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ABSTRACT

of the dissertation for the degree of Doctor of Philosophy

DEVELOPMENT OF AN OPTIMAL SOLUTION METHOD FOR MULTI CRITERION DECISION MAKING PROBLEM UNDER CONDITION OF UNCERTAINTY

Speciality: 3338.01-Systems analysis, control and information processing (by fields)

Field of science: Technical sciences

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GENERAL CHARACTERISTICS OF THE WORK

The relevance and degree of development of the work. At a time when environmental problems are rapidly risening , there is a growing demand for renewable energy sources that improve air quality and benefit human health. Switching to renewable energy allows countries to use rely on own clean energy resources and reduce their dependence on imported fuels. This makes the question of which type of energy to use and how to select it stayed as a pressing issue. On the other hand, there is a need for new approaches or modifications to existing ones in the decision making process.

Considering that the transition to renewable and naturally reproducible energy sources is a significant problem for countries around the world, the topic of choosing alternative and renewable energy sources is of particular importance for the Republic of Azerbaijan. Developing of an optimal solution for such a choice, requires taking various factors together into account (such as uncertainty, multicriteria evaluation and more).

Available methods for solving multicriteria decision making problems presented in the scientific literature should be selected based on the type of problem being addressed, the nature of the data and the level of environmental uncertainty. This requires identifying gaps in existing methods and developing new approaches to address them.

Thus, there is a need to create new approaches that combine both quantitative and qualitative methods in the field of decision-making. The above proves the relevance of the topic of the dissertation work.

The object and subject of the dissertation. The object of the dissertation is the selection of alternative and renewable energy sources, while its subject is the study and implementation of optimization methods that take into account uncertainty and multi-criteria aspects, as well as the development of an optimal approach to solving this problem by combining both quantitative and qualitative methods.

Aim and objectives of the dissertation. The aim of the dissertation is to develop an optimal solution for the selection of alternative and renewable energy sources, which represents a multi-criteria decision making problem under conditions of uncertainty.

To achieve this goal, the dissertation explores several problems from different fields in order to overcome the limitations of current decision making methods. These include issues such as getting stuck in local minima, difficulty in selecting and ranking options, inability to handle multiple or conflicting criteria, limited use of expert opinions and challenges related to uncertainty, fuzziness and working with both objective and subjective information.

- Determining the shortest path for a travelling sales agent using a hybrid ACO-TOPSIS method;
- Development of a fuzzy recurrent neural network trained with a genetic algorithm for long-term forecasting of electricity consumption in Turkey and time series prediction using sunspot data;
- Development of a fuzzy recurrent neural network trained with the backpropagation algorithm for predicting rock porosity, considering C-means clustering for data preprocessing;
- Development of a TOPSIS method extended with fuzzy logic for evaluating the quality of sulfocationites;
- Development of fuzzy extended versions of the AHP, TOPSIS, COPRAS and VIKOR methods as optimal approaches for solving alternative and renewable energy selection problems.

Research methods. The dissertation used fuzzy logic, multi-attribute decision making methods, neural network and genetic algorithm based methods and evolutionary computing methods.

The main provisions presented for defense.

– Comparison of decision making methods;
– Decision making problems in the fields of energy, geology, routing and chemistry;
– Determining the optimal route for a travelling sales agent;

- Forecasting electricity consumption for Turkey;
- Using of forecasting methods for the analysis of the rock porosity problem;
- Assessment of the quality of sulfocationites with multiattribute decision making methods;
- Using of multi attribute decision making methods for selecting of renewable energy source.

Scientific novelty of the dissertation. The main scientific novelty of this work include the following:

- Development of a hybrid ACO+TOPSIS method for selecting of optimal solutions;
- Determination of data for formulating a multiattribute decision making problem, based on a fuzzy recurrent neural network trained with a genetic algorithm;
- Quality assessment of sulfocationites based on the multicriteria decision making method TOPSIS, extented with fuzzy logic;
- Developing of AHP, TOPSIS, COPRAS and VIKOR methods extented with fuzzy logic and using for the selection of renewable energy sources.

Theoretical and practical significance of the dissertation. The theoretical significance of the dissertation lies in the development of adequate theoretical models and approaches for multi criteria decision making problems under conditions of uncertainty.The practical importance of the dissertation is that the proposed methods can be used for decision making in many different fields.

Approbation and implementation of the work. Based on the results of the dissertation work, 23 publications have been produced, including 14 articles (5 published abroad), of which 7 were published without co-authors. Additionally, 6 conference materials have been published, 4 of which were published without co-authors and 3 thesis (2 published abroad).

The main results of the dissertation work were presented and discussed at the following international and domestic conferences.

-14th International conference on applications of fuzzy systems, soft computing and artificial intelligence tools (Monteneqro, Budva, ICAFS -2020);

- “Scientific and practical conference of young scientists and researchers of the ASOIU dedicated to the 100th anniversary Azerbaijan State Oil and Industry University,” (ASOIU 2020);

- 1st International scientific practical conference on modern information, measurment and control Systems:problem and prespectives 2019(ASOIU-2019);

- 23rd Republican scientific conference of doctoral students and young researchers. Azerbaijan University of Architecture and Construction (AUAC 2019);

- International scientific practical conference dedicated to the 94th anniversary of the national leader Heydar Aliyev’s birth (ASMA 2017) ;

- İnternational scientific and practical conference “World Science” (Abu-Dhabi,UAE 2017);

- International scientific practical conference on the topic "İmplication of urbanization and industrialization for cultural heritage and biodiversity " (ATU Ganja 2017);

- International scientific practical conference on "Theoretical and applied problems of mathematics (SSU 2017) ;

- 21st Republican scientific conference of doctoral students and young researchers (BSU 2017) ;

- 3rd Republican conference on applied mathematics problems and new information technologies (SSU 2016) ;

- 20th Republican scientific conference of doctoral students and young Researchers (ASOIU 2016);

- 6th International scientific and practical conference: Problems and prospects for the development of the IT industry (KHEU 2014).

The name of the organization where the dissertation work was carried out. Azerbaijan State Oil and Industry University, Department of “Computer Engineering”.

The structure of the dissertation work. The dissertation consists of an introduction, four chapters, a conclusion, a list of references, appendices and a list of conventional symbols.

MAIN CONTENT OF THE WORK

The **Introduction** of the dissertation justifies the relevance of the topic, defines the subject, aim and objectives, describes the methods used, lists the main points to be defended and highlights the scientific novelty and the theoretical and practical significance of the work.

The **first chapter** discusses existing decision making methods and presents the general formulation of the problem, with the aim of developing an optimal solution for a multicriteria decision making problem under conditions of uncertainty.

Making good decisions requires decision makers to consider all factors together and make choices based on risk, uncertainty, and incomplete information [1]. In the dissertation, uncertainty in operating conditions, inaccuracies in measuring parameters of technological processes, limited information on the qualitative characteristics of processes and fuzziness of the external environment present a relevant problem for decision makers in terms of information processing. This necessitates the development of methods that allow decision makers to solve problems under conditions of uncertainty. Decision making methods based on numerical, interval, fuzzy logic and confidence levels of information processing support this process with new capabilities. Metaheuristic methods are seen as more effective and appropriate for solving complex and large scale optimization problems. The ability to adapt to dynamic environments and environmental changes allows them to find strong solutions over time, based on the principles of natural evolution. Using parallel searches and memory makes optimization faster and more efficient and helps avoid local minima by keeping track of past solutions. The ability to handle fuzzy, subjective and uncertain data helps analyze uncertainty

[1] Mammadova, N. I. Analysis of Existing Decision Making Methods Under Uncertainty // VI International Scientific and Practical Conference: Problems and Prospects for the Development of the IT Industry,- Kharkiv: Kharkiv National University of Economics - 17 april – 18 aapril, -2014,-p.274.

and errors, leading to more effective results. While metaheuristic methods overcome the limitations of classical approaches, they do not always produce absolute optimal solutions. Instead, they typically provide solutions that are close to optimal. Choosing inappropriate parameters can increase the local minimum, which leads to a sensitivity problem. Although these methods take uncertainty into account, the computational complexity increases with the amount of data, resulting in wider intervals and longer computation times. Moreover, solving problems does not produce a single solution but rather a set of optimal solutions.

In scientific literature, the use of fuzzy logic inference systems and fuzzy neural networks, which are based on fuzzy logic and mimic human logic, is considered an effective tool to take uncertainty into account. Various synergies of these approaches are more effective.

Modified multiattribute decision making methods that consider factors like uncertainty and imprecision are more effective than earlier approaches.

Experience shows that in most cases, existing approaches rely on incomplete and conflicting information. The decision maker's opinion and intuition are often not fully considered and the limited use of fuzzy methods in multi-criteria problems highlights the need for new decision making methods.

The selection of alternative and renewable energy sources is one such problem, representing a multicriteria decision making task under uncertainty. On the other hand, the subjective opinions and intuition of decision makers play an important role in such a complex choice. Developing an optimal solution that meets all these conditions is especially important.

The **second chapter** presents the main concepts and methods. It provides a general classification of information processing (based on numerical values, intervals, fuzzy logic and degrees of reliability) and introduces algebraic operations on them. In order to fill the gaps in the methods that emerged as a result of the general analysis conducted in the first chapter, algorithms are described for the problems to be solved in various fields in the dissertation. The algorithms are given in the following order:

- Development of metaheuristic methods;
    - Finding the global optimum with particle swarm optimization (PSO) method.
    - Construction of a fuzzy logic inference system that controls parameters to prevent local minima with FPSO.
    - Construction of Pareto fronts using Multiobjective Particle Swarm Optimization (MOPSO) method.
    - Finding the global minimum using the Ant Colony Optimization (ACO) method.
- Design of a fuzzy recurrent neural network;
    - Design of a fuzzy recurrent neural network trained by Genetic algorithm
    - C-means clustering and construction of a fuzzy recurrent neural network trained with error backpropagation algorithm
- Development of multiattribute decision making methods;
    - Algorithms for processing the methods AHP, TOPSIS, VIKOR, COPRAS, PROMETHEE-II, ELECTRE, ARAS.
    - Conducting sensitivity analysis showing the impact of criteria on the results obtained with multiattribute decision making method.

In the **third chapter**, the dissertation focuses on finding an optimal solution method for the selection of alternative and renewable energy sources. This is achieved by addressing the limitations present in existing decision making methods through the development of problem solving approaches across various fields.

Evolutionary algorithms, which belong to metaheuristic methods, has been shown to be an effective tool for solving high dimensional, non-linear, non-differentiable and complex problems where traditional optimization methods face difficulties.

This section presents detailed information on the use of genetic algorithms, as a method of evolutionary computation, to identify Pareto-optimal frontiers, including convex and concave cases. It also discusses multiobjective optimization methods based on genetic algorithms for finding nonconvex Pareto optimal frontiers.

Thus, falling into local minima, the uneven spacing of points on the Pareto front, high computational time, uncertainty during selection and crossover operations, complexities arising from non-linearity and ambiguity in the comparison of objective functions are explained in detail.

The problem of finding the global minimum using Particle Swarm Optimization (PSO) method [2]**.** This approach is a probabilistic metaheuristic method based on swarm intelligence. Thus, in the problem of finding the global minimum using the metaheuristic methods as Particle swarm optimization (PSO) and Genetic algorithm (GA), the velocity and position of each candidate solution are updated at the end of each iteration with Equations (1) and (2).

$$\mathrm{v_i}(\mathrm{t}+1) = \omega * \mathrm{v_i}(\mathrm{t}) + \mathrm{c_1} * u_1\big(\mathrm{P_i}(\mathrm{t}) - \mathrm{x_i}(\mathrm{t})\big) + \mathrm{c_2} * \\ * u_2\big(\mathrm{G_i}(\mathrm{t}) - \mathrm{x_i}(\mathrm{t})\big) \tag{1}$$

$$\mathrm{x_i}(\mathrm{t}+1) = \mathrm{x_i}(\mathrm{t}) + \mathrm{v_i}(\mathrm{t}+1) \tag{2}$$

here

ω- inertia weight, $\mathrm{v_i}(\mathrm{t})$- previous speed of the candidate, $\mathrm{c_1} = \mathrm{c_2}$-cognitive and social factors, $u_1 - u_2$-random number, $\mathrm{x_i}(\mathrm{t})$- previous position of the candidate, $\mathrm{P_i}(\mathrm{t})$ –local best, $\mathrm{G_i}(\mathrm{t})$-global best.

[2] Gardashova, L.A., Hasanli, N.I. PSO and GA comparison of evolutionary optimization methods // -Baku: Azerbaijan High Technical Educational Institutions, -2018. -Volume 20 №1(111), -p.83-92

The objective function value obtained with computer simulation and traditional calculation was same for both methods -15.9999, but positions were GA – 4 and PSO – 3.4485. The fact that the position indicator is 14% smaller creates confidence that the PSO algorithm can be effectively used in various fields, such as economics, medicine, engineering, flexible manufacturing, robotics, distance estimation, oil extraction and well drilling positioning. In addition, Computer simulations of multi-variable versions of the PSO method were carried out to assess its effectiveness and robustness.

Setting PSO parameters with a fuzzy-logic inference system [3]. In the Particle Swarm Optimization (PSO) method, in order to prevent convergence to local minima, key parameters such as inertia weight, cognitive coefficient and social coefficient are represented with fuzzy numbers. This approach allows the algorithm to effectively handle uncertainties in parameters or the problem space, incomplete information and conflicting objectives. If the best objective function stays the same for a long time, the number of generations without improvement keeps increasing. In this case, the system often gets stuck in a local minimum which express the shortcoming of the approach. To overcome this deficiency, a fuzzy logic inference system was developed to adjust the inertia weight and learning factors based on knowledge. The purpose of the constructed fuzzy logic inference system is to give priority to situations where the best fitness value and inertia weight are low, while the learning factors are high, in order to effectively solve the minimization problem. The input variables of the developed system x_1-the best fitness function and x_2- the number of generations with the best fitness value that stayed stable.The output variables are y_1 -inertia weight (ω) and y_2, y_3 -learning factors (c_1 və c_2) are selected. The rules established in the fuzzy logic inference system shown in Figure 1 are as follows.

[3] Hasanli, N.I. Modeling of Uncertainty in Particle Swarm Optimization (PSO) Methods // International Scientific-Practical Conference on "Theoretical and Applied Problems of Mathematics, - Sumgayit: Sumgayit State University, -25 may-26 may, -2017, -p.184-185.

Rule 1 :IF the best fitness and the number of constant best fitness are SMALL THEN ω – is SMALL; c_1 and c_2 -are LARGE ;

Rule 2: IF the best fitness MEDIUM and the number of constant best fitness is SMALL ; THEN ω – is MEDIUM; c_1 və c_2- are LARGE ;

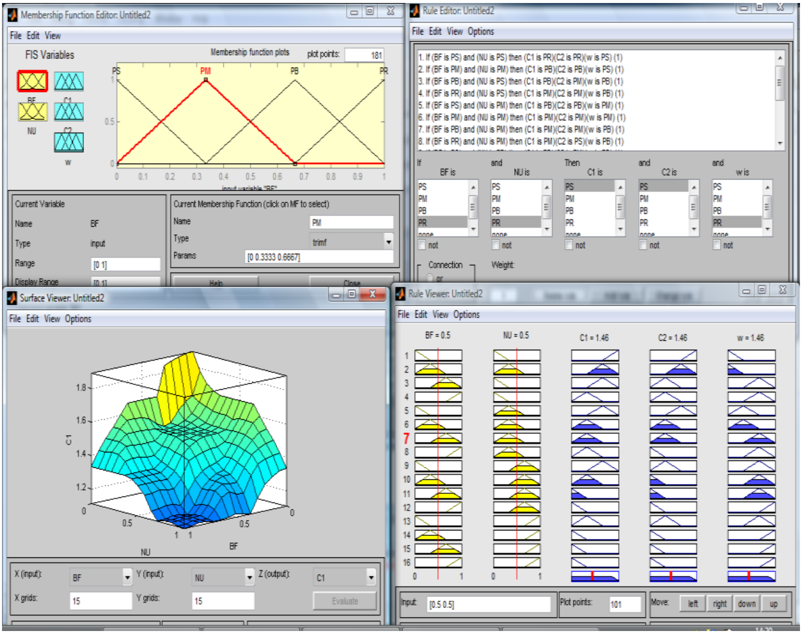

Figure 1. Developed fuzzy logic inference system for PSO parameters

Although the adjustment of PSO parameters based on a fuzzy inference system improves adaptability, drawbacks such as subjectivity, complexity, sensitivity in constructing fuzzy rules, slower convergence and increased computational load require the system to be designed more carefully.

Finding the global minimum using Multiobjective Particle Swarm Optimization (MOPSO) method [4]**.** While PSO is used for single objective optimization, the Multiobjective Particle Swarm Optimization (MOPSO) method constructs the Pareto frontier by optimizing multiple objectives at the same time. The concave Pareto frontier constructed by the MOPSO method (iteration number-200, population number-200, inertia weight ω-0.5, c_1=1, c_2=2) is as shown in Figure 2. In order to verify the effectiveness of multi-objective optimization methods, computer simulations were conducted to construct various Pareto frontiers (convex, concave and truncated) by the MOPSO method with the available ZDT test functions [5].

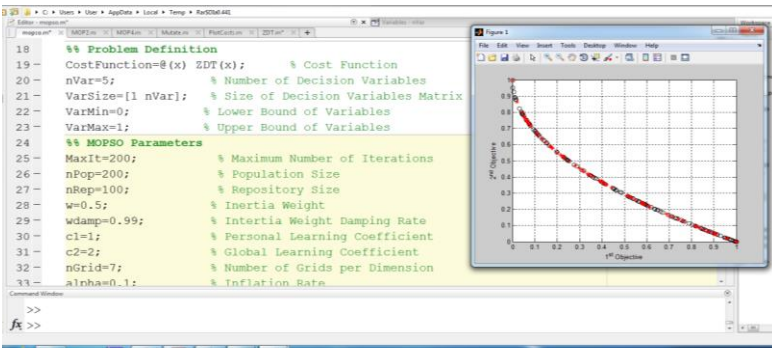

Figure 2. Pareto frontier constructed using the MOPSO method

Solving multiobjective optimization problems with the MOPSO method can lead to several challenges. These include maintaining the diversity of non-dominated solutions, properly selecting leaders (global best solutions) to guide convergence, managing the effect of

[4]Hasanli, N.I. Analysis of the Working Principle of the Multi-Objective Particle Swarm Optimization Method(MOPSO) // -Baku: Proceeding of Azerbaijan State Marine Academy, -2017. №2(26), -p.210-214.

[5]Hasanli, N.I. Solution of ZDT1, ZDT2, and ZDT3 Benchmark Problems Using the Multi-Objective Particle Swarm Optimization (MOPSO) Method // XXI 21st Republican Scientific Conference of Doctoral Students and Young Researchers, -Baku: Baku State University,-24 october-25 october r, -2017, -p.8-10.

archive growth on diversity, sensitivity to parameter settings, difficulty in accurately identifying the true Pareto front and the lack of mathematical guarantees for achieving global convergence.

Finding the shortest and optimal path using PSO, ACO and ACO+TOPSIS methods [6]**.** Compared to the PSO method, the Ant Colony Optimization (ACO) algorithm is less likely to fall into local minima. In ACO, the probability of the paths that a travelling agent (ant) can follow is calculated using Equations 3.

$$P_{ij}^{k} = \frac{\tau_{ij}^{\alpha} * \eta_{ij}^{\beta}}{\sum_{j \epsilon N_i^k} \tau_{ij}^{\alpha} * \eta_{ij}^{\beta}} \tag{3}$$

here

P_{ij}^{k} – the probability of ant (k) which go from city i to city j

τ_{ij}^{α}- is the value of the pheromone trail from city i to city j

α – the relative importance of the pheromone trail

η_{ij}^{β}- is a heuristic function that usually takes the inverse of the distance between node i and node j ($\eta_{ij} = 1/d_{ij}$).

β - is the relative importance of the heuristic factor

$\sum_{j \epsilon N_i^k} \tau_{ij}^{\alpha} * \eta_{ij}^{\beta}$ - it represents the total of all neighboring nodes that ant (k) would explore while it is at node i (taking into account both the amount of pheromone and the shortest distanc)

In solving the Traveling Salesman Problem (TSP) using both PSO and ACO approaches, computer simulation results obtained in Matlab yielded a shortest and optimal distance of 24.53 for both methods. The optimal solution was obtained faster in PSO compared to ACO in terms of time. However, considering that PSO is designed for continuous optimization problems (while ACO is suited for combinatorial optimization), it must be adapted to effectively solve the

[6] Hasanli, N.I. Solving the Travelling Salesman Problem Using PSO and ACO Optimization Methods // -Baku: Scientific works of Azerbaijan Technical University, -2017. №1, -p.51-57.

TSP. If the adaptation is done properly, PSO can perform faster and more efficiently. Otherwise, using PSO to solve the TSP may be ineffective and requires discretization.

In the TSPLIB library, which contains test data for optimization problems, the ATT48 instance consists of the coordinates of 48 cities. The shortest and optimal distance between the cities in this example is 33523 km. This result was found by creating a distance matrix from the 2D coordinates of the 48 cities and using effective optimization methods [7]. In the ATT48 example, the shortest and optimal path found using the ACO method in MATLAB varies among simulations due to the random nature of the search process. As a result, the optimal solution, as well as the number of iterations and computation time, differ in each run. The selection of the most optimal solution among these solutions is carried out using TOPSIS, a Multiple Attribute Decision Making (MADM) method [8]. While other MCDM methods allow for evaluating the importance of criteria, identifying compromise solutions and ranking in more complex problems, TOPSIS ranks alternatives based on their closeness to the ideal solution. The evaluation of the 4 solutions (alternatives) obtained by ACO is carried out based on 3 criteria. Here, the shortest distances obtained in each simulation are the alternatives A_1, A_2, A_3, A_4 and the criteria are C_1 – tour length, C_2 – time and C_3 – the iteration number at which the shortest distance was found. The weight (ω) of each criterion is assigned according to the importance of the criteria. Based on simulations conducted in MATLAB and calculations performed in Excel using the TOPSIS method, the shortest and most optimal solution was identified as alternative A_3 according to the ranking results in Figure 3. This distance of 35732.0737 km was recorded at

[7] Reinelt, G. TSPLIB – A traveling salesman problem library // ORSA Journal on Computing.- 1991.-vol 3(4), -p.376–384.

[8] Hasanli N.I. Finding the shortest and optimal path with meta-heuristic and MADM methods // Chemical Technology, Control and Management.-2025.Volume 2025, N.4, -p.1-7.

the 1,074th iteration, at the 50th second. The small 6.5% difference between the obtained result and the optimal solution (33523) shows that metaheuristic methods like ACO do not guarantee the absolute optimal solution. However, they provide good solutions in a short time. Incorporating fuzzy logic into ACO parameters can help find shorter and more optimal distances.

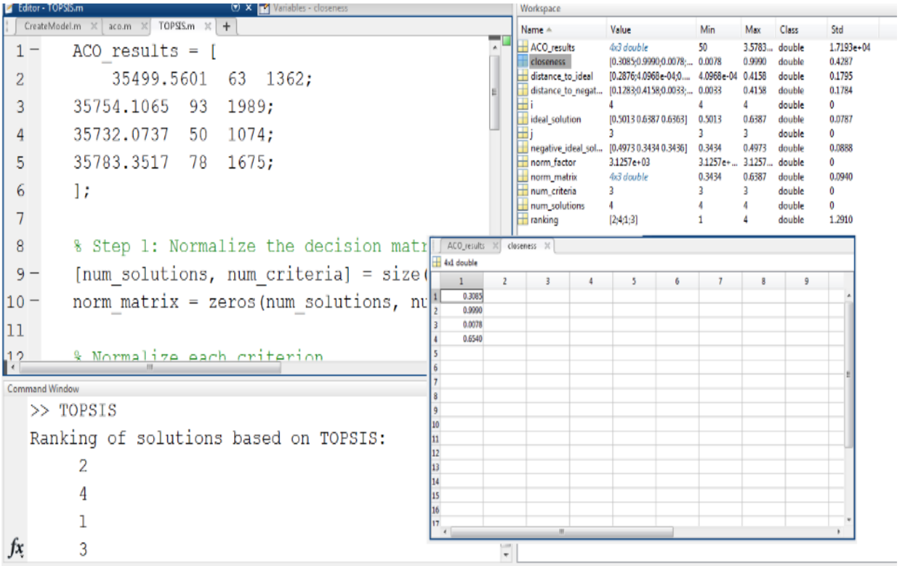

Figure 3. Ranking of alternatives using the TOPSIS method in the MATLAB environment

Fuzzy time series forecasting using fuzzy recurrent neural network [9].

A fuzzy recurrent neural network trained with a genetic algorithm was developed to forecast Turkey's long-term electricity consumption and sunspot-related fuzzy time series by combining quantitative and qualitative methods to handle uncertainty. The results

[9] Gardashova, L.A., Hasanli, N.İ., Akhmadov, S.A. Benchmark fuzzy time-series forecasting using fuzzy recurrent neural network // - London: Black sea scientific journals of academic research. -2019.Volume 51 issue 08,-p.48-56.

obtained using the fuzzy recurrent neural network trained with a genetic algorithm were compared with the forecasting results of Turkey's electricity consumption using artificial neural networks up to the year 2002. Additionally, the forecasting results of sunspot time series were compared with other prediction models. Based on Figure 4, the constructed $\widehat{F}_{NN}$ belongs to the class of wide fuzzy neural networks with n input nodes, one output node and two hidden layers is expressed by formula 4. The box elements represent memory cells that store values of activation of neurons at previous time step, which is a feedback to the input at the next time step.

$$\hat{y}_{t+1} = \widehat{F}_{NN}(y_t, y_{t-1}, \dots, y_{t-n+1}) \tag{4}$$

In the constructed FRNN, the input $x^o(t)$represents the element y_t of the time series, while the output Z^L represents the next step element y y_{t+1} of the series. The fuzzy weights of the neural connections $\widehat{F}_{NN}$, fuzzy biases and neuron activation functions define the network.

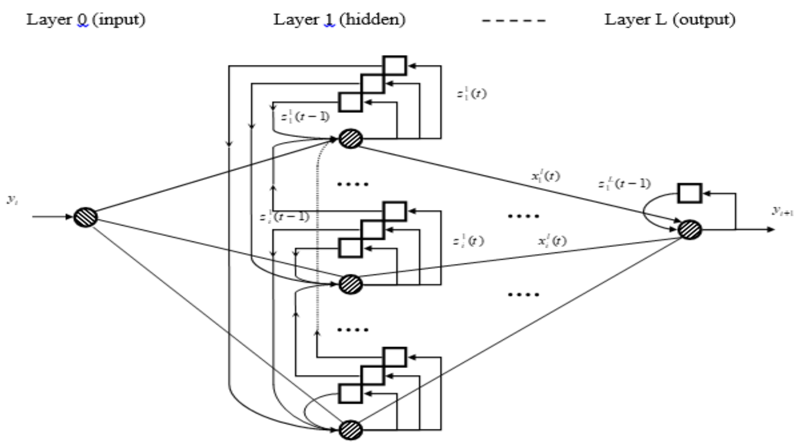

Figure 4. Structure of a simple fuzzy recurrent neural network

The network consists of multiple layers, numbered sequentially from 0 to L. Layer 0 is the input layer and layer L is the output layer. Formula 5 describes how the input signal is assigned to the neurons in the input layer without altering their values.

$$z^{o}(t) = x^{o}(t) \qquad (5)$$

The neurons from layer 1 to layer L are dynamic, and their output signals are calculated using Formula 6.

$$z_i^l = F(\theta_i^l + \sum_j x_j^l(t) w_{ij}^l + \sum_j z_j^l(t-1) v_{ij}^l) \qquad (6)$$

here
z_i^l - is the computed output signal of the neuron at the time step *t*,
θ_i^l - is the fuzzy bias of neuron *i*
$x_j^l(t)$ - is *j*-th fuzzy input to the neuron *i* at layer *l* at the time step *t*
w_{ij}^l - is the fuzzy weight of the connection to neuron *i* from neuron *j* located at the previous layer
$z_j^l(t-1)$- is the activation of neuron *j* at the time step (*t*-1),
v_{ij}^l - is the recurrent connection weight to neuron *i* from neuron *j* at the same layer.

The mean square error of the electricity consumption forecast using the proposed model in Table 1 (MSE=2.83, number of input neurons =1, number of output neurons= 1, number of neurons in hidden layer=2) is smaller than the result obtained using artificial neural networks up to the year 2002 (MSE=3.4280)

Additionally, by training on the sunspot data recorded from 1700 to 1920, two sets of forecasts were generated. The first forecast set (PR1) covers the data from 1921 to 1955, while the second forecast set (PR2) includes the data from 1956 to 1979. In table 2, normalized mean squared error of proposed approach (NMSE=0,066272, input

Table 1. Real and forecasting values

	Year	Real	Forecasting	Mean square error
Learning samples	1991	50295.7		
	1992	54613.1		
	1993	60406.3	60406.3	
	1994	61420.3	61420.3	
	1995	67092.3	67092.3	
	1996	74326.8	74326.8	
	1997	81884.9	81884.9	
	1998	87704.6	87704.6	
Test samples	1999	**91201.9**	**96380.44**	5.37%
	2000	**98295.7**	**97936.16**	0.37%
	2001	**97070**	**96266.04**	0.84%
	2002	**102800**	**98134.77**	4.75%
				2.83%

neurons =1, output neurons= 1, hidden layer neurons=7.Parameters of GA: size of population:100, number of best parent genomes to save: 10, probability of crossover: 0,5, probability of mutation: 0,05) is smaller than the NMSE of compared models (NMSE=0.077).

Based on the forecasting results, the fuzzy recurrent neural network trained with a genetic algorithm allows for better accuracy by handling uncertain and incomplete data, modeling time series effectively using its memory structure and avoiding local minima during training. This makes it suitable for adapting to new data and managing complex, nonlinear systems.

Table 2. Actual and forecast values of PR1 set with time series

Years	Real	Recurent neural network (rnn)	$\lvert real - rnn \rvert$	$\lvert real - avr \rvert$	
1921	26,1	27,19396	1,19674	723,61	
1922	14,2	11,40235	7,826853	1505,44	
1923	5,8	0	33,64	2227,84	
1924	16,7	14,80708	3,583139	1317,69	
......	......	......	......	......	
1954	4,4	0	19,36	2361,96	**PR1**
1955	38	41,2225	10,38453	225	**NMSE**
AVR	53	SUM	3882,146	58580,54	**0,06627**

Prediction of rock porosity using quantitative and qualitative methods [10].

To predict the porosity of reservoir rocks in deeper formations, 211 data samples were taken from key experimental results across different regions of the basins. Porosity depends on depth, carbonate content and other parameters. However, these parameters may not always be related to depth and can be influenced by geological factors.

The main goal of the fuzzy C-means clustering method is to achieve optimal clustering by minimizing the objective function, which considers both the degree of membership of data points to different clusters and their distances from the cluster centers.Since the cluster center is initially selected arbitrarily, the membership degrees and cluster centers are updated at the end of each iteration. This process continues until the cluster centers become stable. Formula 7 is used to update the membership degrees.

[10] Aliyarov, R. Y. , Gardashova, L. A. , Hasanli, N. I. Predicting Porosity Through Fuzzy Logic Based Methods from South Caspian Basin Data // 14th International Conference on Theory and Application of Fuzzy Systems and Soft Computing – ICAFS-2020, -Budva, Montenegro: - 27–28 August, -2020,-p.268-274.

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{j}(\frac{\|x_i - x_j\|}{\|x_i - x_k\|})^{\frac{2}{(m-1)}}} \quad (7)$$

here
x_i –i data
x_j- j-th cluster.

Similarly, the cluster centers are updated according to Formula 8.

$$x_j = \frac{\sum_{i=1}^{n}(\mu_{ij})^m x_i}{\sum_{i=1}^{n}(\mu_{ij})^m} \quad (8)$$

here
x_j- the new centers are calculated as the weighted average of all data points.
A neural network with 5 inputs (cluster centers) and 1 output was used to predict porosity. Out of 211 data points, two-thirds were used for training and one-third for testing. A fragment of the results obtained from the proposed C-means clustering and fuzzy recurrent neural network trained with backpropagation algorithm in MATLAB is shown in Table 3. The main advantage of the proposed model is that it enables modeling of data uncertainty, takes time dependence into account, provides clear results and ensures automatic optimization of parameters in complex networks, thereby increasing the system's adaptability and learning capability. Based on the root mean square error (RMSE) values obtained from different methods used to predict porosity in Matlab and XLSTAT software (0.07332 in linear discriminant analysis, 0.082604 in regression analysis, and 0.068331 in fuzzy neural networks), the proposed model based on fuzzy C-means clustering and fuzzy recurrent neural networks achieved the lowest error value of 0.044879. Based on the results of the dissertation, the use of multi attribute decision making (MADM) methods, fuzzy

logic inference systems (FIS) and fuzzy recurrent neural networks (FRNN) are effective approaches for solving problems under uncertainty. These methods improve the flexibility, accuracy and adaptability of the decision making process in real world conditions.

Table 3. A fragment of the prediction results obtained from C-means clustering and fuzzy recurrent neural network trained with the error backpropagation algorithm

						Real	Prediction	
Basin	**Cc**	**F1+F2Cor**	**F3Cor**	**F4Cor**	**Depth**	**Porosity**		**Root mean square error**
Sang Duv Xara Zire	0,127	0,279	0,379	0,215	4477	**0,208**	**0,198**	0,0001
Djanub	0,182	0,517	0,169	0,133	3212	**0,142**	**0,177**	0,001225
Sang_Duv_Xara_Zire	0,074	0,354	0,341	0,232	3976	**0,178**	**0,177**	1,00E-06
Sang_Duv_Xara_Zire	0,111	0,387	0,286	0,216	3394	**0,17**	**0,176**	3,60E-05
Sang Duv Xara Zire	0,134	0,325	0,393	0,148	3853	**0,184**	**0,175**	8,10E-05
8Mart	0,067	0,335	0,517	0,081	5643	**0,181**	**0,164**	0,000289
Djanub	0,145	0,392	0,365	0,098	3384	**0,166**	**0,173**	4,90E-05
Djanub	0,085	0,357	0,375	0,183	3232	**0,172**	**0,178**	3,60E-05
Bulla	0,065	0,349	0,408	0,179	5353	**0,173**	**0,167**	3,60E-05
Sang_Duv_Xara_Zire	0,146	0,318	0,332	0,204	4573	**0,177**	**0,17**	4,90E-05
…………………………………								
Djanub	0,145	0,031	0,671	0,153	3252	**0,203**	**0,176**	0,000729
Sang_Duv_Xara_Zire	0,094	0,192	0,571	0,143	2541	**0,171**	**0,178**	4,90E-05
Sang Duv Xara Zire	0,144	0,013	0,609	0,234	2561	**0,198**	**0,172**	0,000676
Sang_Duv_Xara_Zire	0,144	0,009	0,609	0,237	2524	**0,198**	**0,172**	0,000676
Guneshli	0,042	0,259	0,536	0,164	2903	**0,152**	**0,184**	0,001024
Djanub	0,078	0,009	0,704	0,208	3196	**0,186**	**0,172**	0,000196
								0,04487885

The classical MADM method offers a structured and mathematical approach. However, it faces challenges such as subjectivity, handling a large number of criteria and dealing with uncertainty effectively. However, by using fuzzy logic, these limitations can be overcome, allowing for the prediction of uncertainty and continuity in various fields by considering high variability and multiple parameters together.

Although fuzzy logic inference systems (FLIS) are effective in decision making under uncertainty and based on expert knowledge, creating accurate rule sets requires careful attention and can be time-consuming .

The learning ability of FRNN makes it more suitable for systems that change over time, but it is computationally intensive and costly.

Quality assessment of sulfocationites using TOPSIS method extended with fuzzy logic [11].

The evaluation of the quality of sulfocationites, which are used as ion-exchange adsorbents in water softening and the separation of non-ferrous metals from ores, is very useful when the precise determination of the extended TOPSIS parameters based on fuzzy logic is uncertain or unclear. This approach helps to manage the uncertainty in the physical and chemical factors that affect the quality of sulfocationites , to predict their stability under high variability and to take multiple parameters into account at the same time.

In the process of solving the problem the alternatives include: A_1- PFO based sulfocationite, A_2- Acetamide-modified PFO-based sulfocationite, A_3- Benzamide modified PFO-based sulfocationite, A_4 - Oxamide-modified PFO-based sulfocationite, A_5 - Terephthaldiamide modified PFO-based sulfocationite and A_6 - Carbamide-modified PFO-based sulfocationite.

The criteria have selected as C_1– static change capacity, C_2 – dynamic change capacity, C_3 – swelling rate, C_4 – specific volume and C_5 – true density.

[11] Naibova, T.M. Abbasova, K.G. Hasanli, N.I. Quality assessment of composite sulfocationites using fuzzy logic // Processes of Petrochemistry and Oil Refining. - 2025. Vol.26 N.3, -p. 807-814.

In fuzzy TOPSIS, a fuzzy decision matrix is initially constructed. The values of alternatives for each criterion are expressed using triangular fuzzy numbers given in Table 4.

Table 4. Fragment of the initial assessment of criteria, weights and alternatives

Weights (ω)		ω_1			ω_2		
		0.1	0.4	0.7	0.15	0.3	…
Meyarlar / Alternativlər (Sulfokationitlər)		C_1			C_2		
		Static change capacity, mg-ekv/g			Dynamic change capacity, mg-ekv/g		
		l	m	u	l	m	…
A_1	PFO-based sulfocationite	1	2.1	3.5	0.6	0.82	…
A_2	Acetamide-modified PFO-based sulfocationite	1	2.84	4	0.5	0.98	…
A_3	Benzamide-modified PFO-based sulfocationite	1.5	2.96	5	0.2	0.98	…
A_4	Oxamide-modified PFO-based sulfocationite	2	3.6	6	0.6	0.96	…
A_5	Terephthaldiamide modified PFO-based sulfocationite	1	3.65	4	0.1	0.98	…
…	…	…	…	…	…	…	…

As a result of the calculations, in Table 5 the A4 alternative (Oxamide-modified PFO-based sulfocationite) shows the highest score of 0.746828 compared to the others.

Table 5. Ranking of alternatives

A_i	Rank	Alternatives	
0.193766	6	A_1	PFO-based sulfocationite
0.525486	3	A_2	Acetamide-modified PFO-based sulfocationite
0.497	4	A_3	Benzamide-modified PFO-based sulfocationite
0.746828	1	A_4	Oxamide-modified PFO-based sulfocationite
0.571232	2	A_5	Terephthaldiamide modified PFO-based sulfocationite
0.47763	5	A_6	Carbamide-modified PFO-based sulfocationite

In **Chapter Four** of the dissertation, the selection of alternative and renewable energy sources for the Republic of Azerbaijan is solved using AHP, TOPSIS, VIKOR, COPRAS, ELECTRE, PROMETHEE-II, ARAS methods and their fuzzy-logic based extensions such as Fuzzy-AHP, Fuzzy-TOPSIS, Fuzzy-VIKOR, and Fuzzy-COPRAS [12]. In the problem being solved, a 5×12 decision matrix is constructed, where the number of alternatives is 5 and the number of criteria is 12.

The alternatives (A) represent the alternative and renewable energy sources.

A_1-Wind energy, A_2-Solar energy, A_3- Hydropower, A_4- Geothermal energy, A_5- Biofuel.

Criteria (C)-

Type of fuel or energy used ($C_1 -$ Thermal energy, $C_2 -$ Electric energy, $C_3 -$ Mechanical energy),

Power by type of energy produced ($C_4 -$ small 250-1000 kWt, $C_5 -$ Medium 1-5 MWt, $C_6 -$ high greater than 5 MWt),

[12] Hasanli, N.I., Gardashova, L.A. Using fuzzy logic in solving the problem of selecting alternative and renewable energy sources through multi-criteria decision-making methods (TOPSIS, AHP, VIKOR, CORPAS) // -Baku: Proceedings Azerbaijan High Technical Educational Institutions, -2020. №1, -p.66-74

Technical economic capacity (C_7 − annual operating hours, C_8 − durability, C_9 − investment),
Environmental cleanliness (C_{10} − oxygen consumption, C_{11} − air consumption for combustion, C_{12} − construction area.) etc.
The criteria for selecting renewable energy sources are classified into four main categories: economic, political, environmental, and historical development [13].

Economical perspective: Thermal energy, Electric energy, Mechanical energy. The transition to alternative energy technologies is beneficial not only from an environmental perspective but also economically. Saving fuel resources, the decreasing cost of alternative energy and the short payback period of power plants support the wider use of these energy sources in the future. Therefore, alternative energy provides a more affordable and sustainable solution compared to traditional energy sources.

Political principles: the time spent during the year, sustainability, financial investment and the payback period. A country that uses alternative energy can become a global leader and influence fuel prices.

Global ecological and social perspective: oxygen consumption, air consumption for combustion, construction area. Today, the environmental effects of traditional energy technologies are well known and it has been proven with evidence that their use has serious consequences for climate change in the 21st century. As the population and its density continue to grow, it becomes harder to find suitable areas to build large, cost-effective and environmentally safe power generation systems. In the regions where these complexes are located, the rise in cancer and other serious diseases increases social tension.

Historical development perspective: Due to the limited fuel reserves on Earth and the increasing catastrophic changes occurring in the planet's atmosphere and biosphere , conventional energy systems

[13] Chatterjee K., Kar S. Multi-criteria decision making for renewable energy selection using Z-numbers in uncertain environment // Technological and Economic Development of Economy.-2018. Vol 24(2), -p.739-764

have reached a deadlock. The transition to alternative energy sources is imperative for the evolutionary development of society.

The weights of the listed criteria across the subcriteria have been provided in Table 6 by experts working in this field.

Table 6. Weights of the subcriteria

Sub Criteria	Weights ω	Sub Criteria	Weights ω	Sub Criteria	Weights ω
C_{11}	0,1633	C_{51}	0,1521	C_{91}	0,0367
C_{12}	0,1367	C_{52}	0,11	C_{92}	0,028
C_{13}	0,7	C_{53}	0,7379	C_{93}	0,9353
C_{21}	0,0084	C_{61}	0,0321	C_{101}	0,1783
C_{22}	0,006	C_{62}	0,012	C_{102}	0,05
C_{23}	0,9856	C_{63}	0,9559	C_{103}	0,7717
C_{31}	0,1482	C_{71}	0,0746	C_{111}	0,0109
C_{32}	0,08	C_{72}	0,023	C_{112}	0,004
C_{33}	0,7718	C_{73}	0,9024	C_{113}	0,9851
C_{41}	0,0639	C_{81}	0,0378	C_{121}	0,0937
C_{42}	0,01	C_{82}	0,028	C_{122}	0,03
C_{43}	0,9261	C_{83}	0,9342	C_{123}	0,8763

To consider uncertainty in the problem, the value of each alternative for each criterion is determined using the triangular fuzzy number, linguistic variable and importance level shown in Table 7.

The results obtained for the multicriteria decision making methods are shown in Table 8. In most methods, alternative A_2 (solar energy) is ranked first. The consistency of results across methods indicates that the selection of renewable energy sources is objective, accurate and balanced.

Table 7. Linguistic variables and importance degree

Importance	Abbreviation	Reliability
		Triangular fuzzy number (TFN)
Very Low	VL	(0.0, 0.0, 0.2)
Low	L	(0.05, 0.2, 0.35)
Medium Low	ML	(0.2, 0.35, 0.5)
Medium	M	(0.35, 0.5, 0.65)
Medium High	MH	(0.5, 0.65, 0.8)
High	H	(0.65, 0.8, 0.95)
Very High	VH	(0.8, 1.0, 1.0)

Sensitivity analysis [14]. Considering that the criteria given in solving the problem are determined by the decision makers, the subjectivity of the decision maker, uncertainties in his opinion and doubts make it impossible to determine whether the decision given is 100% correct or incorrect. Sensitivity analysis allows to assess how much the output results will change in response to small changes in the input parameters of the model or system.

[14] Hasanli, N.I. Sensitivity analysis of multi criteria decision making Methods used in solving the problem of selecting slternative and renewable energy sources // -Baku: Proceedings Azerbaijan High Technical Educational Institutions, -2024. Volume 45 (05) Issue 10, -p.207-217.

Table 8. Final scores and ranking of alternatives

MCDM methods		A_1	A_2	A_3	A_4	A_5
		Wind energy	Solar energy	Hydropower	Geothermal energy	Biofuel
AHP	rank	3	1	4	5	2
	A_i	0.205	0.229	0.179	0.170	0.215
Qeyri-səlis AHP	rank	4	1	2	5	3
	A_i	0.599	0.769	0.715	0.597	0.697
TOPSIS	rank	3	1	4	5	2
	A_i	0.466	0.620	0.420	0.404	0.527
Qeyri-səlis TOPSIS	rank	2	1	4	5	3
	A_i	0.894	0.900	0.823	0.684	0.891
COPRAS	rank	3	1	4	5	2
	A_i	0.205	0.231	0.178	0.169	0.21
Qeyri-səlis COPRAS	rank	1	2	3	4	5
	A_i	0.828	0.722	0.708	0.671	0.667
VIKOR	rank	3	2	5	4	1
	A_i	0.25015	0.22513	0.965169	0.725136	0.045
Qeyri-səlis VIKOR	rank	3	1	4	5	2
	A_i	0.867	0.665	0.924	0.928	0.677
ELECTRE	rank	2	1	3	5	4
	A_i	0.712	0.881	0.382	-1.2551	-0.720
PROMETHEE II	rank	2	3	5	4	1
	A_i	0.071	0.0591	-0.140	-0.136606	0.145
ARAS	rank	3	1	5	4	2
	A_i	0.652	0.734	0.5689	0.596995	0.694

The relative closeness of the values obtained for the alternatives is determined and the sensitivity of these values to changes in the criteria weights is calculated using Formula 9, which provides the sensitivity coefficients ∂_{ij}.

$$\partial_{\mathrm{ij}} = \frac{\mathrm{P_j - P_i}}{\mathrm{a_{jk} - a_{ik}}} \leq \omega_{\mathrm{k}} ; \tag{9}$$

here

$P_j - P_i$ - the difference between the values of alternatives j and i according to criterion k

$a_{jk} - a_{ik}$ - the difference in the relative proximity of alternatives i and j (obtained by the AHP method) according to criterion k

ω_k - is the weight of the k criterion.

When the sensitivity coefficient ∂_{ij} is less than or equal to the weight value $\partial_{ij} \leq \omega_k$ in the same column, the solution is considered determined. If not, it is considered nondetermined (N/D)

The percentage description of the criteria that determine the change in alternative ranks is determined by the formula 10.

$$\partial_{\mathrm{ij}} = \frac{\mathrm{P_j - P_i}}{\mathrm{a_{jk} - a_{ik}}} * \frac{100}{\omega_{\mathrm{k}}} \tag{10}$$

The overall change in activity values is identified using the smallest score, which is considered the critical value. According to the results of the sensitivity analysis in Table 9, the values obtained for the alternative pairs were positive and negative values. A negative value indicates that the weight of the criterion needs to be increased for a change in ranking, while a positive value shows that it should be decreased.

For a change in the ranking of alternatives $A_1 - A_3$ (AHP–COPRAS), the best possible and minimum required change is a

65.05% decrease in the weight of criterion C_4.
To cause an overall change, the most critical criterion in the table must be adjusted by at least 20.74%. Thus, the most significant shift in the overall rankings may occur between alternatives $A_2 - A_4$ (TOPSIS–VIKOR) if the weight of criterion C_4 is reduced by 20.74%.

Table 9. Fragment of the sensitivity analysis result

Alternative pairs	ω-weight				
	0.3199	0.2481	0.1124	0.215	0.1046
	C_1	C_2	C_3	C_4	C_5
$A_1 - A_2$	N/D	N/D	N/D	N/D	N/D
$A_1 - A_3$	N/D	-82.2291	N/D	65.06143	N/D
$A_1 - A_4$	N/D	52047.43	N/D	N/D	-1271.89
$A_1 - A_5$	-655.557	-765.249	-4648.64	91.3628	M/O
$A_1 - A_6$	N/D	N/D	N/D	N/D	N/D
….	….	….	….	….	….
$A_2 - A_4$	-78.3544	-64.2882	88.26774	20.74781	-47.1486
….	….	….	….	….	….
$A_6 - A_7$	N/D	N/D	N/D	N/D	N/D

CONCLUSION

1. The shortest and optimal distance was found using the ACO+TOPSIS hybrid method[23,21].
2. A fuzzy recurrent neural network trained with a genetic algorithm was established to predict long-term and fuzzy time series of electricity consumption in Turkey[15].
3. C-means clustering and fuzzy recurrent neural network trained with backpropagation algorithm was constructed to predict the porosity of reservoir rocks in deeper formations[17].
4. The quality of sulfocations was assessed using the TOPSIS method extended with fuzzy logic[22].
5. Alternative and renewable energy sources were selected using AHP, TOPSIS, VIKOR and COPRAS methods extended with fuzzy logic [19].

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