Information Model of Evaluation and Output Rating of Start-up Projects Development Teams

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Abstract. The problem of constructing an informational model of evaluation and output of the start-up team rating is considered. This model is based on neuro-fuzzy network when there are expert fuzzy data on the teams of developers. As the success of a start-up implementation depends on the quality of the team of developers, then the development of such a model will increase the degree of validity of the decision to finance the start-up projects.

Keywords: start-up team, assessment, rating, neuro-fuzzy model

1 Introduction

For any project, there are people who implement it. Even for a very good start-up project, with a very high score and prospects for success, successful commercialization depends, to a greater extent, on a qualitative form of developers, ready to bring the product to the market and successfully decide on its sale. Therefore, investors in start-ups like to say that they primarily invest in a team.

The urgency of the work consists of the developed informational model of evaluation and withdrawal of the start-up team rating using the neuro-fuzzy network when there are expert and sometimes fuzzy data on the team of developers. The development of such a model will allow increasing the degree of validity of financing start-up projects since the success of the start-up implementation directly depends on the qualitative composition of the team of developers.

2 Formal problem statement

Let's formulate the task of evaluating and eliminating the ranking of teams of developers of start-up projects as follows. Let the set of teams of developers be set $X = (x^1, x^2, ..., x^n)$, which should be evaluated according to many indicators (criteria) $K = (K_{11}, K_{12}, ..., K_{34})$, organize according to a certain rule and draw a linguistic rating $Y = \{y_1, y_2, ..., y_5\}$ by command.

Each criterion for evaluating the team of start-up project developers is evaluated expertly using one of the terms, the next term-set of linguistic variables L={H; HC; C; B}, where: H – “Low-level indicator”; HC – “Indicator below average”; C – “Average level of the indicator”; B – “High level of the indicator”. Also, for every assessment, the expert puts “confidence factor” d in assigning it an assessment, from the interval [0; 1].

3 Literature review

Analysing scientific sources, we see that there is a need to systematize tools and develop algorithms assessment teams of developers’ start-up projects. Still not produced a holistic concept, definition of the rating of the teams of developers for the successful implementation of the start-up of the projects taking into account the subjective aspects of evaluation. Thus, the problems of project start-up evaluation are raised in the work [1], where the fuzzy set is used and the existing group of criteria "authors of the idea" is used, but not enough attention is paid to the analysis of the teamwork on the project. In the work [2] shows a cognitive star rating model that can be used only as an auxiliary tool for improving decision-making accuracy by venture funds. In [3] offers a fuzzy management model that can help select and filter applications for grants. On the one hand, this model considers business ideas, and on the other - the person of the entrepreneur. The approach is based on linguistic variables, which reveals subjectivity.

Fuzzy exclusion systems can use human expertise and perform fuzzy output to obtain initial estimates [4-5]. Formation of rules and related membership functions very much depends on a priori knowledge of the system under consideration. Therefore, there is no universal way of transforming the experimental knowledge of human experts into the knowledge base of the fuzzy output system. Therefore, there is also a need to develop teaching methods for obtaining an initial assessment with the required level of accuracy. In addition, the mechanism of training neural networks does not rely on human expertise, but through a homogeneous structure of neural networks [6-8] it is difficult to extract structured knowledge. Therefore, for the task of evaluating and withdrawing the rating of the team of developers of the start-up projects, it is necessary to develop its own neuro-fuzzy network, working with fuzzy expert input signals and based on the knowledge base displays adequate results [9-10].

Selected theoretical framework within the Simulation and modelling of Security issues is in the work of Fuchs et al. [11] focused on the simulation of dangerous substances outflows into the environment because of traffic accidents by dangerous substances transport, in the study of Dvorak et al. [12] on the enhancing of security on critical accident locations using telematics support, in the work of Balatka et al. [13] on the exposure of the environment and surface water by dangerous liquid - the slop outflow model, or the modelling and evaluation of risks in Soušek et al. [14], or Madarász [15] on the situational Management Methodology and its Application.

Consequently, there are no special models for evaluating and withdrawing the ratings of developers implementing the start-up projects.

4 Neuro-fuzzy model for outputting the ranking of start-up project teams

We describe a neuro-fuzzy model of teams' start-up evaluation, based on input linguistic terms. Input signals are presented in the form of linguistic terms and coefficients of expert confidence in their assignment.

Let the input of the neuro-fuzzy network provide expert data start-up teams (alternatives) $X = (x^1, x^2, ..., x^n)$ by the set of criteria $K = (K_{11}, K_{12}, ..., K_{34})$. The criteria are divided into three groups, and the second group has two subgroups of criteria. For each criterion, we obtain a linguistic variable L= {H; HC; C; B} and "confidence factor" d in the assignment expert assessment [16]. For example, if the answer is not the one that corresponds to the developer team, then the metric d corrects the accuracy of the answer.

Then let's look at the object of the species $Y = f(x^1, x^2, ..., x^n)$ for which the connection "input x^k – output Y" can be submitted in the form of an expert matrix U, Table 1.:

Table 1. Expert matrix U

Name criterion	Input signals						
	x^1		x^2			x^n	
	L	d	L	d	…	L	d
K_{11}	L_{11}^1	d_{11}^1	L_{11}^2	d_{11}^2	…	L_{11}^n	d_{11}^n
K_{12}	L_{12}^1	d_{12}^1	L_{12}^2	d_{12}^2	…	L_{12}^n	d_{12}^n
K_{21}	L_{21}^1	d_{21}^1	L_{21}^2	d_{21}^2	…	L_{21}^n	d_{21}^n
…	…	…	…	…	…	…	…
K_{25}	L_{25}^1	d_{25}^1	L_{25}^2	d_{25}^2	…	L_{25}^n	d_{25}^n
K_{31}	L_{31}^1	d_{31}^1	L_{31}^2	d_{31}^2	…	L_{31}^n	d_{31}^n
…	…	…	…	…	…	…	…
K_{34}	L_{34}^1	d_{34}^1	L_{34}^2	d_{34}^2	…	L_{34}^n	d_{34}^n
Exit by alternatives	y_g		y_g		…	y_g	

The set of fuzzy knowledge base rules of production follows:

If [$K_{11} = (L_{11}^k; d_{11}^k)$ (with weight α_{11}) and $K_{12} = (L_{12}^k; d_{12}^k)$ (with weight α_{12})] (with weight α_1) **also** $\big[$ [$K_{21} = (L_{21}^k; d_{21}^k)$ (with weight α_{21}) and …and $K_{23} = (L_{23}^k; d_{23}^k)$ (with weight α_{23})] (with weight β_{21})] and [$K_{24} = (L_{24}^k; d_{24}^k)$ (with weight α_{24}) and $K_{25} = (L_{25}^k; d_{25}^k)$ (with weight α_{25})] (with weight β_{22})] $\big]$

(with weight α_2) **also** [$K_{31} = (L_{31}^k; d_{31}^k)$ (with weight α_{31}) and ...and $K_{34} = (L_{34}^k; d_{34}^k)$ (with weight α_{34})] (with weight α_3) **then** $Y = y_g$, $k = \overline{1,n}$; $g = \overline{1,5}$.

Where $K_{ij}, i = \overline{1,3}; j = \overline{1,5}$ – criterion of evaluation of the *i*-th group, *j* – serial number of the rule in the group; L_{ij} – variable with term-set *L* for the *j*-th group indicator i; d_{ij} – "confidence factor" expert on assigning a variable L_{ij}; $(L_{ij}^k; d_{ij}^k)$ – grouped input data received from *κ*-th start-up team by K_{ij} criterion; $\alpha_{11}, \alpha_{12}, \alpha_{21}, ..., \alpha_{25}, \alpha_{31}, ..., \alpha_{34}$ – synaptic weight criteria from the interval $[1; b]$; $\beta_{21}, \beta_{22} \in [1; b]$ – synaptic weight for subgroups of the criteria of the second group; $\alpha_1, \alpha_2, \alpha_3$ – synaptic weight groups of criteria according to the interval $[1; b]$; $Y = \{y_1, y_2, y_3, y_4, y_5\}$ – linguistic interpretation of the rankings of the teams of developers of the start-up.

Getting an aggregated rating of the start-up team rating can be presented in the form of a four-layer neuro-fuzzy network of type integrated neuro-fuzzy systems (similar to Mamdani neurofuzzy approximator), Figure 1.

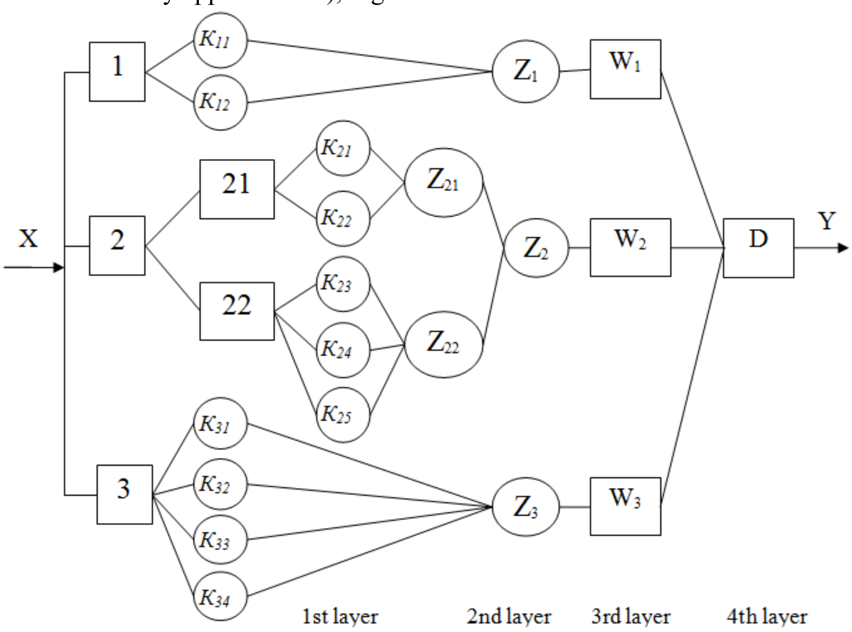

Fig. 1. The structure of the neuro-fuzzy network

Next, consider in more detail what happens on each layer of the neuro-fuzzy network.

1st layer

In the neurons of the first layer, the fuzzification operation is performed, that is, for each input value $(L_{ij}^k; d_{ij}^k)$ the value of the membership function is brought into conformity $\mu(O_{ij}^k)$. Therefore, at the first level, it is necessary to build membership rules in order to get a normalized estimate of the input data.

Let the term-set of linguistic variables L={H; HC; C; B} represent on a certain numerical interval $[a_1; a_5]$, where $H \in [a_1; a_2]$, $HC \in [a_2; a_3]$, $C \in [a_3; a_4]$, $B \in [a_4; a_5]$. The value of breakdowns may be determined in the learning process of a neuro-fuzzy network using real data from teams of developers of start-up projects.

Calculate criterion estimates $O_{ij}^k, k = \overline{1,n}$ with the help of a characteristic function:

$$O_{ij}^k = \begin{cases} a_2 \cdot d_{ij}^k, & if \quad L_{ij}^k \in H; \\ a_3 \cdot d_{ij}^k, & if \quad L_{ij}^k \in HC; \\ a_4 \cdot d_{ij}^k, & if \quad L_{ij}^k \in C; \\ a_5 \cdot d_{ij}^k, & if \quad L_{ij}^k \in B. \end{cases} \tag{1}$$

This will make it possible to adjust the assessment regarding the expert's confidence in its assignment, or how close is the answer to the questions of the team of developers to the truth. Without diminishing generality, for example, we introduce the membership rule to help S-similar membership function [17-18]:

$$\mu(O_{ij}^k) = \begin{cases} 0, & O_{ij}^k \le a_1; \\ 2\left(\dfrac{O_{ij}^k - a_1}{a_5 - a_1}\right)^2, & a_1 < O_{ij}^k \le \dfrac{a_1 + a_5}{2}; \\ 1 - 2\left(\dfrac{a_5 - O_{ij}^k}{a_5 - a_1}\right)^2, & \dfrac{a_1 + a_5}{2} < O_{ij}^k < a_5; \\ 1, & O_{ij}^k \ge a_5. \end{cases} \tag{2}$$

Constructed in this way, the membership function says that the resulting value $\mu(O_{ij}^k)$ will go to 1, in case if the high estimation of the project by the criterion and the sufficiently high confidence of the expert on its assignment. Therefore, of course, S-similar membership function best suited for this task.

Thus, we turn from experts' evaluations of teams of developers of start-up projects and expert confidence in their assignment to normalized comparable data [19].

For example, if we take the interval value $[a_1; a_5] = [0;10]$, then the membership function (2) will have the form:

$$\mu(O_{ij}^k)=\begin{cases}0, & O_{ij}^k \le 0;\\ 0{,}02\cdot\left(O_{ij}^k\right)^2, & 1<O_{ij}^k\le 5;\\ 1-0{,}02\cdot\left(10-O_{ij}^k\right)^2, & 5<O_{ij}^k<10;\\ 1, & O_{ij}^k\ge 10.\end{cases} \qquad (3)$$

The membership function constructed in this way has the following content, if the answer to the question corresponds to the high value of the term – B and "confidence factor" expert is low, at level 0,2, then the value of the membership function is obtained accordingly $\mu(O_{ij}^k)$ will be low – 0,08.

2nd layer

On the second layer, the calculation of functions of postsynaptic potential is grouped according to the criteria of evaluation. The second layer contains the number of neurons that corresponds to the number of groups of criteria.

Let the person who makes the decision set the synaptic weights $\alpha_{11},\alpha_{12},\alpha_{21},...,\alpha_{25},\alpha_{31},...,\alpha_{34}$, from the interval $[1;b]$ for each criterion and set the synaptic weight of the rules for the subgroups of the second group of criteria β_{21},β_{22} from the interval $[1;b]$. We calculate the functions of postsynaptic potential as follows:

$$Z_1^k=\frac{1}{\alpha_{11}+\alpha_{12}}\cdot\left(\mu(O_{11}^k)\cdot\alpha_{11}+\mu(O_{12}^k)\cdot\alpha_{12}\right),\ k=\overline{1,n}, \qquad (4)$$

$$Z_2^k=\frac{1}{\beta_{21}+\beta_{22}}\cdot\left(Z_{21}^k\cdot\beta_{21}+Z_{22}^k\cdot\beta_{22}\right), \qquad (5)$$

$$\text{where } Z_{21}^k=\frac{1}{\alpha_{21}+\alpha_{22}}\cdot\left(\mu(O_{21}^k)\cdot\alpha_{21}+\mu(O_{22}^k)\cdot\alpha_{22}\right), \qquad (6)$$

$$Z_{22}^k=\frac{1}{\alpha_{23}+\alpha_{24}+\alpha_{25}}\cdot\left(\mu(O_{23}^k)\cdot\alpha_{23}+\mu(O_{24}^k)\cdot\alpha_{24}+\mu(O_{25}^k)\cdot\alpha_{25}\right), \qquad (7)$$

$$Z_3^k=\frac{1}{\alpha_{31}+\alpha_{32}+\alpha_{33}+\alpha_{34}}\cdot\begin{pmatrix}\mu(O_{31}^k)\cdot\alpha_{31}+\mu(O_{32}^k)\cdot\alpha_{32}+\\ +\mu(O_{33}^k)\cdot\alpha_{33}+\mu(O_{34}^k)\cdot\alpha_{34}\end{pmatrix},\ k=\overline{1,n}. \qquad (8)$$

Output neurons of the second layer Z_1, Z_2, Z_3 will be normalized since the calculations use the relative importance of the synaptic scales of the criteria.

3rd layer

On the third layer, the second layer of neurons is corrected in relation to the importance of one or the other group of evaluation criteria. In this case, for each group of criteria, person who makes the decision has his own considerations regarding the synaptic weights $\alpha_1, \alpha_2, \alpha_3$ respectively, from some interval $[1;b]$.We compute the functions of the postsynaptic potential of the third layer of neurons in the following way:

$$W_1^k = \frac{\alpha_1}{\alpha_1 + \alpha_2 + \alpha_3} \cdot Z_1^k, \tag{9}$$

$$W_2^k = \frac{\alpha_2}{\alpha_1 + \alpha_2 + \alpha_3} \cdot Z_2^k, \tag{10}$$

$$W_3^k = \frac{\alpha_3}{\alpha_1 + \alpha_2 + \alpha_3} \cdot Z_3^k, \qquad k = \overline{1,n}. \tag{11}$$

Similarly, the output neurons of the third layer W_1, W_2, W_3 will be normalized.

4th layer

On the fourth layer, we will be defuzzification the data. To do this, use the following activation function in the output neuron:

$$Z^k = W_1^k + W_2^k + W_3^k, \qquad k = \overline{1,n}. \tag{12}$$

As a result of the training of the neuro-fuzzy network, the rankings of teams of start-up design teams for comparing the aggregated score are determined Z with output variable $Y = \{y_1, y_2, y_3, y_4, y_5\}$ as follows: $Z \in (0{,}87;\ 1] - y_1$; $Z \in (0{,}67;\ 0{,}87] - y_2$; $Z \in (0{,}37;\ 0{,}67] - y_3$; $Z \in (0{,}21;\ 0{,}37] - y_4$; $Z \in [0;\ 0{,}21] - y_5$.

5 Training a neuro-fuzzy network

We offer the method of forming the knowledge base by generating new production rules that do not contradict the rules from the knowledge base of the system, based on the analysis of experimental data about the teams of developers [9].

Let's have a sample S value pairs $\left\langle x^s, Z^s \right\rangle, s = \overline{1,S}$. Method of the formation knowledge base of the start-up team developer is next.

Stage 1. With $m, (m < S)$ arbitrary values $\left\langle x^s, Z^s \right\rangle$, the initial knowledge base of the model, which is represented by a matrix with strings, is composed $\left\langle x^s, Z^s \right\rangle = \left\langle K_{11}^s, K_{12}^s, ..., K_{34}^s, Z^s \right\rangle$. This representation is equivalent to the formulated set of production rules, the fuzzy knowledge base described above.

Stage 2. Next, for each new experimental point $\left\langle x^*, Z^* \right\rangle$ we calculate the predicted value by the centroid method [8]:

$$Z_{new}^{*} = \frac{\sum_{s=1}^{m} Z^{s} \mu(\left\| x^{s} - x^{*} \right\|)}{\sum_{s=1}^{m} \mu(\left\| x^{s} - x^{*} \right\|)}. \tag{13}$$

Where μ – function of exponential form: $\mu(\left\| x^{s} - x^{*} \right\|) = \exp(-\lambda \sum_{h=1}^{hs} \left| x_{h}^{s} - x_{h}^{*} \right|)$, λ – function parameter (considered predefined), hs – number of rules.

Stage 3. If $\left| Z^{*} - Z_{new}^{*} \right| > \varepsilon$, where ε – a constant is given that determines the error of the approximation, then the knowledge base is replenished by expanding the matrix U, in the opposite case, the matrix U remains unchanged.

Stage 4. The rule of stop is checked. In this variant, the construction of the model is considered complete if, in accordance with steps 2 and 3, all are selected S experimental points, otherwise we go to stage 2.

It was accomplished training of the neuro-fuzzy network on a training set of data from a university team of developers (a total of 23 teams) taken from Incubator of Uzhhorod National University. Verified correctness of work the neuro-fuzzy network based on test data of successful start-up projects and their developers. Based on the training of the neuro-fuzzy network, the rankings of teams of developers of start-up projects are set. The described teaching method corresponds to the simplified method of fuzzy logic output but differs that the knowledge base is not fixed but is complemented by the arrival of experimental data. The contradiction of the new production rule is guaranteed by the procedure for updating the knowledge base [20].

6 Informational model for assessment teams of developers' start-up projects

Consider which characteristics are typical for an effective team? For this purpose, we propose, for example, the following set of criteria for evaluating the start-up team of developers divided into three groups. Evaluation criteria are presented in the form of a questionnaire, where each team chooses the answer that comes closest to them.

The first set of criteria is stability and team cohesion. For this group we offer the following indicators and options for answers:

K_{11} – The length of work in the project, measured in months of work on the project: 1. from 0 to 3 months; 2. from 3 to 6 months; 3. from 6 to 12 months; 4. more than 12 months.

K_{12} – The stability of the team is determined by the change of leaders and team members:

1. Completely new team members and part of the leaders;

2. The slight change in the number of team members;

3. The composition of the team is unchanged, as all members and leaders meet the requirements of professionalism;

4. The initial membership of the team is unchanged, but there was an expansion of the members and team leaders for the highest competence of the project.

The second group of criteria is professional competence and team experience. For this group, we propose to divide into two subgroups: professional competencies of leaders and professional competencies of team members.

The professional competence of leaders.

K_{21} – Successful work experience on topics or close to it:

1. Experience is absent as this project is the first one;
2. Availability of the first experience on the subject and receiving a small income;
3. A successful innovative project on the subject has been implemented;
4. Leaders have implemented a successful project on topics or close to it.

K_{22} – Successful management experience:

1. Management experience is absent as this project is the first;
2. Management experience is available but insignificant;
3. Middle managers are available;
4. Available high-level managers.

K_{23} – Education leaders:

1. Technical or managerial education is absent;
2. Graduated from college or university student in the technical or managerial direction;
3. Completed higher technical or managerial education;
4. Available degree from at least one of the leaders.

Assessment of professional competence of team members.

K_{24} – Successful experience in large or similar projects:

1. Work experience is absent as this project is the first one;
2. Work experience available but in small projects;
3. Available experience in large projects but not in all team members;
4. All team members have experience in large or successful projects.

K_{25} – Professional education of team members:

1. Team members do not have special education to implement the project;
2. Some team members have a special education to implement the project;
3. Most team members have a special education to implement the project;
4. All team members have a special education to implement the project.

The third group of criteria is the professional activity of the team.

K_{31} – Team participation in professional project conferences, investment sessions or profile events:

1. There is no involvement of professional project activities;
2. There is a single activity;
3. Available activity;
4. Existing and systematic activity of advanced training.

K_{32} – Publications in the media or professional online sources for the project:

1. No posts;

2. Available information about the project and the team, but mainly in social networks;

3. There is no single information about the project and the team;

4. Available and systematic activity of publishing and popularizing the project.

K_{33} – The presence of team ties in social networks and messengers:

1. No links; 2. There are insignificant, isolated links; 3. A wide range of mutual friends in various social networks;

4. Great activity with a large number of subscribers.

K_{34} – The presence of communications with advisers in social networks:

1. No links; 2. There are insignificant, isolated links; 3. Available links;

4. Wide circle of friends.

So, "Low-level indicator" will be considered as the first answer to the question, and the last answer, respectively, is "High level of the indicator".

Scale of the output variable $Y = \{y_1, y_2, y_3, y_4, y_5\}$ we (&) offer the following:

y_1 = "The rating of the project start-up team is high". The highest level of start-up team rating. Very low expectations regarding the risks of non-fulfilment of project development obligations. Very high ability to respond and solve current or strategic problems of project realization in a timely manner.

y_2 = "The rating of the project start-up team is higher than the average". High ranking team start-up. Low expectations of non-fulfilment of project development obligations. Ability to react in a timely manner and solve current or strategic problems of project implementation. However, negative changes in circumstances and economic conditions are likely to reduce this ability.

y_3 = "The rating of the project start-up team is average". Speculative level of start-up team rating. There is a possibility of development of project risks or the risk of conflicts in the middle of the team, especially as a result of negative economic changes that may occur over time.

y_4 = "The rating of the project start-up team is low". The rating says that realizing the project in time is not a real opportunity. The ability to fulfil the project obligations of the team entirely depends on the favourable business and economic conditions.

y_5 = "The rating of the project start-up team is very low". Very high risks of non-fulfilment of project development obligations. Formed start-up team is not able to work on a project.

7 General algorithm for obtaining a rating assessments and ranking start-up command

1st step. For the considered teams, developers of start-up projects $X = (x^1, x^2, ..., x^n)$ conduct an expert survey and get the input data separately for each team.

2nd step. Person who makes the decision sets his own wishes for the synaptic scales of the criteria $-\alpha_{11}, \alpha_{12}, \alpha_{21}, ..., \alpha_{25}, \alpha_{31}, ..., \alpha_{34} \in [1; b]$, synaptic weights of sub-groups for the second group of criteria – $\beta_{21}, \beta_{22} \in [1; b]$ and synaptic scales of the criteria groups – $\alpha_1, \alpha_2, \alpha_3 \in [1; b]$.

3rd step. We make fuzzification of the input signals $(L_{ij}^k; d_{ij}^k)$ in neurons of the first layer, according to (1)-(2), and we obtain the value of the membership function $\mu(O_{ij}^k)$.

4th step. We calculate the output of the neuron with the following activation function (14).

$$Z^k = \frac{1}{\alpha_1 + \alpha_2 + \alpha_3} \cdot \left(\begin{array}{l} \alpha_1 \cdot \left(\frac{1}{\alpha_{11} + \alpha_{12}} \cdot \left(\mu(O_{11}^k) \cdot \alpha_{11} + \mu(O_{12}^k) \cdot \alpha_{12} \right) \right) + \\ + \alpha_2 \cdot \left(\frac{1}{\beta_{21} + \beta_{22}} \cdot \left(\begin{array}{l} \left(\frac{1}{\alpha_{21} + \alpha_{22}} \cdot \left(\mu(O_{21}^k) \cdot \alpha_{21} + \mu(O_{22}^k) \cdot \alpha_{22} \right) \right) \cdot \beta_{21} + \\ + \left(\frac{1}{\alpha_{23} + \alpha_{24} + \alpha_{25}} \cdot \left(\begin{array}{l} \mu(O_{23}^k) \cdot \alpha_{23} + \\ + \mu(O_{24}^k) \cdot \alpha_{24} + \\ + \mu(O_{25}^k) \cdot \alpha_{25} \end{array} \right) \right) \cdot \beta_{22} \end{array} \right) \right) + \\ + \alpha_3 \cdot \left(\frac{1}{\alpha_{31} + \alpha_{32} + \alpha_{33} + \alpha_{34}} \cdot \left(\begin{array}{l} \mu(O_{31}^k) \cdot \alpha_{31} + \mu(O_{32}^k) \cdot \alpha_{32} + \\ + \mu(O_{33}^k) \cdot \alpha_{33} + \mu(O_{34}^k) \cdot \alpha_{34} \end{array} \right) \right) \end{array} \right) \quad (14)$$

5th step. Defuzzification of data and ranking of start-up teams $Y = \{y_1, y_2, y_3, y_4, y_5\}$.

6th step. Ranking of teams of developers. Based on quantities $Z^k(x^k), k = \overline{1, n}$ we build a ranking line of developers of start-up projects:

$$Z = (Z^1, Z^2, ..., Z^n). \quad (15)$$

8 Experiments and results

Let the venture fund get 5 start-ups of transport projects submitted by teams of developers – $X = (x^1, x^2, ..., x^5)$, which should be evaluated, bring the rating of the successful implementation of the project by the team and build their ranking line. All considered developers of the start-up projects are real, and data is taken from the university incubators (Uzhhorod National University and Technical university of Kosice). We evaluate according to the developed neuro-fuzzy model and constructed general algorithm.

1st step. The teams were expertly evaluated and received the following input scores. Table 2.

Table 2. Input signals by evaluation criteria

Name criteria	x^1		x^2		x^3		x^4		x^5	
	L	d	L	d	L	d	L	d	L	d
K_{11}	B	0,8	C	0,7	H	0,9	B	0,9	H	0,6
K_{12}	C	0,9	C	0,6	HC	0,8	C	0,8	HC	0,7
K_{21}	B	0,7	H	0,5	C	0,8	B	0,7	B	0,5
K_{22}	C	0,8	HC	0,8	C	0,7	C	0,9	HC	0,8
K_{23}	HC	0,6	HC	0,6	C	0,8	B	0,9	HC	0,6
K_{24}	C	0,5	C	0,8	C	0,6	C	0,8	C	0,9
K_{25}	C	0,7	HC	0,9	C	0,7	HC	0,7	C	0,8
K_{31}	HC	0,8	HC	0,8	B	0,8	HC	0,9	C	0,9
K_{32}	B	0,9	H	0,8	B	0,6	B	0,9	H	0,8
K_{33}	B	0,9	B	0,9	B	0,7	B	0,6	H	0,7
K_{34}	C	0,8	HC	0,8	C	0,8	HC	0,8	C	0,9

2nd step. Person who makes the decision sets his own wishes for the synaptic scales of the criteria (8; 9; 8; 10; 9; 10; 7; 8; 6; 7; 9) $\in [1;10]$, synaptic weights of subgroups for the second group of criteria – (10; 8) $\in [1;10]$ and synaptic scales of the criteria groups – (10; 9; 8) $\in [1;10]$.

3rd step. We perform fuzzification of the input signals in the neurons of the first layer. To do this, we define the membership function on a numerical interval $[0;10]$, where $H \in [0;2]$, $HC \in [2;5]$, $C \in [5;8]$, $B \in [8;10]$. We use formula (3) and get the value of the membership function $\mu(O_{ij}^k)$, the result will be written in Table 3.

4th step. We calculate the output of the neuron by the activation function (14): $Z^1 = 0{,}7383$; $Z^2 = 0{,}4238$; $Z^3 = 0{,}5223$; $Z^4 = 0{,}7381$; $Z^5 = 0{,}3613$.

5th step. Defuzzification of data and ranking of start-up teams:

"team rating x^1 – higher than the average"; "team rating x^2 – average"; "team rating x^3 – average"; "team rating x^4 – higher than the average"; "team rating x^5 – low".

Table 3. Fuzzification of input signals

Name criteria	x^1	x^2	x^3	x^4	x^5
K_{11}	0,920	0,613	0,065	0,980	0,029
K_{12}	0,843	0,461	0,320	0,741	0,245
K_{21}	0,820	0,020	0,741	0,820	0,500
K_{22}	0,741	0,320	0,613	0,843	0,320
K_{23}	0,180	0,180	0,741	0,980	0,180
K_{24}	0,320	0,741	0,461	0,741	0,843
K_{25}	0,613	0,405	0,613	0,245	0,741
K_{31}	0,320	0,320	0,920	0,405	0,843
K_{32}	0,980	0,051	0,680	0,980	0,051
K_{33}	0,980	0,980	0,820	0,680	0,039
K_{34}	0,741	0,320	0,741	0,320	0,843

6th step. Based on the initial estimates, we build a ranking line-up of start-up project developers: $Z = (x^1, x^4, x^3, x^2, x^5)$. We conclude that the best team of developers submitted the start-up of the project – x^1 with a rating higher than the average.

9 Discussion of results

The informational neuro-fuzzy model of the output of the start-up team's ranking has been constructed with a number of advantages, namely: raises the objectivity of expert assessments in the evaluation of teams of developers, using incoming linguistic variables and "confidence factor" expert opinion on their assignment; based on a neuro-fuzzy network that has the ability to change the settings of synaptic weights: criteria and groups of criteria for evaluating teams of developers; when receiving experimental data, we can conduct neuro-fuzzy network training by completing the knowledge base and adjusting the rankings of teams of developers of start-up projects.

The disadvantages of this approach can be attributed to the fact that the acquired membership function in the neuro-fuzzy network corresponds to the stage of rough debugging. Therefore, the process of debugging a neuro-fuzzy network, which depends on the partition of the interval $[a_1; a_5]$ possible if there, is a sample of reliable experimental data. In addition, the learning process of the neuro-fuzzy network requires a large amount of real reliable data from the teams of developers and the results of the successful implementation of the start-up projects.

10 Conclusion

The research of the actual task of the development of an information model of assessment and output of the start-up team rating was conducted using neuro-fuzzy network. To do this, the following tasks were solved. For the first time, a four-layer neuro-fuzzy model was developed to obtain a resultant estimate. The production rules of the fuzzy knowledge base are formulated. The model does not require much computation, reveals the subjectivity of expert opinions and displays the rating of teams of developers. The approach to training developed by the neuro-fuzzy network of team start-up evaluation and the method of forming the knowledge base by generating new production rules are given. A general 5-step algorithm for constructing a rating and rank-starter commands is described. For the information model, for the first time, a set of 11 criteria for evaluating start-up project teams has been formed, classified them into 3 groups and presents the input data in the form of 4 linguistic terms and the expert confidence coefficient for their assignment. For the first time, there are 5 levels of developer team rankings. The research has been tested and the results of the verification have been verified on the real data of five teams of start-up project developers.

The developed neuro-fuzzy informational model will be a useful tool for substantiating the choice of teams by investors for the implementation of their projects. Further study of the problems we see in approbation of the developed model on a large sample to increase the knowledge base and the accuracy of the evaluation.

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