Initial study of general theory of complex systems: physical basis and philosophical understanding

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ABSTRACT

The fundamental difference between neural networks containing and not containing feedback between elements is analyzed. It is shown that in the first of these cases, quantitative relationships describing the functioning of the neural network can be obtained based on an analogy with the theory of noise-resistant codes. In the second case, an analogy with electronic circuits that form memory cells (triggers) is valid. It is shown that feedback between elements of even the simplest neural networks can lead to the appearance of multidimensional hysteresis, when, with the same state of inputs, the system can be in several qualitatively different states, the transition between which can be abrupt. In this case, the state of the neural network outputs depends not only on the current state of its inputs, but also on the path along which this state was formed. The results obtained are used for the philosophical substantiation of a new approach to the interpretation of complex systems of various natures, which are considered analogs of neural networks. According to it, a system that can store and processing information should be considered "complex".

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1. INTRODUCTION

The need for systemic provision of interdisciplinary cooperation is becoming increasingly acute for a number of reasons. Some of them are related to the fact that the existence of pronounced interdisciplinary barriers negatively affects the development of concrete sciences. These reasons have been analyzed in detail in the literature, in particular, in [1]-[3], and there is no need to dwell on them.

At the present stage, however, a somewhat different aspect of the issue under consideration becomes much more important. From the philosophical point of view the phenomenon of science is multifaceted, in particular, it simultaneously acts as both a system of knowledge and as a social institution [4]. At the turn of the 19th and 20th centuries the political elites of the leading countries of the world considered science mainly as a tool for strategy formation. Obviously, science cannot fulfill this function if scientific knowledge continues to disintegrate into loosely connected fragments. Science as a social institution has been progressively losing value in the eyes of political elites throughout the twentieth century, reflected in a significant decline in the social status of scientists in all developed countries over the last one hundred and fifty years [5], [6].

By the end of the 2020s, however, the geopolitical situation began to transform significantly, and this state of affairs was no longer satisfying the demands of society. It is no coincidence that the club of Rome recently put forward the thesis of the new enlightenment [7]. It is becoming obvious that the human civilization is faced with fundamental changes that are comparable in scale to those that took place at the beginning of the new age. The fact acknowledged by political scientists and philosophers from a variety of schools [8], [9]. Namely at the beginning of the new age the totality of attitudes that was and still is the basis of science, understood both as a system of knowledge and as a social institution, took shape [4]. Current profound transformations, of course, require comprehension, and on a systemic level.

None of the concrete sciences (in the form in which they exist today) can ensure the integration of science into a systemic whole, and consequently, the formation of a general coherent picture of the world. This leads to a lack of tools for forming an integrated strategy, which, obviously, cannot but be associated with very significant costs and risks. This paper substantiates that more than a significant number of results have already been accumulated in various scientific disciplines that is enough to build up a unified picture of the universe. Systematization of knowledge becomes necessary, and the fact requires the formation of an adequate methodological framework. Generalization of previously obtained results allows us to assert that the natural basis of such methodology is the general theory of complex systems.

Attempts to develop tools that make it possible to describe phenomena of various natures from uniform positions are known. One of these attempts led to the emergence of synergetics [10], [11], within the framework of which several very interesting results were obtained, related to the description of the emergence of “order from chaos” [12], [13]. There are also attempts to use synergetics to describe processes occurring in society [14], [15]. However, the philosophical basis of synergetics, as a discipline initially completely built on natural science approaches, turned out to be insufficient to build a theoretical foundation for a uniform description of complex systems of arbitrary nature. On the other hand, purely philosophical approaches, based, for example, on the principle of global evolutionism [16], [17], also could not solve the problem under consideration, since within their framework there was and is no basis for obtaining quantitative patterns. The purpose of the work is to prove the fact that establishing analogies between complex systems of various natures and neural networks represents the basis for building a general theory of complex systems, using both the methods of philosophy and the methods of natural sciences and information theory. What is new in the work is the proof that there is a real opportunity to combine the approaches used by classical philosophy, natural sciences, and information technology (in particular, the theory of error-correcting coding) to build a general theory of complex systems.

The work also shows that the use of methods developed in the theory of noise-resistant coding [18], [19] makes it possible to establish quantitative patterns inherent in neural networks. This is also an important step towards creating a general theory of complex systems since the essence of the category of “complex” is interpreted on the basis of an analogy with neural networks. In general, the materials of the work demonstrate that it is possible to build a theory that considers complex systems of any nature (up to social ones) from uniform positions. Moreover, such a theory becomes an adequate “assemblage point” for the formation of holistic knowledge about nature and society.

2. METHOD

2.1. Philosophical aspect

The work uses a classic dialectic approach that corresponds to the consideration of the transition from quantity to quality [20], [21], which constitutes one of Hegel’s laws. This law, among other things, applies to the interpretation of the category of “complex”, applied to systems of arbitrary nature. A system of an arbitrary nature becomes “complex” when a new quality appears in it (in the philosophical meaning of this term), which cannot be reduced to the properties of the elements of the system, taken individually.

There are the following reasons for applying this particular method to the problem under consideration. The fundamental works of Ilya Prigozhin, among other things, gave an impetus to the research in the field of abstract systems corresponding to the category of the complex [22]-[24]. In particular, a large number of papers have been published in the literature in recent decades studying the behavior of complex systems whose elements are endowed with extremely simple properties [25]-[27]. Often, abstract “nodes” with the only property of forming links with each other are considered as such elements [28]-[30]. The works performed in this direction have revealed deep analogies that arise in the theoretical description of seemingly different systems. Thus, it has become clear that the theoretical description of the spread of epidemics turns out to be adequate to the description of the spread of rumors [31], [32]. Moreover, it is no longer in doubt that in both of these cases we can talk about the development of techniques that provide a purposeful impact on a complex system, the optimization of which cannot but take into account the nature of its communication structure [33], [34]. Similar notions of a complex system as a network are also gaining increasing recognition in economic sociology [35], [36].

A number of other reports devoted to physics of complex systems can be formally classified as sociology, as long as they investigate the processes occurring in society. First of all, this refers to the works analyzing the behavior of Internet users [37]-[39]. The factor of emergence [40], which demonstrates the connection of processes occurring in telecommunication space with the problems of the theory of complex systems, is of particular interest. Another prerequisite for the creation of a general theory of complex systems based on the application of dialectical methods is the development of the ideas of L. von Bertalanffy, which are the basis of the systems approach, which continues to be actively developed at present [41]-[43]. This approach was initially aimed at revealing the system properties as such, i.e., at establishing that new quality (in the philosophical sense of the term), which is characteristic of the system as a whole, cannot be reduced to the properties of individual elements [44], [45]. From the point of view of philosophy, the systems approach initially aimed at a consistent description of those processes that are expressed by the dialectical law of the transition of quantity into quality [46].

2.2. Information-theoretic aspect

In this aspect, the work uses methods that establish a connection between the description of neural networks and the theory of noise-immune coding, which are widely used in practice at present [47], [48]. The most famous noise-resistant code is the Hemming code, widely used in practice [49], [50] too. The method by Suleimenov *et al.* [51] used in this work is based on the analogy between it and a neural network. It allows you to reveal the true algorithms of the functioning of some neural networks. Recall that this problem is quite acute, which results, in particular, in the emergence of such scientific trend as explainable neural networks [52], [53]. Most of known neural networks are the result of training on some sample, but real algorithms of their functioning remain unknown, i.e., they are programs obtained empirically. Analogy with noise-resistant codes allows to make the work of neural networks logically transparent [54].

Mentioning of these facts is of interest for the purposes of this article, since ensuring the logical transparency of neural networks in the future can reveal, among other things, the essence of intelligence [51]. This problem, in its turn, is methodologically related to the disclosure of the mechanism of functioning of other systems, which are analogs of neural networks. The basic idea of the use of noise-resistant codes to establish an analogy with neural networks is as follows. In accordance with the noise-resistant coding technique, in the original digital sequence.

$$A = (0,1,1,0,0,\dots,0,1,1,0) \tag{1}$$

Additionally entered characters associated by a certain rule with the characters contained in the original sequence.

$$A \to A^{+} = (0,1,1,0,0,\dots,0,1,1,0,a_1^{+},..,a_n^{+}) \tag{2}$$

This redundant information allows to reconstruct the source code in the same way as redundant information contained in messages in natural languages allows to reconstruct their meaning from the context. The work of Hemming codes can be reflected by the diagram shown in Figure 1.

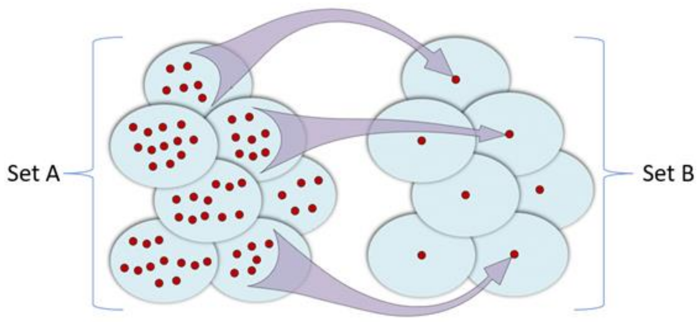


Figure 1. A morphism of a set A into a set B, defining a partition of the set A into subsets A_i, each of which corresponds to a particular code combination with no error [54]

The set A of all possible code combinations is divided into subsets A_i, the number of which is equal to the number of code combinations r treated as code with a corrected error. Any $a \in A_i$ is matched with a code combination with a missing (or corrected) error from the set B. The procedure of image recognition by a neural network can be considered from exactly the same positions. As is known, this procedure consists in [55]. The inputs of neurons forming the first layer of the network are fed with a set of binary variables, interpreted as a recognized image, possibly containing errors. At the outputs of neurons of the last layer of the network a set of signals is formed, which constitute in the aggregate the original image, which does not contain errors.

For this situation the scheme of Figure 1 is also applicable. Elements of the subset to which the mapping is performed can be treated as recognizable images and elements of the original set as images containing errors. This analogy makes it possible to identify quantitative patterns that characterize neural networks of various structures.

3. RESULTS

3.1. Philosophical and general methodological aspect

Summarizing the results of the works cited in section 2.1, as well as taking into account the philosophical aspect of the problem under consideration (specifically, applying the dialectical law of the transition of quantity to quality), we can assert the following. The characteristics of elements of complex system are secondary for establishing regularities reflecting the behavior of any complex system that is considering as a systemic whole. The architecture of links between elements is at the forefront. The relations between elements and transformations of the links in time (including, due to the impact of external factors [56], [57]) is primary for any system corresponding to the category of the complex. Moreover, such transformations can be permissibly interpreted as the evolution of complex systems [58], [59]. The phase transitions that are observed in this case are quite adequately described formally and explain the logic of emergence.

This generalization allows us to give the following preliminary definition of a complex system. A complex system is one for which the primary consideration is the architecture of connections between its elements, while the properties of the elements themselves fade into the background. This preliminary definition will be further clarified, but on its basis, it is possible to hypothesize that the general theory of complex systems can remove the problem of disintegration of science and become the basis for the construction of a holistic picture of the world. Indeed, if the behavior of a complex system is determined only by the nature of relations between the elements, and the nature of the elements themselves is secondary, then it becomes possible to describe from a unified position both those systems which previously belonged to the competence of natural science and those whose analysis traditionally belonged to the competence of the humanities.

Such tendencies are also clearly visible. Investigations carried out in the field of the internet's impact on society, such as [60]-[62], show that not so complicated mathematical models perfectly describe many features of society's behavior as a complex system. We emphasize that it is the reports devoted to the mechanisms of rumor spreading [63], [64], devoted to the analysis of the internet users' behavior [37]-[39], that formed the basis of the creation of very effective tools for influencing society (most clearly seen in the methods for promoting specific groups of goods and services [65]). Transformations comparable in scale to those that led to the formation of science and ideology of the new age are already taking place.

Let us emphasize that the science of that epoch was by no means alien to philosophy. Moreover, philosophy was the basis of science in the eighteenth and nineteenth centuries. Newton's seminal work was called mathematical beginnings of natural philosophy (Philosophiæ Naturalis Principia Mathematica, 1686-1687). He continued the tradition. Recall that R. Descartes' work was called principia philosophiae (Principia Philosophiae, 1644).

During that historical period, philosophy served, in the modern language, as the main tool of interdisciplinary cooperation. It is worth noting that the thesis concerning the importance of such cooperation was widely accepted only when philosophy lost this role, and no other effective tools were created. At present, based on the results obtained in the field of studying complex systems, as well as in the field of applied philosophy, it can be stated that a new synthesis of concrete sciences and philosophy is possible, which is expressed by the thesis of convergence of natural science and humanities knowledge, more generally, by the renaissance of philosophical knowledge [66]. The theory of complex systems comes close to returning to the idea of the necessity and possibility of the holistic description of the world, but already at another turn of the historical development. This, however, requires a synthesis of the results of this theory with a new neural network methodological approach.

Even in the review [67] it was clearly shown that the evolution of complex systems cannot be considered without the information aspect. The development of the ideas reflected in [67], considering the results obtained in the works cited above, allows us to formulate refined definition of a complex system. A system should be considered as “complex” when it acquires the ability to process information. This statement generalizes both points of view going back to I. Prigozhin (emergence of order through chaos) and L. von Bertalanffy (description of system properties as generating new quality).

This definition can be illustrated as follows. The behavior of a fox smelling the henhouse cannot be described in terms of classical thermodynamics. The impact of the corresponding molecules present in the air on receptors can be reduced to specific biophysical processes, but this impact is primarily informational in nature. Accordingly, the question of what exactly separates living matter from dense matter, as well as the question of the origin of life, at the general methodological level is reduced to the question of the exact moment at which a “complex” system acquires the ability to process information, i.e., when and why physical interactions in it is converting into signals, in the sense that the communication theory attaches to this term.

Consequently, already at this stage of reasoning we can conclude that neural networks and their analogues have special role for the general theory of complex systems. On the one hand, such networks can be realized physically, and not by such complex means (thus, optical neural networks are known [68], [69]). On the other hand, neural networks are known to be information processing systems, i.e., the behavior of a physical system, converted into a neural network, can depend, among other things, on the information component of the external influence.

Questions of this kind can also be viewed from another perspective, which returns to the thesis of the unity of the world. If the world is an integrity, and if it is known to have complex systems (more precisely, subsystems), then it is also a complex system and, therefore, it–namely as an integrity–cannot be described, avoiding the informational aspect. In this connection V. Vanchurin's report [70] is of significant interest. The hypothesis, according to which the Universe as a whole is a neural network and, consequently, an information processing system was substantiated in this report. The conclusions of this work remain largely debatable. However, it should be emphasized that a similar point of view (consideration of complex systems based on analogy with neural networks) has been previously substantiated with respect to objects belonging to different levels of matter organization as well. It was shown that there are examples of hydrophilic polymer solutions, whose behavior can also be considered based on the analogy with neural networks [71].

Moreover, there is every reason to believe that all phenomena occurring in the society are somehow related to the neural network formed by individuals in the aggregate. Communication between individuals is reduced to the exchange of signals between the neurons that make up their brains. That is, a common neural network emerges [51]. The often-used statement “people exchange information” is nothing more than a rather crude approximation. Information transfer can be performed only by means of some signals, and these signals are received not by the brain as a whole, but by separate neurons (more exactly, separate neuronal layers), in particular, physiologically the human eye can be considered as a part of its brain [72]. Here a crucial and rather non-trivial question arises: can a neural network generated by the most ordinary communication between individuals lead to the emergence of a new quality? If the answer to this question is affirmative, then we should conclude that humanity already represents a quite definite informational integrity–a system of collective information processing.

However, an affirmative answer to the above question has already been obtained in studies on neural networks [73]-[75]. Indeed, the emergence of a new quality, in the above sense, means that the information processing efficiency of a neural network composed of two identical subnetworks is not twice, but more than twice the given characteristic taken for each of them separately. Otherwise, it would not make sense to use neural networks consisting of more and more elements, as it is the case in the current practice [73]-[75]. Initial evidence for this was given in [51], and the next section discusses a generalization of this approach.

3.2. Nonlinear properties of neural networks from the point of view of the philosophical law of the transition of quantity to quality

Let us emphasize once again that the nonlinear properties of neural networks themselves are well known. Their ability to store and process information depends nonlinearly on the number of network elements [76], [77]. Otherwise, there would be no need to create networks containing an increasing number of elements. However, this conclusion is primarily empirical in nature. In relation to the problem under consideration, it should be confirmed by the most general considerations. Part of this step was taken in the work cited above [51].

The analogy with noise-resistant coding makes clear [51] a technique for a general estimate of the number of images that can be recognized/recovered by a neural network without feedbacks (e.g., forward propagation networks often used in practice [78], [79]). Of course, their architecture may be different, and the values of weighting coefficients may be different as well. However, the above analogy allows one to make estimates based on consideration of code distances (the code distance between two sequences of binary symbols is equal to the number of mismatched symbols in these sequences). These estimates do not depend on the specifics of artificial neural networks of the considered type and, therefore, are very general.

Let the extended sequence contain N symbols, and the admissible number of errors be m. Then the formula for estimating the number of sequences recoverable when correcting m errors is valid:

$$k_{N,m} = \frac{2^N}{1+\sum_1^m C_N^i}, \tag{3}$$

where C_N^i is binomial coefficient.

The logarithm of $k_{N,m}$ on basis 2 allows to estimate the number of symbols in binary sequences, the set of which provides coverage of the whole set of N-digit sequences with m admissible errors. Suleimenov *et al*. [54] the following estimate for the asymptotics $\log_2 k_{N,qN}$ was used for the conditions $N \to \infty$, $\frac{m}{N} = o$.

$$\frac{\log_2 k_{N,qN}}{N} \sim 1 + q \log_2 q + (1-q)\log_2(1-q) \tag{4}$$

In (4) shows that the degree of information compression in the general case does not depend on N. The last two terms in the right part of (4) coincide with the formula for the Shannon’s entropy H of a sequence of binary signals, taken with an opposite sign:

$$H = -q \log_2 q + (1-q)\log_2(1-q) \tag{5}$$

treating q as the probability of an error occurring in a sequence of binary characters, we can write (6).

$$\frac{\log_2 k_{N,qN}}{N} \sim 1 - H(q) \tag{6}$$

From (6) has an extremely transparent meaning: information entropy is a measure of uncertainty introduced by the appearance of errors. If such uncertainty is introduced artificially, i.e., the appearance of errors with frequency q is admissible (since they are treated as admissible deviations), then the measure of information compression provided by this factor should also be determined by the entropy factor. The fundamental conclusion from result (6) is the following. If we consider a neural network corresponding to Figure 1, in particular, if in such a network there are no mechanisms that form “memory cells” or their varieties, then the nonlinear properties of the network cannot take place. The situation changes fundamentally when the elements of the ANN turn out to be covered by a feedback loop (or their analogues). The proof of this statement is given in [51] on the example of model ANNs, which are direct analogs of the RS-trigger widely used in modern computing [80]. However, before moving on to consider this model example, we will show that memory cells that can be implemented on the basis of well-studied systems with neural network properties can be very diverse.

Let's start from the classical scheme of RS-trigger widely used in modern computing [53] (Figure 2(a)). It contains two elements; it is the simplest electronic circuit capable of storing information while it can be in two different states in the absence of a signal at the inputs. For the purposes of this work, it is essential that RS-trigger circuit topologically coincides with Hopfield neuroprocessor circuit with the difference that it contains only two elements. This is emphasized in Figure 2(b), which shows a variation of the Hopfield neuroprocessor circuit for the case of a network consisting of three elements. You can see that these schemes really differ only in the number of elements.

Moreover, Figure 2 emphasizes that there is no fundamental difference between classical electronic circuits and neural networks. From the point of view of the consequences arising from (6), this also means that networks can have nonlinear properties, the fundamental difference of which is the presence of feedback. To simplify, it can be argued that in such networks “local memory cells” can arise, or rather fragments in structure and properties similar to RS-trigger.

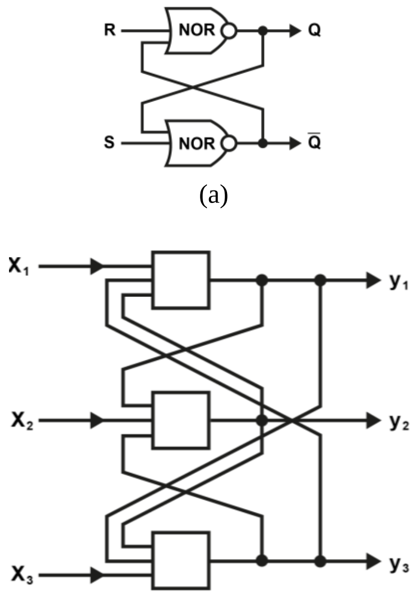
Let's consider another system that can be called a BS-trigger (Figure 3). We will assume that each of its elements is described by a sigmoidal activation function, which is often used to train ANNs.

$$f(x) = \frac{e^{\alpha x} - e^{-\alpha x}}{e^{\alpha x} + e^{-\alpha x}} \tag{7}$$

where

$$x=w_1q_1+w_2q_2+w_3q_3 \tag{8}$$

w_i are weighting coefficients, q_i are variables describing the state of the neuron inputs, and α is a constant coefficient for a given circuit.



(a)

(b)

Figure 2. Comparison of RS-trigger assembled on NOR logic elements; (a) NOR logic configuration and (b) Hopfield neural processor circuit with three neurons

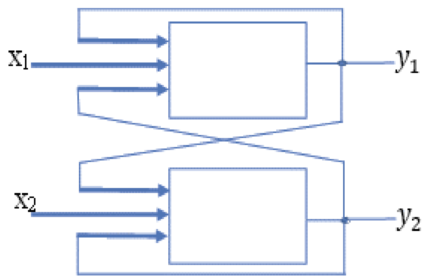


Figure 3. Scheme of a BS-trigger on two neurons with a sigmoidal activation function

For simplicity, we will assume that the connection is symmetrical and the weighting coefficients corresponding to the feedback in this circuit are the same. In this case, the BS-trigger is described by the system of (9):

$$\begin{cases} f_1 = f(z + x_1) \\ f_2 = f(z + x_2) \\ z = k \cdot (f_1 + f_2) \end{cases} \tag{9}$$

The variables x_1 and x_2 in (9) can take values ranging from -1 to +1. Examples of solutions to system of (9), obtained by standard numerical methods, are shown in Figure 4 for two different sets of control parameters. It is evident that in both cases the solutions of the system under consideration form a folded surface, i.e., for the same set of control variables, more than one solution can exist. Comparison of

Figures 4(a) and (b) also shows that the values of the control parameters influence the configuration of the folded surface.

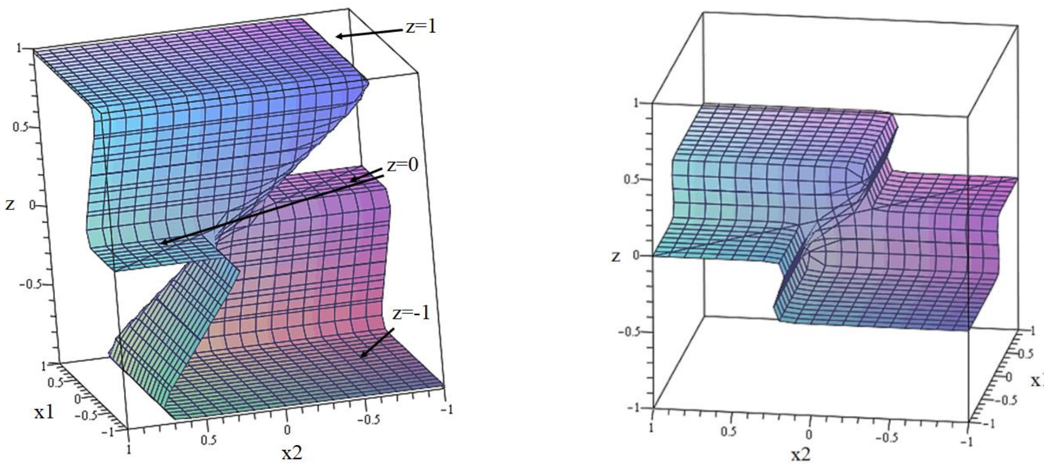


Figure 4. Three-dimensional graph of the dependence of the solution z of the system of (9) at the different values of variables x_1, x_2; (a) α=10, k=0.49 and (b) α=10, k=0.2

Diagrams illustrating the existence of several solutions for the same set of control variables (x_1, x_2) are shown in Figure 5. This figure highlights areas that correspond to different numbers of solutions to the system of (9). The darkest color in this figure shows the areas that correspond to three possible solutions of the system of (9). The lightest color shows the areas that correspond to only one possible solution. The intermediate color corresponds to two solutions. In this figure, the dotted lines also show the areas that correspond to z≈-1, z≈0, z≈1.

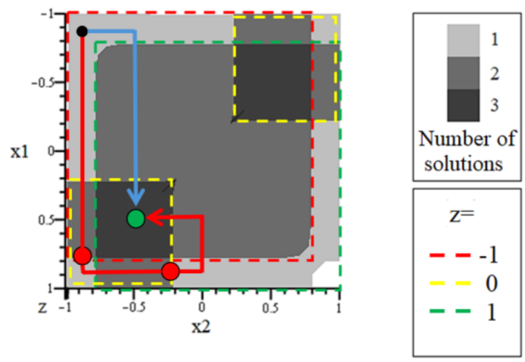


Figure 5. Decision map for a BS-trigger based on two neurons; parameters: a=10, k=0.5

The obtained result can be interpreted as a kind of "two-dimensional hysteresis". As Figures 4 and 5 show, an abrupt change in the state of the system may occur at crossing the boundaries areas. As an example, Figure 5 shows two possible trajectories of the representative point. It is evident that for the same initial and final values of the pair of control parameters, the point can move in different ways. The trajectory shown in red corresponds to two jump-like transitions, shown by bold red dots. One of these transitions is from the state z≈1 to the state z≈0, the second is from the state z≈0 to the state z≈1, which corresponds to the final point of the trajectory. When moving along the trajectory shown in blue, no transitions occur, i.e., upon reaching the final point of the trajectory, the system remains in the state z≈-1.

We emphasize that the literature has long established a connection between the existence of a hysteresis loop and abrupt transitions from one state to another [81], [82]. The result obtained shows that such a relationship can also be “multidimensional” in nature. The result presented in Figure 5 also shows that for systems of the type under consideration, the final state of the system depends not only on the current state of thermodynamic variables, but also on the prehistory, i.e., on exactly how they previously changed over time. Such a “prehistory” corresponds to the path along which the representing point moved either on a plane (Figure 5) or in multidimensional space (such a space corresponds to the case of several elements of a system similar to that presented in Figure 3).

Each specific trajectory of a representing point in a thought experiment can be divided into two parts. The first part can be correlated with the prehistory of the system (i.e., with those influences that were applied to it before the “zero” point in time), and the second part with the predicted response to additional external influences. This reasoning clearly demonstrates that systems that can be considered analogues of the simplest neural networks (and even containing a relatively small number of elements) become programmable with a slight complication.

We emphasize that the considered example, with all its apparent simplicity, creates the prerequisites for answering a fundamental question: where in the process of evolution could a fox come from that recognizes the smell of a chicken coop? More precisely, this model example at least partially answers the question of when exactly physical influences on the system become signals carrying information. From the point of view of classical physics, the given example of “multidimensional” hysteresis allows us to make the following judgment. A physical influence is converted into a signal (understood already at the philosophical level of this term) when the system has a certain “prehistory”, which determines the nature of the response, say, to a particular sequence of changes in thermodynamic variables, and the nature of the response to external influences depends most significantly on "prehistory".

We emphasize that such a “prehistory” does not necessarily have to be associated with the presence of instinct or other abilities characteristic of highly developed systems. It can be implemented even at the level of simple systems based on hydrophilic macromolecules, which, in particular, is confirmed by the results obtained in [71]. Figure 6 shows another diagram confirming the conclusions made above. This scheme is also topologically equivalent to some neural network (or fragment thereof). At a minimum, this circuit can be assembled using elements identical to formal neurons.

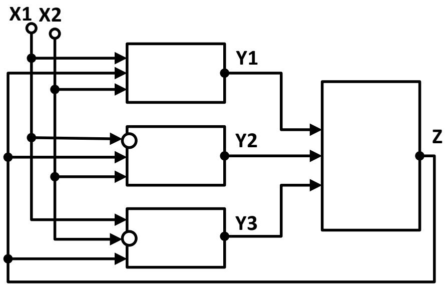


Figure 6. A circuit assembled using formal neurons and having 8 valid states

Each of the Y_i elements (neurons) have three inputs; control signals are supplied to inputs $X_{1,2}$, the third input is used to generate feedback. We emphasize that the same control signals are supplied to the inputs of each element of the first layer of the neural network with numbers 1, 2, and 3.

The outputs of the neural network elements are connected to a single neuron of the second layer $\boldsymbol{Z}$, the output of which is connected to the inputs of the neurons of the first layer. Further, if the activation function of a neuron is close to the threshold (which, in relation to the system under consideration, corresponds to an abrupt change in the degree of swelling of the hydrogel), then the operations performed by the neurons of the network can be reduced to logical functions. Let's consider the case when the neurons of the first layer of the network shown in Figure 6, are described by logical functions of the form (10).

$$Y_i = (X_1+a_{1i})(X_2+a_{2i}) + (X_1+a_{1i})(Z + a_{3i}) + (X_2+a_{2i})(Z + a_{3i}) \tag{10}$$

In this formula, the coefficients a_{ij} can take values of either 0 or 1: a_{ij}= (0,1), which corresponds to the situation when individual inputs of the neurons of the first layer are inverse. The output state of a single neuron of the second layer is described by a similar formula:

$$Z = Y_1Y_2+Y_2Y_3+Y_1Y_3 \tag{11}$$

Accordingly, the specific implementation of this neural network is described by the matrix $\widehat{A}$ coefficients a_{ij}. Let's use a specific case to illustrate.

$$\widehat{A} = \begin{pmatrix} 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix} \tag{12}$$

It is easy to show that for any combination of input variables X_1 and X_2 in each logic circuit, the variable Z can acquire the value of both logical zero and logical one. In other words, four possible combinations of input variables correspond to eight possible combinations of values of logical variables that describe the state of the outputs of the neurons of the first layer. In other words, in this case, all possible eight combinations of logical variables can be realized at the output of the neurons of the first layer. Which of these options is implemented in practice depends not on the current state of the control variables, but on how exactly they changed over time.

Thus, if we consider the analogy between electronic circuits and neural networks, it turns out that the nonlinear properties of a neural network appear when its elements are covered by feedback connections. Moreover, in this case, the neural network can become programmable, and more broadly, acquire the ability to respond to influences in which the information component is expressed. With regard to the simplest models, the nonlinear properties of the systems under consideration can be described quantitatively [53].

The formula describing the functioning of a model neural network-an analogue of both Hopfield neural processor and RS-trigger has form (13) [53]:

$$Y_j = \theta\left(\sum_{i \neq j}^{m} \bar{Y}_i + X_j - \frac{m}{2}\right) \tag{13}$$

where $Y_j = 0.1$ is a variable describing the output state of j-th element; $\bar{Y}_i$ is its inverse value; $X_j = 0.1$ is a variable describing the input state of j-th element; and $\theta(x)$ is a Heaviside function equal to 0 at $x < 0$ and 1 at $x \geq 0$.

For such a system containing m elements, the number of stable states n is expressed through the binomial coefficient [53]:

$$n = C_m^{\frac{m-1}{2}} \tag{14}$$

where it is assumed that the number of elements m in the system is odd.

The dependence graph given by (14) is shown in Figure 7. On the same figure the dependence of the number of admissible stable states $\frac{n}{m}$, falling on one element of the system on m is presented. It is seen that the contribution of a separate element in the ability of a network to operate with information really essentially increases in the process of increasing the number of elements in the network of the considered type.

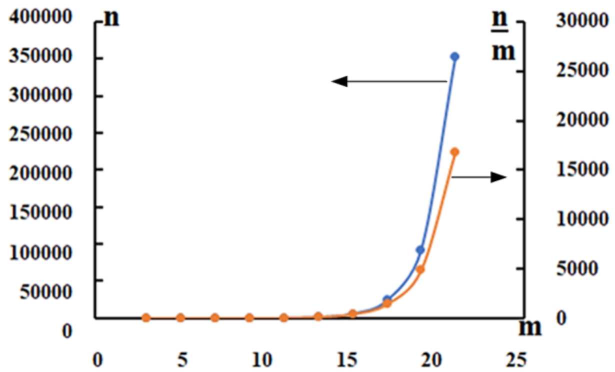


Figure 7. The dependence of the number of admissible states of the RS-trigger analog containing m elements (left axis) and the number of admissible states per element (right axis) on the number m

Thus, there are simple enough models, reflecting the appearance of a new quality in complex systems. Such models are no more than illustration, especially if we take into account that human thinking cannot be reduced to binary logic. However, based on the results presented in [83], similar models can be constructed based on multivalued logic too. The main thing is that these models confirm one of the main theses of this work - a system becomes complex (in the philosophical meaning of this term) when it acquires the ability to process information.

4. DISCUSSION

The analogy between complex systems and neural networks, as shown by even the simplest models discussed in this work, allows us to solve a very non-trivial problem, which has not received due attention in the current literature. It can be formulated as follows. There is a philosophical law of the transition from quantity to quality, which really reflects many phenomena occurring in nature and society. However, until recently there were no quantitative theories that would allow expressing this law in mathematical form, at least at a level with the same degree of generality as this law. The idea of a complex system as a system capable of processing information allows us to take a significant step in this direction. Indeed, as even the simplest models used in this work show, it is possible to describe the transition from quantity to quality through the ability of a system to store and process information, and it is not necessary to specify the nature of the system in question. Thus, a comparison of the result expressed by (6) and models in which feedback appears demonstrates that it is the latter factor that is responsible for the emergence of a new quality (nonlinearity), and the nature of the system under consideration is not significant. It is important that this system can be analyzed based on the analogy with a neural network.

Further, the fact that a neural network with the ability to store information has nonlinear properties (i.e., its ability to store and process information nonlinearly depends on the number of elements), allows us to draw conclusions of a fundamental nature, including in relation to social systems nature. In particular, we can assert that in the global neural network arising only due to ordinary communication of individuals with each other, at least, the preconditions for appearance of a new quality–transpersonal informational structures are created. Evidence of the emergence of this quality allows, in turn, to give a consistent natural-scientific justification to such notions as mentality and socio-cultural (civilizational) code. The “spirit” of each particular ethnos in this sense is by no means a metaphor but reflects the existence of quite certain transpersonal informational structures.

Their nature is completely like the nature of the formation of such information entities as the human intellect, mind, and consciousness. The only difference is that in one case the information exchange involves neurons localized within the brain of different people, while in the other–only one person. Further, it follows that intellect, mind, and consciousness of people (these notions are by no means identical and still require their precise definition) are only partially individual. More precisely, these informational entities have a dual nature - both the collective and the individual “components” are present in them simultaneously. This conclusion seems to be very important. In particular, it allows, among other things, to make a significant step forward in justifying V.I. Vernadsky's concept of the noosphere, which is still actively discussed in the literature [84], [85]. Over the past decades, this concept has been criticized several times, often quite sharply. However, in accordance with the above, the noosphere can be considered a complexly structured global neural network, in various components of which, in turn, various transpersonal information structures and objects can develop.

An example of a transpersonal information object is any natural language. There is no need to prove that language – as a systemic integrity – is not at all fixed in the memory of individuals or even a group. It emerges and develops only within a quite definite information-communicative environment (people, as a communicative community), which can exist only because of signal exchange between separate relatively independent fragments of the noosphere, localized within the brain of individual people. Umberto Eco metaphorically expressed the fact as follows [86]: "It is not we who speak with language; it is language that speaks by us. Another important example of a transpersonal information object is any highly developed scientific theory. Its carriers form a certain sub-network of the global communication network (noosphere), and the theory is actually recorded in their collective memory. This approach, among other things, creates the prerequisites for a quantitative description of the change in scientific paradigms, i.e. mechanisms of scientific and technological revolutions. In this case, there is competition between two or more transpersonal information objects. From the same positions, many aspects of geopolitical competition can be considered - as collisions between transpersonal information objects, which are metaphysically called the “soul of nations”, but consideration of this issue is beyond the scope of this work.

Taking into account transpersonal informational structures, one can justify the existence of the collective unconscious, as well as the existence of archetypes understood according to Jung, which constitute one of the foundations of modern analytical psychology [87], [88]. This approach also clearly correlates with the ideas of transpersonal psychology [89], [90] founded by Stanislav Grof. Let us also note that from this point of view the myths about ancient gods and heroes are also quite rationally interpreted as reflecting specific transpersonal informational objects that emerged at a certain historical stage, but a detailed consideration of this issue is beyond the scope of this paper. Further, the functioning of a neural network does not at all require that all of its constituent neurons be the same. It is possible to take the next step in reasoning by including the neurons that make up the animal brain. Moving along this way, we can come to J. Lovelock's concept of Gaia [91] (with certain refinements, of course). Let us recall that it is Lovelock's ideas that are largely connected with the formation of ecological discourse in its modern form [92], [93].

However, there is a very important nuance here, which requires involvement of the methods of applied philosophy. If we are talking about the exchange of signals between neurons (including nerve cells of animals), we really have a full right to talk about signals. Further generalization requires solving the question of exactly under what conditions physical interaction acquires a pronounced informational aspect, i.e., becomes a signal.

The thesis on the dual nature of human intellect, reason and consciousness makes it possible to largely revise the existing approaches to the problem of mind conception and, more generally, to the problem of mechanisms for the evolution of complex systems. The dominant point of view on this issue dates back to the theory of the origin of species by Ch. Darwin. According to this theory, the driving force of evolution is random fluctuations/mutations, the result of which is fixed if it corresponds to the appearance of a favorable trait. This point of view does not answer many questions; in any case, the problem of the origin of life is still unsolved, despite more than significant efforts in this direction [94]-[96].

In fact, there is still the problem of the “Jenkin’s nightmare” [97]. Estimates of the time required for appearance of biological objects possessing a genetic code by mutation mechanism result in a vanishingly small probability of arising life on Earth. Such estimations are given, in particular, in [67] and remain actual. They vary in a very wide range from $\sim 10^{-40000}$ to $\sim 10^{-400}$ (depending on the specific evolutionary mechanism used for the calculations), but in any case, remain absurdly small.

More precisely, the Darwinist point of view satisfactorily describes those stages of evolution in which already emerged species master new ecological niches and adapt to them. However, real evolution knows other stages (great leaps or aromorphoses [67]) when new species with fundamentally different functions emerged. One of the most striking examples is the emergence of photosynthetic organisms capable of decomposing water and assimilating sunlight. Absorption of light and subsequent utilization of its energy requires a very complex sequence of operations, each of which is performed by specific proteins. The emergence of each of these proteins in isolation does not provide any evolutionary advantages [67]. The advantages arise only when the system evolves as a whole. Consideration of complex analogues of neural networks capable of information processing allows to remove this kind of contradiction by proposing an evolutionary mechanism that is fundamentally different from the mutational one.

According to this mechanism, at the first stage the properties of elements composing the physical implementation of a neural network remain unchanged. Only the neural network itself evolves, which is physically expressed in transformation of architecture of connections between its elements and/or character of signal exchange. The difference from the Darwinian mechanism of evolution is obvious. In one case selection is performed by purely random factors, while in the other case it is determined by the nature of system evolution as a whole. Consequently, if there are objective regularities of systems evolution, which can be admissibly considered as realization of neural networks, then there are also objective regularities that led to the emergence of mind.

The authors are aware that the consideration of a limited number of examples confirming such a general conclusion cannot in itself be considered as its proof. But there is a very definite nuance here. The proposed concept of complex systems is so fundamental and involves such principles and such "fundamentals" that it cannot be substantiated either by means of physics or by means of philosophy separately.

In this regard, we consider the materials of this article not so much as a review of previously obtained results that allow us to systematize the foundations of the theory of the complex, but as another argument in favor of the thesis of the convergence of natural science and humanitarian knowledge, which includes a kind of synthesis of physics and philosophy on a new round of historical development. We also emphasize that we consider this report only as the first step towards creating a general theory of complex systems. The question remains to be answered about exactly under what conditions one or another physically realizable system can really be considered as an analogue of a neural network and the corresponding criteria must be developed. This is what will allow us to establish a quantitative criterion for when exactly a system can be considered complex. Numerous questions related to the theoretical description of the evolution of neural networks remain to be answered. Works carried out in this direction are known [98]-[101], but here it is the synthesis of philosophical and natural science approaches that becomes important.

5. CONCLUSION

Thus, at the present stage of development of science, the problem of creating a methodological basis for constructing a uniform picture of the universe is acute. The achievements of specific sciences, accumulated to date, allow us to assert that the general theory of complex systems can become such a basis. The basis for a uniform description is the analogy between complex systems of arbitrary nature and neural networks, as well as the fact that for a complex system, the architecture of connections between its elements is primary, and the properties of the elements themselves are secondary. Such an analogy, among other things, makes it possible to substantiate the thesis, which is one of the basic ones for the theory of complex systems. A system should be considered complex if and only if it acquires the ability to process and store information.

These abilities are inseparable from the quantitative and qualitative transition from “simply” physical interactions to processes that ensure the transfer of information, i.e., to signals. As the materials of this report show, the arguments in favor of the proposed concept of "complex" are based on experimental material relating to the most diverse levels of matter organization (physico-chemical and social). The next step is to consider evolving neural networks from the same perspective.

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