Prediction of the Rating of the University Using Hybrid Cognitive Maps and Selective Dendritic Networks of Neurons

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Abstract. The aim of the work is to substantiate and predict activities to ensure the increments of the values of target indicators (indicators) of the university's activities in the international institutional rating QS to the values required to increase the rating in subsequent years. The scenario of planning measures obtained as a result of modeling made it possible to substantiate the value of the necessary increments in the values of the identified latent factors that affect the target indicators and ensure the achievement of the required value of the main indicator. Mathematical modeling of cognitive maps is used in combination with selective dendritic networks of neurons, which, in a certain organization, have computational and cognitive properties. The possibility of increasing the efficiency of using cognitive maps to predict the development of the university using selective dendritic networks of neurons is shown. The proposed structure of hybrid cognitive maps allows a natural simplification of the structure due to the removal of non-working network connections of the global structure, allows a universal matrix description of the network mathematical model, allows for the effective formation of a computational algorithm and software for predicting university development indicators. In the course, a hybrid cognitive model of scenario forecasting of measures to achieve the required values of the target indicators of the university's activity in the international institutional ranking QS was developed, based on the developed model. The results obtained made it possible to formulate a scenario plan for the necessary stepwise increase in the values of target indicators, considering the latent factors affecting them in the interval of 2020 -2025. The possibility of forming a cognitive map based on a multilayer dendritic network of direct propagation in the presence of unidirectional content connections is shown.

Keywords: cognitive model, scenario forecasting, targets, institutional ranking, dendrites, selective dendritic networks of neurons.

1 Introduction

The aim of the work is to substantiate and predict activities to ensure the increments of the values of target indicators (indicators) of the university's activities in the international institutional rating QS to the values required to increase the rating in subsequent years.

The relevance of the problem being solved is due to the need to develop scientifically grounded proposals to achieve the required values of the target

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indicators of the Plekhanov Russian University of Economics by 2025 by calculating the necessary increments of latent factors (particular indicators), taking into account their correlations with the target indicators. In turn, the main indicator, called the functional F (aka the university rating R), is calculated as the sum of the products of the values of the target indicators by their weight coefficients [1-2]. The analysis of the problem posed showed that it belongs to the class of semi-structured tasks, which is solved under the conditions of a limited amount of initial data and several uncertainties.

2 Literature Review

To solve the problem, the method of cognitive maps was used. Cognitive maps are a kind of mathematical models describing problem situations or complex semi-structured systems [3-21]. For the first time the term "cognitive maps" (Cogntve Maps) was proposed by E. Tolman in [22]. R. Axelrod proposed to consider a cognitive map as a directed graph, the arcs of which are assigned a plus or minus sign. In [23], he applied this model to construct a theory of decision-making in politics and economics. Thus, classical sign cognitive maps are specified in the form of a directed graph and represent the modeled system in the form of a set of vertices (concepts) and arcs, weighted by two-level values. The basic elements of such a map are links that describe the influence of one concept (the initial vertex in graph theory) on another concept (the final vertex in graph theory). The directionality of this connection w means that the concept source influences the concept receiver, i.e. a change in the values (states) of the concept-source leads to a change in the values (states) of the concept-receiver. At the same time, the transfer of influence is considered qualitatively: with a positive connection and an increase in the concept, the concept increases, and with a decrease, it decreases. If the relationship is negative, an increase in the value will cause a decrease (and vice versa). Such a cognitive map can be used for a qualitative assessment of the impact of individual concepts on the stability of the system. By identifying the contours formed in the map, analyzing the resulting signs of each of the contours and using the theory of feedbacks, it is possible to assess the stability of the modeled system. This analysis is based, in fact, on the methodology for analyzing conventional linear systems based on comparing various contours formed from concepts. The possibilities of such analysis are limited and do not allow identifying the features of the mutual influence of concepts, as well as ranking them according to the degree of influence on each other. This becomes especially noticeable when solving multicriteria optimization problems with given quantitative criteria.

In 1986, in work [24] B. Kosko proposed a new type of cognitive maps called Fuzzy Cogntve Maps. Concepts in a fuzzy cognitive map (FCM) can take values from the range of real numbers [0, 1]. The term "fuzzy" means only that causal links can take not only a value equal to 0 or 1, but lie in the range of real numbers, reflecting the "strength" of the influence of one concept on another. The approach based on the theory of fuzzy sets by L. Zadeh, at least in the computational aspect, is not used in B. Kosko's model. The structure of the influence of several input concepts on the output in maps of this type corresponds to the structure of a single-layer perceptron described in the theory of neural networks. The paper proposes a method for accumulating individual influences, like the weighted summation of the input vector components by an artificial neuron, followed by a nonlinear transformation of the results of this summation. The distinct distinct influences of the input concepts are summed up and a special non-linear function is used to prevent the output concept from going out of range.

$$K_j = f(\sum_{i=1}^{n} w_{ij} * K_i) \tag{1}$$

where w_{ij} is the weight of the concept's i influence on the concept j;

n - the number of concepts that directly affect the concept j [8];

K_i and K_j - the values of the input and output concepts, respectively.

The sigmoid is used as an activation function

$$f(x) = \frac{1}{1+e^{-Ax}} \tag{2}$$

Even though in the computational aspect, B. Kosko's fuzzy cognitive maps are like an artificial neural network, there are differences between the two models. Fuzzy cognitive maps can be purely expert in nature (although they can be trained) and correspond to a “white box” model, while an artificial neural network is fundamentally focused on learning (a “black box” model).

Let's consider the formation of hybrid cognitive maps for predicting the development of the university based on selective dendritic networks of neurons.

The use of this approach makes it possible to increase the accuracy of prediction by using the nodes of a fuzzy cognitive map as input data of the neural network. It is no secret that the data sample on which the forecast is based has a great influence on the forecast accuracy.

The approach has two main stages. At the first stage, a fuzzy cognitive map model is developed based on historical time series data using a genetic learning algorithm. The first stage can be described in stages as follows.

1. Initialization of a fuzzy cognitive map from historical data of time series.
2. Construction of an optimized fuzzy cognitive map (choosing the most significant concepts and their connections) using a genetic algorithm.
3. Testing a fuzzy cognitive map based on normalized test data.

Using fuzzy cognitive map concepts to define inputs for a neural fuzzy network [18] to improve prediction accuracy. The second stage consists of the following steps.

1. Improving forecasting accuracy using the selected input data - the concepts of the developed cognitive map.
2. Training the neural network.
3. Testing the resulting neural network on test data.

A similar example, shown in Figure 2, represents the process of predicting such an indicator as the quality of life of the population. The use of a cognitive map in this situation is the most appropriate for the following reason: in order to build a qualitative forecast of this indicator, like many others, it is necessary to single out the factors most influencing the indicator. A cognitive map is the best way to help solve such a problem and thereby feed the prepared data of cognitive map concepts to the inputs of the neural network.

The results of this work show the effectiveness of creating hybrid systems, both for the problem of decision making and for the problem of forecasting time series [25-26]. An integrated hybrid model of decision support and forecasting based on fuzzy cognitive maps is presented. In the work of A. N. Averkin, a hybrid cognitive map is considered, consisting of a combination of a fuzzy cognitive map and a neuro-fuzzy network.

3 Main Part. Using Dendritic Networks of Neurons to Form Cognitive Maps

Cognitive maps are a type of mathematical model that describes problem situations or complex semi-structured systems. It is possible to use deterministic and fuzzy cognitive maps. Fuzzy cognitive maps can be purely expert in nature (although they can be trained) and correspond to a “white box” model, while an artificial neural network is fundamentally focused on learning (a “black box” model). Further studies have shown the feasibility of using neural networks of types: multilayer neural networks of direct propagation of perceptrons, Kosco's neural networks and Hopfield's neural networks [27-29]. These neural networks are illustrated in Fig. 1.

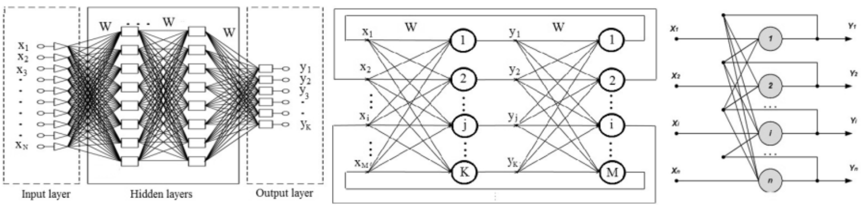

Fig. 1. Neural networks: on the left - a multi-layer neural network of feedforward perceptron, in the center - Kosco's neural network, on the right - Hopfield's neural network [27-29]

It should be noted that the use of neural networks in combination with cognitive maps is redundant in the sense that the neural network is used as a system of adders, and nonlinear elements of neurons are not used as part of the neural network. In this regard, it is advisable to use networks composed of neuron dendrites. Dendritic networks, as recent studies have shown, can be very complex and perform specific cognitive functions. In this case, dendrite networks can have a complex hierarchical structure, each level of which can perform certain cognitive functions. For a better representation of dendritic networks in neurons, we present illustrations of some dendritic networks of neurons. These illustrations are shown in Fig. 2. [30-37].

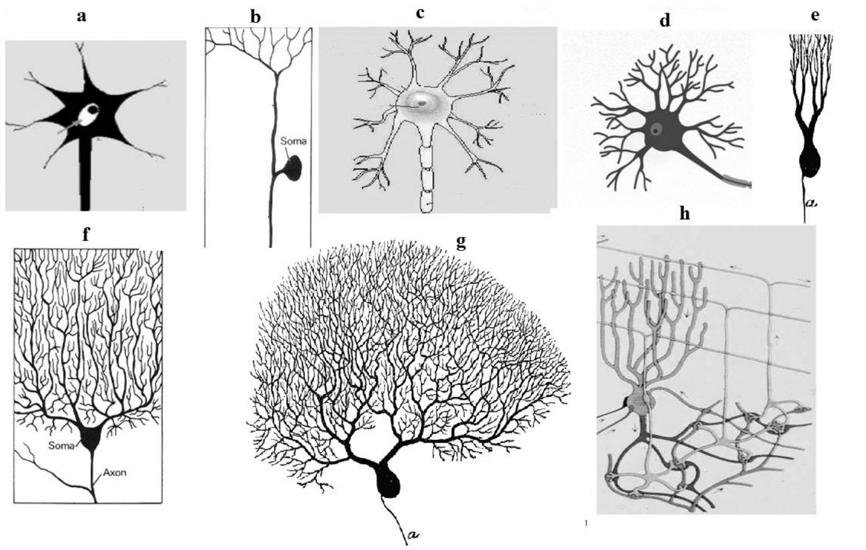

Fig. 2. The structure of neuron dendrites. In fig. 2 shows: a) a single-layer network of dandrites, b), c) two-layer networks, d), e) three-layer networks, f), g) complex multilayer networks of dendrites of brain neurons, h) shows dendrites coming from the outside to the dendritic network of a cerebellar neuron for the formation of complex control actions

From the above description of the hierarchical structure of some dendritic networks, these networks have extensive capabilities for processing input information and the ability to control the processes of neuron response to input information. Dendritic networks are usually hierarchical. Networks of this type are widespread in nature. A classic example is the device of the root system of the crown of trees. One of the possible variants of the root system and crown of trees is shown in Fig. 3.

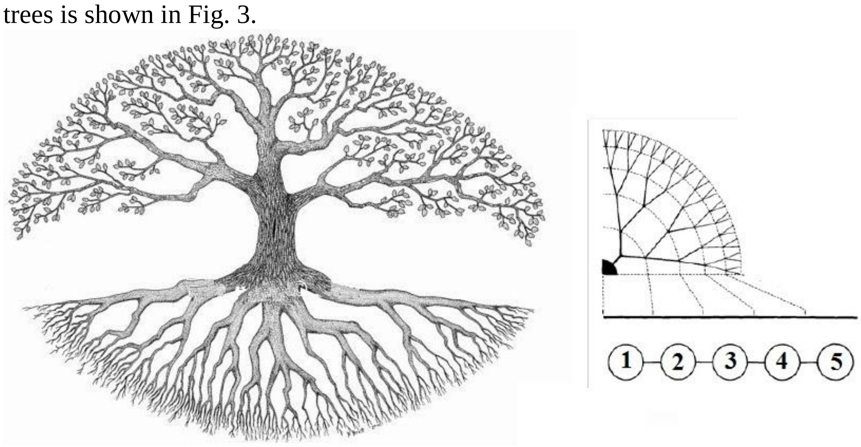

Fig. 3. Root system and crown of trees as tree-like hierarchical systems. The tree-like hierarchical structure of the root system and crown is schematically shown on the right

4 Predicting the Development of the University by Cognitive Maps Based on Selective Dendritic Networks of Neurons

The university rankings are assessed using the QS World University Rankings system, which has been published since 2004. The following indicators are used to calculate the ranking of the university, called the main factors: 1. Academic reputation; 2. Reputation with the employer; 3. The ratio between the number of teachers and the number of students. 4. Indicator of citation of teachers; 5. Number of international teachers; 6. Number of international students. To assess the ranking of a university, a functional of the form

$$y = w_1x_1 + w_2x_2 + w_3x_3 + w_4x_4 + w_5x_5 + w_6x_6 \quad (3)$$

where $w_1, w_2, w_3, w_4, w_5, w_6$ - the weighting factors are set, according to the QS recommendations, equal respectively: 0.4; 0.1; 0.2; 0.2; 0.05; 0.05.

Taking into account the values of the correlation dependences between the functional and target indicators obtained on the basis of factor analysis in [4], as well as expert estimates of the mutual influence of latent factors and their influence on target indicators, a cognitive model was built that reflects the relationship of latent factors, target indicators and functional is shown in Fig. 3 was proposed in [2].

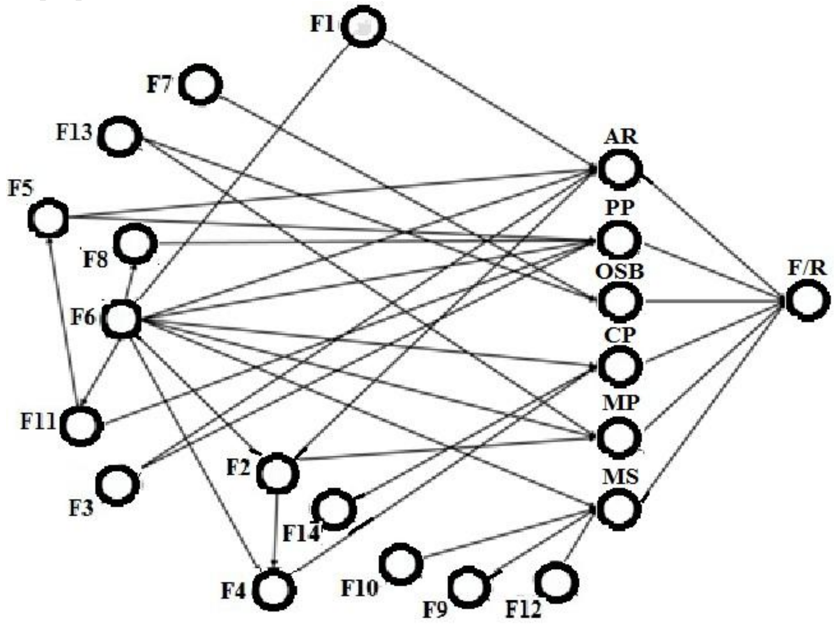

Fig. 3. Cognitive model of the relationship between latent factors, target indicators and functionality. In fig. 3 accepted designations: F - functional; R - university rating; target indicators: AR - academic reputation; PP - reputation with the employer; OSB - the ratio of the number of students to the number of teachers; CP - indicator of citation of teachers; MP - number of international teachers; MS is the number of international students; latent factors: F1 - "Scientific schools and dissertation councils"; F2 - "Joint research projects"; F3 - "Availability of basic departments"; F4 - "Number of publications in the Scopus database"; F5 - "Popular areas of training"; F6 - "The level of

qualifications of scientific and pedagogical workers (SPD)"; F7 - "Number of teaching staff"; F8 - "The level of competence of students"; F9 - "CPD with language training"; F10 - "Places in the hostel"; F11 - “Demand for graduates from employers”; F12 - "Areas for educational activities"; F13 - "Level of payment for the teaching staff"; F14 - "Stimulating factors")

5 Cognitive Maps Based on Selective Dendritic Networks of Neurons

Hybrid cognitive maps, including fuzzy neural networks, have been proposed by A. N. Averkin and others [25, 26]. In this paper, a hybrid intelligent system for predicting the development of the university with cognitive maps in combination with selective dendritic networks of a neuron is proposed, shown in Fig. 4.

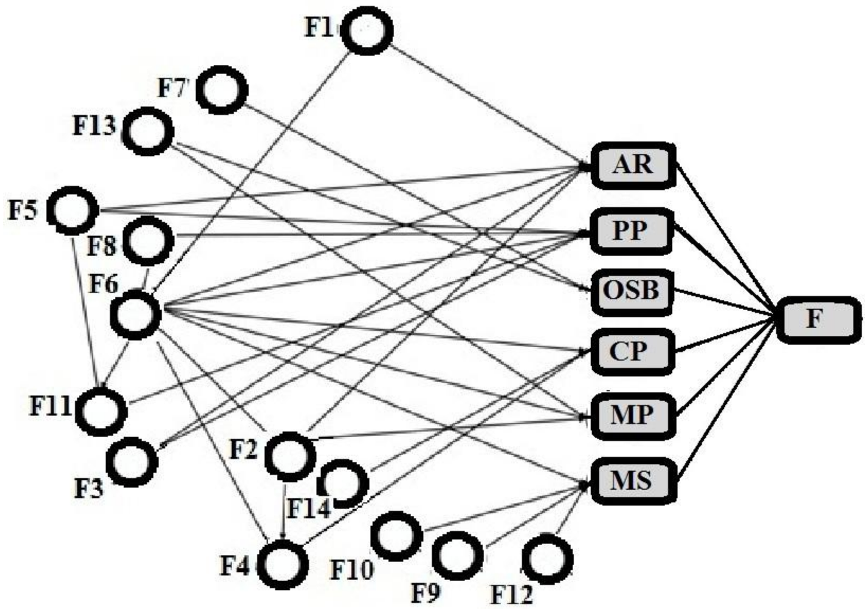

Fig. 4. Hybrid intelligent system for predicting the development of the university with cognitive maps in combination with selective dendritic networks of a neuron

The hybrid system does not take into account the effects of feedback from the main factors. Usually this influence is not significant and as a first approximation they can be ignored. If the influence of feedback is noticeable, then it can be taken into account by introducing additional connections, as is done for Hopfield neural networks.

The proposed hybrid intelligent system for predicting the development of the university with cognitive maps in combination with selective dendritic networks of a neuron is topologically equivalent to a hybrid map representing a combination of a cognitive map with a neural network proposed by AN Averkin in [9, 10].

The structure of a hybrid cognitive map of a general view, taking into account the latent factors of the first order, affecting the formation of the main factors, is shown in Fig. 5.

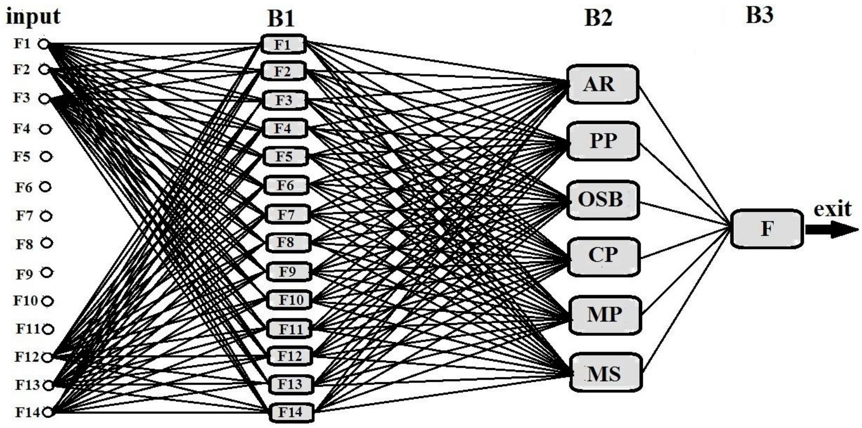

Fig. 5. The structure of a hybrid cognitive map of a general view, taking into account factors of the first and second orders in combination with dendritic networks of neurons. The map shows inputs F1, F2, F3, as well as inputs F12, F13, F14. Links from other inputs are not shown in the figure. The designations of the hidden factors are the same as in Fig. 4

The proposed cognitive map does not take into account the influence of feedback from the main factors. Usually this influence is not significant and as a first approximation it can be ignored. If the influence of feedback is noticeable, then it can be taken into account by introducing additional connections, as is done for Kosko's neural networks.

Some latent factors from among those taken into account have a noticeable effect on only some of the main factors and do not affect other main factors. The selective nature of the influence of hidden factors can be taken into account by selective clustering of connections in the cognitive map by removing insignificant connections. As a result, the whole cognitive map becomes simpler and more descriptive. Such a cognitive map with non-essential connections removed is shown in Fig. 6.

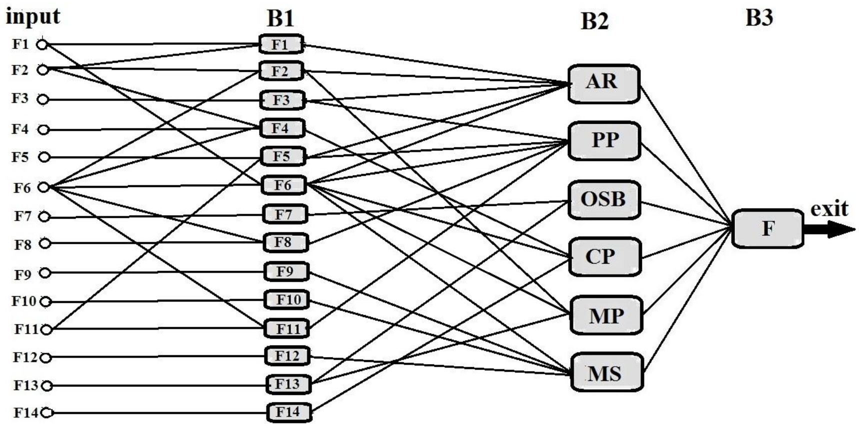

Fig. 6. The structure of the hybrid cognitive map with remote irrelevant connections. The figure uses the same designations for the factors as in Fig. 4

Consider a mathematical method for describing the processes occurring in the system of a modeled hybrid cognitive map.

6 Mathematical Description of a Cognitive Map Based on a Neuron Dendritic Network

The values of the vectors of the main target factors are fed to the input of the dendritic network $\boldsymbol{x}_i = (x_i, \ldots, x_{in})$, $(i = 1, \ldots, m)$ .The number n is equal to the number of years when these factors were considered.

The sums are formed based on the matrix equation

$$\boldsymbol{S} = \boldsymbol{W}\boldsymbol{X}\ , \tag{4}$$

where $\boldsymbol{W}$ is the matrix of weight coefficients, $\boldsymbol{X} = (\boldsymbol{x}_1, \ldots, \boldsymbol{x}_m)$

$$S_i = \sum_{j=1}^{n} w_{ij} x_{ij}\ , (i = 1, \ldots, m)\ . \tag{5}$$

The formation of sums S_i can be compared with the addition of signals at the nodes of the dendritic tree of a neuron.

In the terminal block, the error functional is formed

$$F = \sum_{j=1}^{n} (y_j - (a_0 + \sum_{i=1}^{m} (a_i x_{ij}))^2 \tag{6}$$

The error functional is minimized and the parameter values are determined a_i $(i = 1, \ldots, m)$, characterizing the degree of influence of factors x_i on the value of the error functional. The minimization of the error functional is possible by any known method, for example, the gradient method, the backpropagation method. Analytically minimizing the functional can be achieved by methods of finding the extremum of a function of several variables. The equations for determining the parameters $a_0, a_1, \ldots, a_m$ will have the form

$$\begin{pmatrix} (1,\boldsymbol{x}_1)(\boldsymbol{x}_1,\boldsymbol{x}_1)...(\boldsymbol{x}_1,\boldsymbol{x}_m) \\ (1,\boldsymbol{x}_2)(\boldsymbol{x}_2,\boldsymbol{x}_1)...(\boldsymbol{x}_2,\boldsymbol{x}_m) \\ \cdots\cdots\cdots\cdots\cdots\cdots \\ (1,\boldsymbol{x}_m)(\boldsymbol{x}_m,\boldsymbol{x}_1)...(\boldsymbol{x}_m,\boldsymbol{x}_m) \end{pmatrix} = \begin{pmatrix} (\boldsymbol{y},\boldsymbol{x}_1) \\ (\boldsymbol{y},\boldsymbol{x}_2) \\ \\ (\boldsymbol{y},\boldsymbol{x}_m) \end{pmatrix} \tag{7}$$

The vectors $\boldsymbol{X}^{(1)} = (\boldsymbol{x}_1^{(1)},...,\boldsymbol{x}_m^{(1)})$ are determined considering the influence of hidden factors of the first order by the relation

$$\boldsymbol{X}^{(1)} = \boldsymbol{X} + \boldsymbol{W}\boldsymbol{X} ,$$

where $\boldsymbol{W}$ is the matrix of weighting coefficients, determined by expert method.

The last formula allows you to represent the increment of the main factors as a linear combination of hidden factors of the first order with weight coefficients determined by expert methods. This is the standard way of using fuzzy set methods. Further, the minimization of the functional (1) and the use of multiple regression methods allow us to determine the change in the rating of the object under study and the range of change of the hidden factors of the first order to achieve the set goal.

Latent first-order factors may depend on other more subtle second-order factors. The proposed technique, based on the use of information processing methods in the dendritic networks of a neuron, allows us to study the task of forming a university rating with any degree of detail.

7 Results Interpretation of a Numerical Experiment Based on a Scenario Forecasting Model

The calculation of rating indicators for the functional F was carried out for individual universities according to the main factors using the multiple regression method in the Matlab language7. Let us use the dynamics of the main factors of the MGSU University for 5 years 2015-2019, shown in Fig. 7.

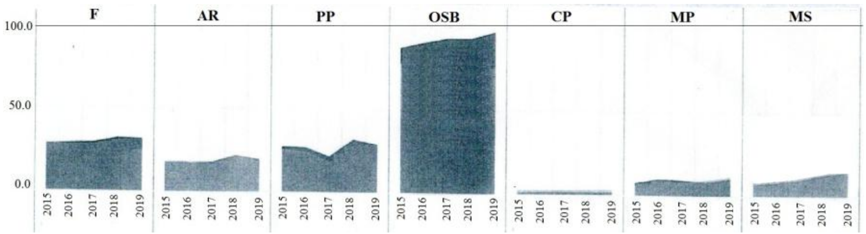

Fig. 7. Dynamics of the main factors of MGSU University for 5 years 2015-2019

The values of the main factors are shown in Table 1.

Table 1. Main factors values.

№	the years	F	AR	PP	OSB	CP	MP	MS
1	2015	28.0	17.3	27.0	86.9	1.2	7.5	7.0
2	2016	29.0	17.6	26.8	90.1	1.4	10.0	8.3
3	2017	29.1	17.7	21.3	92.7	1.5	9.3	9.8
4	2018	31.9	21.8	31.6	92.8	1.5	8.4	12.6
5	2019	31.6	19.4	28.8	96.6	1.7	10.3	14.5

The table uses the designations of the main factors as in Fig. 4. As a result of calculations that implement the minimization of the functional F, the dependence of the rating indicator of the Moscow State Construction University on the main factors was obtained. It is of interest to calculate the rating according to the equations of multiple linear regression according to the indicators for the first 3, 4, and 5 main factors for the data in Table 1. As a result of calculations using the Matlab7 programming system for the functional describing the rating, the following ratios were obtained:

$$R = 0.4767\ x1 + 0.0775\ x2 + 0.2056\ x3$$

$$R = 0.4195\ x1 + 0.1030\ x2 + 0.1868\ x3 + 1.4415\ x4$$

$$R = 0.4229\ x1 + 0.1023\ x2 + 0.1863\ x3 + 1.4049x4 + 0.0066\ x5.$$

The weight coefficients in these relations are close to the weight coefficients of the functional (1).

Let's consider the calculation of the rating indicator using the first equation. For example, substituting the data for 2019 (19.4, 28.8, 96.6, 1.7, 10.3, 14.5), we get the value of the rating indicator 31.341, which is in good agreement with the tabular value of 31.6. Using the second equation, we get the value of the rating indicator 31.6, which is in perfect agreement with the table value. The obtained dependencies allow predicting the value of rating indicators for the next years 2020-2021 based on the values of the main factors.

The given calculated data show that the most essential main factors are: AR - academic reputation; PP - reputation with the employer; OSB is the ratio of the number of students to the number of teachers. The highest growth rate will be required for the following latent factors: 1) Joint research projects; 2) The number of publications in the Scopus database; 3) Demand for graduates from employers. Among the latent factors, the highest growth rate is required for the factors: 1) The number of teaching staff; 2) Areas for educational activities.

As a result of the calculations performed, the following conclusions can be drawn: For a guaranteed place in the QS rating, a stepwise (with an interval of one year) increase in the values of target indicators that influence latent factors is necessary.

8 Results Discussion

The analysis of changes in the values of the main factors and rating values for the Plekhanov Russian University of Economics shows their chaotic non-deterministic nature. In this regard, QS Russian University of Economics is inferior to the rating of other universities, which requires the need for several special measures to improve it.

A hybrid cognitive map based on a cognitive map in combination with a dendritic network of neurons has been developed. Such a hybrid cognitive map can be useful in predicting poorly defined social systems. The considered hybrid map can be useful for optimizing processes in the system, for comparing the effectiveness of various social systems. The possibility of forming a cognitive map based on a multilayer dendritic network of direct propagation in the presence of unidirectional content connections is shown.

Conclusion

The proposed structure of hybrid cognitive maps allows a natural simplification of the structure due to the removal of non-working network connections of the global structure, allows a universal matrix description of the network mathematical model, allows for the effective formation of a computational algorithm and software for predicting university development indicators.

To achieve the stated goal of the study, the application of methods for solving poorly structured problems was substantiated based on the development of a forecasting model using hybrid cognitive maps, which made it possible to choose the most preferable alternative. The proposed approach allows, under the given constraints, to find the most acceptable scenario for planning the increment of the functional values and target indicators to the required values due to the impact on the latent factors that ensure the guaranteed achievement of the goal. The possibility of forming a cognitive map based on a multilayer dendritic network of direct propagation in the presence of unidirectional content connections is shown.

In the course of the study, the following tasks were solved: a hybrid cognitive model of scenario forecasting of measures to achieve the required values of the target performance indicators of the university in the international institutional ranking QS was developed, based on the developed model. The results obtained made it possible to formulate a scenario plan for the necessary stepwise increase in the values of target indicators, considering the latent factors affecting them in the interval of 2020 -2025.

Acknowledgments

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