Fuzzy Expert System of the Decision Making Support on Foreign Direct Investment

Eugene E. Fedorov[1] [a], Liubov O. Kibalnyk[2] [b], Lesya O. Petkova[1] [c], Maryna M. Leshchenko[1] [d] and Vladyslav M. Pasenko[1] [e]

[1] *Cherkasy State Technological University, 460 Shevchenko Blvd., Cherkasy, 18006, Ukraine*

[2] *The Bohdan Khmelnytsky National University of Cherkasy, 81 Shevchenko Blvd., Cherkasy, 18031, Ukraine*

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Abstract: The fuzzy expert decision support system for foreign direct investment was developed in the research. A quality criterion was chosen for the proposed fuzzy expert system, which considers the created fuzzy expert system's specifics and allows assessing the probability of future decisions. A metaheuristic method was created based on an adaptive gravitational search algorithm to determine the parameters of the proposed fuzzy expert system. A numerical study was carried out; the parameters of membership functions for linguistic input variables were determined; the parameters of the membership functions for the values of the linguistic output variable were determined. The proposed optimization method based on swarm metaheuristics and a fuzzy expert system make it possible to intellectualize the technology of making decisions on foreign direct investment.

1 INTRODUCTION

The decision-making systems for foreign direct investment are very popular nowadays. The regression (Milovanović and Marković, 2022) and autoregressive (Kurecic and Kokotovic, 2017) methods are usually used to create decision-making systems for foreign direct investment based on machine learning. The construction of only linear models is the disadvantage of such methods. The knowledge base (most often in the form of production rules) and an inference mechanism are used to create decision-making systems for foreign direct investment based on expert systems (Šamanović et al., 2010). The disadvantages of such systems include the fact that they operate only with quantitative estimates, while it is easier for the operator to work with qualitative estimates.

The fuzzy expert systems are currently used to simplify the interaction between a human and a computer system. These expert systems usually use the Larsen, Mamdani, Tsukamoto, and Sugeno fuzzy inference mechanisms (Ruan, 1997; Tsoukalas and Uhrig, 1997).

The disadvantages of such systems include the fact that the procedure for determining their parameters is not automated (Abe, 1997; Rotshtein et al., 2001). The optimization methods are currently actively used to determine the parameters of fuzzy expert systems.

Modern optimization methods suffer from one or more of the following disadvantages:

- have high computational complexity;
- fall into a local extremum with a high probability;
- do not guarantee convergence.

In this regard, there is an actual problem of optimization methods' insufficient efficiency.

Metaheuristics (modern heuristics) are used to speed up finding a quasi-optimal solution to optimization problems and reduce the probability of hitting a local extremum (Talbi, 2009; Engelbrecht, 2007; Yu and Gen, 2010; Nakib and Talbi, 2017; Yang, 2018a; Subbotin et al., 2016). Metaheuristics expand the possibilities of heuristics by combining heuristic methods based on a high-level strategy (Blum and Raidl, 2016;

[a] https://orcid.org/0000-0003-3841-7373
[b] https://orcid.org/0000-0001-7659-5627
[c] https://orcid.org/0000-0003-4519-3726
[d] https://orcid.org/0000-0002-0210-9582
[e] https://orcid.org/0000-0002-7411-2625

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Glover and Kochenberger, 2003; Yang, 2018b; Martí et al., 2018; Gendreau and Potvin, 2019).

Modern metaheuristics suffer from one or more of the following disadvantages:

- insufficient method accuracy (Alba et al., 2013);
- there is only an abstract description of the method or the description of the method is focused on solving only a specific problem (Doerner et al., 2007);
- the procedure for determining parameter values is not automated (Grygor et al., 2019);
- the influence of the iteration number on the solution search process is not taken into account (Bozorg-Haddad, 2017);
- there is no possibility to solve problems of conditional optimization (Fedorov et al., 2019);
- there is no possibility to use non-binary potential solutions (Radosavljević, 2018);
- the method convergence is not guaranteed (Chopard and Tomassini, 2018).

In this regard, the problem of constructing efficient metaheuristic optimization methods arises (Du and Swamy, 2016; Brownlee, 2011).

One of the popular metaheuristics is the gravitational search algorithm (Rashedi et al., 2009), which belongs to swarm metaheuristics.

The task of building fuzzy expert systems that use the method of parametric identification for adaptation and tuning is actual for our research.

The *goal* of this research is to improve the efficiency of decisions on foreign direct investment by creating a fuzzy expert system trained based on metaheuristics.

The following tasks were set and solved:

1) to develop a fuzzy expert decision support system for foreign direct investment;
2) to select a quality criterion for the proposed fuzzy expert system;
3) to create a metaheuristic method based on an adaptive gravitational search algorithm to determine the proposed fuzzy expert system parameters;
4) to conduct numerical research.

2 THE FUZZY EXPERT DECISION SUPPORT SYSTEM FOR FOREIGN DIRECT INVESTMENT

The foreign direct investment analysis is based on the data of the GDP per capita volume, inflation rates, goods and services exports volume, and labor force indicators. To make decisions on foreign direct investment, a fuzzy expert system is proposed. It involves the following steps:

1) linguistic variables formation;
2) fuzzy knowledge base formation;
3) Mamdani fuzzy inference mechanism formation:
   - fuzzification;
   - sub-conditions aggregation;
   - conclusions activation;
   - aggregation of conclusions;
   - defuzzification.
4) identification of parameters based on metaheuristics.

2.1 Linguistic Variables Formation

The following input variables were chosen:

- the volume of gross domestic product (GDP) per capita (per year, US dollars), x_1;
- the inflation indicator (according to the consumer price index, which reflects the annual percentage change in the cost for the average consumer of purchasing a goods and services basket, per year, %), x_2;
- the volume of goods and services export indicator (total volume, per year, USD), x_3;
- the labor force indicator (labor force is people aged 15 and over who provide labor for the production of goods and services, per year, number of people), x_4.

The following indicators were chosen as linguistic input variables. They are qualitative indicators:

- the GDP volume $\tilde{x}_1$ with values $\widetilde{\alpha}_{11} = little$, $\widetilde{\alpha}_{12} = medium$, $\widetilde{\alpha}_{13} = much$, where the ranges are fuzzy sets $\tilde{A}_{11} = \{(x_1, \mu_{\tilde{A}_{11}}(x_1))\}$, $\tilde{A}_{12} = \{(x_1, \mu_{\tilde{A}_{12}}(x_1))\}, \tilde{A}_{13} = \{(x_1, \mu_{\tilde{A}_{13}}(x_1))\}$;
- the inflation indicator $\tilde{x}_2$ with values $\widetilde{\alpha}_{21} = little$, $\widetilde{\alpha}_{22} = medium, \widetilde{\alpha}_{23} = much$, where the ranges are fuzzy sets $\tilde{A}_{21} = \{(x_2, \mu_{\tilde{A}_{21}}(x_2))\}$, $\tilde{A}_{22} = \{(x_2, \mu_{\tilde{A}_{22}}(x_2))\}, \tilde{A}_{23} = \{(x_2, \mu_{\tilde{A}_{23}}(x_2))\}$;

- the volume of goods and services export indicator $\tilde{x}_3$ with values $\widetilde{\alpha}_{31} = little$, $\widetilde{\alpha}_{32} = medium$, $\widetilde{\alpha}_{33} = much$, where the ranges are fuzzy sets $\tilde{A}_{31} = \{(x_3, \mu_{\tilde{A}_{31}}(x_3))\}$, $\tilde{A}_{32} = \{(x_3, \mu_{\tilde{A}_{32}}(x_3))\}$, $\tilde{A}_{33} = \{(x_3, \mu_{\tilde{A}_{33}}(x_3))\}$;
- the labor force indicator $\tilde{x}_4$ with values $\widetilde{\alpha}_{41} = little$, $\widetilde{\alpha}_{42} = medium$, $\widetilde{\alpha}_{43} = much$, where the ranges are fuzzy sets $\tilde{A}_{41} = \{(x_4, \mu_{\tilde{A}_{41}}(x_4))\}$, $\tilde{A}_{42} = \{(x_4, \mu_{\tilde{A}_{42}}(x_4))\}$, $\tilde{A}_{43} = \{(x_4, \mu_{\tilde{A}_{43}}(x_4))\}$.

The volume of foreign direct investment (net flows for the year, USD) was chosen as a clear output variable $\tilde{y}$. It is a qualitative indicator.

The volume of foreign direct investment was chosen $\underset{\sim}{\tilde{y}}$ with its values $\widetilde{\beta}_1 = little$, $\widetilde{\beta}_2 = medium$, $\widetilde{\beta}_3 = much$, where the ranges are fuzzy sets $\tilde{B}_1 = \{(y, \mu_{\tilde{B}_1}(y))\}$, $\tilde{B}_2 = \{(y, \mu_{\tilde{B}_{42}}(y))\}$, $\tilde{B}_3 = \{(y, \mu_{\tilde{B}_3}(y))\}$;

2.2 Fuzzy Knowledge Base Formation

Fuzzy knowledge is represented as the following fuzzy rules that contain a linguistic output variable R^n : IF $\tilde{x}_1$ is $\tilde{a}_{1i}$ AND $\tilde{x}_2$ is $\tilde{a}_{2j}$ AND $\tilde{x}_3$ is $\tilde{a}_{3k}$ AND $\tilde{x}_4$ is $\tilde{a}_{4p}$ then $\tilde{y}$ is $\tilde{B}_m$

In the case of linguistic variables specific values, fuzzy knowledge is presented in relational form in table 1.

Table 1: Relational form of fuzzy knowledge representation.

The rule	$\tilde{x}_1$	$\tilde{x}_2$	$\tilde{x}_3$	$\tilde{x}_4$	$\tilde{y}$
R^1	$\widetilde{\alpha}_{11}$	$\widetilde{\alpha}_{21}$	$\widetilde{\alpha}_{31}$	$\widetilde{\alpha}_{41}$	$\widetilde{\alpha}_1$
R^2	$\widetilde{\alpha}_{12}$	$\widetilde{\alpha}_{21}$	$\widetilde{\alpha}_{31}$	$\widetilde{\alpha}_{41}$	$\widetilde{\alpha}_1$
R^3	$\widetilde{\alpha}_{13}$	$\widetilde{\alpha}_{21}$	$\widetilde{\alpha}_{31}$	$\widetilde{\alpha}_{41}$	$\widetilde{\alpha}_2$
R^4	$\widetilde{\alpha}_{11}$	$\widetilde{\alpha}_{22}$	$\widetilde{\alpha}_{31}$	$\widetilde{\alpha}_{41}$	$\widetilde{\alpha}_2$
...	...	...	...	...	...
R^{81}	$\widetilde{\alpha}_{13}$	$\widetilde{\alpha}_{23}$	$\widetilde{\alpha}_{33}$	$\widetilde{\alpha}_{43}$	$\widetilde{\alpha}_3$

2.3 Mamdani Fuzzy Inference Mechanism Formation

2.3.1 Fuzzification

We will determine the truth degree of each sub-condition of each rule, using the membership function $\mu_{\tilde{A}_{ij}}(x_i)$.

As membership functions of sub-conditions, we chose:

- piecewise linear Z-shaped function, i.e.

$$\mu_{\tilde{A}_{i1}}(x_i) = \begin{cases} 1, & x_i \le a_i \\ \frac{b_i - x_i}{b_i - a_i}, & a_i < x_i < b_i \\ 0, & x_i \ge b_i \end{cases}, i \in \overline{1,4}$$

- piecewise linear Π-shaped function, i.e.

$$\mu_{\tilde{A}_{i2}}(x_i) = \begin{cases} 0, & x_i \le a_i \\ \frac{x_i - a_i}{b_i - a_i}, & a_i \le x_i \le b_i \\ 1, & b_i \le x_i \le c_i \\ \frac{d_i - x_i}{d_i - c_i}, & c_i \le x_i \le d_i \\ 0, & x_i \ge d_i \end{cases}, i \in \overline{1,4}$$

- piecewise linear S-shaped function, i.e.

$$\mu_{\tilde{A}_{i3}}(x_i) = \begin{cases} 0, & x_i \le c_i \\ \frac{x_i - c_i}{d_i - c_i}, & c_i < x_i < d_i \\ 1, & x_i \ge d_i \end{cases}, i \in \overline{1,4},$$

where a_i, b_i, c_i, d_i - membership function parameters.

2.3.2 Sub-Condition Aggregation

The condition membership functions for each rule R^n are determined based on the minimum value method:

$$\mu_{\bigcup_{i=1}^{4} \tilde{A}_{i,f(n,i)}}(x_1, x_2, x_3, x_4) = \underset{i \in \overline{1,4}}{min} \left\{ \mu_{\tilde{A}_{i,f(n,i)}}(x_i) \right\},$$

where f – a function that returns the value number of the i-th linguistic input variable of the n-th rule and is determined on the basis of table 1. For example, if the linguistic input variable $\tilde{x}_1$ rules R^{81} matters $\widetilde{\alpha}_{13}$, then $f(81,1) = 3$.

2.3.3 Activation of Conclusions

The membership functions of the conclusion for each rule R^n are determined based on the minimum value method (based on the Mamdani rule):

$$\mu_{\tilde{B}_{g(n)}}(y) = \min \left\{ \mu_{U_{i=1}^{4} \tilde{A}_{i,f(n,i)}}(x_1, x_2, x_3, x_4), \mu_{\tilde{B}_{g(n)}}(y) \right\},$$

where g – a function that returns the value number of the linguistic output variable of n-th rule and determined on the basis of table 1.

For example, if the linguistic output variable $\tilde{y}$ of the rule R^{81} is $\widetilde{\beta}_3$, then $g(81) = 3$.

A piecewise linear triangular function was chosen as the membership functions of the conclusions, i.e.

$$\mu_{\tilde{B}_m}(y) = \begin{cases} 0, & y \le e_m \\ \frac{y - e_m}{u_m - e_m}, & e_m \le y \le u_m \\ \frac{v_m - y}{v_m - u_m}, & u_m \le y \le v_m \\ 0, & y \ge v_m \end{cases}, m \in \overline{1,3},$$

where e_m, u_m, v_m – membership function parameters.

In the case of such a membership function, the kernel of each fuzzy set $\tilde{B}_m$ is:

$$\ker \tilde{B}_m = \{ y \in Y | \mu_{\tilde{B}_m}(y) = 1 \} = \{u_m\}.$$

2.3.4 Aggregation of Conclusions

The membership functions of the final conclusion are defined, which contains a linguistic output variable based on the maximum value method:

$$\mu_{\tilde{B}_m}(Y) = \max_{n \in 1,81} \{\mu_{\tilde{B}_g(n)}(y)\}$$

2.3.5 Defuzzification

The volumes of foreign direct investment are determined basedon the centroid method:

$$y^* = \frac{\sum_{y \in Y} \mu_{\tilde{B}}(y) y}{\sum_{y \in Y} \mu_{\tilde{B}}(y)}, Y = \{1,2,3\}$$

3 QUALITY CRITERION FOR THE PROPOSED FUZZY EXPERT SYSTEM

The objective function is chosen as a quality criterion, representing the accuracy as probability of correct foreign direct investment

$$F = \frac{1}{P} \sum_{p=1}^{P}, [y_p = d_p] \to \max_{\theta},$$
$$[p = q] = \begin{cases} 1, & p = q \\ 0, & p \neq q \end{cases}, \quad (1)$$

where d_p – test foreign direct investment,

y_p – foreign direct investment received as a result of fuzzy inference,

P – number of test implementations,

$\theta = (a_1, b_1, c_1, d_1, ..., a_4, b_4, c_4, d_4, e_1, u_1, v_1, ..., e_3, u_3, v_3)$ – parameter vector of membership functions.

4 METAHEURISTIC METHOD BASED ON AN ADAPTIVE GRAVITATIONAL SEARCH ALGORITHM FOR DETERMINING THE PARAMETERS OF THE PROPOSED FUZZY EXPERT SYSTEM

The particle velocity (not the gravitational constant) depends on the iteration number in this method, which provides control over the convergence rate of the method, as well as providing a global search at the initial iterations, and a local search at the final iterations. The parameter vector of membership functions corresponds to the position vector of one particle x. The quality criterion is used as the goal function (1).

1. Initialization.

1.1. Setting the gravitational constant G, the maximum number of iterations N, the population size K, the length of the particle position vector M (it corresponds to the length of the parameter vector of membership functions and is equal to 25), the minimum and maximum values for the position vector $x_j^{\min}$, $x_j^{\max}$, $j \in \overline{1,M}$, the minimum and maximum values for the velocity vector $v_j^{\min}$, $v_j^{\max}$, $j \in \overline{1,M}$.

1.2. The best position vector randomly generating $x^* = (x_1^*, ..., x_M^*)$,
$x_j^* = x_j^{\min} + (x_j^{\max} - x_j^{\min}) U(0,1)$,
where $U(0,1)$ – a function that returns a uniformly distributed random number in a range $[0,1]$.

1.3. The initial population creation

1.3.1. Particle number $k = 1$, $P = \emptyset$.

1.3.2. A position vector at random x_k generating $x_k = (x_{k1}, ..., x_{kM})$,
$x_{kj} = x_j^{\min} + (x_j^{\max} - x_j^{\min}) U(0,1)$.

1.3.3. Random velocity vector v_k generating $v_k = (v_{k1}, ..., v_{kM})$,
$v_{ij} = v_j^{\min} + (v_j^{\max} - v_j^{\min}) U(0,1)$.

1.3.4. If $(x_k, v_k) \notin P$, then $P = P \cup \{(x_k, v_k)\}$, $k = k + 1$.

1.3.5. If $k \le K$, then go to step 1.3.2.

2. Iteration number $n = 1$.

3. The computation of the best and worst particle of a population from a target function

$$l = arg\min_k F(x_k), x^{best} = x_l,$$
$$l = arg\max_k F(x_k), x^{worst} = x_l.$$

4. The computation of all particles masses.

5. The computation of the gravitational force acting between all pairs of particles

5.1. $m_k = G \frac{F(x_k) - F(x^{worst})}{F(x^{best}) - F(x^{worst})}, k \in \overline{1,K}$.

5.2. $M_k = \frac{m_k}{\sum_{s=1}^{K} m_s}, k \in \overline{1,K}$.

6. The computation of the gravitational force acting between all pairs of particles

$$f_{kl} = G \frac{M_k M_l}{d(x_k, x_l) + \varepsilon} (x_l - x_k), k, l \in \overline{1,K},$$

where $d(x_k, x_l)$ – distance between particles k and l (e.g. Euclid distance).

7. The computation of the resulting force acting on all particles

$$r_{kl} = U(0,1), k,l \in \overline{1,K}$$

$$f_k = \sum_{\substack{l=1 \\ l \neq k}}^{K} r_{kl} f_{kl}, k \in \overline{1,K}$$

8. Modification of the acceleration of all particles

$$a_k = \frac{f_k}{M_k}, k \in \overline{1,K}$$

9. Speed modification of all particles

$$r_k = U(0,1), k \in \overline{1,K}$$

$$v_k = r_k v_k + a_k, k \in \overline{1,K}$$

10. Modification all of the particles' position, taking into account the iteration number
    10.1. $x_k = x_k + v_k \left(1 - \frac{n}{N}\right), k \in \overline{1,K}$
    10.2. $x_{kj} = \max\{x_j^{\min}, x_{kj}\}, x_{kj} = \min\{x_j^{\max}, x_{kj}\}, j \in \overline{1,M}, k \in \overline{1,K}$
11. If $n < N$, then $n = n + 1$, go to step 3
    The result is x^*.

5 NUMERICAL RESEARCH

Numerical research was carried out using the Keras submodule of the TensorFlow module. The Pandas module was used to fill in missing values through linear interpolation, as well as for tabular data I/O operations. The Scikit-fuzzy module was used to create a fuzzy expert system.

The fuzzy expert system was researched using the World Bank economic indicators database (https://databank.worldbank.org/home.aspx). The economic indicators of 145 countries for 10 years were used. The size of the original sample was 1450.

For the proposed adaptive gravity search algorithm, the gravity constant G was 100, the maximum number of iterations was 1000, and the population size was 50.

The comparison results of the proposed fuzzy expert system with the operator are presented in table 2.

Table 2: Comparison results of the proposed fuzzy expert system with an operator.

Accuracy	
fuzzy expert system	operator
0.98	0.8

The comparison results of the proposed fuzzy expert system with the proposed meta-heuristic adaptive gravitational search algorithm (AGSA) and the traditional meta-heuristic adaptive gravitational search algorithm (AGSA) operator are presented in table 3.

Table 3: Comparison results of the proposed fuzzy expert system of the proposed meta-heuristic and the traditional meta-heuristic.

Accuracy	
GSA	AGSA
0.93	0.98

Figure 1 shows the accuracy for the proposed fuzzy expert system trained based on the proposed meta-heuristic adaptive gravitational search algorithm (AGSA) and on the proposed meta-heuristic gravitational search algorithm (GSA).

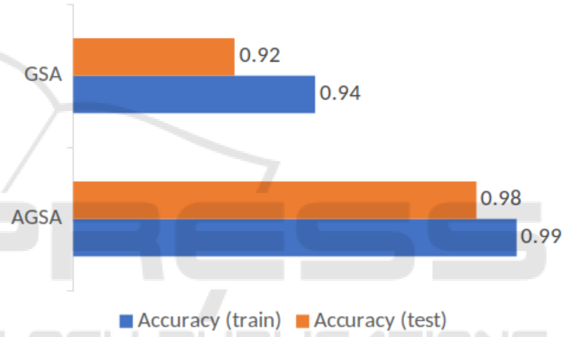

Figure 1: Accuracy of the proposed fuzzy expert system with GSA and AGSA.

The comparison results of the proposed fuzzy expert system trained on the basis of back-propagation (BP) and the proposed meta-heuristic adaptive gravitational search algorithm (AGSA) are presented in table 4.

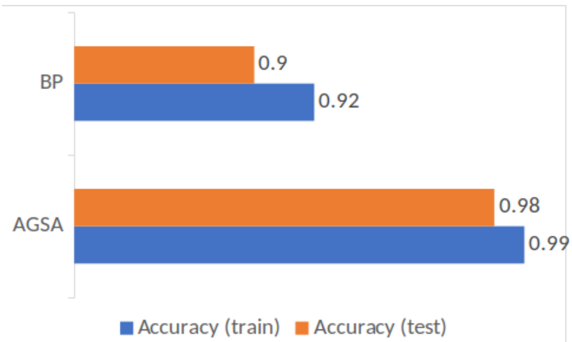

Figure 2: Accuracy of the proposed fuzzy expert system with BP and AGSA.

Figure 2 shows the accuracy for the proposed

Table 4: Comparison results of the proposed fuzzy expert system based on the back-propagation method and proposed meta-heuristic.

Accuracy	
BP	AGSA
0.90	0.98

fuzzy expert system trained on the basis of back-propagation (BP) and the proposed meta-heuristic adaptive gravitational search algorithm (AGSA).

Figures 3-7 shows the membership functions for the values of linguistic variables $\tilde{x}_1$, $\tilde{x}_2$, $\tilde{x}_3$, $\tilde{x}_4$ and y.

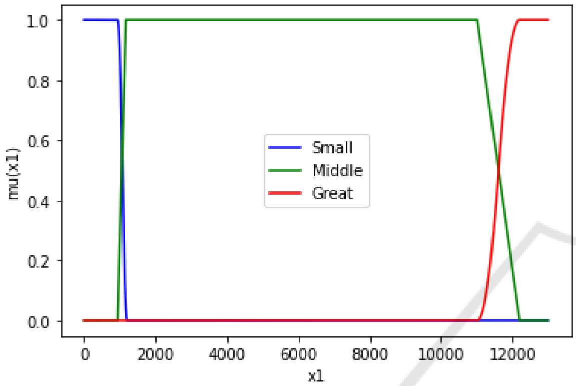

Figure 3: Membership functions for linguistic variable values $\tilde{x}_1$.

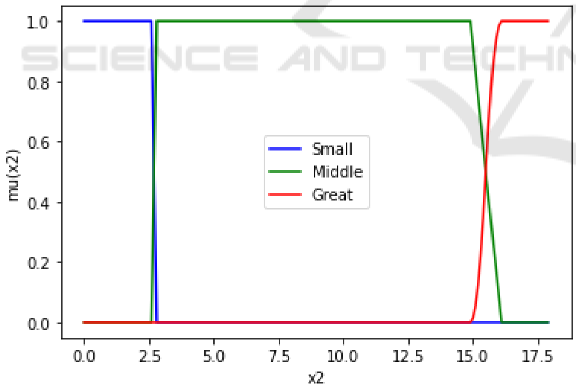

Figure 4: Membership functions for linguistic variable values $\tilde{x}_2$.

6 DISCUSSION

The traditional non-automatic approach to assessing the foreign direct investment effectiveness reduces the accuracy of a correct assessment (table 2). The proposed method eliminates this disadvantage.

The traditional method of the gravitational search algorithm ignores the iteration number during the particle position calculating; this reduces the accuracy of

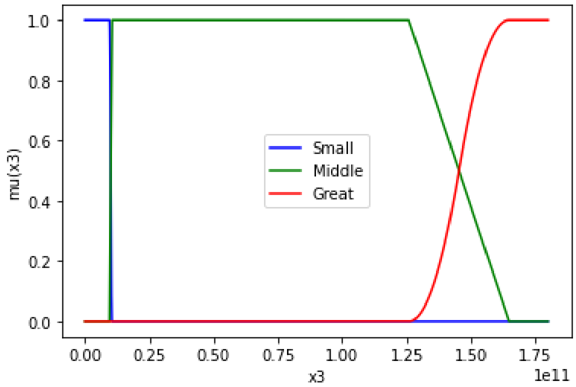

Figure 5: Membership functions for linguistic variable values $\tilde{x}_3$.

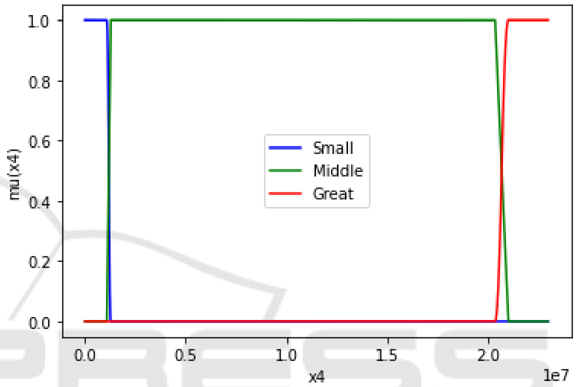

Figure 6: Membership functions for linguistic variable values $\tilde{x}_4$.

finding a solution (table 3); requires a large number of parameters associated with the gravitational constant calculating. The proposed method eliminates these shortcomings.

The traditional approach to training a fuzzy expert system based on back propagation reduces the probability of correct estimation (table 4). The proposed method eliminates this disadvantage.

7 CONCLUSIONS

1. Relevant optimization methods and expert systems were investigated as part of the decision-making technology for foreign direct investment. The research results showed that the most effective is the use of fuzzy expert systems, the parameters of which are identified by means of meta-heuristic methods today.
2. A fuzzy expert decision support system for foreign direct investment has been developed. The proposed system simplifies the interaction between the operator and the computer system

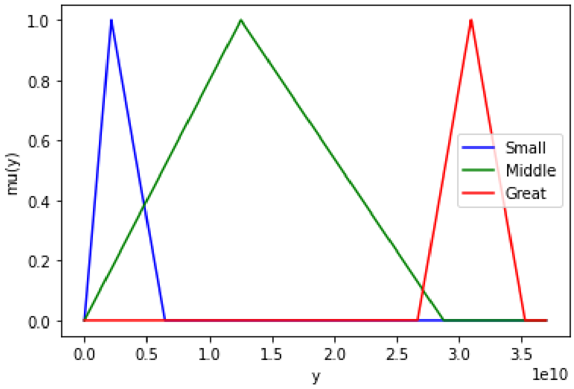

Figure 7: Membership functions for linguistic variable values $\tilde{y}$.

through the use of qualitative indicators, and also allows to identify its parameters using the proposed swarm metaheuristics.

3. A quality criterion is proposed; it considers the specifics of the created fuzzy expert system and allows assessing of the decisions accuracy.

4. A swarm metaheuristic algorithm based on an adaptive gravitational search algorithm has been created; it provides control over the rate of method convergence, as well as providing global search at the initial iterations, and local search at the final iterations due to adaptive control of the particle velocity.

5. The proposed optimization method based on swarm metaheuristics and a fuzzy expert system make it possible to intellectualize the technology of making decisions on foreign direct investment. Prospects for further research involve testing the proposed method and system on a wider test database set.

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