valued	Impulse (temporal tags)	Electrochemical spikes	Hybrid (analog + impulse)
Time Processing	None	Discrete steps	Continuous temporal coding	Continuous dynamics	Dynamic time windows
Energy Consumption	Low	High (GPU/TPU)	Moderate (neuromorphic chips)	Extremely low (~20 W)	Optimized (memristors)
Plasticity	Fixed weights	Backpropagation	STDP	Hebbian+ homeostatic	Self-organizing topology
Implementation Examples	Logical circuits	ResNet, Transformer	ResNet, Transformer	Hebbian+ homeostatic	Memristive ensembles

In general, spiking networks are closer to biological systems in terms of energy efficiency and temporal encoding, but are inferior in adaptability. The proposed SNUE architecture combines the advantages of impulse transmission with self-organization mechanisms absent in classical ANNs.

CONCLUSIONS

The proposed SNUE concept represents a promising synthesis of neurobiological principles and modern computational paradigms. Unlike traditional approaches, it takes into account spatio-temporal dynamics, supports genuine self-organization, and provides biologically plausible plasticity. The implementation of this approach opens up prospects for creating a fundamentally new class of computational systems that combine the advantages of biological information processing with the capabilities of modern digital technologies.

Certainly, the implementation of SNUE requires solving certain problems, first of all, it is necessary to answer existing theoretical challenges, namely, to formalize the principles of self-organization, develop, if necessary, new mathematical apparatus, create metrics for assessing bio-likeness. There are also technological barriers that need to be overcome. Solve scaling problems, develop energy-efficient implementations and interfaces of SNUE with traditional systems.

Let us emphasize once again that the proposed computational complex does not necessarily have to rely on physical or chemical processes in a biological neural network. It is necessary to find and formulate general principles on which it is possible to organize network interaction of uniform elements regardless of their nature with the possibility of organizing a neural-like network. For the creation and ensuring the operability of the SNUE network, several stages can be distinguished. At the first stage, it is necessary to develop algorithms for forming a set of non-interacting uniform objects randomly distributed in 3D space. Each object must have a set of randomly distributed points of information reception in 3D space (a-la dendrites) and at least one point of information output to a random point in the space occupied by the network (axon). At the next stage, it will be necessary to establish connections between the elements of the created network. As already mentioned, the topology of artificial neural networks is usually set initially and does not change during the training and application of the trained network. It is desirable to formulate simple principles that allow the SNUE to self-organize depending on the type of input signals. A detailed discussion of the issues of self-organization of interacting objects will be carried out in the next article.

SNUE systems can be used in various applied areas, such as Adaptive robotics, neuroprosthetics, cognitive architectures, and predictive systems.

ACKNOWLEDGMENTS

This article was supported by the scientific grant agency of the Slovak Republic under the grant KEGA No. 012ŽU-4/2025 Implementation of methods and proposal of educational modules for the design of automated and robotic production systems with the aspect of safety and risk elimination

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