ISSN (Online): 2455-7838
SJIF Impact Factor : 6.093

EPRA International Journal of

Research & Development

(IJRD)

Monthly Peer Reviewed & Indexed
International Online Journal

Volume: 4, Issue:4, April 2019

Published By
EPRA Publishing

SJIF Impact Factor: 6.093 Volume: 4 | Issue: 4 | April | 2019 ISSN: 2455-7838(Online)
EPRA International Journal of Research and Development (IJRD)
Peer Reviewed Journal

INTELLIGENT SUPPORT ACCEPTANCE SOLUTIONS IN MULTICRITERIA TASKS OPTIMIZATION IN UNCERTAINTY CONDITIONS

Kabildjanov Aleksandr Sabitovich
Head of the laboratory "Intellectual systems of management" of the Scientific and Innovation center of Information Technologies at Tashkent University of Information Technologies, Tashkent, Uzbekistan

Okhunboboyeva Charos Zukhriddin kizi
Assistant, Tashkent institute of irrigation and agricultural mechanization engineers, Tashkent, Uzbekistan

ABSTRACT
The intellectual method of decision support in problems of multicriteria parametric optimization based on neural network approximation of the function of the preference of the decision maker is considered. An example of using the described method in the optimization problems of the design parameters of land reclamation equipment is given.
KEYWORDS: ***technical system, technological process, parametric optimization, vector criterion, scalarization, decision making, function of preferences, neural networks, approximation.***

INTRODUCTION

When designing technical systems (TS), the problem of multicriteria optimization often arises, which consists in finding a vector of design parameters that satisfies the constraints imposed and optimizes the vector function [1-5]. The task of multi-criteria optimization in this case is formulated as follows:

$$f(x) = (f_1(x), f_2(x), \dots, f_k(x)) \to \min_{x \in \Omega}, \quad (1)$$

where $f(x)$ is the vector function of the criteria being optimized; $x = (x_1, x_2, \dots, x_n)$ - vector of variable variables; Ω - the scope of feasible solutions.[1]

The function in expression (1) does not limit the generality of the formulation of the multi-criteria optimization problem, since any function φ to be maximized can be replaced by the inverse φ^{-1}, which must be minimized.

The decision-making methods for multicriteria optimization tasks used in practice are very diverse. When classifying them, three large groups of methods can be distinguished:

• a priori methods in which the preferences of the decision maker are taken into account by setting priorities for each of the individual optimality criteria by ranking them by importance, or by introducing weights $\alpha_i;\ i = \overline{1,k}$, based on the condition: $\alpha_i > 0; \sum_{i=1}^{k} \alpha_i = 1$;

• a posteriori methods in which the decision maker pre-adds additional information about their preferences after a certain number of non-dominated decisions have been received;

• iterativemethods consisting of a set of iterations, each of which includes solving a multicriteria optimization problem and evaluating the result of the decision by the decision maker. Evaluation of the result of the decision is made using a linguistic variable with values such as «excellent», «good», etc., or based on the introduction of the function of preferences [2]

Let us dwell on the last two groups of methods, since they ensure the active participation of the decision maker (DM) in solving complex optimization problems and have a tendency to develop on the basis of the methods of the theory of artificial intelligence. Consider an example of optimizing the design parameters of reclamation equipment.[2,3]

MATERIALS AND METHODS

Research has been fulfilled in 2008-2012 in mountainous, foothill and plain areas of Tashkent and Kashkadarya regions (Photo 1). Objects of investigation were all species of *Agaricus* mushrooms registered by other scientists and in our own investigations. Field works were realized mainly in the route observations.

Imagine a mathematical model of the vehicle in the following form:

$$y = f(x,a), \qquad (2)$$

where $y = (y_1, y_2, ..., y_k)$ is the vector of the output parameters of the TS, which are partial criteria of optimality; $x = (x_1, x_2, ..., x_n)$ - vector of variable parameters of the TS; $f(x,a) = (f_1(x,a), f_2(x,a), ..., f_k(x,a))$ - vector function; $a = (a_1, a_2, ..., a_l)$ - the parameters of the mathematical model of the TS.

As a rule, the following restrictions are imposed on the vehicle parameters: 1) $y_i \geq t_i$; $y_j = t_j$; $y_l \leq t_l$ - functional limitations on the output parameters that determine the operating conditions of the TS; t_i, t_j, t_l -specified values;

2) $x_{j\min} \leq x_j \leq x_{j\max}$; $j = \overline{1,n}$ - direct restrictions on the internal parameters of the TS; $x_{j\min}$, $x_{j\max}$; $j = \overline{1,n}$ - given lower and upper limits of variation of the variable parameter x_j.

Having rewritten the functional limitations on the output parameters of the TS in the form $g_i(x) \leq 0$, the general deterministic decision-making problem for choosing the optimal values of the vector of variable parameters can be formalized as follows:

$$f_i(x,a) \to \min_x, \; x \in \Omega_x, \; i = \overline{1,k}, \qquad (3)$$

where $\Omega_x = \left\{ x \in R^n \left| g_i(x) \leq 0; \; i = \overline{1,k}; \; x_{j\min} \leq x_j \leq x_{j\max}; \; j = \overline{1,n} \right. \right\}$ is the set of admissible solutions.

Problem (3) is not standard due to the presence of the vector optimality criterion. Therefore, for its effective numerical solution by conventional means, it is necessary to perform the scalarization of the vector optimality criterion.[4]

We will proceed from the fact that in practice in most engineering problems it is sufficient to determine such values of the parameter vector *x*, for which functional limitations will be fulfilledfor all output parameters of the TS with sufficient reserve for practical purposes. Then the minimization problem (3) can be replaced by the task of maximizing the estimates of the degree of fulfillment of functional constraints for each of the output parameters of the TS.

The assessment of the degree of fulfillment of each of the functional limitations $f_i(x,a) \leq t_i, \; i = \overline{1,k}$ can be stocks [6, 7], determined by the following formula

$$z_i(x,a) = \alpha_i \left[\left(t_i - f_i(x,a) \right) / \delta_i - 1 \right] \geq 0; \; \alpha_i > 0; \; \sum_{i=1}^{k} \alpha_i = 1, \qquad (4)$$

where δ_i is the estimate of the scattering of the *i*-th output parameter, which is set on the basis of practical considerations, or is determined using the method of statistical tests; α_i - weight coefficients that determine the relative significance of individual criteria f_i.

As a result, we obtained the multicriterial optimization problem

$$z_i(x,a) \to \max_{x \in D}; \; i = \overline{1,k}, \qquad (5)$$

where D is a set in which direct restrictions on the variable parameters with the help of a corresponding replacement, for example $x_j = x_{j\max} + \left(x_{j\min} - x_{j\max}\right) * \sin^2(x_j^{'})$, are translated into functional ones; $x_j^{'}$ - the value of the *j*-th variable parameter from the set Ω_x .[5]

Let us apply the maximin convolution of the vector criterion (5), which will lead to the global criterion:

$$F(x) = \min_{i=1,k} z_i(x,a) \to \max_{x \in D}, \qquad (6)$$

The functional (6) is not smooth, which significantly complicates the situation and requires the use of special optimizing procedures, which are highly complex [6, 8]. Apply the smoothing procedure of the functional (6).

It's obvious that $\arg\min_i \left(z_i(x,\mathrm{a})\right) = \arg\max_i \left[\exp\left(-z_i(x,a)\right)\right]$. Therefore, problem (6) is rewritten as follows

$$\max_i \left[\exp\left(-z_i(x,a)\right)\right] \to \min_{\mathrm{x}}, \qquad (7)$$

If we accept $\varphi_i(x,a) \overset{\Delta}{=} \exp\left(-z_i(x,a)\right)$, then in relation to the problem (6) a medium-level convolution can be used

$$F(x) = \sum_{i=1}^{k} \varphi_i^{\gamma}(x,a) \to \min_{x \in D};\ \gamma = 1,2,... \qquad (8)$$

As a result, we arrive at the following modified optimality criterion

$$F(x) = \sum_{i=1}^{k} \exp\left(-\gamma \cdot z_i(x,a)\right) \to \min_{x \in D};\ \gamma = 1,2,... \qquad (9)$$

When solving practical problems based on the modified criterion (9), it is reasonable to increase the parameter γ step by step, which will allow, firstly, to avoid overfilling the computer's discharge grid, and, secondly, when obtaining a satisfactory solution during the process.

Application in practice of the modified criterion (9) allows to realize the scaling of the vector criterion, to overcome the «ravine» problem and, due to the limited and closed set of the set $\mathrm{A}_x = \left\{ x \in R^n \left| x_{j\min} \le x_j \le x_{j\max};\ j = \overline{1,n} \right. \right\}$, to obtain a unique solution, using the simplest algorithms for smooth optimization [5, 6].

The main problem in solving problem (9) is that the values $\alpha_i,\ i = \overline{1,k}$ may not be known in advance, which leads to the uncertainty of the priorities.

Solution technique. Denote the vector of values of weight coefficients as $L = \left(\alpha_1, \alpha_2, ..., \alpha_k\right)$. Then the solution of the single-criterion optimization problem (9) has the form:

$$\min_{X Î D} F(x,L) = F(x^*, L). \qquad (10)$$

Denote the reachability set of the problem (the set into which the vector optimality criterion displays the set Ω_X) as Ω_F ; front Pareto task - Ω_F^* , $\Omega_F^* \subset \Omega_F$; Pareto set - Ω_X^* . If $x \in \Omega_X^*$, then we will assume that the vector x is an effective Pareto vector [9].

If for each $L \in D_L = \{L | \alpha_i \le 0, \sum_{i=1}^{k} \alpha_i = 1\}$ solution of problem (10) is unique, then this means that each of the admissible vectors corresponds to a single vector x^* and the corresponding values of the particular criteria $f_1(x,a),\ f_2(x,a), ... f_k(x,a)$. On this basis, it is possible to construct some preference function (FP) of the DM $\zeta(L)$ defined on the set D_L :

$$\zeta : L \to R. \qquad (11)$$

Then the problem of multi-criteria optimization is reduced to the choice of such a vector of values $L^* \in D_L$ for which $\max_{L \in D_L} \zeta(L) = \zeta(L^*)$.

We will assume that ζ it is a linguistic variable that has some number of final values, for example, e = 5: «Very bad», «Bad», «Average», «Well», «Very well». The kernel of a fuzzy variable ζ is denoted by ζ^0 [6] and we introduce the following correspondence: the value of «Very bad» corresponds to $\zeta^0 = 1$, the value of «Bad» corresponds to $\zeta^0 = 2$, the value of «Average» corresponds to $z^0 = 3$, the value of «Well» corresponds to $z^0 = 4$, the value of «Very well» corresponds to $z^0 = 5$.

Thus, the problem of multicriteria optimization is reduced to finding a vector $L^* \in D_L$ that provides the maximum of a discrete function $\zeta(L)$:

$$\max_{L \in D_L} \zeta(L) = \zeta(L^*), \qquad (12)$$

those, approximation of the FP of DM.

The general scheme for solving such a problem is iterative in nature and has several stages [3].

At the *first stage*, randomly or in some other way is generated by m vectors *L₁*, *L₂*, ..., *Lₘ*. Theorderofthefollowingstepsisasfollows.

1) The single-criterion problem is solved:

$$\min_{X \hat{I} D} F(x, L_l) = F(x^*, L_l),\ l = \overline{1, m}. \qquad (13)$$

2) The found values are displayed $x_l^*; l = \overline{1, m}$; $f_i(x_l^*);\ i = \overline{1, k}$.
3) Estimated values obtained $f_i(x_l^*);\ i = \overline{1, k};\ l = \overline{1, m}$ and values are entered FP $z(L_l);\ l = \overline{1, m}$.

At the *second stage*, based on the values of L_1, L_2, ..., L_m and estimates $z(L_l);\ l = \overline{1, m}$ the following actions are performed:

1) A function $\tilde{\zeta}_1(L)$ is constructed that approximates $\zeta(L)$ in the neighborhood of the tochekL_1, L_2, ..., L_m;
2) Solves a singlecriterionproblem

$$\max_{L \in D_L} \tilde{\zeta}_1(L) = \tilde{\zeta}(L_1^*); \qquad (14)$$

3) A single-criterion problem is solved $\min_{X \hat{I} D} F(z, L_1^*) = F(x^*, L_1^*)$;
4) The found values are displayed x^*; $f_i(x^*);\ i = \overline{1, k}$;
5) Estimated values obtained $f_i(x^*);\ i = \overline{1, k}$ and the value of FP $\zeta(L_1^*)$ is entered.

At the third stage, on the basis of the available values of L_1, L_2, ..., L_m, and the corresponding estimates of the FP $\zeta(L_1),\ \zeta(L_2), ..., \zeta(L_k),\ \zeta(L_1^*)$ the function $\zeta(L)$ is approximated in a neighborhood of the points L_1, L_2,…, L_m, L_1^*, as a result of which the function $\tilde{\zeta}_2(L)$ is constructed. Further, the procedure continues according to the scheme of the second stage until the DM decides to stop the calculations. At each iteration, it is allowed to «roll back» in order to change the previously entered estimates of its own FP.[10]

Let us dwell on the approximation of the FP of the DM by neural networks. The peculiarity of this approach is that the learning process of neural networks occurs in a small training set. This circumstance is due to the fact that the number of overclocking iterations should not be too large, otherwise the DM can terminate the computation process without getting a final decision. As a result, only two-layer MLP neural networks are used for approximation of the FP of the DM.

Since the components of the weight multipliers vector L are constrained by $\sum_{i=1}^{k} \alpha_i = 1$ one of the weighting factors (let it be a multiplier α_k) can be expressed through the remaining multipliers: $\alpha_k = 1 - \sum_{i=1}^{k-1} \alpha_i$. As a result, only the components $\alpha_1, \alpha_2, ..., \alpha_{k-1}$ of the vector L are considered as inputs to the neural networks. [11]

RESULTS AND DISCUSSION

The solution of the problem of multi-criteria optimization of the parameters of the scrubber rhizomes weeds WRC-1,8 was carried out.

The mathematical model of the weed rhizome comber in the dimensionless scale has the following form [10]:

$$\hat{y}_1 = 79.55 - 1.01x_2 - 2.37x_3 + 8.07x_4 + 16.57x_5 + 1.80x_1x_2 - 0.92x_1x_5 - \\ - 0.96x_3x_5 - 5.71x_4x_5 + 3.33x_{12} + 3.08x_{22} - 5.17x_{42} - 17.00x_{52}; \quad (15)$$

$$\hat{y}_2 = - 0.31x_1 - 1.02x_2 + 0.39x_3 + 0.33x_4 + 0.38x_5 + 3.92x_{12} + 4.13x_{22} + \\ + 2.82x_{32} + 3.07x_{42} - 3.20x_{52}, \quad (16)$$

where y_1 is the degree of separation of the stones by the safety drums of the weed bark remover; y_2 - loss of weeds rhizomes; $x_1, x_2, x_3, x_4, x_5 \in [-1,1]$- variable parameters.

The set of permissible decisions in natural scale was defined as:

$$\Omega_n = Y \cap X = \{Y \in R^k \,|\, y_1 \geq 60\%; y_2 \leq 10\%; X \in R^n \,|\, -1 \leq x_i \leq 1; i = \overline{1,5}\}. \quad (17)$$

The scatter estimates of the output parameters were chosen as follows: $d_1 = d_2 = 20\%$. The problem of static optimization with fixed values α_i; $i = \overline{1,2}$ in formulation (9) was solved by coordinatewise descent. The step of changing the values α_1 and α_2 was set equal to 0.1.

Software implementation of the algorithm for solving the problem (9) was carried out in a Lazarus environment on a personal computer with an Intel (R) Pentium (R) CPU 4560 3.50 GHz and 8 GB RAM. The time to solve the problem of multi-criteria optimization for each set of combinations of values of α_1 and α_2 was 4.5 seconds. The results of the decision are summarized in table 1.

When solving the problem (12), the partial optimality criteria were normalized by the formula: $f_i'(x) = \frac{f_i(x) - f_i^{\min}}{f_i^{\max} - f_i^{\min}} \in [0,1]$, where $f_i^{\max} = \max f_i(x); \quad f_i^{\min} = \min f_i(x); \; i = \overline{1,2}$.

The reachability set is shown in Figure 1. For each particular criterion of optimality $f_i(z); \; i = \overline{1,2}$ the estimations of linguistic variables $\vartheta_i; \; i = \overline{1,2}$ were entered, systematized in table 2.

The rules for forming the values of a function ζ on the basis of $\vartheta_i; \; i = \overline{1,2}$ are systematized in Table 3. Since there is a one-to-one functional relationship between the values of α_1 and α_2, $\alpha_2 = 1 - \alpha_1$, only the dependence $\zeta(\alpha_1)$ was studied in the approximation of the preference function.[11]

Table 1. The results of the software implementation of the optimization model (9)

α_1	α_2	$y_i;\ i=\overline{1,2}$	$y_1 - t_1$	$t_2 - y_2$	F	x_1	x_2	x_3	x_4	x_5
0	1	y_1=78.1437 y_2=0.1027	18.143	9.897	2.0024	0.0395	0.1235	-0.0691	-0.053	-0.059
0.1	0.9	y_1=82.2025 y_2=0.0738	22.202	9.926	2.0022	0.0450	0.1202	-0.1184	0.0636	0.1401
0.2	0.8	y_1=83.8363 y_2=0.3507	23.836	9.649	2.0018	0.0494	0.1124	-0.1842	0.1509	0.2400
0.3	0.7	y_1=84.7781 y_2=0.6603	24.778	9.339	2.0015	0.0534	0.0963	-0.2706	0.2229	0.2986
0.4	0.6	y_1=85.5158 y_2=1.0578	25.515	8.942	2.0011	0.0501	0.0560	-0.3868	0.2861	0.3368
0.5	0.5	y_1=91.0826 y_2=6.5512	31.082	3.448	2.0006	1.0000	0.7185	-0.5468	0.3088	0.3471
0.6	0.4	y_1=93.4784 y_2=9.2129	33.478	0.787	1.9999	1.0000	1.0000	-0.7917	0.3324	0.3724
0.7	0.3	y_1=94.1242 y_2=**10.3233**	34.124	**-0.323**	1.9990	1.0000	1.0000	-1.0000	0.3682	0.3903
0.8	0.2	y_1=94.1647 y_2=**10.4431**	34.164	**-0.443**	1.9981	1.0000	1.0000	-1.0000	0.4030	0.3992
0.9	0.1	y_1=94.1848 y_2=**10.5555**	34.184	**-0.555**	1.9973	1.0000	1.0000	1.0000	0.4351	0.4057
1	0	y_1=94.1906 y_2=**10.6618**	34.190	**-0.661**	1.9964	1.0000	1.0000	1.0000	0.4648	0.4105

Fig.1- Set of reachability Ω_F

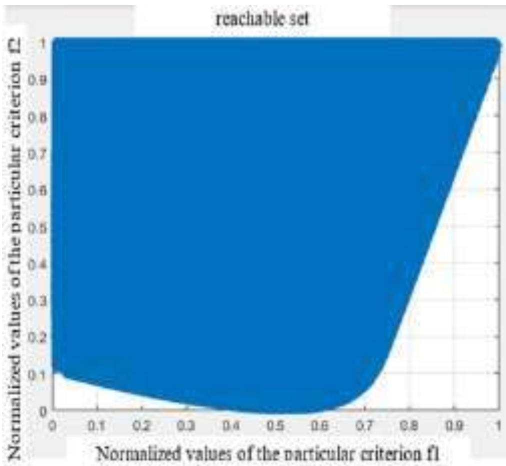


Table 2. Estimates of linguistic variables

f_1	f_2	$f_1^{'}$	$f_2^{'}$	$\vartheta_i;\ i=\overline{1,2}$
[0; 70]	[12;15]	[0; 0.7]	[0.8; 1]	«Very bad» (VB)
[70;80]	[10;12]	[0.7; 0.8]	[0.666; 0.8]	« Bad» (B)
[80;90]	[5;10]	[0.8; 0.9]	[0.333; 0.666]	«Average» (A)
[90;94]	[2;5]	[0.9; 0.94]	[0.133; 0.333]	«Well» (W)
[94;100]	[0; 2]	[0.94; 1]	[0; 0.133]	«VeryWell» (VW)

At each step of solving the problem (12) for each fixed value, problem (13), as in the first case, was solved using the coordinate descent method. To solve problem (12), the golden section method was used. The approximation of the FP of the DM was performed using a two-layer perceptron in the Statistica Neural Networks (SNN) software environment. The MLP network was trained using the Levenberg-Markar method. Values α_1 for «overclocking» iterations were randomly generated. The total time to solve the problem (12) was 56 s.

Table 3. Rules for the formation of the values of FP of DM

	J_1 = VW	ϑ_1 = W	ϑ_1 = A	ϑ_1 = B	J_1 = VB
J_2 = VW	z = 5 (VW)	z = 5 (VW)	z = 4 (W)	z = 3 (A)	z = 2 (B)
ϑ_2 = W	z = 5 (VW)	z = 4 (W)	z = 3 (A)	z = 2 (B)	z = 2 (B)
ϑ_2 = A	z = 4 (W)	z = 3 (A)	z = 3 (A)	z = 2 (B)	z = 1 (VB)
ϑ_2 = B	z = 3 (A)	z = 2 (B)	z = 2 (B)	z = 2 (B)	z = 1 (VB)
J_2 = VB	z = 2 (B)	z = 1 (VB)	z = 1 (VB)	z = 1 (VB)	z = 1 (VB)

The results of solving the problem (12) are given in Table 4 and are illustrated in Fig. 2. In Table 4, «overclocking» iterations are highlighted in gray. In fig. 2 the blue circles mark the results of the acceleration iterations, and the raspberry circle marks the value of the function $\zeta(L)$ at the last iteration.

Table 4. Results of solving the problem (12)

№	α_1	f_1	f_2	$f_1^{'}$	$f_2^{'}$	ζ
1	0	78.1437	0.1027	0.78	0.00684	A (3)
2	0.32	84.9325	0.7296	0.84	0.04864	W(4)
3	0.87	94.1805	10.5225	0.94	0.70150	A(3)
4	0.59	93.3867	9.0786	0.93	0.60524	A(3)
5	0.26	84.4437	0.5307	0.84	0.35385	W(4)
6	1	94.1906	10.6618	0.94	0.71078	A(3)
7	0.15	81.1602	0.2086	0.81	0.0139	W(4)
8	0.24	84.2686	0.4692	0.84	0.0312	W(4)
9	0.35	85.1543	0.8410	0,85	0.0560	W(4)
10	0.37	85.2986	0.9221	0.85	0.0614	W(4)

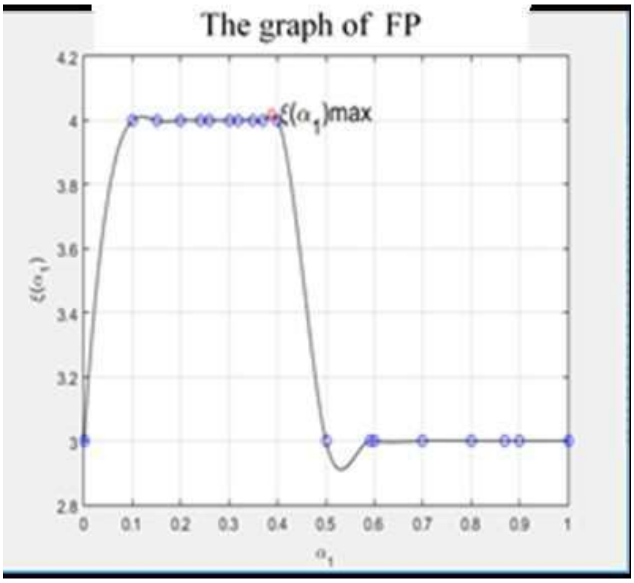
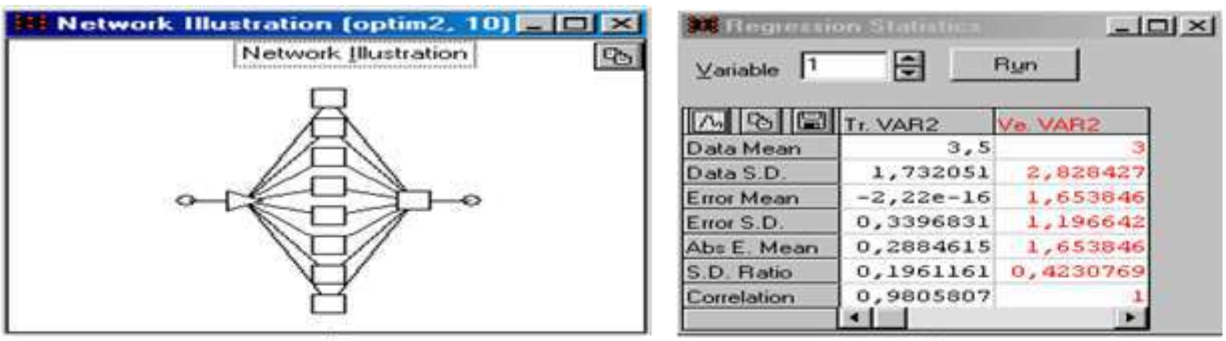


Fig. 2- Face preference function, decision maker



a *b*

Fig. 3- Neural network architecture and regression statistics at the final iteration step
a - MLP architecture; *b*-window Regression Statistics

CONCLUSIONS

The proposed method of intellectual decision support in multi-criteria optimization problems in conditions of uncertainty has a number of positive qualities. First, the use of a combination of maximin and medium-level convolution allows scalarization of the vector criterion, overcome the problem of «ravine» and obtain a unique solution using simple algorithms of smooth optimization. Secondly, the use of neural networks provides a high accuracy of the approximation of the FP of DM with relatively small computational costs for their training. Third, the preferences of DM are taken into account, and therefore it is ensured that it is directly involved in the choice of the final decision.

REFERENCES

1. *Lotov A.V., Pospelova I.I. Multi-criteria decision-making tasks: studies. allowance. M .: MAKS Press, 2008. - 197 p.*
2. *Shvarts D.T. Interactive Methods for Solving the Multi-Criteria Optimization Problem. Review // Science and Education. MGTU them. N.E. Bauman. Electron. journals 2013. № 4. Access mode: http://technomag.bmstu.ru/doc/547747.html.*
3. *Karpenko A.P., Fedoruk V.G. Approximation of the function of the preferences of the person making the decision in the problem of multicriteria optimization. 3. Methods based on neural networks and fuzzy logic // Science and Education. MGTU them. N.E. Bauman. Electron. journals 2008. № 4. Access mode: http://www.technomag.edu.ru/doc/86335.html.*
4. *Karpenko A.P., Semenikhin A.S., Mitina E.V. Population methods of approximation of the Pareto set in the problem of multicriteria optimization. Review // Science and Education. MGTU them. N.E. Bauman. Electron. journals 2012. № 4. Access mode: http://www.technomag.edu.ru/doc/363023.html.*
5. *Chernorutsky I.G. Decision making methods.-SPb .: BHV-Petersburg, 2005.- 416 p.*
6. *Kabildjanov A.S. Fuzzy approximation in problems of optimal parametric synthesis of technical objects. - Journal «Problems of Informatics and Energetics». Tashkent, №5. 2016. pp. 23-32.*
7. *Kabildjanov A.S., OkhunboboevCh.Z., Avazbaev A.A. Methods of choosing the optimal values of the parameters of land-reclamation technology in a multi-criteria environment. - Journal «Bulletin of Agrarian Science of Uzbekistan», Tashkent, No. 4, 2017. P. 98-105.*
8. *Abdujabborov A.A. Ohunboboeva. Algorithmization of the parametric optimization problem under conditions of goal uncertainty. «Modern Problems of Agriculture and Water Management» Traditional XV Young Scholars, Masters and Scholarly Students Conference. Section II.TIMI. Tashkent. 2016.- pp. 192-195.*
9. *Moiseev N.N. Mathematical problems of system analysis. - M .: Science, 1981. - 488 p.*
10. *Augambaev M., Ivanov A., Terekhov Yu. Fundamentals of Planning a Scientific Research Investigation Experiment: Tutorial. - Tashkent: Ukituvchi, 1993. - 336 p.*
11. *Kabildjanov A.S., Okhunboboeva Ch.Z. Synthesis of optimization models of multidemensional objectsin conditions of inhomogeneity of statistics experimental data. / Scientific an technical journal. Sustainable Agreculture. №1.(1).2018.*