Modified Network of Generalized Neural Elements as an Example of a New Generation Neural Network

Evgeniy Konovalov
P.G. Demidov Yaroslavl State University
Yaroslavl, Russia
e.konovalov@uniyar.ac.ru

***Abstract*—The article is devoted to the analysis of neural networks consisting of generalized neural elements.**

The first part of the article proposes a new neural network model — a modified network of generalized neural elements (MGNE-network). This network developes the model of generalized neural element, whose formal description contains some flaws. In the model of the MGNE-network these drawbacks are overcome. A neural network is introduced all at once, without preliminary description of the model of a single neural element and method of such elements interaction. The description of neural network mathematical model is simplified and makes it relatively easy to construct on its basis a simulation model to conduct numerical experiments. The model of the MGNE-network is universal, uniting properties of networks consisting of neurons-oscillators and neurons-detectors.

In the second part of the article we prove the equivalence of the dynamics of the two considered neural networks: the network, consisting of classical generalized neural elements, and MGNE-network. We introduce the definition of equivalence in the functioning of the generalized neural element and the MGNE-network consisting of a single element. Then we introduce the definition of the equivalence of the dynamics of the two neural networks in general. It is determined the correlation of different parameters of the two considered neural network models. We discuss the issue of matching the initial conditions of the two considered neural network models. We prove the theorem about the equivalence of the dynamics of the two considered neural networks. This theorem allows us to apply all previously obtained results for the networks, consisting of classical generalized neural elements, to the MGNE-network.

I. Introduction

Modeling and studying neural networks is now one of the priority research areas. At the same time, there is a certain lack of models of the neural element, on the one hand, rather simple, and on the other hand,potentially capable of spawning neural networks with complex behavior. It is also important to have the opportunity to study the obtained neural networks by both analytical and numerical methods.

The well-known Hodgkin-Huxley model [1], for example, is mathematically complex and allows only computer research. The same is true for simplifications of the Hodgkin-Huxley system of equations, as well as for phenomenological continuous models like the Hindmarsh-Rose model [2], FitzHugh-Nagumo [3]–[4], Morris-Lekar [5], Wilson-Cowan oscillator[6] et al. It is difficult to introduce the mechanism of mutual influence of neurons into all these models; therefore, it is difficult to consider large networks based on these models.

On the other hand, many classical discrete models, such as perceptrons [7], Hopfield networks [8], self-organizing maps [9], show too simple behavior. This does not allow their effective use for solving complex cognitive tasks. Modern neural network models, such as convolutional [10] or recurrent networks [11], also have fairly simple behavior. The discrete nature of these models and effective learning algorithms [12] made it possible to achieve great progress in solving many practical problems. However, their dynamics are significantly different from the continuous biological processes that occur in the human brain. It seems likely that the new generation neural networks should not only take into account the outstanding achievements of discrete neural network models, but also approach biological continuous systems in order to solve truly complex cognitive problems.

II. Generalized neural element

On the way of building this model in [13]–[14] we introduce model of a generalized neural element (GNE), originally called the generalized neural automat. Its full formal description is given in [15].

A. Global model parameters

The generalized neural element is a neural model that operates in continuous time t and is given by the set of parameters p; r; α; T_R; n; m; $q_1, q_2, \ldots, q_n$ and T_m. Positive values p, r, α, T_R and T_m do not change over time and are the same for all elements included in the neural networks consisting of GNE. The number of inputs n and outputs m for each element is fixed,but, generally speaking, may not be the same for different elements, depending on the architecture of a particular neural network.

The inputs of each element are characterized by the values $q_1, q_2, \ldots, q_n$, where n is the number of inputs of this element. The synaptic weights q_i determine the effectiveness of the input. Each such weight characterizes a unidirectional synaptic connection that connects the output of one element and input another. Now and in the future we will consider only links with positive weights.

The internal state of an element at time t is given by three functions: $u(t)$, $s(t)$ $\sigma(t)$. The function $s(t)$ having the following values:

$$s(t) = \begin{cases} \text{sensibility} \\ \text{generation of impulse} \\ \text{refractory} \end{cases}.$$

The function $\sigma(t)$ is equal to one when the element generates output impulse (spike). This impulse arrives at all m outputs of a given element. At other times, $\sigma(t) = 0$.

Input impulses $\sigma_1(t), \sigma_2(t), \ldots, \sigma_n(t)$ depend on time point t. Namely, $\sigma_i(t) = 1$ at all such times t, when impulse enter by the i-th entrance. At other times, $\sigma_i(t) = 0$.

We introduce auxiliary functions $\sigma_1^m(t), \sigma_2^m(t), \ldots, \sigma_n^m(t)$. For each individual $i = 1, 2, \ldots, n$, we set $\sigma_i^m(t) = 1$for all $t \in [t^s; t^s + T_m]$, where t^s is such that simultaneously $s(t^s) = \{\text{sensibility}\}$ and $\sigma_i(t^s) = 1$. At other times, $\sigma_i^m(t) = 0$.

B. Dynamics of an element

We now describe the functioning of the generalized neural element. At any time point t one of the three following options is possible.

I. Let $s(t) = \{\text{generation of impulse}\}$. Then $u(t) = p$, $\sigma(t) = 1$; for arbitrarily small $\varepsilon > 0$: $s(t+\varepsilon) = \{\text{refractory}\}$.

II. Let $s(t) = \{\text{refractory}\}$. Then $u(t) = 0$, $\sigma(t) = 0$; $s(t_1^{sp} + T_R) = \{\text{sensibility}\}$, where

$$t_1^{sp} = \max_{\tau<t}\{\tau : \sigma(\tau) = 1\}. \quad (1)$$

III. Let $s(t) = \{\text{sensibility}\}$. Then $\sigma(t) = 0$, and the membrane potential function $u(t)$ is determined by the differential equation:

$$\dot{u} = \alpha(r + q(t) - u), \quad (2)$$

where the function $q(t)$ is defined as follows:

$$q(t) = \sum_{i=1}^{n} q_i \sigma_i^m(t).$$

The initial state for the equation (2) is taken the value of $u(t^0)$, which is defined as follows:

$$u(t^0) = u(t^0 - 0),$$
$$t^0 = \begin{cases} t^*, \text{ if } t^* > t_1^{sp} + T_R \\ t_1^{sp} + T_R, \text{ if } t^* \le t_1^{sp} + T_R \end{cases},$$

where t_1^{sp} is determined by (1),

$$t^* = \max\{t^+; t^-\}, \qquad t^+ = \max_i \max_{\tau \le t}\{\tau : \sigma_i(\tau) = 1\},$$
$$t^- = \max_i \max_{\tau \le t}\{\tau : \sigma_i^m(\tau) = 1, \sigma_i^m(\tau + 0) = 0\},$$

where t_1^{sp} — the moment of the last impulse of this element, t^+ — the time of the last input signal to this element, t^- — the moment of the last completion of any input influence on this element.

An element enters a generation of impulse state if the value of the membrane potential $u(t)$ is equal to the threshold value p. That is $s(t_2^{sp}) = \{\text{generation of impulse}\}$, where

$$t_2^{sp} = \min_{\tau>t}\{\tau : u(\tau) = p\}.$$

If the inequality $u(\tau) < p$ holds for all $u(\tau) < p$, then $s(\tau) = \{\text{sensibility}\}$ for all $\tau > t$. In this case, the element does not generate a pulse. The analyzed cases completely exhaust the behavior of the generalized neural element.

Formally defined membrane potential dynamicsof the generalized neuronal element corresponds to the development of the potential of a biological neuron. It is consistent with the ”base neural model” [16] and is close to the model of biologicalneuron, built on the basis of differential equations with delay [17]. At the same time, the GNE model is characterized by simplicity of operation and allowsavoid technical difficulties associated withintegration of systems of differential equations with delay. In addition, the GNE model is generalized. In particular, for $p < r$, the element behaves like a neurons-oscillators, and for $p > r$ it is like a neurons-detectors.

This relatively simple model allows you to build neural networks with complex behavior (in particular, dynamic attractors of neural activity) and control this behavior in advance using synaptic weights [14]; to adapt one and several generalized neural elements [15]; investigate the behavior of the model under the influence of bursting [18] and others. All this shows the promise of both the model itself and the neural networks it generates.

However, the formal description of the GNE model does not demonstrate its basic simplicity. Difficulties arose due to the fact that at first a model of a single neural element was introduced, the description of which made it difficult to formalize a dynamically changing external influence. Then, on the basis of the element model, one or another neural network was built, the configuration of which changed depending on the problem to be solved. As a result, the formal description of the model turned out to be overloaded with technical details, and the neural networks generated by the model did not seem to belong to a single neural network class. To overcome these shortcomings, this article introduces a modified network of generalized neural elements.

C. Formulation of the problem

Based on the model of a generalized neural element, we consider an arbitrary network of generalized neural elements (GNE-network). Then we introduce a mathematical model of a modified network of generalized neural elements (MGNE-network). Elements of such a network will have a certain similarity with generalized neural elements (GNE), but the network will be introduced immediately.

Next, we prove the equivalence of the functioning of the two neural networks considered: the GNE-network and the MGNE-network. This will allow to transfer all previously obtained results to the class of modified networks. Such an approach will emphasize the clarity and fundamental simplicity of the considered neural networks and their belonging to a single class, including for the convenience of further analytical and numerical research.

D. Network of generalized neural elements

Consider an arbitrary neural network consisting of N numbered generalized neural elements, generally speaking, a fully connected architecture. Elements with numbers i and j ($i, j = 1, \ldots, N$) are connected by a synaptic connection with a non-negative weight $q_{i,j}$ ($q_{i,i} = 0$) .

The parameters p, r, α, T_R and T_m are the same for all network elements. The number of inputs n and outputs m with this description is also the same for all network elements and is $N - 1$. This arbitrary network consisting of generalized neural elements will be referred to as the GNE-network. A model is considered.

E. Initial state

The dynamics of this model is uniquely determined by the initial stateat the zero moment of time. Let us set the initial state of the GNE-network. This means that you need to specify the state of all elements at the zero moment of time, that is, $s^k(0)$ (k is the element number). For simplicity, we assume that at the zero moment of time, no element generates an impulse.

Further, for elements for which $s^k(0) = \{\text{sensibility}\}$, you must specify the values of membrane potentials $u^k(0)$ ($k = 1, \ldots, N$); which neighboring elements influence each given element (if any),and how much time each such impact will last. Let us denote the time interval of such an influence from the i-th element on the k-th element ($i, k = 1, \ldots, N$) as $T_0^{i,k}$. If there is no influence, we will assume $T_0^{i,k} = 0$.

For those elements for which $s^k(0) = \{\text{refractory}\}$, we need to specify the time after which they will leave the refractory period. Denote this value for the k-th element as R_0^k ($k = 1, \ldots, N$). The initial state of the GNE-network is established.

III. The modified network of generalized neural elements

We now introduce a new model — a modified network of generalized neural elements (MGNE-network). So that the designations of the parameters of the new network do not duplicate the parameters of the old network (but there is a correspondence between them), in all such cases we will use the upper underscore.

A. Global model parameters

Consider a neural network of $\overline{N}$ numbered elements that also function in continuous time t. A network is defined by the following set of parameters:

- $\overline{p}$ — membrane potential threshold;
- $\overline{r}$ — equilibrium value of membrane potential;
- $\overline{\alpha}$ — speed parameter;
- $\overline{T}_R$ — duration of refractory period;
- $W = (w_{ij})_{i=1,j=1}^{\overline{N},\overline{N}}$ — synaptic weights matrix, $w_{ij} \in 0 \cup \Re^+$;
- $M = (m_{ij})_{i=1,j=1}^{\overline{N},\overline{N}}$ — synaptic exposure indicators matrix, $m_{ij} \in 0, 1$.

Positive real parameters $\overline{p}$, $\overline{r}$, $\overline{\alpha}$, $\overline{T}_R$ and the matrix W are established in advance and do not change during the dynamics of tne network. The elements of the matrix M change in the course of the the dynamics of tne network. The elements of the matrices W and M have the following meaning: w_{ij} is the weight of the synaptic connection leading from the i-th element to the j-th element; m_{ij} is a binary indicator of synaptic influence, which is transmitted via a link leading from the i-th element to j-th element. Namely, if at the moment of time t there is no influence, then $m_{ij}(t) = 0$; if there is an influence, then $m_{ij}(t) = 1$.

B. Dynamics of such element and initial state

The behavior of an arbitrary k-th element of an MGNE-network at the time t is determined by two time-dependent functions:

- $S^k(t)$ — state of element, $S^k(t) \in \{0, 1\}\ \forall t\ \forall k$;
- $U^k(t)$ — membrane potential value, $-1 \leq U^k(t) \leq \overline{p}\ \forall t\ \forall k$.

The function of the state of element $S^k(t)$ has the following meaning. If at an arbitrary time instant t: $S^k(t) = 1$, then the k-th element is in a state of sensibility. If at an arbitrary time instant t: $S^k(t) = 0$, then the k-th element is in a state of refractory.

Let us set the initial state of the MGNE-network at the zero moment of time:

- for each k we fix $S^k(0) = \{0, 1\}$, i.e. part of the elements is in a state of sensibility, part — in a state of refractory;
- if for an arbitrary k-th element $S^k(0) = 0$, then $U^k(0) = U_0^k$, $U_0^k \in [-1, 0)$;
- if for an arbitrary k-th element $S^k(0) = 1$, then $U^k(0) = U_0^k$, $U_0^k \in [0, \min(\overline{r}, \overline{p}))$;
- $m_{ij} = 0\ \forall i, j$ is the absence of the initial effect of the elements on each other.

Turning to the description of the dynamics of the MGNE-network, we introduce some definitions.

We will say that at the moment of time t^* a 0-event occurs for the k-th element, if $\exists k : S^k(t^*) = 0, U^k(t^*) = 0$. The biological meaning of the 0-event is the exit of the k-th element from the state of refractory.

We will say that at the moment of time t^* a p-event occurs for the k-th element, if $\exists k : U^k(t^*) = \overline{p}$. The biological meaning of the p-event is the generation of the k-th element of the nerve impulse (spike).

Under the influence of these events in the MGNE-network the following changes occur.

If at the time moment t^* a 0-event occurs for the k-th element, then

- $S^k(t^* + 0) = 1$ (the k-th element goes into a sensibility state);
- $m_{ik} = 0\ \forall i$ (eliminates external influence on the k-th element).

If at the moment of time t^* a p-event occurs for the k-th element, then

- $S^k(t^* + 0) = 0$ (the k-th element generates an impulse and immediately goes into a state of refractory);
- $U^k(t^* + 0) = -1$ (depolarization of the membrane potential);
- $m_{kj} = 1 \; \forall j$ (the k-th element begins to affect the remaining network elements).

If at the time moment t^* in the MGNE-network several events occur for different elements, first, all 0-events are processed in an arbitrary order (for example, in ascending element numbers),then all the p-events, also in an arbitrary order.

Between events, binary values $S^k(t)$ do not change. Only the values of membrane potentials $U^k(t)$ change. We define the mechanism of these changes, thereby setting the network dynamics at arbitrary points in time.

At zero time there are no events in the MGNE-network. Starting from zero time and to the first event in the considered network the dynamics of an arbitrary k-th element at an arbitrary time instant t is defined as follows.

If $S^k(t) = 0$, then $U^k(t)$ is the solution of the differential equation

$$\dot{U}^k = \frac{1}{\overline{T}_R} \tag{3}$$

with the initial state $U^k(t_0) = U^k(0) = U_0^k$.

If $S^k(t) = 1$, then $U^k(t)$ is the solution of the differential equation

$$\dot{U}^k = \overline{\alpha}(\overline{r} + \sum_{i=1}^{\overline{N}} m_{ik} w_{ik} - U^k) \tag{4}$$

with the initial state $U^k(t_0) = U^k(0) = U_0^k$.

The dynamics of the MGNE-network between any pair of consecutive events is determined in a similar way at time points t_1 and t_2 ($t_1 < t_2$). For the initial state, t_1 with known values of $U^k(t_1) \; \forall k$ is taken as the time point.

The presentation of the modified network model of generalized neural elements is completed.

The function graph “Fig. 1” shows the example of possible dynamics of k-th element of the MGNE-network provided $r > p$. The function of the membrane potential $U^k(t)$ changes stepwise at the moments of p-events of other elements. In particular, at the moments of p-events of other elements, the exponential asymptotic behavior of the function $U^k(t)$ varies depending on the elements of the matrix W. Thus, the influence of the elements within the MGNE-network on each other is determined by the weights of the connections between them. Namely, the larger the weight w_{ik}, the faster the p-event (spike generation) for the k-th element.

The equation (4) is similar to the equation proposed by J. Hopfield in 1984 for describing the continuous network [7], but much simpler than it,because between each pair of events is an equation with constant coefficients. The equation (4) does not containand the lagging argument, which distinguishes it favorably from the Hopfield-type neural network models described by the delay equations [8].

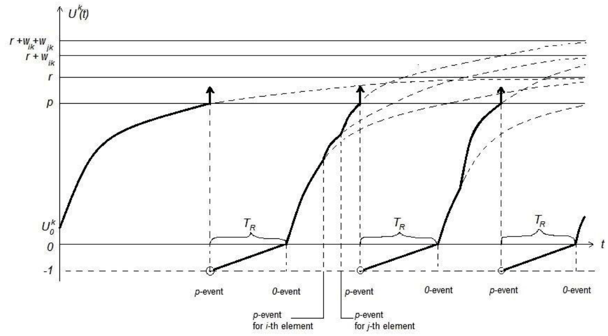

Fig. 1. Example of dynamics of the k-th element of the MGNE-network

All this makes it easy to explore MGNE-networks of arbitrarily large size and arbitrary topology,as well as simulate their dynamics on a computer in numerical research.

IV. Equivalence of the Dynamics of the Two Considered Neural Networks

Let us turn to the proof of the equivalence of the dynamics of the two neural networks considered: the GNE-network and the MGNE-network.

A. Equivalence definition

First introduce the definition of the equivalence of the dynamics of a generalized neural element and a separate element of the MGNE network.

Definition 1. *We will say that the generalized neural element and the element of the MGNE-network with the number k have equivalent dynamics,if in the same time scale and at any arbitrary time moment t the following is done:*

- *if a generalized neural element generates an impulse, then a p-event occurs for the k-th element of the MGNE-network;*
- *if the generalized neural element is in a state of refractory, then for the k-th element of the MGNE-network $S^k(t) = 0$;*
- *if the generalized neural element is in a state of sensibility, then for the k-th element of the MGNE-network $S^k(t) = 1$.*

Next we introduce the definition of the equivalence of the dynamics of the neural networks in general.

Definition 2. *We will say that the GNE-network and the MGNE-network have equivalent dynamics if*

- *on these two networks the same number of items;*
- *in these two networks can be numbered elements so that each i-th generalized neural element and i-th element of the MGNE-network have equivalent dynamics.*

B. The correspondence between the parameters of the models

Next, we establish a correspondence between the parameters of the models of the GNE-network and the MGNE-network. Namely:

$$\begin{array}{c} \overline{N} = N, \quad \overline{p} = p, \quad \overline{r} = r, \quad \overline{\alpha} = \alpha, \\ \overline{T}_R = T_R, \quad w_{ij} = q_{i,j}, \quad T_m = +\infty. \end{array} \tag{5}$$

It is also necessary to agree on the initial states for the GNE-network and the MGNE-network. Namely, let it be at zero time:

$$S^k(0) = \begin{cases} 1, & s^k(0) = \{\text{sensibility}\} \\ 0, & s^k(0) = \{\text{refractory}\} \end{cases} \tag{6}$$

It is also necessary to synchronize the values of the membrane potentials of all elements at the zero point in time:

$$U^k(0) = \begin{cases} u^k(0), \text{ if } s^k(0) = \{\text{sensibility}\} \\ -R_0^k/T_R, \text{ if } s^k(0) = \{\text{refractory}\} \end{cases} \tag{7}$$

Finally, we impose the state of the absence of external influence in the GNE-network at zero time:

$$T_0^{i,j} = 0 \; \forall i, j. \tag{8}$$

In the MGNE-network, this corresponds to the condition $m_{ij} = 0 \; \forall i, j$. It has already been imposed when setting the initial state of the MGNE-network.

C. Theorem about equivalent dynamics

We formulate and prove the following theorem.

Theorem 1. *Let an arbitrary GNE-network and MGNE-network be given, whose parameters satisfy the formulas (5), and the initial state are selected according to the formulas (6) — (8).*

Then this GNE-network and the MGNE-network have equivalent dynamics in the sense of definition 2.

Proof. The condition $\overline{N} = N$ means that there are an equal number of elements in the GNE-network and the MGNE-network. Consistently numbering the elements in these networks. Consider a generalized neural element (included in this GNE-network) and an element of this MGNE-network with the same arbitrary number k. It is necessary to show that these elements have equivalent dynamics, that is, to check the conditions of Definition 1 at an arbitrary time instant t.

We first consider the situation with $t = 0$. As already noted, there are no events in the MGNE-network at the zero point of time. There are no events in the MGNE-network at the zero point of time too. That is neither the impulse generation by any element nor the output of any element from the state of refractory occurs either in the GNE-network. The formula (6) provides a consistent choice of the state of the k-th generalized neural element and k-th element of the MGNE-network. Thus, the conditions of Definition 1 are satisfied for $t = 0$.

Now consider the time interval $(0; t_1)$, where t_1 is the moment of the first time event in the MGNE-network. The formula (7)–(8) and the equation (2) of model of the generalized neural element ensure that for $t \in (0; t_1)$ in GNE-networks neither does the generation of an impulse by any element, nor the output of any element from the state of refractory.

This makes it easy to consider the dynamics of changes in the membrane potential of the k-th generalized neural element and k-th element of the MGNE-network at once over the entire span of $(0; t_1)$. Depending on the state of the generalized neural element, two cases are possible.

If $s^k(0) = \{\text{refractory}\}$ and by condition (6) $S^k(0) = 0$, then condition $U^k(0) = -R_0^k/T_R$ ensures the output of the k-th generalized neural element from the state of refractory and the 0-event for the k-th element of the MGNE-network (taking into account the equation (3)) at the same time instant R_0^k. In particular, $s^k(t) = \{\text{refractory}\}$ and $S^k(t) = 0$ for $t \in (0; t_1)$.

If $s^k(0) = \{\text{sensibility}\}$ and by condition (6) $S^k(0) = 1$, then condition $U^k(0) = u^k(0)$ provides the following. The equation (2) of the dynamics of a membrane potential of a k-th generalized neural element takes the form $\dot{u}^k = \alpha(r - u^k)$ with the initial state $u^k(0) = u_0^k$. The equation (4) of the membrane potential dynamics of the k-th element of the MGNE-network takes the form $\dot{U}^k = \overline{\alpha}(\overline{r} - U^k)$with the same initial state $U^k(0) = U_0^k$. Obviously, their solutions $u^k(t)$ and $U^k(t)$ coincide as $t \in (0; t_1)$. This means that the generation of impulse given k-th generalized neural element (with $u^k(t) = p$) and the p-event for a given k-th element of the MGNE-network will occur at the same time.

At least, if there is no external influence on the considered elements in their networks. If such an external effect occurs, then a consistent form of the equations (2) and (4) will also provide the same dynamics of changes in membrane potentialsfor the k-th generalized neural element and the k-th element of the MGNE-network. Let's demonstrate it a bit later. For the time being, for $t \in (0; t_1)$ the conditions of Definition 1 are fulfilled.

At the moment of time t_1 some event occurs for the j-th element (including, possibly, $j = k$) of the MGNE-network. Considering the dynamics of the j-th generalized neural element with $t \in (0; t_1)$, it is easy to verify that it is at the time point t_1 this j-th generalized neural element either generates an impulse or goes out of a state of refractory. Namely, if in the MGNE-network a 0-event occurs for the j-th element, then the j-th generalized neural element goes out of a state of refractory.

If, however, an p-event for the j-th element occurs in the MGNE-network, then the j-th generalized neural element generates an impulse. This is achieved by matching the parameters of the networks (4) and the coordinated specification of the initial state (6) — (8). The actions during the processing of a 0-event and a p-event occurring in the description of the MGNE-network model result in the state $S^j(t)$and the dynamics of the membrane potential of the j-th element of the MGNE-network (and all the others in the case of a p-event) are changed so thatconditions of Definition 1 are met at $t = t_1$.

Moreover, changes in the matrix M of indicators of synaptic effects (in the case of a p-event) lead to a change in the right side of the equation (4) for some elements of the MGNE-network (it is possible that the k-th element). But exactly the same changes for GNE with the same numbers undergo the right side of the equation (2), which describes the dynamics of the GNE membrane potential. This is due to the stepwise form of the functions $\sigma_i^m(t)$ and the condition $T_m = +\infty$.

Now consider the time interval $(t_1; t_2)$, where t_2 is the moment of the next time event in the MGNE-network. In this interval, the reasoning is carried out in a similar way. Then we can consider the point in time t_2 and so on.

Since both models are deterministic, the conditions of Definition 1 remain valid for arbitrary k-th GNE and k-th element of the MGNE-network. This means that the GNE-network and the MGNE-network have equivalent dynamics in the sense of definition 2. The theorem is proved.

V. Conclusion

This theorem allows us to apply all previously obtained results for the networks, consisting of classical generalized neural elements, to the MGNE-network.

The MGNE-network is able to dynamically store a given sequence of impulses. If we accept the hypothesis about the wave nature of memory, then the MGNE-network can be considered as a model of a neural population that stores a trace of memory. Moreover, the values of the mismatch between events are information carriers. The results obtained can be used in problems of researching the capabilities of networks, as well as in their practical implementation on neurocomputers.

References

[1] A. L. Hodgkin, A. F. Huxely "A quantitative description of membrane current and its applications to conduction and excitation in nerve", *J. Physiol.*, vol.117, 1952, pp. 500-544.

[2] J. L. Hindmarsh, R. M. Rose "A model of neuronal bursting using three coupled first order differential equations", *Proc. R. Soc.; Ser.B Biol. Sci.*, vol.221, 1984, pp. 87-102.

[3] R. A. FitzHugh "Impulses and physiological states in theoretical models of nerve membrane", *Biophys. J.*, vol.1, 1961, pp. 445-466.

[4] J. S. Nagumo, S. Arimoto, S. Yoshizawa "An active pulse transmission line simulating nerve axon", *Proc. Ire.*, vol.50, 1962, pp. 2061-2070.

[5] C. Morris, H. Lecar "Voltage oscillations in the Barnacle giant muscle fiber", *Biophys. J.*, vol.35, 1981, pp. 193-213.

[6] H. R. Wilson, J. D. Cowan "Excitatory and Inhibitory Interactions in Localized Populations of Model Neurons", *Biophysical J.*, vol.12, 1972, pp. 1-24.

[7] F. Rosenblatt "The perceptron: a probabilistic model for information storage and organization in the brain", *Psychological Review.*, vol.65, 1958, pp. 386-408.

[8] J. J. Hopfield "Neural networks and physical systems mith emergent collective computational abilities", *Proc. Nat. Acad. Sci.*, vol.79, 1982, pp. 2554-2558.

[9] T. Kohonen "Self-organized formation of topologically correct feature maps", *Biological Cybernetics.*, vol.43, 1982, pp. 59-69.

[10] Y. LeCun, B. Boser, J. S. Denker, D. Henderson, R. E. Howard, W. Hubbard, L. D. Jackel, "Backpropagation Applied to Handwritten Zip Code Recognition", *Neural Computation*, vol.1, no.4, 1989, pp. 541-551.

[11] S. Hochreiter, J. Schmidhuber, "Long short-term memory", *Neural Computation*, vol.9, no.8., 1997, pp. 1735-1780.

[12] D. E. Rumelhart, J. L. McClelland, and the PDF Research Group, eds. *Parralel Disrtibuted Processing: Explorations in the Microstructure of Cognition (Vols 1 and 2).* Cambridge, MA: TheM.I.T. Press, 1986.

[13] V.V. Mayorov, E.V. Konovalov "General automatic neuron in task of wave excitement spreading in neuron net", *Neurocomputers*, no.7, 2007, pp. 3-8.

[14] E.V. Konovalov "The stable oscillatory regime in a neuron net consisting of generalized automatic neuron-detectors", *Modeling and Analysis of Information Systems*, vol.14, no.2, 2007, pp. 30-35.

[15] E.V. Konovalov "The problem of adaptation of the generalized neural element", *Modeling and Analysis of Information Systems*, vol.19, no.1, 2012, pp. 69-83.

[16] V.I. Kryukov, G.N. Borisyuk, R.M. Borisyuk, A.B. Kirillov and E.I. Kovalenko. *Metastable and unstable states in the brain*. Pushchino: NTsBI AN SSSR, 1986.

[17] V.V. Mayorov, I.Yu. Myshkin "Mathematical modeling of a neuron net on the basis of the equation with delays", *Mathematical modeling*, vol.2, no.11, pp. 64-76.

[18] E.V. Konovalov "The problem of berst influence on the generalized automatic neuron", *Modeling and Analysis of Information Systems*, vol.14, no.3, 2007, pp. 43-49.

[19] J. J. Hopfield "Neurons with graded response have collective computational properties like those of two-state neurons", *Proc. Nat. Acad. Sci. USA*, vol 81, 1984, pp. 3088-3092.

[20] S.D. Glyzin, A.Yu. Kolesov, N.Kh. Rozov "Relaxation self-oscillations in Hopfield networks with delay", *Izvestiya, Mathematics*, vol.77, no.2, 2013, pp. 271-312.