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The principle of multi-alternativity in intelligent systems. Active neural network models

S.L. Podvalny[a,b]*, E.M. Vasiljev[b]

[a]Voronezh State Technical University, Moscow Av., 14, Voronezh, 394026, Russia,
[b]The Russian Presidential Academy of National Economy and Public Administration, Vernadskogo Av., Moscow, 119571, Russia

Abstract

The article deals with intelligent systems that contain artificial neural networks. After a close comparison of artificial and biological neural networks the authors reveal some fundamental flaws of artificial neural networks. It is shown that the reason for those disadvantages is the constancy of structure or the so called passivity of the neural network. To avoid this problem it is proposed to simulate the information processes in the neural network instead of simulating neurons themselves. The following consideration involves several evolutionary principles of multi-alternativity, such as multilevel approach, diversity and modularity. Those principles find their implementation in facet memory organization that is characterized by the reconfigurable structure and therefore close to its biological prototype. The advantage of the suggested approach is demonstrated by the example of an intellectual system based on an active neural network. The system applied to control an electrical supply network under critical events, such as breaks and overloads. In case of a critical event neural network takes the blocking decision that prevents breakage or accident conditions in the electrical network.

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1. Introduction

Building intelligent systems on the basis of neural networks is based on a direct analogy between the tasks solved by these systems and motives of higher nervous activity of living organisms.

* Corresponding author.
E-mail address: spodvalny@yandex.ru

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Currently, the implementation of the above-mentioned analogy is reduced primarily to the attempts of artificial reproduction of electrochemical processes of biological neural systems through the development of different patterns of excitation and inhibition of elementary neurons and organization of relationships between them.

In the classic form, a neural can be presented by the functional:

$$y_{j_N}(x) = F\left(\sum_{i_N} b_{i_N j_N} \cdot \ldots \cdot F\left(\sum_{i_2, j_2} b_{i_2 j_2} \times F\left(\sum_{i_1, j_1} b_{i_1 j_1} x_{i_1 j_1} + c_{j_1}\right) + c_{j_2}\right) + \ldots + c_{j_N}\right), \quad (1)$$

where b, c are the vectors of configurable parameters (weight coefficients); r is the number of the network layer; j_r is the neuron number r in the layer; i_r is the entry number in the neuron; N is the number of layers of the network; x, y are the vectors of input and output variables of the network; $x_{i,j}$ is an element i of the vector x supplied to the neuron j in the layer r; $F(b,c,x)$ is the function of neuronal activation of the sigmoid form.

The formal justification for the use of neural networks in problems of decision-making is the completeness theorem which says that every continuous function on a closed bounded set may be uniformly approximated by functions, computed by the neural networks of type (1), if the activation function $F(b,c,x)$ of a neuron is continuously differentiable twice.

However, in practice these formal grounds for the implementation of artificial properties of biological networks are not enough, and the artificial neural networks of type (1) are inherent in the fundamental inconsistency of their biological prototype.

These inconsistencies are associated primarily with the attempt to reproduce biological processes using a functional with a predetermined constant structure, whose alteration is made only at the low-level parametric: the network is not able to change its structure during training, i.e. it is passive.

The failure of passive neural network to change its structure leads to deficiencies in these networks that are not typical of their biological prototypes[1,2].

The most important of these are:

the problem of retraining, which consists in the growth of a network error when presenting an apriori unknown excessive number of training vectors. In natural neural networks memory elements have a high selectivity, and the nature of memory is cumulative, allowing to keep old information without distortion on the network in almost unlimited volume;

low generalizing properties, establishing the relationship of “private-general” between the recognizable situations, for which the network should have developed a multi-level, hierarchical structure;

the lack of functional autonomy of the elements of artificial neural networks, resulting in a non-linear increase in the number of adjustable parameters to increase the dimension of the tasks, i.e. the manifestation of the “curse of dimensionality” in teaching. In biological neural networks limitations on re-memorize information are not observed.

In order to eliminate these shortcomings, a new approach to the construction of a neural network intelligent control system model is suggested, and it is based on general evolutionary principles of the organization of its functioning – principles of multi-alternative[3-5]:

multilevel principle (hierarchy) implemented by the organization in biological systems of at least two management levels, one of which functions as the tolerance variations of the system state, and the other responds only to critical deviation from this condition;

the principle of diversity of the control algorithms and the separation of functions (multi-mode and switch structures), which is closely associated with the principle of multilevel and reflects the flexibility of the control algorithms in the changing conditions of operation of the system;

the principle of modularity of the structure, which provides a variety of levels and modes of control based on a limited set of elementary modules of the system combinations.

Further it will be shown that a set of defined principles can solve the above-mentioned problem of constructing neural network intelligent systems not as a result of the qualitative complexity of the algorithms, but by increasing in the system the number of its simple ingredients, gradually embedded into the structure of the neural network.

2. Active neural network based on the principles of multi-alternativity

Modern understanding of the nervous system as a structured ensemble of nerve cells suggests that biological neural networks are characterized by:

independent storage of events of neural activity in the form of associated ensemble of neurons that are excited only by certain sensory signals. This independence eliminates retraining;

neural network activity, ensuring the restructuring of relations between the structure of ensembles after each training event (the formation of a new stable ensemble and its embedment into the overall structure of the network).

To implement these properties in an artificial neural network, it is proposed to abandon attempts to simulate the biological nervous system at the level of elementary functioning of neuronal processes and to go to reproducing the information structure of storing and processing information.

As such structure, it is possible to use a faceted principle of classification of objects (from the French. facette - brink), which is characterized by the fact that for every event, an ensemble (set) $\{f, s\}$ of properties f is formed, the set of their values s defines a specific object $a(f,s)$:

$$a \in A, \quad |A| = z, \quad f = \{f_1, f_2, ..., f_n\}, \; s = \left\{s^{f_1}, s^{f_2}, ..., s^{f_n}\right\}, \; s^{f_i} = \left\{s_1^{f_i}, s_2^{f_i}, ..., s_t^{f_i}\right\}, \; i = \overline{1,n}. \tag{2}$$

The faceted principle of data storage allows to combine different objects in a network structure $A^i = a_1^i \cap a_2^i \cap ... \cap a_z^i$ separately for each feature f_i, and the introduction of this additional feature or object does not require any adjustment in the previously existing structure of relations, but complements it.

The graphic illustration of the relations (2) describing the memory faceted organization in the neural network is shown in Fig. 1.

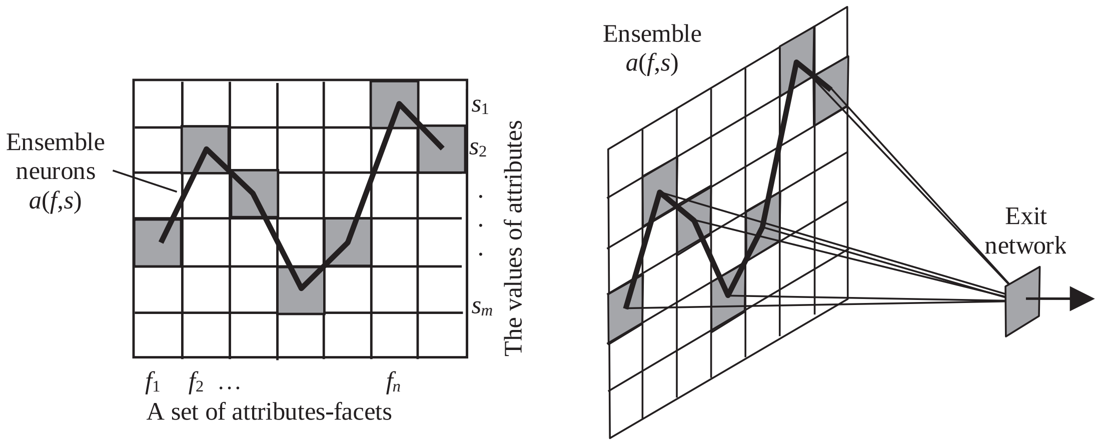

Fig. 1. . Faceted organization of memory in neural networks.

Fig. 2 shows a possible structure of the neural network type of a facet type with three hierarchical levels of neuron ensembles $a(f,s)$, which can be excited or inhibited by specific receptor-facets f and other ensembles.

In particular, the excitation of receptors f_4, f_5, f_6 activates ensemble $a_{1,2}$, and then, in the absence of inhibition by the ensemble $a_{1,1}$, ensemble $a_{2,1}$ is excited, and it is activated not directly from the primary receptor f, but on condition of a previous activation of $a_{1,2}$.

Thus, in the system a sequence of controlled events happens, corresponding to the ensembles $a_{1,2}$ and $a_{2,1}$. At the same time, excitation of ensemble $a_{2,1}$ in the absence of inhibition by other ensembles, such as $a_{2,2}$, $a_{2,3}$, leads to the activation of event $a_{3,1}$.

As a result, under the influence of external influence $\{f_4, f_5, f_6\}$ there was formed the sequence of events corresponding to the specified excitation.

3. Example of a neural network of the active facet type

As an example, consider an electric distribution network consisting of an input high voltage substation and thirty low voltage transformer substations, Fig. 3[6].

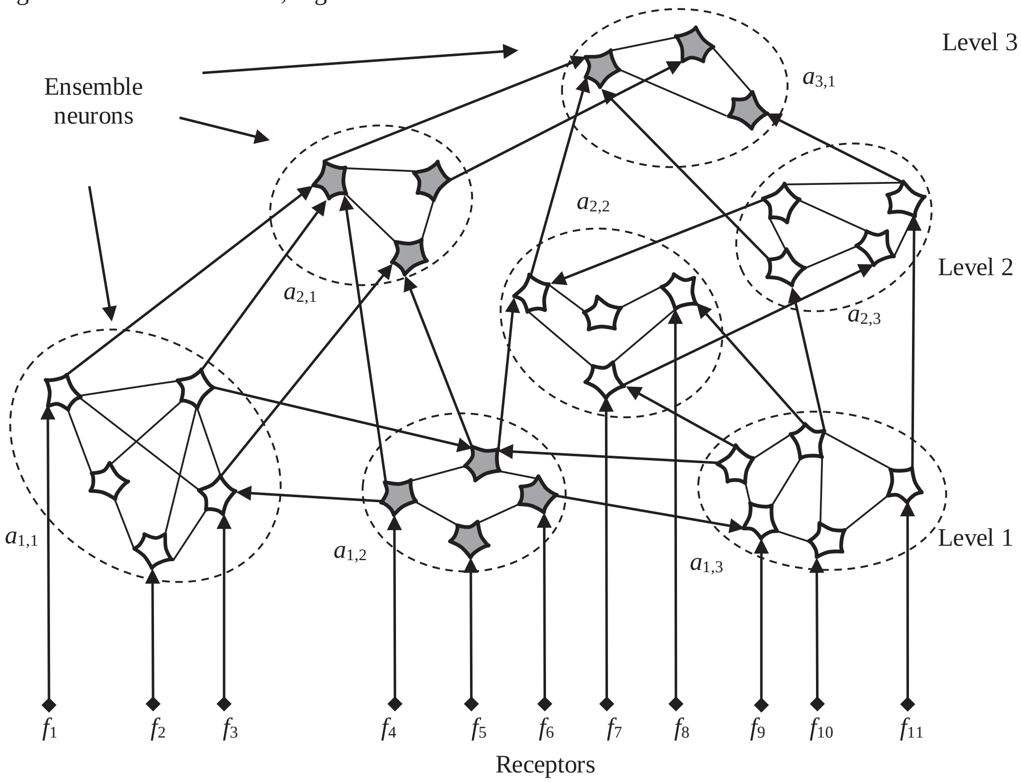

Fig. 2. The structure of the neural network type facet.

Assume that the power transmission cables, indicated by dashed lines, are reserved and are connected to the system in a critical event, e.g. overload or failure of the main power cables.

For the given power supply system there can be set a task of developing a neural network model of decision-making, providing, in a critical event, the order to connect the corresponding spare line.

The numbers of these events with the numbers of the substations linked by the failed line are shown in Table 1.

In this situation, a list of facets $f = \{f_1, f_2, ..., f_n\}$, n=30, makes up the number of the de-energized substations; the number of objects-events is z = 30; the number of characteristics of each property is t=2: $s^{f_i} = \{0;1\}$.

The graphic illustration of networking facet fragment is shown in Fig. 4, where the ensembles of neurons F perform a logical operation “and”.

The numbering of ensembles F corresponds to the number of the event.

An important feature of the resulting model is its structural similarity of the object model, i.e. the structure of the model displays an object environment.

For example, in case of failure of the main line 11-12, substations 12,13 and 14 will be de-energized that corresponds to event 26 (F26 in Fig. 4) and the acceptance of the decision on switching-on reserve line 10 (see Fig.

3). At the same time, Fig. 3 shows that de-energizing substations 13 and 14 is a special case. This case corresponds to event 27, and the decision on switching-on reserve line 5.

Table 1. The set of critical events

Number events	1	2	3	4	5	6	7	8	9	10
Number of substations	0 -1	1 – 2	2 – 3	3 – 4	3 – 8	8 – 9	8 – 7	7 - 6	6 – 5	0 - 26
Number events	11	12	13	14	15	16	17	18	19	20
Number of substations	26 – 27	27 – 22	23 – 28	28 – 29	29 – 30	23 - 22	22 – 21	21 – 20	20 - 19	0 - 10
Number events	21	22	23	24	25	26	27	28	29	30
Number of substations	10 - 16	16 - 18	18 - 17	18 - 15	15 - 11	11 - 12	12 - 13	13 - 14	27 - 14	24 - 25

Thus, the use of the model will lead to switching-on two reserve lines with numbers 10 and 5. The analysis of the electrical circuit in Fig. 3 shows that with the failure of the main line 11-12, both solutions are equivalent. From this, it follows that the model has a generalizing properties to the extent the object structure allows. Indeed, if the learning network is charged with situation 20 (F_{20} in Fig. 4), this will be sufficient to correct parry critical situations 21,22,24,25,26,27,28 which were not considered, because they are special cases of the general situation 20.

It should be noted that the emergence of generalizing properties of faceted neural network is due to the presence of hierarchical relationships, i.e. its multi-level.

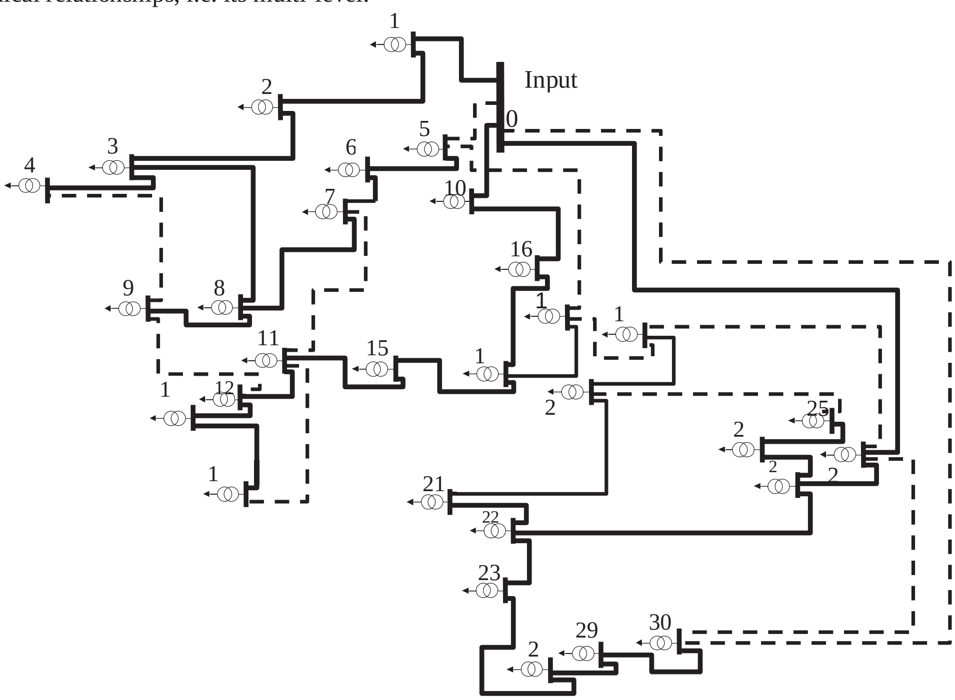

Fig. 3. The configuration of the electrical network under consideration

The learning procedure in such a neural network includes adding a new object in the form of an ensemble of characteristic values $a(f, s)_{z+1}$ and including each feature-facet of the object in the network structure of this feature. With this, the relationships formed earlier are not destroyed in the network, this eliminates the possibility of the phenomenon of retraining. Since the block nature of training is reduced to a simple extension of information about new situations and does not require a multi-parameter optimization, the network accumulates highly selective properties: for each emergency situation it is generated a single decision with a superposition of these decisions, with occurrence of multiple failures. For example, in events 10 and 11 the model will work out solutions 7, 8 and 9, fully restoring power supply (see Fig. 3).

4. Conclusion

Using passive models of neural network management systems and decision-making faces significant difficulties for their implementation due to the propensity of these models to retrain and low extrapolating opportunities.

Designing neural systems based on evolutionary principles can create multiple-active neural models with a reconfigurable structure, in its properties to a much greater degree approaching their biological prototypes:

multi-level hierarchical scheme of internal connections in the network provides high generalizing ability of the system when decision-making in situations not encountered during training;

modular structure allows to build the structure of the new system of ensembles of neurons, without meeting the restrictions "curse of dimensionality" and retraining;

facet memory organization according to the rule "one event – one ensemble" enables unlimited selectively increasing the number of events in the system and the practical implementation of the principle of requisite variety of information.

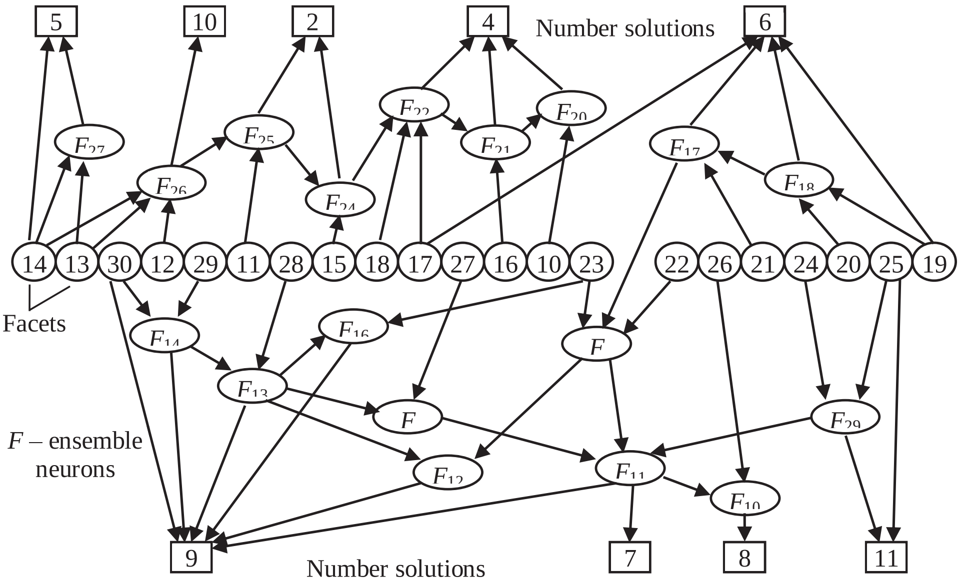

Fig. 4. Faceted active neural network structure.

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