

This paper considers objects that affect the social security of the country. The complexity of such objects makes the development of computer systems in sociological research a difficult algorithmic task because of information uncertainty. Human thinking is based on inaccurate, approximate data, the analysis of which makes it possible to formulate clear decisions. In practice, there are usually no precise mathematical models that describe social objects. In such cases, it is advisable to use fuzzy mathematics as a tool for solving this problem. The main advantage of this approach compared to other artificial intelligence methods is the ability to interpret the results obtained. To assess the level of social well-being of the population, we used the mathematical apparatus of fuzzy set theory and fuzzy inference. The study is based on the OECD Better Life Index, which was developed by the Organization for Economic Cooperation and Development (OECD) to help countries assess and improve the quality of life of their citizens. In the course of the study, a fuzzy inference system was built to measure the social well-being of the population based on the indicators of the OECD Better Life Index. Since determining the level of social well-being is a complex task, a hierarchical structure with two main groups of social well-being indicators was constructed to simplify it. The resultant system evaluates each social indicator included in the OECD's Better Life Index. Using the fuzzy inference model built, it was possible to assess the social well-being of the country's population in a simple and transparent way in comparison with the OECD member countries. The results of the study make it possible to understand which indicators of social well-being of the country's population are desirable or need to be improved in the future

Keywords: *fuzzy sets, social well-being, fuzzy modelling, FIS-tree, fuzzy inference system*

BUILDING A FUZZY MODEL FOR DETERMINING THE LEVEL OF SOCIAL WELL-BEING OF THE POPULATION

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1. Introduction

Active implementation of digital technologies in the modern world demonstrates successful results. Current information technologies are widely used in many domains of human activity, in particular, they are intensively implemented in the everyday practice of sociological research.

One of the components of the national security of any country is social security. It represents a state of protection of the social interests and needs of the individual, society, and the state against the influence of internal and external threats within the defined limit values that may pose a threat to the national security of the state. Social security is a complex multifactorial category that characterizes the state of protection of the social interests of a person, business entities, society, and the state as a whole. Social security, as a rule, can be expressed through a system of parameters and indicators. Parameters of social security include a specific set of characteristics of social security as a social phenomenon while indicators define specific quantitative values of the corresponding parameters [1].

Under today's conditions, when there is a war in Ukraine, researching the level and quality of life of the population is an urgent problem. The standard of living is a multifaceted concept that reflects the level of social needs and covers a wide

range of socio-economic relations. The central place in the system of determining the standard of living of the population is occupied by income indicators as the main source of satisfying personal needs in goods and services and increasing the level of well-being.

In today's fast-changing and stimulating world, well-being cannot be measured only by economic indicators. The multifaceted well-being of the population is illustrated by study [2], in which well-being is defined according to 3 main components: a sense of security, a sense of love, and a sense of self-realization. A sense of security encompasses not only a sense of economic security but also strong mental and physical health. The extent to which, for example, the environment can influence the social well-being of the population is discussed in [3].

The Better Life Index of the Organization for Economic Co-operation and Development (OECD) also uses a number of indicators to compare the well-being of the population in the member countries of the organization. These indicators were used in many scientific works. Paper [4] also examines the indicators of the OECD Better Life Index. The study points to the expansion of the Better Life Index indicators, and not to the comparison of the well-being of the population with countries that are not members of the OECD. In [5], a comparative study has already been conducted, so to speak.

This work examines the OECD Better Living Index from an Italian perspective. Paper [6] considers health-related indicators of the OECD Better Life Index. This work carefully analyzes the Better Life Index indicators for each OECD member country.

Fuzzy modeling is one of the most popular and rapidly developing areas in the field of modern methods for managing objects that are poorly formalized. The use of fuzzy sets is common in sociological research.

Recently, Ukraine and the OECD have had quite close relations. In 2023, the Government of Ukraine and the OECD launched a four-year program aimed at supporting reforms, reconstruction, and recovery of Ukraine, as well as supporting Ukraine's ambitions for membership in the OECD and the EU. Scientific research on this topic is of practical use as it shows which indicators of the social well-being of the population could and should be improved. Given the above, it is a relevant task to carry out a study that uses indicators of the OECD Better Life Index in order to analyze the social well-being of Ukraine's population.

2. Literature review and problem statement

Work [4] examines the indicators of the OECD Better Life Index. The study points to the expansion of the Better Life Index indicators, and not to the comparison of the well-being of the population with countries that are not members of the OECD. In [5], a comparative study has already been carried out, so to speak. This work also examines the OECD Better Living Index from an Italian perspective. Paper [6] provides health-related indicators of the OECD Better Life Index and carefully analyzes the indicators of the Better Life Index for each OECD member country.

Modern research confirms that well-being is a multidimensional concept that includes physical, mental, economic, social, and emotional well-being. For example, study [7] emphasizes that well-being depends on factors such as income, education, health, social relationships, employment, and government policies. These factors affect both the individual level of well-being and the well-being of society as a whole. The work also considers the main components of the social welfare of the population, but they are considered only in an overview form, without using these indicators in applied tasks.

Another important study [8] showed that the concept of subjective well-being (SWB) includes an assessment of personal life and a sense of satisfaction with life. Theories that explain SWB fall into several categories, including performance and involvement, personal orientation, appraisal, and affective theories. The study is also only a survey study of subjective well-being.

To measure well-being, complex composite indicators are devised that take into account different aspects of well-being, in contrast to traditional economic indicators such as GDP. For example, in work [9], a multifactor indicator of psychological well-being is used to assess the individual level of well-being by several criteria at the same time, which makes this approach more informative and accurate. Although the work examines the well-being of the population of Ukraine along with several other European countries, it is not based on the indicators of the OECD Better Life Index.

Study [10] investigated the well-being of the population of Ukraine under the conditions of the COVID-19 pandemic, while the indicators used were mostly of an economic nature.

Another scientific work [11] investigated the well-being of the population of Ukraine using six indicators, including those related to the environment and education. But fuzzy sets are used not only in Ukrainian but also in international sociological research. For example, in work [12], the influence of economic crises on the health of the population was studied with the help of fuzzy sets. As can be seen from the above studies, fuzzy mathematics is widely used in welfare research and other economic research. However, in the above literature, the social welfare of the population is not given or only little attention is given.

Paper [13] examines the economic well-being of the population of Ukraine. However, the level of well-being of the population is determined not only by economic indicators. The comparison of these indicators in different regions of the state makes it possible not only to draw relevant scientific, theoretical, and practical conclusions, but also to model a certain predictive situation regarding the possible socio-economic development of society and the state, both for the near future and over the long term.

Despite the fact that a number of studies on the well-being of the population are based on the OECD Better Life Index, no studies have been found that determine the well-being of the population of Ukraine in comparison with OECD member countries.

3. The aim and objectives of the study

The purpose of our study is to build a system of fuzzy inference, which determines the level of social welfare of the population of Ukraine in comparison with OECD member countries. The construction of such a mathematical model makes it possible to assess the level of well-being of the population of Ukraine in comparison with OECD countries.

To achieve the goal, the following tasks were set:

- to build a hierarchical structure of indicators of social well-being;
- to build a tree-like structure of the fuzzy inference system using MATLAB software;
- to study the indicators of the OECD Better Life Index and build a fuzzy inference system for each indicator;
- to build knowledge bases for each fuzzy inference system;
- to validate operation of the constructed system of fuzzy inference on real data.

4. The study materials and methods

The object of research is the processes affecting the level and quality of life of the population under current conditions.

The main hypothesis of the study is to find out the possibilities of combining statistical and sociological approaches to carry out a quantitative and qualitative analysis of the level of safety of the individual's life activities using the apparatus of fuzzy mathematics on the example of the population welfare indicator.

To build decision-making models for problems that are weakly formalized and operate with statistical and expert information [14], it is advisable to use the theory of fuzzy sets and fuzzy logic systems.

Formalization of expert knowledge through fuzzy sets requires appropriate procedures for constructing membership functions. These procedures are a key stage of decision-making

since the quality of the decision depends on the adequacy of the membership function, which reproduces expert knowledge. The choice of the type of fuzzy set for the construction of membership functions and the corresponding fuzzy model presents the researcher with the task of optimal selection [15].

The task of constructing membership functions is one of the key issues in fuzzy logic; many scientists, starting with the founder of fuzzy logic Zade, addressed it in their research. In fuzzy set theory, the membership function is the main characteristic of a fuzzy object, and all operations on fuzzy objects are performed through their membership functions. Defining the membership function is the first and very important step for further work with fuzzy sets. The membership function can be built on the basis of statistical data or with the participation of an expert or a group of experts. Depending on this, we get a frequency or interpretation with the participation of an expert.

The general interpretation of fuzzy sets for solving practical problems [14] takes the following form:

$$A = \{x, \mu_A(x) \mid x \in X, 0 \leq \mu_A(x) \leq 1\}, \quad (1)$$

where X is the universal set, and $\mu_A(x)$ is the membership function of the element x in the set A , which is a subset of the universal set.

Fuzzy models, which are based on first-order fuzzy sets, use membership functions with distinct values of membership degrees and produce only a point (discrete) value at the output. Various models and algorithms were developed for solving uncertainty problems, such as, for example, the model for evaluating the effectiveness of investment projects [16].

The object of this study is to determine the level of social well-being of the population of Ukraine. The level of social well-being is determined by constructing fuzzy inference systems based on indicators of the OECD Better Life Index.

To solve the given problem, it is proposed to use fuzzy models, which are an adequate application in the field of sociological research and are able to take into account knowledge in terms of descriptive and qualitative data.

The task of sociological research can be stated as the problem of determining the level of belonging to a certain class. Such a problem can be solved by finding a suitable classifier, that is, a mathematical function F , which matches a set of features $X = \{x_1, x_2, \dots, x_n\} = \{x_i, i = 1, n\}$ with a certain class R_{k_j} label:

$$F(X): X \rightarrow R_{k_j}. \quad (2)$$

It is proposed to use a fuzzy modeling approach based on observation data in the form of a level classifier. This approach makes it possible to maintain a compromise between the accuracy of the classification and the interpretation of the obtained result.

The task of classification is to predict the class of an object based on its vector of feature values. Let the set of features $X = \{x_1, x_2, \dots, x_n\} = \{x_i, i = 1, n\}$ and the set of classes $K = \{k_1, k_2, \dots, k_m\} = \{k_j, j = 1, m\}$ be given. The fuzzy level classifier is represented in the form of a function that assigns a class label to a point from the space of input features with a calculated degree of confidence:

$$F(X): X_1 \times X_2 \times \dots \times X_n \rightarrow [0, 1]^n. \quad (3)$$

The basis of the fuzzy classifier is the production rule in the following form:

$$\begin{aligned} R_{pj} : & \text{if } x_1 = A_{1j} \ \& \ x_2 = \\ & = A_{2j} \ \& \dots \ \& \ x_{nj} = A_{nj} \ \text{then } level = R_{k_j}, \end{aligned} \quad (4)$$

where A_{ij} is a linguistic term that characterizes the i -th feature in the j -th rule and is determined by its membership function $\mu_{A_{ij}}(x_i)$ at point x_i , $p = \overline{1, P}$, P is the number of rules.

The class is defined by the rule for which the *If* part maximally corresponds to the description given to the input vector X :

$$level = R_{k_j}, j^* = \arg \max_{1 \leq j \leq m} \prod_{i=1}^n \mu_{A_{ij}}(x_i). \quad (5)$$

The construction of a fuzzy level classifier requires solving the following tasks: selection of informative features, formalization of knowledge, formulation of the base of fuzzy rules, optimization of the parameters of the membership function.

The problem of selecting informative features is to find such input attributes from the data set that most realistically reflect the social state of the environment and the understanding of the result. These can be both statistical and information-theoretic and metaheuristic methods.

Formalization of knowledge is a problem, the solution of which is to build a model that adequately reflects the information of the subject area.

The software of the MATLAB mathematical program package, in particular the Fuzzy Logic Designer application, was used for the research.

In general, logical inference involves four stages:

1. Fuzzification. The membership functions defined for the input variables are applied to their actual values to determine the degree to which each premise of each rule is true.

2. Logical inference. The computed truth value for the premises of each rule is applied to the conclusions of each rule. This results in one fuzzy subset that will correspond to the output variable for each rule. Min (minimum) or prod (multiplication) operations are usually used as logical inference rules.

3. Composition. The fuzzy subsets assigned to each output variable (in all rules) are combined together to form one fuzzy subset for each output variable. With such a combination, the operations max (maximum) or sum (amount) are usually used.

4. Defuzzification – bringing to clarity (i.e., defuzzification). Transforming a fuzzy set of inferences into a number.

The Mamdani algorithm is used in the fuzzy inference system. Mamdani's algorithm consists of the following steps:

1. Fuzzification: measures of truth are found for the premises of each rule.

2. Inference: cut-off levels are found for the prerequisites of each of the rules using the minimum operation, then the truncated membership functions are found.

3. Composition: using the maximum operation, the found truncated functions are combined, which leads to obtaining the final fuzzy subset for the output variable with the membership function.

4. Defuzzification – in our case, it is performed by the method of the center of gravity (the centroid method).

Mamdani's algorithm is illustrated in Fig. 1.

Fig. 1 clearly shows all the steps of the algorithm. There are several defuzzification algorithms. Fig. 1 illustrates the method of defuzzification of the center of gravity. The geometric content of the specified algorithm is to determine the center of gravity for the curve of the membership function of the obtained output.

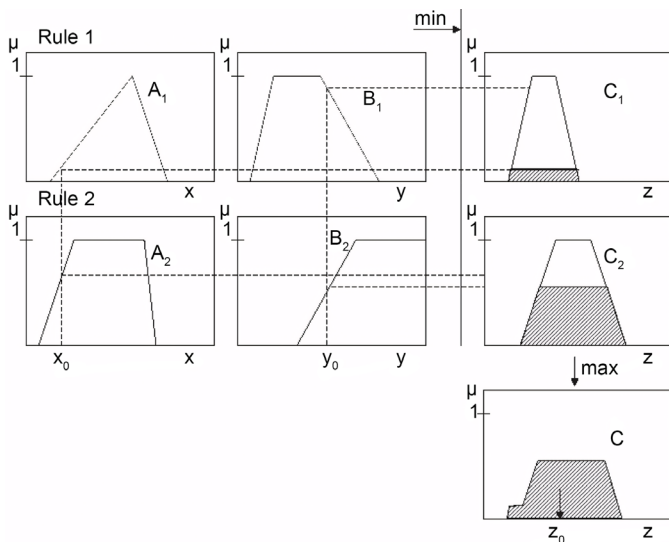


Fig. 1. Mamdani's algorithm [17]

5. Results of the study on determining the level of social well-being of the population

5.1. Building a hierarchical structure of social welfare indicators.

Paper [13] notes that determining the level of welfare of the population is a complex task. To simplify this process, indicators of well-being are divided into three main groups: economic well-being, social well-being, and the state of the environment. As an example, Fig. 2 shows the hierarchical structure of this system.

Fig. 2 demonstrates that social well-being consists of more indicators than economic. That is why it is worth dividing these indicators into two separate groups: basic needs for life (education, health, safety) and public and social indicators (community, civic engagement, life satisfaction). Fig. 3 shows a hierarchical structure for assessing the level of social well-being.

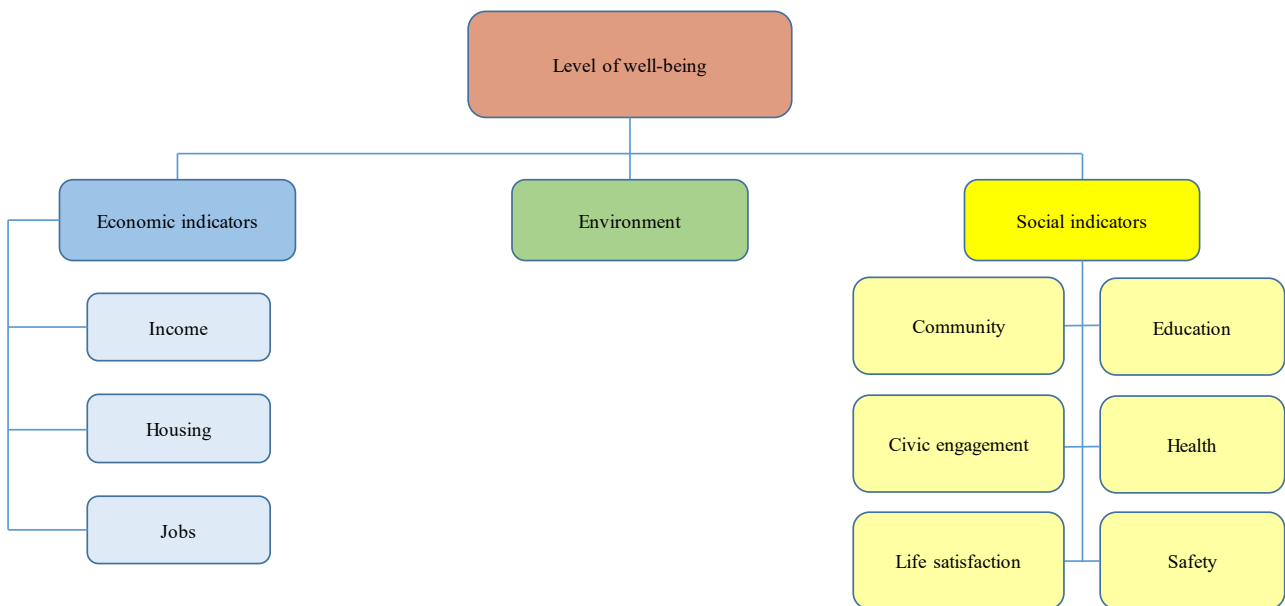


Fig. 2. Hierarchical structure for assessing the level of well-being

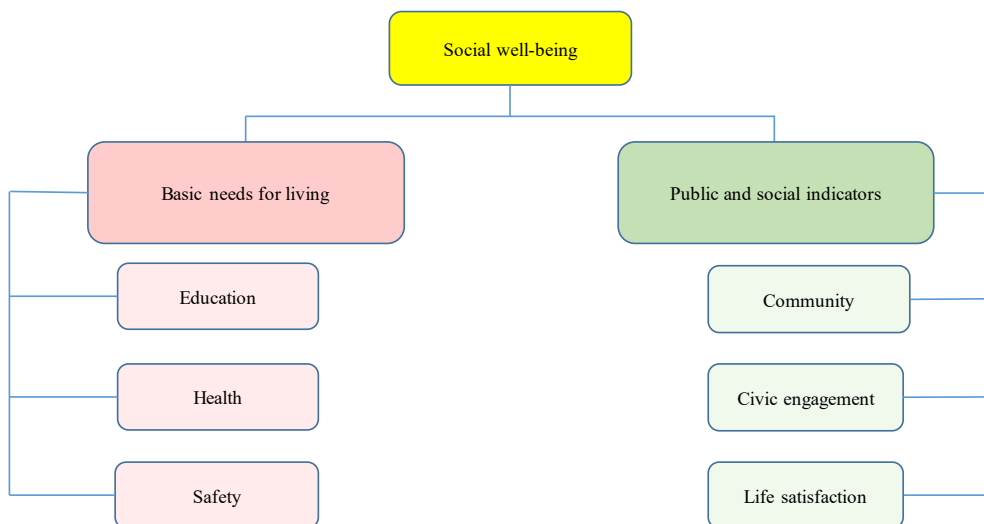


Fig. 3. Hierarchical structure for assessing the level of social well-being

The established hierarchical structure (Fig. 3) will contribute to the correct construction of the tree structure of the fuzzy inference system. Owing to this distribution, it was possible to significantly simplify a rather complex system. Although Fig. 3 does not show it, but these indicators have their own input data. These inputs consist of different quantities for each indicator.

5. 2. Building a tree-like structure of fuzzy inference systems

After building a hierarchical system, we move on to building a system of fuzzy inference in the form of a FIS tree. Each module in the system becomes a fuzzy inference system in the FIS tree. The MATLAB mathematical program package was used to build the FIS tree, and the FIS tree itself is shown in Fig. 4.

Mamdani’s algorithm was used to build a fuzzy inference system. A fuzzy logical conclusion according to the Mamdani algorithm is formed according to formula (6):

$$\bigcup_{p=1}^{k_j} \left(\bigcap_{i=1}^n x_i = a_{i,jp} \text{ with weight } w_{jp} \right) \rightarrow y = d_j, j = \overline{1, m}, \quad (6)$$

where $a_{i,jp}$ is a fuzzy term that evaluates the variable x_i in the line with the number jp ($p = \overline{1, k_j}$); w_{jp} – the weight coefficient of the rule with the ordinal number jp from the range $[0,1]$, which specifies the relative weight of the rule in the case of a fuzzy logical conclusion; d_j is the fuzzy conclusion of the j -th rule (in the Mamdani-type algorithm, the conclusions of the d_j rules are given by fuzzy terms); m is the number of terms used for linguistic assessment of the source variable [18]. Fig. 5 shows a typical structure of a fuzzy inference model.

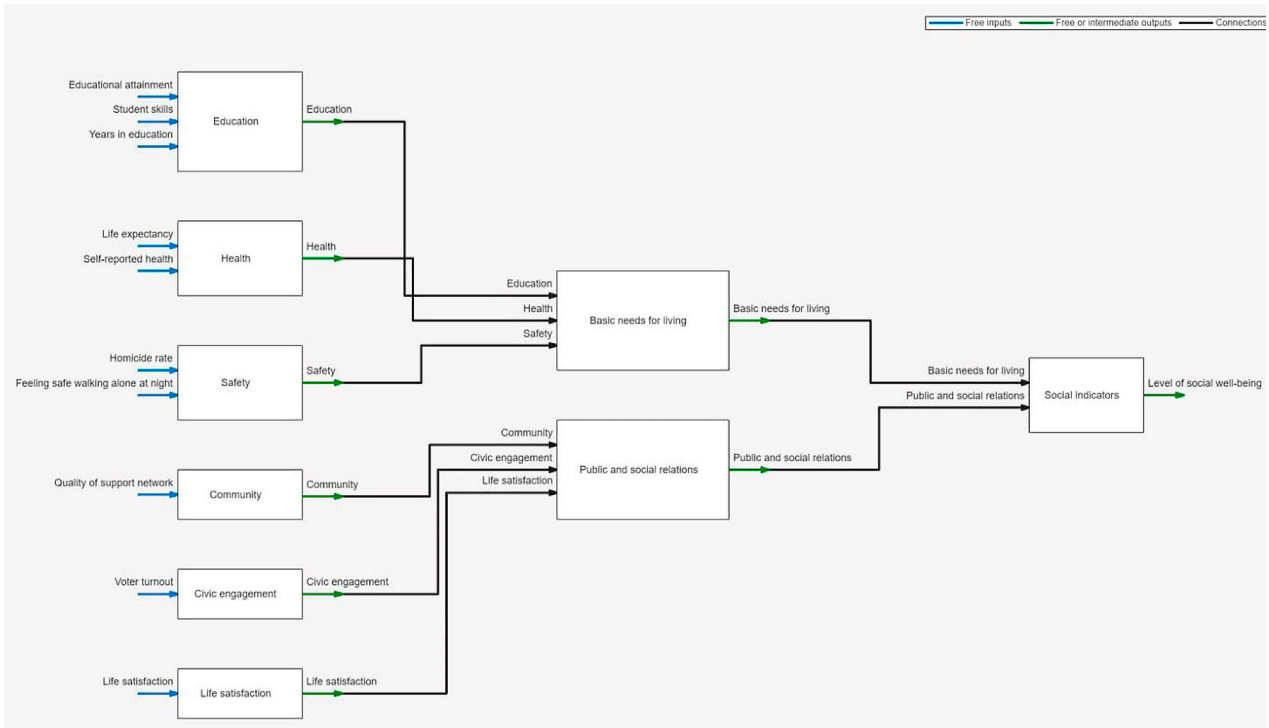


Fig. 4. FIS tree for determining the level of social well-being

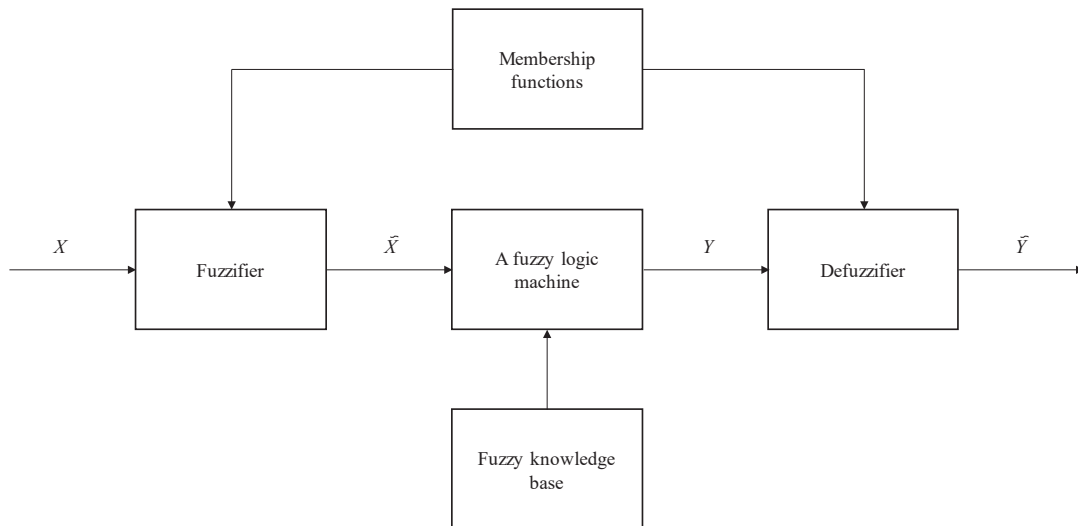


Fig. 5. Typical structure of the fuzzy inference model [18]

Fig. 5 shows a typical structure of a fuzzy inference model. Such a structure begins with a fuzzification procedure and ends with a defuzzification procedure. As mentioned above, there are several defuzzification methods. In this study, defuzzification was carried out using the center of gravity method.

5. 3. Study of indicators of the better life index by the Organization for Economic Cooperation and Development

After building the FIS tree, all input data (indicators) were divided into three groups – low, medium, high. The data were grouped in two ways: the first way – by quartiles. Quartiles divide the data distribution into four equal parts. The values that divide the series of the distribution are termed the first (Q1), second (Q2), and third quartiles (Q3). The second quartile value corresponds to the median value because exactly 50 % of the values are before the second quartile and 50 % of the values are after the second quartile. The first quartile is the value halfway between the smallest value and the second quartile. The second method of data grouping was based on the z-criterion. Depending on the result of the z-test, we can determine how far from the mean our point is in a normally distributed sample. In this study, the mean value was taken when the z-score was between –1 and 1. All z-score values below –1 were classified as low, and all z-score values above 1 were classified as high.

After grouping the data, a separate system of fuzzy inference was built for each indicator. All inputs are described by three membership functions: low, medium, and high. For input data belonging to the «low» category, a linear z-like membership function is proposed, which is described by the following formula (7):

$$f(x,a,b) = \begin{cases} 1, & x \leq a; \\ \frac{b-x}{b-a}, & a < x < b; \\ 0, & b \leq x. \end{cases} \quad (7)$$

For input data belonging to the «average» category, a triangular membership function is proposed, which is described by the following formula (8):

$$f(x,a,b,c) = \begin{cases} 0, & x \leq a; \\ \frac{x-a}{b-a}, & a \leq x \leq b; \\ \frac{c-x}{c-b}, & b \leq x \leq c; \\ 0, & c \leq x. \end{cases} \quad (8)$$

And for the input data belonging to the «high» group, a linear s-shaped membership function is proposed, which is described by the following formula (9):

$$f(x,a,b) = \begin{cases} 1, & x \leq a; \\ \frac{x-a}{b-a}, & a < x < b; \\ 0, & b \leq x. \end{cases} \quad (9)$$

After assigning the above membership functions to each input value, the following system of fuzzy inference is obtained, which is shown in Fig. 6.

This system is proposed for the «Education» indicator. This indicator has three input criteria: the level of education of the population, the skills of students, and the expected duration of education. Fuzzy inference systems for other indicators were designed in the same way.

5. 4. Building a knowledge base

In order for the fuzzy inference system to work, a knowledge base must be formed. It consists of an individual set of rules for each fuzzy inference system. In this case, since we have three input variables described by 3 membership functions (low, medium, high), 3×3×3, i.e., 27 fuzzy IF-THEN rules, are formed. Fig. 7 shows part of the fuzzy logic rules for the «Education» indicator.

The number of fuzzy logic rules for each fuzzy inference system is shown in Table 1.

Each rule (Fig. 7) takes into account one of the possible states of each input criterion and gives the result «Education level» at the output. Table 1 gives the number of fuzzy rules for each fuzzy inference system. The number of fuzzy rules depends on the number of input data and the number of membership functions.

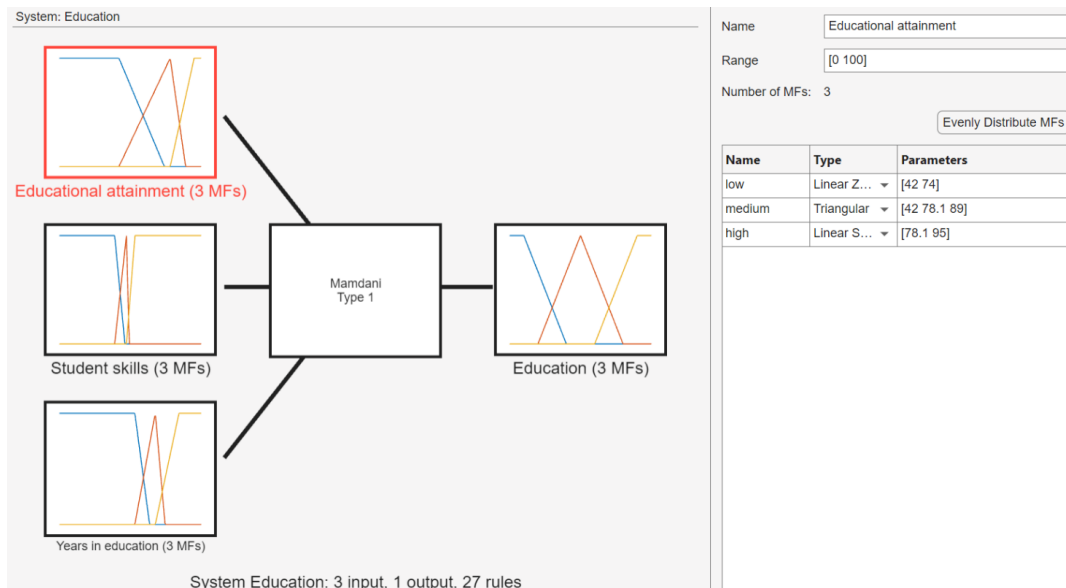


Fig. 6. Fuzzy inference system for the «Education» indicator

	Rule	Weight	Name
1	If Educational attainment is low and Student skills is low and Years in education is low then Education is low	1	rule1
2	If Educational attainment is medium and Student skills is low and Years in education is low then Education is low	1	rule2
3	If Educational attainment is high and Student skills is low and Years in education is low then Education is medium	1	rule3
4	If Educational attainment is low and Student skills is medium and Years in education is low then Education is low	1	rule4
5	If Educational attainment is medium and Student skills is medium and Years in education is low then Education is medium	1	rule5
6	If Educational attainment is high and Student skills is medium and Years in education is low then Education is medium	1	rule6
7	If Educational attainment is low and Student skills is high and Years in education is low then Education is medium	1	rule7
8	If Educational attainment is medium and Student skills is high and Years in education is low then Education is medium	1	rule8
9	If Educational attainment is high and Student skills is high and Years in education is low then Education is medium	1	rule9
10	If Educational attainment is low and Student skills is low and Years in education is medium then Education is low	1	rule10
11	If Educational attainment is medium and Student skills is low and Years in education is medium then Education is medium	1	rule11
12	If Educational attainment is high and Student skills is low and Years in education is medium then Education is medium	1	rule12
13	If Educational attainment is low and Student skills is medium and Years in education is medium then Education is medium	1	rule13
14	If Educational attainment is medium and Student skills is medium and Years in education is medium then Education is medium	1	rule14
15	If Educational attainment is high and Student skills is medium and Years in education is medium then Education is medium	1	rule15
16	If Educational attainment is low and Student skills is high and Years in education is medium then Education is medium	1	rule16
17	If Educational attainment is medium and Student skills is high and Years in education is medium then Education is medium	1	rule17
18	If Educational attainment is high and Student skills is high and Years in education is medium then Education is high	1	rule18
19	If Educational attainment is low and Student skills is low and Years in education is high then Education is medium	1	rule19
20	If Educational attainment is medium and Student skills is low and Years in education is high then Education is medium	1	rule20
21	If Educational attainment is high and Student skills is low and Years in education is high then Education is high	1	rule21

Fig. 7. Part of the fuzzy rules for the «Education» fuzzy inference system

Table 1
The number of fuzzy logic rules for fuzzy inference systems

Fuzzy inference system	Number of fuzzy rules
Education	27
Health	9
Safety	9
Community	3
Civic engagement	3
Life satisfaction	3
Basic living conditions	27
Public and social relations	27
Social indicators	25

5. 5. Verifying the built system of fuzzy inference on real data

After devising fuzzy rules, it is possible to test the constructed system. To this end, you need to enter the input values

in the «Input values» field. After entering the input variables, the result of the education indicator is automatically obtained. Fig. 8, 9 show the evaluation of the «Education» indicator by the z-criterion and by quartiles, respectively.

Thus, a separate system of fuzzy inference is built for each of the input data. At the output of each fuzzy inference system, a new fuzzy set with three membership functions is obtained – low, medium, high. Then, as shown in Fig. 3, these fuzzy inference systems are divided into two parts. Fig. 4 demonstrates that two new fuzzy inference systems are constructed with inputs derived from the outputs of previous fuzzy inference systems. Thus, the two new fuzzy inference systems consist of 3 variables, each of which is described by 3 membership functions – low, medium, high. The output, in turn, is described by 5 membership functions – very low, low, medium, high, very high. After performing defuzzification at this stage, the output data of the two fuzzy inference systems were used as input data for a new fuzzy inference system. This new system of fuzzy inference consists of two variables with 5 membership functions for each of them (Fig. 10). It is owing to this last system of fuzzy inference that the level of social welfare of the population is obtained.

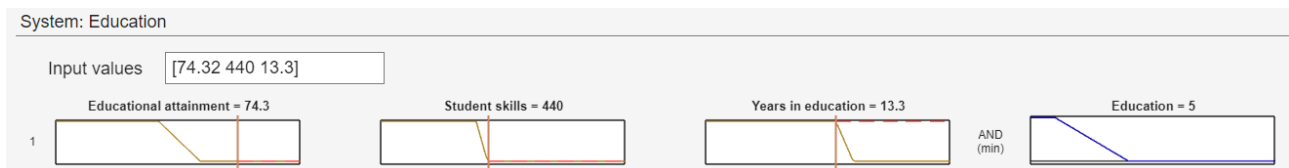


Fig. 8. Evaluation of the «Education» indicator according to the z-test

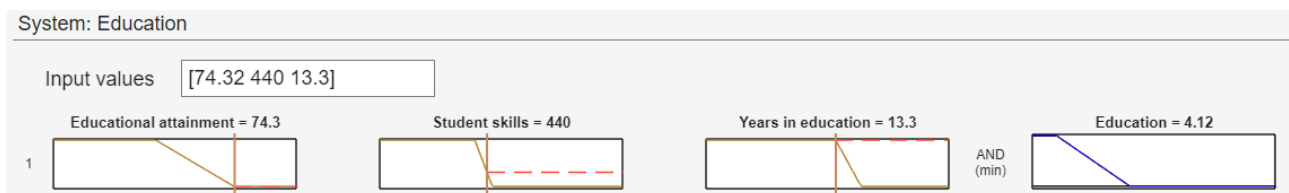


Fig. 9. Evaluation of the «Education» indicator by quartiles

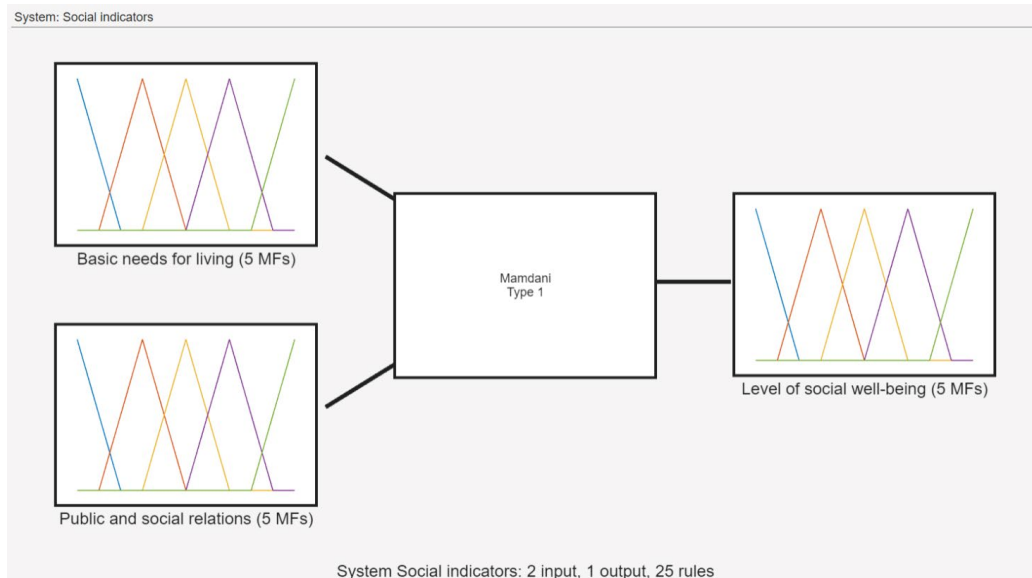


Fig. 10. A system of fuzzy inference of social welfare

Defuzzification in all fuzzy inference systems was performed using the center of gravity method (area centroid). The center of gravity or centroid of the area is calculated from the following formula (10):

$$y = \frac{\int_{\min}^{\max} x \cdot \mu(x) dx}{\int_{\min}^{\max} \mu(x) dx}, \tag{10}$$

where y is the result of defuzzification; x is a variable corresponding to the original linguistic variable; $\mu(x)$ is the membership function of the fuzzy set corresponding to the corresponding output variable after the accumulation stage; min and max are the left and right points of the carrier interval of the fuzzy set of the corresponding output variable [19].

Defuzzification by the center of gravity method is shown in Fig. 11.

The results for all indicators, according to the two methods of data grouping, are given in Table 2.

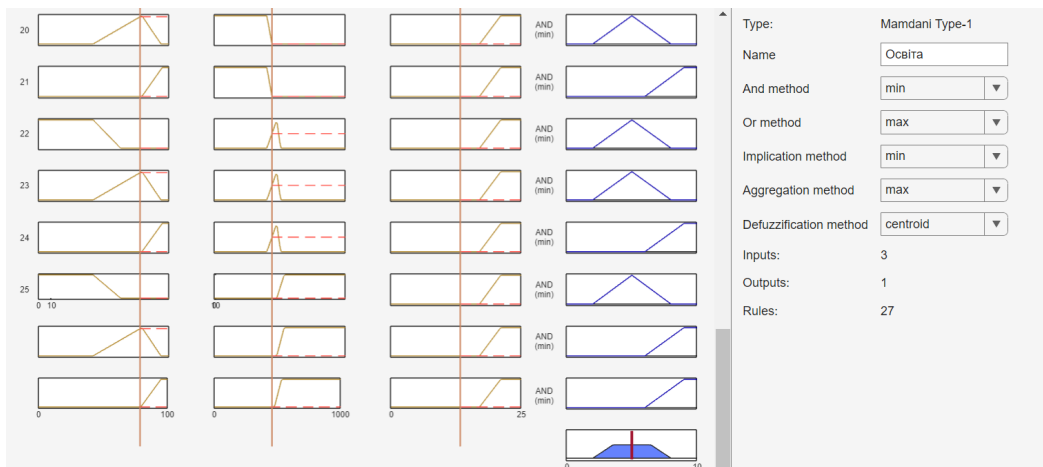


Fig. 11. Defuzzification of the original linguistic variable by the center of gravity method

Table 2

Performance result of the constructed mathematical model

Indicator ID	The result of the fuzzy inference system by grouping by z-test	The result of the fuzzy inference system by grouping by quartiles
Education	5	4.12
Health	3.13	3.03
Safety	4.93	3.89
Community	5	4.29
Civic engagement	5	5
Life satisfaction	1.37	1.37
Basic needs for life	5	4.82
Public and social relations	5	5
Social welfare	5	4.76

Table 2 demonstrates that the results of fuzzy inference systems by grouping by quartiles and the z -criterion practically do not differ. The result for both groupings is «average». This allows us to conclude that the social well-being of the population of Ukraine is «average» compared to OECD countries.

6. Discussion of results related to fuzzy modeling to determine the level of social well-being of the population

The constructed hierarchical structure (Fig. 2) makes it possible to assess the well-being of the population of Ukraine in comparison with the OECD countries in three groups. This grouping was necessary because it allows us to build 3 simpler and more transparent fuzzy inference systems. In this study, the main emphasis is on the third main group – social indicators.

After constructing the hierarchical structure, a tree-like structure of fuzzy inference systems was constructed. Owing to the construction of a tree-like structure, the work of the constructed fuzzy inference system has become more understandable. A tree-like structure allows one to connect several smaller fuzzy inference systems. Such a system is computationally more efficient and easier to understand than a single fuzzy inference system with the same number of inputs.

When researching the indicators of the OECD Better Life Index, data were collected from all OECD countries and statistical data on Ukraine were added to them. An important task of research is to determine membership functions. The number of membership functions is determined by the number of linguistic variables used. Usually, between three and ten linguistic variables are used. This can be explained by the fact that the average person cannot distinguish more than ten linguistic variables in a certain topic. In the case when the number of linguistic variables is less than three, the feasibility of using the system becomes questionable. The formulas of membership functions used in the study are given in formulas (7) to (9). The use of a linear z -like membership function (7) is a logical choice for data that belongs to the «low» category, since at the specified minimum value (and below) the membership function takes the value 1. Then the value of the membership function decreases linearly the higher the value is considered. According to the same principle, a linear s -like membership function (9) was chosen for the data belonging to the «high» category. This membership function is essentially a mirror image of membership function (7). A triangular membership function (8) was chosen for «average» values. The advantage of this membership function is that its centroid and area can be easily calculated, which reduces the time required for defuzzification.

The next important task in building a fuzzy inference system is the development of a rule base. In the rule base, connections of inputs and inferences with linguistic variables are summarized in the form of IF – THEN rules. Such fuzzy rules are unique to each fuzzy inference system. An example of fuzzy rules is shown in Fig. 7.

The constructed fuzzy inference system was successfully tested on real statistical data for the population of Ukraine. The results of testing according to two methods of classification are given in Table 2. From these results, it can be concluded that based on the results from fuzzy inference systems according to both classification methods, the social well-being of the population of Ukraine is «average» compared to OECD countries.

Unlike [10, 11], in which the well-being of the population of Ukraine is also investigated, the constructed tree-like sys-

tem of fuzzy inference (Fig. 4) makes it possible to assess the social well-being of the population of Ukraine in comparison with the OECD countries.

Although the Mamdani algorithm is one of the most popular fuzzy inference algorithms, it also has its limitations. For the Mamdani algorithm, the maximum values for the inference variables are mostly unattainable. The disadvantage of this study is that the OECD better life index contains indicators that are not measured in Ukraine.

The practical significance of this study lies in a deeper understanding of the state of social well-being of the population of Ukraine in comparison with OECD countries. According to the results of the mathematical model built during the research, it can be concluded that the social well-being of the population of Ukraine is «average» compared to OECD countries.

The study focuses on the social welfare of the population of Ukraine. In order to get a complete picture of the well-being of the population of Ukraine in comparison with OECD member countries, it is necessary to continue the research in other categories of well-being. Future research will focus on determining the level of economic and environmental well-being of the population of Ukraine in comparison with OECD member countries.

7. Conclusions

1. On the basis of the OECD better life index, the indicators have been divided into three parts – economic, environmental, and social, that is, a hierarchical structure of indicators was built. Indicators of the OECD Better Life Index are divided into three large groups:

- 1) economic ones consisting of indicators: «Income», «Housing», «Jobs»;
- 2) environmental;
- 3) social ones consisting of indicators: «Education», «Safety», «Health», «Civic engagement», «Life satisfaction», «Community».

2. Using the MATLAB software package, a tree-like structure was built for the study of social welfare, which made it possible to manage the fuzzy system in a simpler and more transparent way. The tree-like structure (FIS-tree) consists of 9 fuzzy inference systems and has 10 inputs and 9 outputs.

3. When studying the indicators of the OECD Better Life Index, the data were collected in a table, to which statistical data regarding the population of Ukraine were later added. In the course of the study, the data were classified in two ways – by quartiles and by the z -criterion. This classification made it possible to divide the data into three groups – low, medium, high. After obtaining the classification result, membership functions were determined for each group. Thus, a linear z -shaped membership function was proposed for the «low» group, a triangular one for the «average», and a linear s -shaped membership function for the data belonging to the «high» group. Next, fuzzy logic inference systems were built for each indicator separately. The peculiarity of such a system is that it is possible to obtain a result for each system separately. This allows us to conclude which aspects of the social well-being of the population of Ukraine are subject to improvement.

4. A knowledge base was built in the form of fuzzy rules of the «If – Then» type for each system of fuzzy inference. In general, the constructed fuzzy inference system has 133 fuzzy

logical rules. The constructed tree-like structure of the fuzzy inference system made it possible to build a knowledge base for each system separately. This makes the constructed fuzzy inference tree system easy to understand and faster to compute than one large fuzzy inference system with the same number of inputs. That is, the peculiarity of the built system of fuzzy inference and the knowledge base is the transparency and efficiency of the mathematical model.

5. Our mathematical model was tested on real statistical data, from which it was found that the social well-being of the population of Ukraine compared to OECD countries is «average». Results of fuzzy inference systems by grouping by quartiles and z-criterion practically do not differ.

authorship, or any other, that could affect the study, as well as the results reported in this paper.

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Data availability

All data are available, either in numerical or graphical form, in the main text of the manuscript.

Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal,

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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