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Applications of Artificial Neural Networks in Multi-Criteria Decision-Making in Civil Engineering

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ABSTRACT

The paper deals with the multi-criteria decision making using Hopfield network which belongs to a class of artificial neural networks. The general procedure has been defined based on the application of Hopfield network. By using the model based on Hopfield auto-associative memory, the defined procedure has been applied for solving a specific problem, which is to select the best variant solution of the route of gas trunk line.

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1. Introduction

Reaching business decisions increasingly complex business conditions requires a multi-criteria approach. In the presence of multiple and most often conflicting criteria this approach enables an objective comparison of the offered alternatives. The development of multi-criteria decision-making is closely related to the development of computer technology. Regarding the large number of elements that include variables, functions and parameters that are an integral part of many decisions, computer support for decision-making has enabled the implementation of systematic analysis of multi-criteria problems (Pamucar and Savin, 2020; Milosevic et al., 2021; Youssef et al., 2022; Muhammad et al., 2021).

In construction as an extremely complex area, with significant material resources, manpower and mechanization engaged, very significant financial and time savings can be achieved by using the methods of multi-criteria decision-making. Artificial Neural Networks can also be used to solve certain tasks in the process of multi-criteria decision-making, in addition to classical (SAW, AHP, TOPSIS, ELECTRE, PROMETHEE, VIKOR) and phase methods (Coarse Assemblies).

2. Artificial Neural Networks

Artificial neural networks are one of the methods of artificial intelligence. Instead of conceptualizing the problem in mathematical form, neural networks use the principles of the biological nervous system (human brain) to develop a data processing strategy. They are composed of a large number of mutually parallel elements (nodes, neurons) in structures of a certain shape. Neural networks are not programmed to perform a specific task. The basic condition for the use of artificial neural networks is the existence of a database of historical data. Since based on that knowledge, neural networks are "learned" and trained to make decisions in new situations (Bozanic et al., 2021).

Although the commencements of the development of neural networks do not go far back in time, the methods built on them are widely used in both social and technical sciences. Its application in construction is related to forecasting and classification tasks. The success of neural networks in performing these functions qualifies them as an exceptional tool of multi-criteria analysis. Depending on the problem under consideration, it is possible to use different types of networks (backward propagation error networks, networks with radial base functions, Hopfield networks, Bidirectional associative memory). The following paper presents the application of the Hopfield network, which is used in solving classification problems in multi-criteria decision-making.

2.1 Hopfield Network

The Hopfield network belongs to the type of single-layer recurrent networks that is used for the realization of nonlinear associative memory, i.e. memory addressed by content. Associative memory is an important tool for intelligent behavior (Filipović, 2004). If the pattern is found in memory based on a sufficiently similar pattern presented to the network, then the memory is called auto-associative. If the input and output samples have completely different meanings, the memory is called hetero-associative memory (Nikolić & Litovski, 2003).

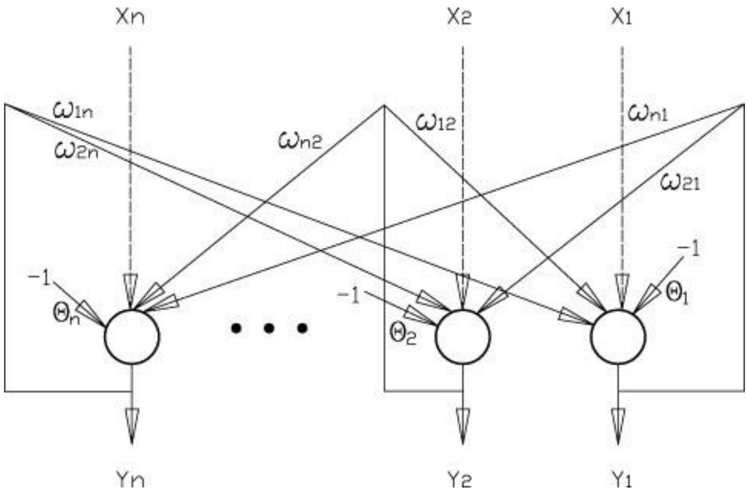

Figure 1. Hopfield network

Except for the possibility to address the content, the Hopfield neural network has the property of correcting errors (despite the presence of incorrect data at the input of the network, we can get accurate information at the output). The Hopfield neural network does not have a training phase, but synaptic weights can be determined by calculation.

The Hopfield neural network also has its drawbacks. The first is that the network is not completely stable. A measure of network stability is the signal-to-noise ratio (Haykin, 1993). The signal-to-noise ratio is:

$$\rho = N / (p-1) \qquad (1)$$

wherein:

p - number of steady states
N - number of neurons.

The network will be stable solely in the conditions when the signal-to-noise ratio is high. As long as the network is not overloaded, i.e. as long as the number of steady states is small compared to the number of neurons N the network is stable.

In conjunction with the potential instability, the Hopfield neural network has the property that the complement of a stable state is also a stable state. The linear combination of an odd number of desired steady states is a steady state, but this phenomenon occurs in networks with a large number of neurons. This results from the symmetry of the network. These two phenomena degrade the efficiency of the Hopfield network for the realization of memory addressed by content.

An essential parameter of the network is its capacity, i.e. how many stable states the network can have, while the network response has a satisfactory accuracy. In order for the network to be able to give the correct response with appropriate accuracy based on (Haykin, 1993) it is necessary that:

ρmin = 2ln (N) (2)

so that the maximum network capacity is:

pmax = N / ρmin
i.e. pmax = N / 2ln (N) (3)

If we want the probability of correct response to be 99%, we obtain a stricter condition for the maximum network capacity pmax, i.e.

pmax = N / 4ln (N) (4)

Regardless of which of the two conditions we use to determine the maximum capacity, we must keep the number of steady states small enough for the specified ratios to determine the pmax. This significantly limits the efficiency of the Hopfield network.

The basic process unit for the realization of the Hopfield network is a neuron. It has two states depending on the activation potential acting on it. In the "active" state, the output value of the neuron is **si = + 1**, while in the "off" state, the output value is **si = -1**. For a network of **N** neurons, the state of the network is determined by the vector **s = [s1, s2,…, sn]** T. As the state of a neuron has two values **s = + - 1**, one information bit is needed for its memory, and for a neural network with **N** neurons, an information word of **N** bits is required, which are represented by a vector of dimensions **N × 1**. The connection of neurons **i** and **j** is modeled by the synaptic weight **Wij**, which represents the influence of neuron output on the activation potential of neurons **j**. The effect can be positive (excitatory synapse) or negative (inhibitory synapse). The potential **vj** acting on a neuron **j** is the superposition of all the potentials acting on it. The following relation applies:

$$\boldsymbol{v_j = \sum_{j=1}^{N} w_{ji}\ s_i - \Theta_j} \quad (5)$$

where **Θj** is the threshold of neurons **j**. Neuron **j** changes its state according to the following rule:

$$\boldsymbol{s_j = \begin{Bmatrix} 1\ za\ v_j > 0 \\ -1\ za\ v_j < 0 \end{Bmatrix}} \quad (6)$$

There are two phases in the work of the Hopfield network: the learning phase and the information acquisition phase.

2.2. Learning phase

Suppose we want to remember a set of p N-dimensional vectors (binary words) given by **S = {ξ1, ξ2, .., ξμ; p = 1,2, ..., p}**. These **p** vectors represent the memory, which will be "contained" in the network. Let **ξμ,í** denote the **i-th** element of the steady state **ξμ**. According to the generalization of Heb's teaching postulate (Haykin, 1993), synaptic weights are defined by:

$$\boldsymbol{w_{ji} = \frac{1}{N} \sum_{\mu=1}^{p} \xi_{\mu,j}\ \xi_{\mu,i}} \quad (7)$$

The relation for the synaptic weight matrix is:

$$\boldsymbol{W} = \frac{\mathbf{1}}{\boldsymbol{N}} \sum_{\mu=1}^{p} \xi_{\mu} \xi_{\mu}^{T} - \frac{\boldsymbol{p}}{\boldsymbol{N}} \tag{8}$$

The synaptic weight matrix is a symmetric matrix **W = WT**, i.e. the output of each neuron is led to the input of all but its own.

2.3. Information acquisition phase

During this phase, we bring an N dimensional vector x to the network input which represents the initial state of the network. The network changes the state dynamically according to the rule that each neuron randomly but with a certain frequency examines its activation potential and updates its state according to its value. Updating the state from iteration to iteration is deterministic, but the selection of neurons to perform the update is random. The update is performed until the network reaches a stable state, i.e. time-invariant state, i.e. if the relation is satisfied

$$x = sgn\ (Wx - \theta) \tag{9}$$

This way of updating is called asynchronous. The synchronous model uses the same matrix of synaptic weights as the Hopfield model, while state changes are updated synchronously. The difference in the update method affects the number of iterations required for the network to become stable. Hopfield networks are suitable for use in cases where we have a large number of criteria and a large number of alternative characteristics, where information on individual characteristics or criterion functions is incomplete. In these cases, using the knowledge of experts, the values of the characteristics of alternatives and the values of their criterion functions are modeled with binary values (0 and 1, respectively, -1 and 1). In general, the procedure for implementing the Hopfield network is as follows:

$$\boldsymbol{K} = \{\boldsymbol{K_1}, \boldsymbol{K_2} \dots \dots, \boldsymbol{K_n}, \} \tag{10}$$

A set of relevant criteria K is defined on the basis of which alternatives are evaluated.

Reference vectors are defined. In this model, reference vectors are defined by a single vector whose values, in theoretical terms, represent the stable states of the network. In the case of multi-criteria decision-making, the values of these vectors may represent the values of the criterion functions or the values of the characteristics of the alternatives. The total number of reference vectors and their values depend on the type of problem (the greater the number of characteristics of alternatives and the criteria for their evaluation, the greater the number of reference vectors can be defined).

The network is designed - the weight coefficients of the network are determined based on the values of reference vectors. The number of nodes in the network should correspond to the number of criterion functions. In this way, the network is designed and ready for use. Hebb's learning rule is used to calculate synaptic weights (**wji**) in the network:

$$\boldsymbol{w_{ji}} = \frac{\mathbf{1}}{\boldsymbol{N}} \sum_{\mu=1}^{p} \xi_{\mu,j}\, \xi_{\mu,i} \tag{11}$$

The process of initiating the network is approached by skipping individual vectors from the given set of new input vectors (X):

$$x_j(0) = \xi_{start\ j}, \quad j=1,\dots N$$

xj (0) - state of neurons at time **t = 0**
ξ_{start} is the **j-th** element of the initial vector ξ_{start}

The network starts an iterative procedure and after a certain number of iterations the network converges to the most similar reference vector, which represents a multidimensional assessment of the observed alternative for the defined model:

$$x_j(t+1) = sign\left(\sum_{i=1}^{N} w_{ji}\, x_i(t) + b_j\right), \quad j=1,2\dots,N \tag{12}$$

The procedure is repeated for all alternatives from the given set. The result is an appropriate set of reference vectors (alternative):

$$\mathbf{Y=(x_{ref})} \tag{13}$$

At the end of the procedure, the best alternative is chosen - the alternative to which the reference vector with the highest prescribed scalar or qualitative grade corresponds. If we have more than one such alternative, additional conditions (criteria) are introduced or expert preference is used.

3. Example

To select the optimal variant of the crossing of the main gas pipeline MG-04 under the Danube near Beska, the evaluation of 32 proposed variant solutions based on nine criterion functions should be performed (Table 1).

Table 1. Description of criterion functions for selection of the best variant solutions of section crossing of the main gas pipeline MG-04 below the Danube near Beška

Ordinal. number of criteria	Description of criterion functions
1	Investment value
2	Exploitation costs
3	Building construction time
4	Impact of future facilities on the pipeline
5	Convenience of the crossing location and project conditions
6	Geo-mechanical, hydrological-hydraulic and psamological influences
7	The impact of the pipeline on the environment
8	Impact on water transport
9	Safety of operation

In order to select the optimal variant, K. Golić in her doctoral dissertation (Golić 2007) proposed a solution procedure based on the application of Hopfield's auto-associative memory. The first step was to take into account the characteristics of Hopfield's auto-associative memory so that the observed set of alternatives was "narrowed" to a set of "best" alternatives, while the "complex" criteria defined at the beginning were broken down into a number of "simple" ones with 11 alternatives □A1, A5, A6, A9, A13, A14, A17, A21, A22, A29, A30□ and 19 criteria (Table 2).

Table 2. Description of criterion functions and display of their values for a number of alternative solutions

O.n	Criteria description	Alternative no.1	Alternative no.2	Alternative no.3	Alternative no.4
1	Costs of mechanical work	84894404	1.08E+08	98376892	1.14E+08
2	Civil engineering costs	37730845	37306244	29513067	42923066
3	Costs of hydro construction work	28298134	33161106	29513067	33384607
4	Costs of electrical work	28298134	29015968	29513067	33384607
5	Costs of measuring regulation	9432711	10362846	9837689	14307689
6	Fixed maintenance costs	280000	288000	272000	350000
7	Occasional maintenance costs	120000	112000	128000	150000
8	Time to perform mechanical work	12	13	13.5	13.5
9	Time for civil engineering works	4.8	4.8	4.7	5.4
10	Time for hydro construction works	3.6	2.6	3.9	4.05
11	Time for performing electrical work	3.6	3.6	3.9	4.05

12	Influence of existing facilities on an alternative solution	1	1	5	3
13	Convenience of the crossing location and project conditions	2	3	4	5
14	Geo-mechanical impact	2	4	5	5
15	Hydrological impact	2	4	5	5
16	Psamological influence	2	4	5	5
17	Environmental impact	2	4	4	5
18	Impact on water transport	5	5	5	5

The values of the criteria used have been modified on the bases of expert assessment. The maximum number of 4 reference vectors has been determined and their limit values (best and worst) have been defined. The values of the reference vector rated as "best" were adopted to meet all criteria, and the values of the reference vector rated as "worst" were adopted so not to meet any of the criteria. After defining the reference vectors, using the ready-made program for Hopfield networks in the Matlab 6.5 software package, the weights of the network were determined (Table 3) on the bases of for the defined model. The values of weight matrices were normalized to the value **[-1,1]** before their calculations.

Table 3. Display of values of reference vectors and weight coefficients of criteria

Ordinal number	Criteria description	Weights criteria	Reference Vector no. 1	Reference Vector no. 2	Reference Vector no. 3	Reference Vector no. 4
1	Costs of mechanical work	0.1075	-1	-1	1	1
2	Civil engineering costs	0.1075	-1	-1	1	1
3	Costs of hydro construction work	0.1075	-1	-1	1	1
4	Costs of electrical work	0.1075	-1	-1	1	1
5	Costs of measuring regulation	0.1075	-1	-1	1	1
6	Fixed maintenance costs	0.0358	-1	1	-1	1
7	Occasional maintenance costs	0.0358	-1	1	-1	1
8	Time to perform mechanical work	0.0538	-1	-1	1	1
9	Time for civil engineering works	0.0538	-1	-1	1	1
10	Time for hydro construction works	0.0538	-1	1	-1	1
11	Time for performing electrical work	0.0538	-1	1	-1	1
12	Influence of existing facilities on an alternative solution	0.0072	-1	1	-1	1
13	Convenience of the crossing location and project conditions	0.0072	-1	1	-1	1
14	Geo-mechanical impact	0.0251	-1	1	-1	1
15	Hydrological impact	0.0072	-1	1	-1	1
16	Psamological influence	0.0072	-1	1	-1	1
17	Environmental impact	0.0072	-1	1	-1	1
18	Impact on water transport	0.0072	-1	1	-1	1
19	Safety of operation	0.1075	1	1	-1	-1

Using the proposed methodology, the calculations provided the best alternative - number 13 (Table 4). In order to control the obtained result, a comparative analysis was performed with the results obtained by applying the method of multi-criteria compromise ranking and the method of rough sets made for the same problem by Ž. Praščević and G. Ćirović (Praščević & Ćirović, 2003). The results of the analysis indicated that there is a very good agreement between the results obtained using Hopfield's auto-associative memory and the results obtained using the other two methods.

4. Conclusion

The problem of multi-criteria decision-making is a very important segment of decision-making in construction. In addition to classical and phase methods of multi-criteria decision-making, certain types of problems from this class can be solved by using artificial neural networks. Artificial neural networks are a relatively new concept in data analysis and represent a robust tool adapted for application in situations of uncertainty and incompleteness of data. A significant feature of neural networks is related to their ability to generalize, i.e. give a satisfactory output value even when some input values are not known. In addition, neural networks, unlike standard methods of multi-criteria analysis, do not have a problem with nonlinear interdependence between dependent and independent variables. Neural networks have the ability to learn by example. When a network is "learned" or trained, it can provide outputs for the input values we assign to it. The application of the concept of neural networks in multi-criteria analysis is essentially different from the application of other techniques, such as multiple regression, discriminant analysis, etc.

Neural networks and methods developed on them are widely used in construction. The application is mainly related to the prediction of future values that are observed for the purpose of classification. The success of neural networks in performing these two functions qualifies them as an exceptional means of multi-criteria decision-making. To solve the problem of multi-criteria decision-making, the paper emphasizes the possibilities of using the Hopfield network. The general procedure of use is given, and through a concrete example from practice, a model based on Hopfield's auto - associative memory is presented, which is used in the case when the comparison is made on the basis of a large number of criteria or characteristics.

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