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INVESTIGATION OF HUMAN FACTORS WHILE SOLVING MULTIPLE CRITERIA OPTIMIZATION PROBLEMS IN COMPUTER NETWORK

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Abstract. The aim of this investigation is to analyze a class of multiple criteria optimization problems that are solved by human-computer interaction, using a computer network. A multiple criteria problem is iterated by interactively selecting different weight coefficients of the criteria. Several parallel solution strategies for solving this optimization problem have been developed and analyzed. The experiments have shown the importance of human assistance in solving this multiple criteria problem. New experimental investigations have been carried out with a different number of computers and different strategies where the human factors are analyzed. We have investigated the time necessary for human's training to solve this multiple criteria optimization problem, the dependence of human factors on the strategy of parallel solution and on the number of computers in a computer network.

Keywords: multiple criteria optimization, human factors, parallel computing, MPI, decision support system, interactive optimization.

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1. Introduction

The intensive current development of new technologies requires solving complex problems of computer-aided design and control. Here a search for an optimal solution acquires the essential significance. Methods based on decision making to get optimal solution are often used. Decision making can be classified as (I) multiple attribute decision making for the sorting or the ranking of alternatives according to several attributes (Turskis 2008; Zavadskas *et al.* 2006); (II) multiple criteria decision making, for driving a vector optimization based design

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process to a solution. In this paper we use the second case for investigating a multiple criteria optimization problem. Comprehensive surveys of the multiple criteria optimization methods are presented in (Andersson 2000; Collette and Siarry 2003; Ehrgott 2005; Figueira *et al.* 2005; Miettinen 1999). However, new ways for solving multiple criteria optimization problems are being developed (Cai and Wang 2006; Eichfelder 2008; Kim and de Weck 2006). The investigations are carried out in two directions: development of new optimization methods as well as software that would embrace various realizations of the methods developed.

Computer networks are widespread and permit us to solve complex optimization problems by using ordinary personal computers. Furthermore, the networks enable us to solve considerably more complex problems by using the aggregate power of many computers (Čiegis 2005). The usage samples of grid computing for solving complex multiple criteria problems are given in (Nebro *et al.* 2007). A general overview of parallel approaches for multiple criteria optimization is presented in (Talbi *et al.* 2008). Evolutionary algorithms and their parallel versions are often applied for solving multiple criteria optimization problems (Coello *et al.* 2006; De Toro Negro *et al.* 2004; Talbi *et al.* 2008; Van Veldhuizen *et al.* 2003).

In this paper the methods are analyzed for interactive solving of a complex multiple criteria optimization problem by using a computer network. Two interactive strategies were investigated when the experiments were carried out by one decision maker (DM) (Petkus and Filatovas 2008). The new aim of investigation is to detect the effect of influence of human factors on the solution of multiple criteria optimization problems. Some decision makers took part in this investigation.

2. Statement of the optimization problem

In everyday life we often deal with problems of multiple criteria. In the general case, the ideal solution with respect to one criterion can be absolutely unacceptable with respect to another. Thus, it is necessary to seek an optimal solution that could satisfy all the criteria.

Let us analyze a multiple criteria optimization problem:

$$\min_{X=(x_1,\dots,x_n)\in\bar{A}} f_j(X), \quad j=\overline{1,\mu}, \tag{1}$$

where $\bar{A}$ is a bounded domain in the n-dimensional Euclidean space R^n, μ is the number of criteria comprising problem (1), and the functions $f_j(X): R^n \to R^1$ are criteria.

Let some functions $f_j(X),\ j=\overline{1,m},\ (m\le\mu)$ among $f_j(X),\ j=\overline{1,\mu}$, have the following properties:

$f_j(X)=\min_{Y\in\bar{A}} f_j(Y)=0$ as $X\in\bar{A}_j\subset\bar{A}$;

$f_j(X)=f_j(\delta_j(X))$, i. e., the functions $f_j(\cdot)$ are dependent on other functions $\delta_j(X)$;

$f_j(X)=\min_{Y\in\bar{A}} f_j(Y)$ as $\delta_j(X)\in[\delta^j_{\min},\delta^j_{\max}]$.

It follows from the last property that the dependence of $f_j(\cdot)$ on $\delta_j(X)$ has a zone of constant values as $\delta_j(X)\in[\delta^j_{\min},\delta^j_{\max}]$.

One of the possible ways of solving the system of problems (1) is to form a single criterion problem by summing up all the criteria that are multiplied by the positive weight coefficients $\lambda_j,\ j=\overline{1,\mu}$:

$$\min_{X=(x_1,\ldots,x_n)\in \bar{A}} \sum_{j=1}^{\mu} \lambda_j f_j(X). \tag{2}$$

Then the solving process of problem (2) is reiterated by selecting different combinations of the coefficient values $\lambda_j,\ j=\overline{1,\mu}$. Many solutions are obtained and they are the points of Pareto. The most acceptable ones are selected by DM.

In this paper, a multiple criteria problem of selecting the optimal nutritive value is investigated. This problem was presented and researched in (Dzemyda and Petkus 1998, 2001; Petkus and Filatovas 2008). The aim of the research presented in this paper is to investigate human factors when solving multiple criteria optimization problems in computer network.

The objective of the problem is to minimize farmers' expenditure on nutrition by the optimal selection of feed ingredients in cattle-breeding. The cost price must be minimized in order to meet the necessary requirements of the nutritive value. The fact that animal diets consist of different ingredients is taken into consideration, on the one hand, and each ingredient varies in different nutritive characteristics, on the other hand. The feed cost price is calculated by the formula:

$$\varphi(x_1,\ldots,x_n) = \sum_{i=1}^{n} x_i k_i, \tag{3}$$

where x_i is a constituent part of the i-th ingredient in feed; k_i is the price of the i-th ingredient for a weight unit; n is the number of ingredients. The recommended permissible maximal and minimal violation of the requirements $\Psi_j(x_1,\ldots,x_n),\ j=\overline{1,m}$ is calculated by the following formula (m is the number of nutritive characteristics in feed):

$$\Psi_j(x_1,\ldots,x_n) = \begin{cases} 0, \text{ if } R^j_{\min} \le \sum_{i=1}^{n} x_i A_{ij}(x_1,\ldots,x_n) \le R^j_{\max}, \\ \sum_{i=1}^{n} x_i A_{ij}(x_1,\ldots,x_n) - R^j_{\max}\ , \text{ if } \sum_{i=1}^{n} x_i A_{ij}(x_1,\ldots,x_n) - R^j_{\max} > 0, \\ R^j_{\min} - \sum_{i=1}^{n} x_i A_{ij}(x_1,\ldots,x_n), \text{ if } R^j_{\min} - \sum_{i=1}^{n} x_i A_{ij}(x_1,\ldots,x_n) > 0, \end{cases} \tag{4}$$

where $R^j_{\min}$ ($R^j_{\max}$) is the recommended permissible minimal (maximal) amount of the j-th nutritive characteristics in feed; A_{ij} is a nonlinear function that expresses the value of the j-th nutritive characteristics of the i-th ingredient.

Criteria (3), (4) are contradictory, – with an increase in violation of the permissible amount of nutritive characteristics the price of feed is falling. The following objective function (5) that should be minimized to select the optimal nutritive value is:

$$\min_{x_1,\ldots,x_n} f(x_1,\ldots,x_n) = \min_{x_1,\ldots,x_n} \left\{ \sum_{j=1}^{m} r_j \Psi_j^2(x_1,\ldots,x_n) + \sum_{i=1}^{n} x_i k_i + s\left(\sum_{i=1}^{n} x_i - 1\right)^2 + \right. \tag{5}$$

$$\left. \sum_{v=1}^{w} s_v \left(\sum_{i=1}^{n} x_i \left(A_{it_1^v}(x_1,\ldots,x_n) - c_v A_{it_2^v}(x_1,\ldots,x_n)\right)\right)^2 \right\},$$

$$z_{\min}^i \le x_i \le z_{\max}^i,\ i = \overline{1,n},$$

where c_v is the required v-th ratio of nutritive characteristics; the values of the coefficients s and s_v, $v = \overline{1,w}$ have been fixed relatively large.

In comparison with problem (2), the coefficients r_j of problem (5) correspond to the coefficients λ_j of problem (2); the coefficient of the criterion $\varphi(x_1,\ldots,x_n)$ is equal to 1, i.e., $\lambda_{m+1} = 1$; $\delta_j(X) = \sum_{i=1}^{n} x_i A_{ij}(x_1,\ldots,x_n)$; $\delta_{\min}^j$ corresponds to $R_{\min}^j$, and $\delta_{\max}^j$ corresponds to $R_{\max}^j$.

Selection of different values of the coefficients r_j as well as the initial values of the argument $X = (x_1,\ldots,x_n)$ results in different solutions.

3. Interactive usage of computer network

3.1. The idea of interactive multiple criteria optimization

The multiple criteria optimization problem (5) needs many iterations and much computation time. So, in order to accelerate the solving process, we can use the power of many computers. There are two possible ways to use computer network solving this optimization problem:

1. Parallelization of the optimization algorithm (e.g. variable metric) that is used to solve the problem (5) when the values of the weight coefficients r_j, $j = \overline{1,\mu}$ are fixed.
2. Interactive decision making on the basis of several solutions of problem (5) obtained by using local optimization by different computers with various values of the coefficients r_j, $j = \overline{1,\mu}$.

Computers are used more effectively by the second way of solving the problem: time expenditures for sending-receiving data between computers are less.

So, the multiple criteria optimization problem (5) is solved by interactive decision making on the basis of several solutions of problem (5), obtained by using local optimization (variable metrics algorithm) with various values of the coefficients r_j, $j = \overline{1,\mu}$. The preference of DM is taken into account as well. The solving process of problem (5) is reiterated by selecting different combinations of coefficient values r_j, $j = \overline{1,\mu}$ that are called tasks and many solutions are obtained, called as intermediate solutions. The most acceptable solutions are selected by DM (Dzemyda and Petkus 1998, 2001).

3.2. Decision support system

The DM's participation is essential in solving a multiple criteria optimization problem interactively (Huang *et al.* 2005; Miettinen and Mäkelä 2006; Klamroth and Miettinen 2008).

His/her working skills along with formal and informal information obtained on the solved problem affect the calculation process. Thus, the decision support system was designed with user's interface that facilitates his/her work and permits to review the results and to plan the process of calculation (Fig. 1). When solving a multiple criteria problem, the graphical representation plays an important role for decision making (Blasco *et al.* 2008; Ginevičius and Podvezko 2008; Zavadskas *et al.* 2003).

Fig. 1 presents a graphic interface of a decision support system for solving a concrete problem (it is designed according to the specificity of the problem). The problem of optimal selection of the nutritive value has been presented and researched in (Dzemyda and Petkus 1998, 2001; Petkus and Filatovas 2008). The objective of the problem is to minimize farmers' expenditure on nutrition by the optimal selection of feed ingredients in cattle-breeding. The cost price must be minimized in order to meet the necessary requirements of the nutritive value. It is taken into consideration that animal diets consist of different ingredients, on the one hand, and each ingredient differs in different nutritive characteristics, on the other hand. Here, the cost price is one of the major criteria. The rest of the 14 criteria are squared levels of permissible minimal and maximal norm violations.

In Fig. 1, the blocks show the results of a single problem. The left dotted vertical line denotes the permissible minimal level, and the right one – the permissible maximal level of the norm of feed ingredients. Fourteen horizontal bars present deviations from the norm of values of the corresponding nutritive characteristics. A horizontal light grey bar shows the permissible level of the feed ingredient; a dark grey horizontal bar shows a violation of the requirement. On the right side of the block, weight coefficients of the criteria are located.

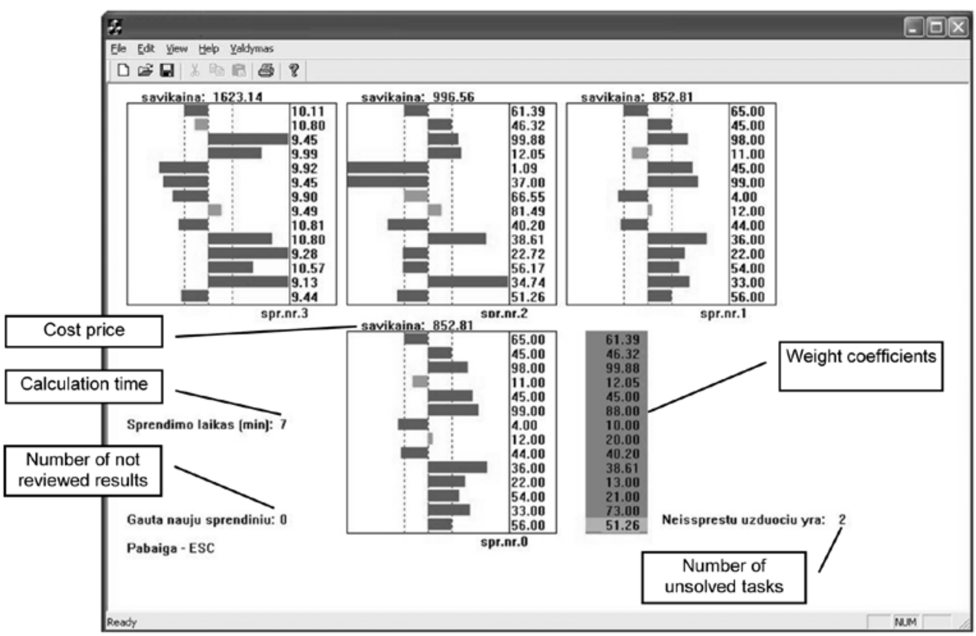

Fig. 1. Graphic interface of decision support system

The top of the window presents the solutions (3 blocks) that have been obtained and memorized up to the moment. The blocks display only three memorized solutions, nevertheless, it is possible to review and use for further editing any other memorized solution with the help of toolbar buttons or the cursor keys. There has been provided a possibility to delete any of the memorized solutions that is improper and therefore needless of editing, as far as the DM is concerned.

The bottom of the window displays the last obtained or edited solution. A small grey block is designed for changing the weight coefficients r_j. The number of the tasks formed but unsolved is shown on the bottom right side of the window. If problem (5) is solved using a computer network, the number of computers that do not solve any tasks at the moment (free computers) are shown, too. The number of solutions obtained and not reviewed by the DM is displayed on the left side of the window. In the case, where the recent solution satisfies the DM more or less, it may be memorized and, in the case of necessity, compared to others after some time. The value of one criterion of the problem has been displayed above. This criterion (the cost price) and the diagram that represents the violations of the requirements allow the DM to predict acceptability of the solution.

An example of the solving process of problem (5) is described in the sequence. The aim of the problem is to achieve the solution with minimal violations of the recommended permissible minimal and maximal amounts of the nutritive characteristics in feed at a lower price.

DM starts solving the problem with the initial data (combinations of coefficient values r_j, $j = \overline{1,\mu}$, selected by the DM). It is in fact impossible to select a proper combination of coefficient values to achieve a preferable solution for DM. The solving process is continued by reiterating different combinations of coefficient values r_j, $j = \overline{1,\mu}$. When the DM finds a preferable solution he/she stops the solving process. Many intermediate solutions are obtained by the DM but only the sequence of the improved solutions is shown in Fig. 2. The cost price $\overline{K}$ and the sum $\overline{S}$ of violations of the requirements are shown below each block. Deviations from the norm of values of the corresponding nutritive characteristics (horizontal bars) are displayed, too. Light grey bars show the permissible level of the feed ingredient and dark grey bars show violations of the requirements. The aim is to select such combination of coefficient values r_j, $j = \overline{1,\mu}$ for the most part of the bars not to be longer than a gap between the central and the left (or the right) vertical dotted lines, i.e., the permissible minimal and maximal level of the norm of feed ingredients not to be exceeded. Longer bars are light grey and shorter bars are dark grey.

3.3. The idea of interactive multiple criteria optimization using a computer network

The multiple criteria optimization problem (5) needs many iterations and much computation time, so, in order to accelerate the solving process, we can use the power of many computers. In this paper, the multiple criteria optimization problem (5) is solved by some interactive strategies using a computer network.

Solving the optimization problem with different values of the weight coefficients r_j in parallel. Different computers solve the same optimization problem (5), only the values of coefficients

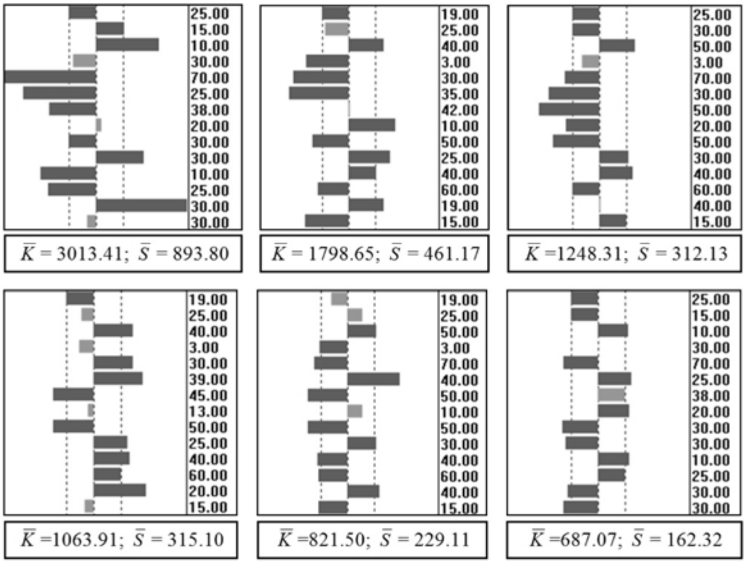

Fig. 2. Intermediate solutions

r_j differ (tasks). The process is organized by designating the computers as the *master* and the *slaves*. The *slaves* (P_1, P_2, P_3, …) solve the tasks and send intermediate solutions to the *master*. The *master* controls the process of computer network members (*slaves*).

Visual comparison of the obtained intermediate solutions and allocation of new tasks for the computer network. The DM communicates with the *master* and selects a new combination of weight coefficients r_j for a single criterion optimization problem (5) that will be allocated by the *master* to one of the *slaves*.

A generalized scheme of the algorithm for solving the optimization problem is presented in Fig. 3. Many computers-slaves enable a DM to form many tasks and send them to the computer network. A special memory (list of tasks) is realized to memorize the newly formed tasks, if all the computers-slaves are busy. The DM starts the solving process, forms a task and sends it to the computer network. If there are free computers, the task is solved by one of the computers-slaves. Otherwise, the task is added to the list of the unsolved tasks. The first unsolved task from the list will be solved as soon as one of the computers-slaves becomes free. When the computer-slave has solved the task, it sends the intermediate solution to computer-master and the DM analyzes the solution of the task. When the DM gets a preferable solution, he/she stops the solving process, otherwise, the DM forms a new task by changing a combination of coefficient values r_j, $j = \overline{1, \mu}$. The formation of the tasks, the analysis of the obtained solution and the decision making are performed in the computer-master (see Fig. 3, the bigger gray block). Each computer-slave P_m, ($m = \overline{1, n}$) solves the local optimization problem with different values of the coefficients r_j, $j = \overline{1, \mu}$ (see Fig. 3, the smaller gray block).

The solution time of a multiple criteria optimization problem depends on the DM's attitude. The DM decides when to stop the solving process according to his opinion. A convenient tool of visualization for interactive decision making has been developed earlier and described in subsection 3.2.

The multiple criteria optimization problem (5) has been solved by using a computer network with the software package MPI (Message Passing Interface … 2009). The package permits separate computers to design a single parallel computer. In our case, the cluster is composed of 26 computers (Pentium 4, 3.2 GHz) connected to the local network under Windows XP (1 Gbps). The optimization problem (5) has been solved with different values of the weights of criteria, using a variable metrics algorithm from the optimization software package MINIMUM (Dzemyda 1985). A special graphic interface, applying Microsoft Visual Studio 2008, has been designed for solving the multiple criteria optimization problem in accordance with the selected calculation strategies (Dzemyda and Petkus 2001; Petkus and Filatovas 2008) (Fig. 1). The data were interchanged by the MPICH2 v.1.0.8 package (MPICH2: High-performance … 2009) which allows us to run the programs realized by Microsoft Visual Studio 2008.

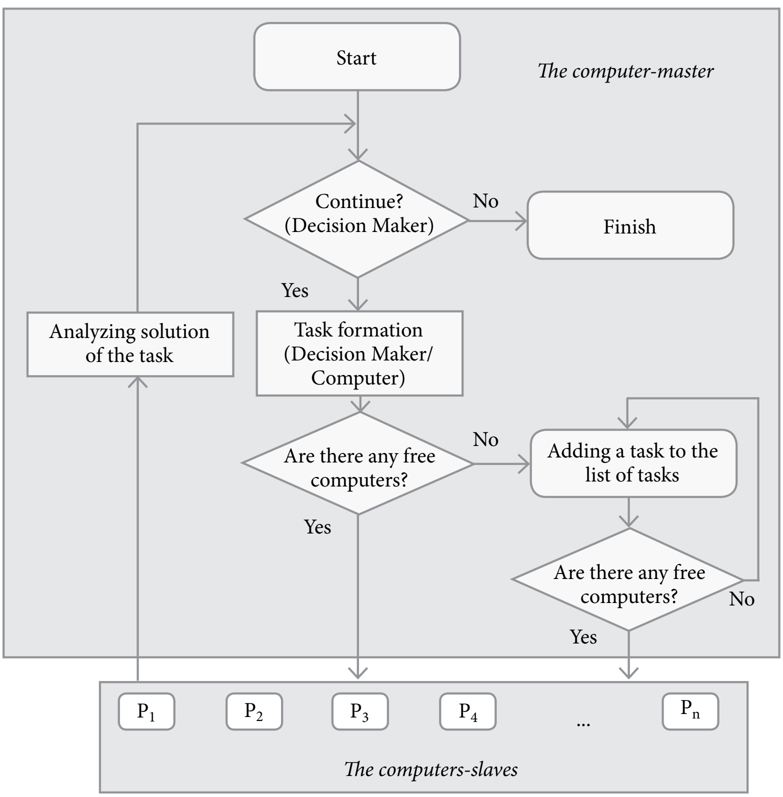

Fig. 3. A scheme of solving the optimization problem

3.4. Parallel strategies of interactive optimization

Several strategies of interactive multiple criteria optimization, applying a computer network, have been developed and investigated in (Dzemyda and Petkus 1998; Petkus and Filatovas 2008). The main ideas of these strategies are described below.

Basic strategy. Tasks for the computer network (different combinations of coefficient values r_j, $j = \overline{1, \mu}$) are formed only by the DM (Dzemyda and Petkus 1998).

First strategy. Tasks for the computer network are formed only by the computer-master. The computer-master generates all the tasks for the computer network: starting tasks, and further tasks that depend on the solutions obtained. The DM does not form any tasks for the computer network. He/she only decides when and which solution is acceptable (Petkus and Filatovas 2008).

Second strategy. Tasks for the computer network are formed by both the DM and the computer-master. The computer-master generates initial tasks. The DM forms new tasks, taking into account the obtained solutions and his experience. The computer-master generates new tasks in case the DM was late to do that. The weight coefficients are generated with regard to the last DM's decisions on selecting the starting point of a task (Petkus and Filatovas 2008).

In the case where the multiple criteria optimization problem is solved by the first or second strategies, the computer-master can form tasks much faster than the DM can do. So, if the network consists of many computers, they will not be idle. We can apply more computers in the first and second strategy than in the basic strategy. In (Petkus and Filatovas 2008) it has been shown that the first and second strategies are superior to the basic strategy when the problem was solved using six computers and more.

As shown in (Petkus and Filatovas 2008), the second strategy is better as compared with the first one. Human attendance is necessary to select the coefficient values r_j, $j = \overline{1, \mu}$, when solving the multiple criteria optimization problem. Therefore, the basic and second strategies are used in this investigation. The aim of this research is to define how a DM learns to solve the problem when a computer assists him to form the tasks and when only the DM forms the tasks.

3.5. Calculation of a combined criterion

In this research, the experiments are done while solving a multiple criteria optimization problem of the class described in Section 2. This is a problem of diet formation for animals. The aim is to select the optimal nutritive value. In solving this multiple criteria problem interactively, the cost price is one of the major criteria, and the other 14 criteria are nutritive characteristics. These 14 criteria are the squared levels of permissible minimal and maximal norm violations.

The human factor was investigated in this paper: the time necessary for a human's (DM) training to solve this multiple criteria optimization problem and the dependence of human factors on the strategy of parallel solution and the number of computers in a computer network. In solving the multiple criteria optimization problem (5), a DM selects the most preferable solution; but in order to estimate the human factor we need the numerical estimation which can help us to assess the DM's training. To this end, the so-called combined criterion was proposed. The quality of solutions, obtained in solving this multiple criteria problem (5), is estimated according to the combined criterion. The values of the combined criterion were calculated by the formula $V_i = \sqrt{K_i^2 + S_i^2}$, where i is the time moment, K_i is the normalized cost price, S_i is the normalized sum of violations of the requirements. The values of S_i and K_i were arranged in the interval [0, 1].

It is obvious that the found minimal value of this combined criterion is not definitely the best solution of the multiple criteria problem, and it is not the best way of estimating solutions. We use this combined criterion only to estimate how a human is learning to solve the problem analyzed.

4. Experimental investigation

In this paper, the human influence on the problem solution has been investigated experimentally. The experimental investigation has been pursued on the basis of the basic and second strategies designed for multiple criteria optimization problems to be solved interactively by applying a computer network. Selection of the optimal nutritive value problem has also been investigated. Five cases have been analyzed:

- Basic strategy applying one computer (denote it as *basic* (*with 1 comp.*));
- Basic strategy applying six computers (denote it as *basic* (*with 6 comp.*));
- Second strategy applying six computers (denote it as *second* (*with 6 comp.*));
- Second strategy applying 12 computers (denote it as *second* (*with 12 comp.*));
- Second strategy applying 24 computers (denote it as *second* (*with 24 comp.*)).

Fifty decision makers took part in this investigation, i.e. solved the multiple criteria optimization problem (2) (10 DMs in each of the five cases). Each DM has iterated the experiment for ten times. An experiment iterated once is called a trial. Each iterated experiment has been recorded: the values of a combined criterion that includes requirement violations and the cost price have been fixed every minute since the zero time moment. The duration of a trial was at least 30 minutes. Therefore, each DM has attended the experiment no less than five hours. Great time expenditure was necessary to carry out all the experiments.

For each time moment t (t is an integer from 1 to 30), the achieved minimal value of the combined criterion V_i is calculated ($\min V_i,\ i = \overline{1,t}$). The average values of the combined criterion, obtained by all the 10 DMs in all the 10 trials, have been calculated and presented in Fig. 4. The best results (the minimal values of the combined criterion) are obtained when the multiple criteria problem is solved by the second strategy with 24 computers, and worse results are obtained when the problem is solved by the basic strategy with one computer. Since the averaged results are presented here, we can state that the second strategy is superior to the basic one, indeed. Moreover, it is not reasonable to increase the number of computers much more in the second strategy because the difference between the results, obtained using 12 or 24 computers, is insignificant.

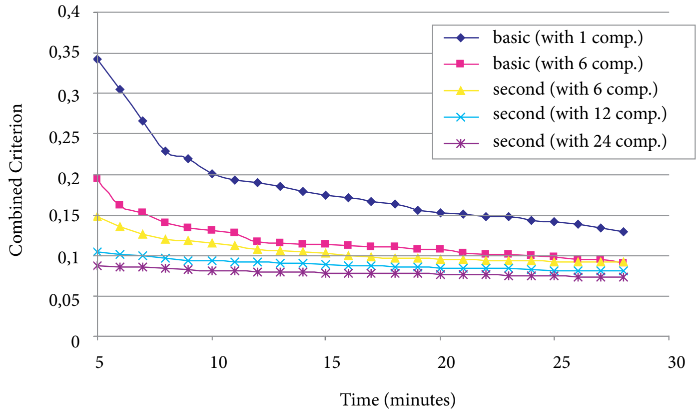

Fig. 4. Average values of the combined criterion (all DMs in all the trials)

The next stage of the research is to analyze the dependence of the results obtained on the DM's experience gained during the experiment. The results, obtained during each trial, are compared. The human factors are investigated. We study how a DM solves the problem for the first time (trial No. 1), for the second time (trial No. 2), etc., whether he learns how to solve a multiple criteria problem and obtains better results.

The average values of the combined criterion of each trial are presented in Fig. 5. When a DM is solving the problem for the first time (Fig. 5, trial No. 1), he lacks experience and he is not able to apply more computers-slaves properly. In solving the problem for the second time (Fig. 5, trial No. 2), better results are obtained. When the problem is solved by the second strategy with 12 and 24 computers, the results are inconsiderably better, as compared with the case where six computers are applied. We conclude that it was not enough time for the DMs to learn and apply a lot of computers effectively in the second trial. In next trials (Fig. 5, Trials No. 3–10), the results obtained with six computers slightly differ, as compared with that obtained in the second trial. The DM has learned to solve the problem with this number of computers during the first trial.

While analyzing the curves, presented in Fig. 5, we notice that if the problem is solved with 12 and 24 computers, the results are similar up to the fifth trial. Later on, better results are obtained with 24 computers and they are improving up to the last trial. We conclude that the DMs learn faster when less computers are applied in solving a multiple criteria optimization problem and the training lasts longer with many computers. However, many computers allow obtaining better results. Moreover, it is not worth applying more than 24 computers-slaves because it will be too difficult for the investigator to solve this problem interactively. He will not have enough time to properly estimate an intermediate solution obtained from the computer network. The DM will also be late to form new tasks.

In Table 1, we present the results of the data analysis where the values of the combined criterion are achieved at the end of the trials. The duration of one experiment was 30 minutes;

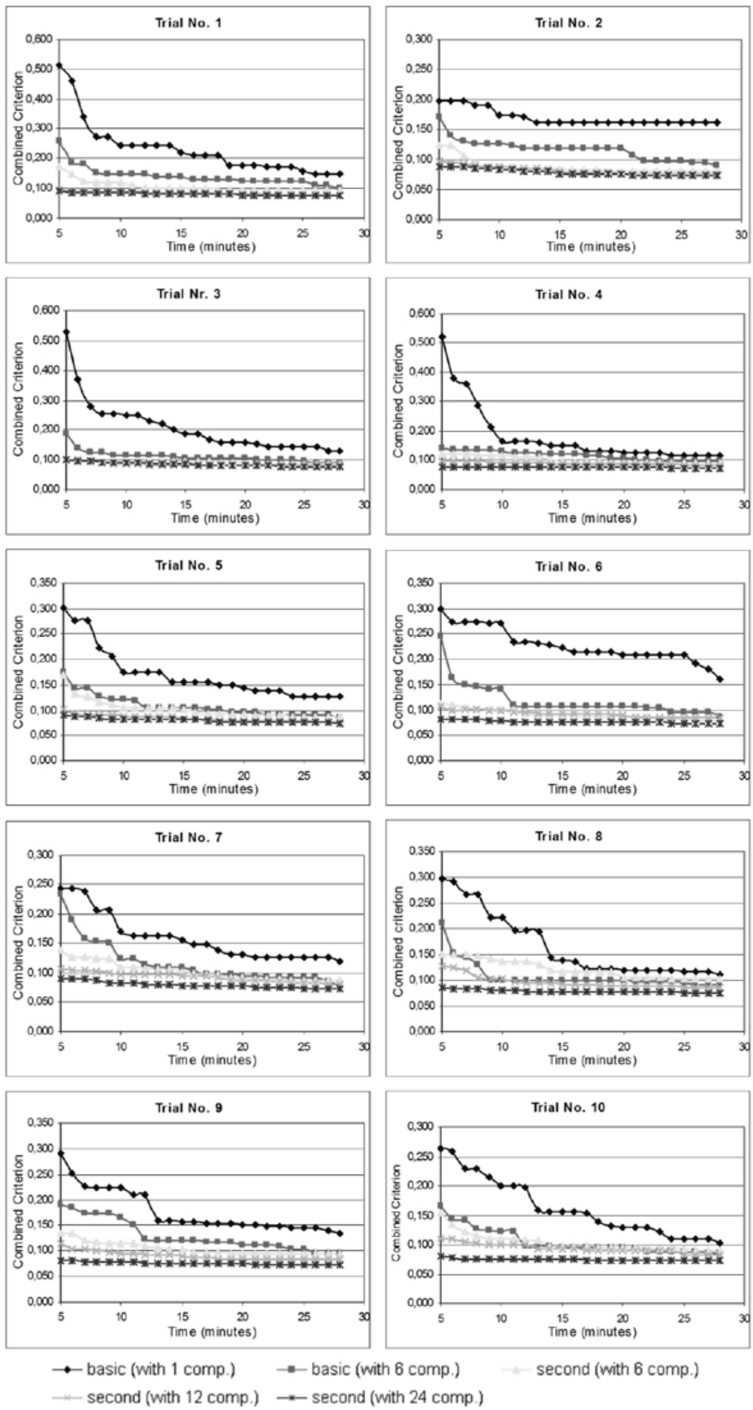

Fig. 5. Average values of the combined criterion of each trial

therefore we analyze the best results obtained up till this moment. At the end of each trial, the best obtained values of the combined criterion are fixed, and then the average values are calculated for each strategy with the selected number of computers (Table 1). Three smallest values of the combined criterion are written in bold style for each analyzed case. When the problem is solved by the basic strategy with only one computer, the best results are obtained during the last trials. We suppose that the reason is the small number of intermediate solutions; therefore, more trials are necessary for the DM to learn to solve the problem.

When the DM is solving the problem by the basic strategy with six computers, he learns faster (Table 1, trials No. 5–7) as he obtains and estimates much more intermediate solutions. When a computer assists the DM to form the tasks (second strategy, six computers), much better results are obtained. The DM learns faster, if he is solving the problem by the second strategy with 12 computers. The reason is that the DM has a chance to analyze many intermediate solutions. However, if the DM solves the problem with 24 computers, the training is slower and the results up to the fifth trial are similar to that obtained applying 12 computers. Starting with the sixth trial the results "exceed" other cases. We conclude that if more computers are applied, a DM learns to make a preferable decision slower; however, better results are obtained.

Table 1. Average values of the combined criterion obtained up till the end of each trial

Cases	**Number of trial**									
	1	2	3	4	5	6	7	8	9	10
basic (with 1 comp.)	0.1547	0.1441	0.1436	0.1246	**0.1144**	0.1779	0.1209	**0.1045**	0.1289	**0.0987**
basic (with 6 comp.)	0.0920	0.0923	0.0935	0.0988	**0.0822**	**0.0842**	**0.0762**	0.0974	0.0915	0.0880
second (with 6 comp.)	0.0943	**0.0801**	**0.0857**	0.0939	0.0872	**0.0790**	0.0876	0.1022	0.0940	0.0912
second (with 12 comp.)	**0.0770**	**0.0758**	0.0793	0.0832	**0.0776**	0.0835	0.0806	0.0853	0.0828	0.0835
second (with 24 comp.)	0.0778	0.0742	0.0747	0.0740	0.0742	0.0736	**0.0732**	0.0752	**0.0717**	**0.0730**
Average values	0.0991	0.0933	0.0954	0.0949	0.0871	0.0996	**0.0877**	0.0929	0.0938	**0.0869**

5. Conclusions

In this paper, solution of a multiple criteria optimization problem in an interactive way, applying a computer network, has been investigated. Two strategies of interactive multiple criteria optimization have been analyzed. The experiments have been carried out with various numbers of computers. The human influence is an important factor in solving the problems of the analyzed class in an interactive way. It is necessary to estimate the dependence of the obtained optimization results on the experience of decision maker's gained during the experiment.

The investigation has shown that:

- Ordinary personal computers, connected into a network, are enough to solve a complex multiple criteria optimization problem. The system developed for solving this optimization problem does not require great additional economic expenditure.

- In solving a multiple criteria optimization problem in an interactive way, when a computer helps a DM to form new tasks, better results are obtained faster.
- DM's experience makes it possible to apply many computers effectively and to obtain optimal solutions faster.
- Human attendance allows solving multiple criteria optimization problems that require especially complex decision making.

With a view to determine a more precise dependence of the obtained optimization results on a DM's experience, the number of DMs should be increased. Then it will be possible to draw more reliable conclusions. However, in that case, great time expenditure is necessary.

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ŽMOGIŠKOJO FAKTORIAUS TYRIMAS SPRENDŽIANT DAUGIAKRITERINIUS OPTIMIZAVIMO UŽDAVINIUS KOMPIUTERIŲ TINKLE

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Santrauka

Tyrimo tikslas – ištirti daugiakriterinių optimizavimo uždavinių klasę, kai uždaviniai sprendžiami kompiuterio ir žmogaus sąveikai naudojant kompiuterių tinklą. Daugiakriterinio optimizavimo uždavinys sprendžiamas interaktyviai, kiekvienam kriterijui parenkami skirtingi svoriniai koeficientai. Šiam uždaviniui spręsti buvo sukurtos ir ištirtos kelios lygiagretaus sprendimo strategijos. Eksperimentai parodė žmogaus, dalyvaujančio sprendžiant šį uždavinį, svarbą. Tiriant žmogiškąjį faktorių buvo atlikti eksperimentiniai tyrimai naudojant skirtingą kompiuterių skaičių pagal skirtingas strategijas. Ištirtas laikas, reikalingas žmogui išmokti spręsti šį daugiakriterinį optimizavimo uždavinį, nustatyta žmogiškojo faktoriaus priklausomybė nuo pasirinktos lygiagretaus sprendimo strategijos ir kompiuterių skaičiaus kompiuterių tinkle.

Reikšminiai žodžiai: daugiakriterinis optimizavimas, žmogiškasis faktorius, lygiagretieji skaičiavimai, MPI, sprendimų rengimo sistema, interaktyvus optimizavimas, sprendimų priėmimas.

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