

Comprehensive Approach to the Design of Information Systems and Optimization of Technical Solutions according to Many Criteria *

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Abstract. One of the problems of the modern information society is the development of effective complex multiprocessor information systems, taking into account the rational use of system resources. The problem of finding the optimal variant of a multiprocessor system is presented as a problem of multicriteria optimization and makes it possible to search for a trade-off between several alternatives. The paper describes several approaches to the comparative assessment of multiprocessor systems, including the search for the non-dominated solutions; narrowing down the Pareto space, using the additional expert information; converting the problem to single-criteria optimization with convolution of criteria; searching for the optimal solution that is closest to the reference point. In the paper the authors propose a ranking method to evaluate technical solutions. The method is based on ranking individual alternatives for each optimization criterion separately, followed by aggregation of ordered ranked lists. The advantage of using the ranking methods is to obtain a complete rating of technical solutions based on their effectiveness, assessed by several criteria. The paper has an educational character and considers the problem of finding a trade-off between system parameters when looking for technical solutions. The practical results of applying different approaches are demonstrated using a simple example.

Keywords: multiprocessor information systems, genetic algorithm, multicriteria optimization.

1. Introduction

One of the problems of the modern information society is the development of effective complex multiprocessor information systems, taking into account the rational use of system resources [18]. Examples of such complex systems are global search systems, new

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1 generation information systems “smart home”, “smart city”, “smart government”, cyber-
2 physical systems of autonomous transport, robotic enterprises, etc. Different types of sys-
3 tem resources can be considered, including technical resources - functional complexity, al-
4 gorithmic complexity, hardware complexity, computing performance, mass-dimensional
5 characteristics, energy consumption, etc.; operational resources - reliability, safety, ac-
6 ceptable service life, etc.; economic resources – cost of the system, cost of maintenance,
7 cost of development support and modifications, etc. It is obvious that most of the resources
8 available for optimization are closely interconnected and their rational distribution during
9 design is only possible using a comprehensive approach.

10 A comprehensive approach and the search for a trade off between the key parameters
11 of the system for new technical solutions include the following subtasks:

- 12 – determining the scope of possible technical solutions when using a given method (or
13 architecture, or concept) of implementation;
- 14 – scientific justification of objective limitations in the design of complex systems;
- 15 – determination of criteria for choosing technical solutions;
- 16 – comparative assessment and ranking of technical solutions;
- 17 – identifying trends in the development of complex information systems, etc.

18 These multi-criteria tasks are difficult to formalize and therefore developers often rely
19 on their experience in solving similar problems or informal methods of expert assess-
20 ments. From formal system analysis tools, methods of mathematical statistics and oper-
21 ations research are usually used [8],[4]. The determination of the feasible solution set is
22 a major challenge in engineering optimization problems. In multi-criteria problems the
23 researcher can often identify the main variables, establish connections between them, i.e.
24 build a model that adequately reflects the situation, but the preferred combinations of cri-
25 teria cannot be determined on the basis of objective information. For selection the best
26 solutions a compromise between various criteria is required.

27 In this paper we observe several approaches to solving the technical problem together
28 with proposing the method of searching for the optimal multi-criteria ranking of alter-
29 natives on the basis of individual single-criterion rankings. The proposed research is the
30 extended version of conference paper [18], presented at CERCIRAS 2021 Workshop. Pre-
31 vious paper described the basics of the problem of complex assessments of the technical
32 solutions and the formal approach for solving this problem, including the methods from
33 the theory of Data Mining and Operation Research. It introduced the concept of multicri-
34 teria optimization in finding the optimal variant of a multiprocessor system and in search-
35 ing for a trade-off between several alternatives. The current study extends the research in
36 this direction. Based on a simple example it demonstrates several approaches to search-
37 ing and narrowing down the Pareto space, including those involving expert knowledge.
38 The approaches for converting a multi-criteria problem to a single-criteria optimization
39 problem by criteria convolution, as well as for ranking solutions based on distances to
40 the ideal point are described and presented on the example. In the last section it is pro-
41 posed a method based on aggregating ordered ranked lists for searching for the effective
42 technical solutions, characterized by several system resources. The initial rankings of al-
43 ternatives for each criterion are aggregated in order to find the optimal solution. In this
44 case a single-criteria minimization problem takes into account the sum of distances of the
45 solution candidates to the initial rankings. The proposed method provides more flexibility

1 in selecting the best variant of solution based on several criteria. The method allows to
2 take into account both the objective values of criteria and the decision maker preferences.

3 The paper notes the advantages and disadvantages of various approaches, as well as
4 the dependence of the result on both the initial parameters of the mathematical models
5 and the expert preferences. It is noted that the use of the methods for ranking solutions
6 allows determining not only the best solution, which is often of primary interest, but a
7 complete rating of all solutions, which provides information for decision-making.

8 **2. Related work**

9 Multi-criteria decision analysis (MCDA) is a multi-step process consisting of a set of
10 methods to structure and formalise decision-making processes in a transparent and con-
11 sistent manner. Over the years, MCDA methods and software tools are used for a large
12 number of applications from modeling, optimization and decision-making tasks, to per-
13 formance's simulation [10].

14 To date, a lot of research has been carried out in the field of multi-criteria decision
15 selection [17]. They are aimed to model decision making process and require the partici-
16 pation of experts in reaching a decision based on many criteria [9]. The most popular are
17 the AHP method, based on pairwise comparison of hierarchical criteria considering dif-
18 ference information; ANP method, which is a non-linear and more general type of AHP
19 using Markov-chain-based aggregation; FUZZY AHP method with the fuzzy evaluation
20 of the alternatives; ELECTRE method, based on outranking the relationship of the alterna-
21 tives and using pairwise comparison; PRAGMA method, which compares partial profiles
22 of alternatives considering all the possible criteria pairs and etc.

23 In traditional MCDA methods often the single optimal solution is chosen by collecting
24 the DM's preferences where multicriteria optimization (MCO) and decision-making tasks
25 are combined for obtaining a point by point search approach [10]. The final obtained
26 solutions must be as close to the true optimal solution as possible and the solution must
27 satisfy the preference information.

28 When considering multi-criteria task from the point of view of MCO theory, a non-
29 dominated set in the criteria space or a Pareto-efficient set in the solution space is usually
30 considered. In multicriteria methods, a solution to an MCO problem is understood as a
31 single point of a Pareto-efficient set that is preferable for the decision maker. Although
32 sometimes MCO methods require finding a small number of solutions that are interesting
33 from the decision maker's point of view [6].

34 Methods for solving the MCO problem in the framework of MCDA are extremely
35 diverse [11]. There are several ways to classify these methods [17]. Considering the
36 decision-making process and the additional information about the preferences of the de-
37 cision maker the following classes can be distinguished:

- 38 – methods that do not take into account the preferences of the decision maker (no-
39 preference methods);
- 40 – a posteriori methods;
- 41 – a priori methods;
- 42 – interactive methods.

1 In the first class of methods the task is to find some compromise solution, usually in
2 the central part of the Pareto front or the construction of a scalar optimization function
3 without the participation of decision makers. A posteriori methods involve the decision
4 maker entering information about their preferences into the MCO system after a certain
5 set of non-dominated solutions has been obtained. In this regard, all methods of this class
6 at the first stage construct an approximation of the Pareto set. A priori methods are de-
7 signed to overcome the main disadvantage of a posteriori methods associated with the
8 construction of the entire reachability set. Here it is assumed that the decision maker
9 introduces additional information about his preferences before starting to solve the prob-
10 lem, a priori. Most often, this information is formalized in such a way as to reduce a
11 multi-criteria problem to a single-criteria one. Examples include the scalar convolution
12 method, the e-constraint method [12], lexicographic ordering and goal programming [1].
13 Interactive methods consist of a set of iterations, each of which includes an analysis stage
14 performed by the decision maker and a calculation stage performed by the MCO system
15 [7]. Based on the nature of the information received by the MCO system from the decision
16 maker at the analysis stage, classes of interactive methods can be distinguished, in which
17 the decision maker directly assigns weighting coefficients to particular optimality criteria;
18 imposes restrictions on the values of particular optimality criteria or evaluates the alter-
19 natives proposed by the MCO system. The selection of the appropriate MCO method for
20 new technical solutions depends on the complexity of the decision space, existence and
21 type of expert knowledge and available time. Each MCO method has its own definition of
22 best alternative and it is not determined if using same input data in different methods will
23 give the same results.

24 Our paper makes the overview and comparative assessment of several a posteriori and
25 a priori approaches to the selection of best variant of technical system based on several
26 criteria, formulating this problem as a MCO task. In the course of describing the methods
27 and applying them using a simple example we demonstrate how similar or different results
28 might evolve. Together with several popular approaches, the method based on aggregation
29 of ordered ranked lists is described. It can be considered as a way of integration between
30 MCO and MCDA processes and shows its consistency on a par with well-known methods.
31 The method allows searching for solution based on both the available numerical criteria
32 values and the expert preferences in ranking alternatives on several criteria.

33 The described approaches can be applied to the practical tasks in the area of technical
34 system design and can be integrated as the component of a computer system that supports
35 engineering decision-making activities.

36 **3. Comprehensive Approach to System Design of Multiprocessor** 37 **Information Systems**

38 **3.1. Formulation of the System Design Problem**

39 The scope of application of an information system is mainly determined by both functions
40 and technical characteristics, which are specified by numerical or nominal values and
41 limitations. For example, the multiprocessor on-board electronics system of a modern car
42 or robotic mobile platform has a distributed multiprocessor architecture, which allows
43 for real-time control of units (i.e., with a given performance). To provide interprocessor

1 interfaces, a CAN (Controller Area Network) bus is used, which provides sufficient noise
2 immunity and reliability of communications. The number of peripheral processors is a
3 consequence of the number of terminal devices (i.e., the required functional performance).
4 In addition, a consequence of the second order are the parameters of power consumption
5 and mass-dimensional characteristics. If the design domain is a distributed computing
6 system on a chip (SoC), then the priority relationships of mutual influence will be changed
7 and supplemented, perhaps significantly.

8 The composition and mutual influence of the specified characteristics (and/or param-
9 eters) of the system can be represented in the form of an undirected graph, as shown in
10 Fig. 1. In Fig. 1, the graph reflects only qualitative dependencies. Even a quick analysis
11 of a fragment of the original graph indicates the close interdependence of parameters in
12 the system. Sometimes the named dependencies are obvious, for example, performance
13 versus the number of processors, and they are easy to represent in the form of formulas.
14 However, this is not always the case. For example, it is difficult (and perhaps impossible)
15 to indicate the dependence of the reliability or mechanical layout (weight and dimensions)
16 of a microprocessor system on the selected type of interface, although it is obvious to ev-
17 ery designer that such a dependence exists. This graph is for demonstration purposes and,
18 naturally, can be supplemented with other parameters and connections.

19 In general, the task of system design is to find a conceptual solution whose parameters
20 will be within acceptable, or better yet, optimal values.

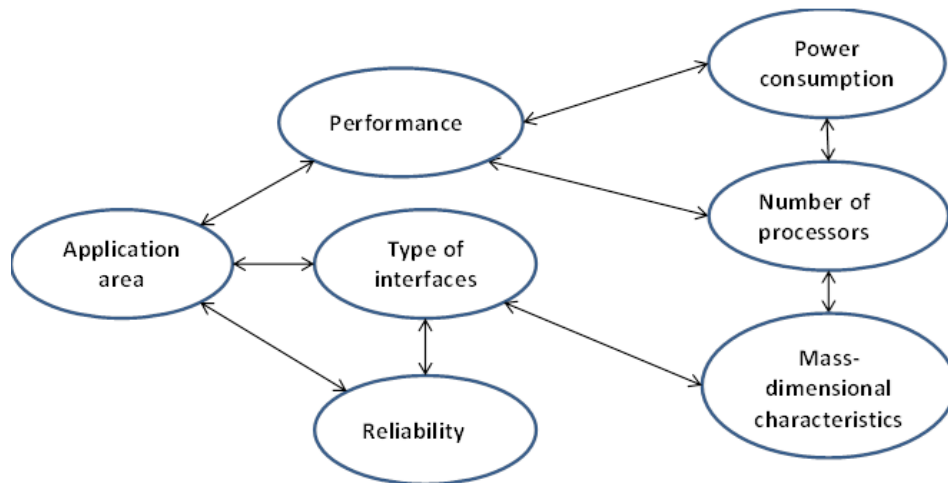


Fig. 1. Undirected graph, reflecting the subject area of system design

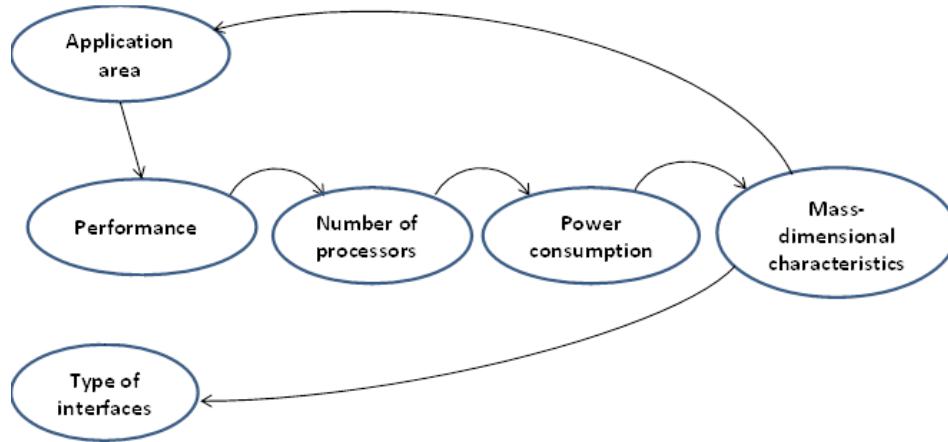


Fig. 2. A directed graph reflects one of the possible system design scenarios

1 3.2. System Design Methodology

2 The proposed system design methodology is as follows:

- 3 1. The developer (or general designer, or system architect) draws up an initial graph,
4 similar to Fig. 1, reflecting two-way relationships in system design in a given subject
5 area.
- 6 2. In the undirected graph, the expert identifies key and derived parameters (the reliabil-
7 ity parameter is not considered as a key one).
- 8 3. The original graph is modified into a directed one, and the number of mutual (less
9 significant) connections is reduced. Ideally, there could be a chain of cause and effect
10 relationships. In Fig. 2 on the basis of expert experience and understanding of all the
11 restrictions available to him, a special case of relationships are considered. Accord-
12 ing to Fig. 2, to ensure a given performance it is necessary to use, for example, 6
13 processors, which in turn will increase energy consumption by 6 times compared to a
14 single-processor implementation. These changes will cause an increase in weight and
15 size characteristics and will affect the appearance of the interface.
- 16 4. The found chain is supplemented (detailed) with the necessary (known) quantitative
17 data and restrictions. A rapid evaluation of the possibility of achieving the result is
18 carried out using known theoretical dependencies, expert knowledge, as well as multi-
19 criteria data analysis.
- 20 5. Very often parameters have implicit and mutually exclusive relationships. Therefore,
21 it is important to “check feedback” during system design. For example, it may turn
22 out that the obtained mass-dimensional characteristics are not consistent with the

1 conceptually accepted interface, or the subject area. In this case, the system design
2 process is iteratively repeated until an acceptable system solution is found.

3 **4. Comparative Evaluation of Multiprocessor Systems as a Problem** 4 **of Multicriteria Optimization**

5 The greatest difficulty in designing complex multiprocessor information systems lies in
6 the need to solve the problem of multicriteria optimization according to multiple opti-
7 mization criteria, which are individual system parameters or used system resources. As a
8 rule, the criteria are interdependent, i.e. an increase in one of them can lead to a decrease
9 in the value for the other. Using multicriteria optimization makes it possible to identify
10 compromise or non-dominant solutions, where none of them is better than the other in all
11 the parameters under consideration and, therefore, are of equal importance. In this case,
12 many solutions are allowed, each of which is acceptable in the absence of preliminary
13 information about the importance of the criteria.

14 In general, the problem of multicriteria optimization is formulated as follows: Find the
15 vector $\bar{x}^* = (x_1^*, x_2^*, \dots, x_n^*)^T$ of the values of parameters, which satisfy m inequalities:

$$g_i(\bar{x}) \geq 0, \quad i = 1, 2, \dots, m, \quad (1)$$

16 and p equalities

$$h_i(\bar{x}) = 0, \quad i = 1, 2, \dots, p, \quad (2)$$

17 and optimize the vector function

$$f(\bar{x}) = [f_1(\bar{x}), f_2(\bar{x}), \dots, f_k(\bar{x})]^T. \quad (3)$$

18 Constraints (1), (2) define the domain G , which contains all feasible solutions to the prob-
19 lem. The vector \bar{x}^* corresponds to the optimal solution in the domain G . In this case, the
20 optimality is meant according to the Pareto concept, the formal definition of which from
21 the point of view of the maximization problem is as follows [3]:

22 The vector of solution \bar{x}^* is called Pareto-optimal if and only if there is no other vector
23 \bar{x} , which dominate \bar{x}^* , i.e. if

$$\forall i \in 1, 2, \dots, k, f_i(\bar{x}) \leq f_i(\bar{x}^*) \text{ and } \exists i \in 1, 2, \dots, k, \text{ where } f_i(\bar{x}) < f_i(\bar{x}^*)$$

24 In other words, \bar{x}^* is Pareto optimal if there are no acceptable vectors \bar{x} , which allow
25 you to increase the value of one of the criteria, while not decreasing the value of at least
26 one of the remaining criteria. The solution \bar{x}^* strictly dominates the solution \bar{x} , if $\forall i \in$
27 $1, 2, \dots, k, f_i(\bar{x}) < f_i(\bar{x}^*)$. In general, the solution to the optimization problem is a set
28 of non-dominated solutions. Having a set of several non-dominated solutions obtained
29 as a result of multicriteria optimization, it is possible to choose a solution that is most
30 preferable for a specific applied problem.

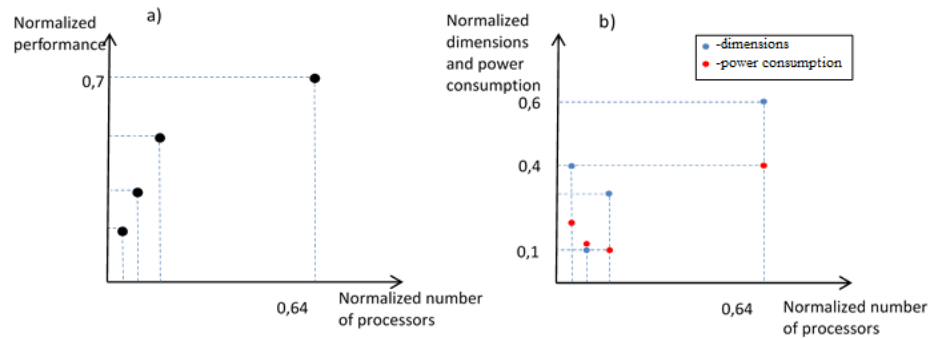
31 Consider a demonstration example of solving the problem of comparative evalua-
32 tion of multiprocessor systems. Table 1 presents four multiprocessor systems, which are
33 characterized by several parameters: the number of processors, performance, dimensions,
34 power consumption. We will assume that these systems can programmatically solve the
35 same problem, but are implemented in a different design.

Table 1. Parameters of multiprocessor systems

System	Number of processors (items)	Performance (Gflops)	Dimensions (Volume, dm ³)	Power consumption (W)
System 1	4/0,04	2,0/0,2	4,0/0,4	20,0/0,2
System 2	8/0,08	3,0/0,3	1,0/0,1	12,0/0,12
System 3	16/0,16	5,0/0,5	3,0/0,3	10,0/0,1
System 4	64/0,64	7,0/0,7	6,0/0,6	40,0/0,4

1 For clarity and simplicity of reasoning, we use the simplest normalization method,
 2 when the parameters are reduced to some fixed maximum value (in our case, 100, 10,
 3 10 and 100, respectively). The normalized values of the parameters of multiprocessor
 4 systems are shown in Table 1 in the corresponding columns after the sign (/).

5 If the number of processors and performance are known, statistically confirmed para-
 6 metric dependencies (Fig. 3a), then the dependences of dimensions and power consump-
 7 tion in this example are not visible (Fig. 3b). (Although, in theory, we know that with an
 8 increase in the number of processors and performance, the power consumption and size
 9 should increase). But this example deliberately does not provide any information about
 10 the technology, element base, design, purpose, generation, etc., which directly affects both
 11 the dimensions and power consumption of the implemented systems.

**Fig. 3.** Representation of multiprocessor systems in two-dimensional parameter space

12 Let perform the assessment of the systems presented in Table 1 based on the concept
 13 of non-dominated solutions, considering the value of each criterion separately. We will
 14 assume that it makes no sense to include the number of processors as an individual cri-
 15 terion, since it is indirectly in the performance of systems. In our case we will perform a
 16 manual assessment of the systems. To solve more complex problems with a large num-
 17 ber of alternatives, characterized by a large number of parameters, special methods of
 18 multicriteria optimization are used [15], [3],[19].

1 In the presented example, the criteria to be optimized correspond to the parameters of
 2 the system, and the problem of multicriteria optimization in this case can be written in the
 3 following form:

4 Optimize vector function

$$F(x) = [x_1, x_2, x_3] \quad (4)$$

$$x_1 \rightarrow \max, x_2 \rightarrow \min, x_3 \rightarrow \min$$

5 and $a_1 \leq x_1 \leq b_1, a_2 \leq x_2 \leq b_2, a_3 \leq x_3 \leq b_3$ – allowed parameter range, where
 6 x_1, x_2, x_3 - performance, dimensions and power consumption.

7 Consider Systems 1 and 2, where the value of the performance criterion of System
 8 2 are higher than the corresponding value of System 1, and the value of the dimensions
 9 and power consumption criteria for System 2 are lower. Consequently, System 2 has more
 10 optimal parameter values and thus dominates System 1. If we compare Systems 2 and 3,
 11 then we see that System 3 has higher performance and less power consumption, while
 12 its dimensions are larger than the dimensions of System 2. Therefore, Systems 2 and 3
 13 are non-dominated solutions. Likewise, the non-dominated solutions are Systems 2 and
 14 4, Systems 3 and 4.

15 In Fig. 4 the systems under consideration are shown as points in the space of two
 criteria. Non-dominated solutions are connected with a line.

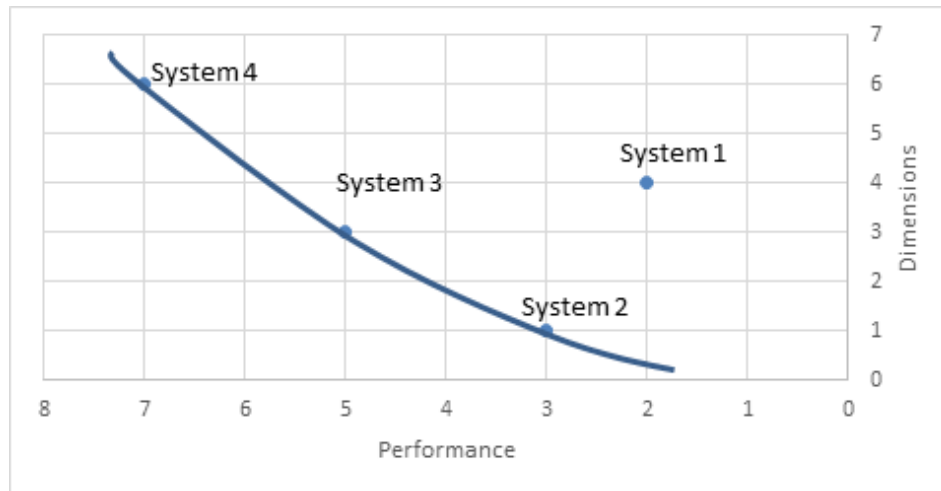


Fig. 4. Graphic presentation of technical solutions in a two-criteria space

16
 17 It should be noted that Systems 2, 3, 4 are not dominant in the specific problem under
 18 consideration, i.e. they are locally non-dominated solutions. In the case of adding addi-
 19 tional alternative solutions for multiprocessor systems, the number and composition of
 20 non-dominated solutions may change, although in this case the solutions will be locally
 21 non-dominated. According to the analysis System 1 can be excluded from further consid-
 22 eration due to the fact that it is the dominant solution for all the considered optimization
 23 criteria.

1 To further narrow down the Pareto set and identify the single best solution, some addi-
 2 tional information is needed [14]. One of the main types of additional information, often
 3 used when solving various multicriteria problems, is information about the comparative
 4 importance of partial criteria, which is usually given in the form of numerical coefficients
 5 $w_k \geq 0$, characterizing the importance of partial criterion $f_i, i = 1, \dots, k$. The impor-
 6 tance coefficients together constitute a weight vector $w = (w_1, \dots, w_k)$, the components
 7 of which are usually normalized by the condition $\sum_k w_k = 1$. The most well-known
 8 methods for calculating coefficients include sequential comparison of criteria by impor-
 9 tance, pairwise comparison of criteria by absolute or relative importance.

10 Using additional information about the importance of criteria, you can narrow down
 11 the set of non-dominated solutions. Consider two non-dominated solutions $y_1 = (y_{11}, \dots,$
 12 $y_{1k})$ and $y_2 = (y_{21}, \dots, y_{2k})$, where $y_{1p} > y_{2p}, y_{1q} < y_{2q}$ and $y_{1h} = y_{2h}$ for all
 13 $h \neq p, q$. Formally, these alternatives are incomparable in terms of dominance. How-
 14 ever, for the decision maker (DM), alternative y_1 is preferable to y_2 . This means that
 15 the p -th partial criterion is more important than the q -th partial criterion with parameters
 16 $r_p = y_{1p} - y_{2p} > 0, r_q = y_{2q} - y_{1q} > 0$. When choosing one of two solutions, the DM
 17 agrees to lose the value r_q according to a less important criterion in order to receive an
 18 additional gain r_p according to a more important criterion.

19 The number $t_{pq} = \frac{r_q}{(r_p+r_q)}$ is called the proportional coefficient of relative importance
 20 for the p -th and q -th criteria. At $t_{pq} = 0, 5$, the values of losses and gains coincide. Thus,
 21 the set of selected solutions is contained in the restricted Pareto boundary, consisting of
 22 vectors $y' = f'(x) = (f'_1(x), \dots, f'_k(x))$ with components determined by the expres-
 23 sions:

$$f'_q(x) = t_{pq}f_p(x) + (1 - t_{pq})f_q(x); f'_h(x) = f_h(x), \forall h \neq q \quad (5)$$

24 According to (5), new values of the criteria vector are obtained from the previous
 25 ones by replacing the less important criterion $f_q(x)$ with a convex combination of criteria
 26 $f_p(x)$ and $f_q(x)$.

27 Consider the application of the above-mentioned method of narrowing the Pareto
 28 space using the example described in Table 1. Let us consider three previously obtained
 29 non-dominated solutions, represented by vectors of three criteria values $S_2 = (0, 3; -0, 1;$
 30 $-0, 12), S_3 = (0, 5; -0, 3; -0, 1)$ and $S_4 = (0, 7; -0, 6; -0, 4)$, where the values of the
 31 last two criteria are inverted in order to bring them to the maximization problem.

32 Let us assume that the DM considers the first criterion f_1 more important than the
 33 second f_2 with a proportional coefficient of relative importance $t_{12} = 0, 8$. Recalcu-
 34 late the second component of each vector $S_i, i = 2, \dots, 4$ using the formula $f'_2(S_i) =$
 35 $0, 8f_1(S_i) + 0, 2f_2(S_i)$. We obtain new vectors $S'_2 = (0, 3; 0, 22; -0, 12), S'_3 = (0, 5; 0, 34;$
 36 $-0, 1)$ and $S'_4 = (0, 7; 0, 44; -0, 4)$. It is obvious that solution S'_3 dominates solution S'_2 .
 37 Therefore, in the narrowed Pareto space there will remain two solutions S'_3 and S'_4 , which
 38 correspond to System 3 and System 4.

39 5. Approaches to Converting a Multi-Criteria Problem to a 40 Single-Criteria One

41 One of the ways to solve a multi-criteria problem for selection a technical solution is to
 42 transform it into a single-criteria one by combining all partial criteria $f_j(x), j = 1, \dots, k$

1 into one general quality criterion $f(x) = F(f_1(x), f_2(x), \dots, f_k(x))$, which is otherwise
 2 called criteria convolution. Then the search for the best solution reduces to finding the
 3 extremum of the single function $f(x)$

$$x^* \in \operatorname{argmax}_{x \in X^a} f(x), \quad (6)$$

4 where x is an alternative from the acceptable set X^a .

5 As a rule, weighted convolutions of partial criteria for the effectiveness of a technical
 6 solution are used

$$f(x) = \sum_{j=1}^k w_j f_j(x) \quad (7)$$

$$f(x) = \prod_{j=1}^k w_j f_j(x) \quad f(x) = \prod_{j=1}^k [f_j(x)]^{w_j},$$

7 where $w_j \geq 0$ is a weight of the partial criterion $f_j(x)$.

8 Partial performance criteria are usually normalized in one of the following ways:

$$f'_j(x) = \frac{f_j(x)}{y_j^{max}}, \quad f'_j(x) = \frac{f_j(x)}{(y_j^{max} - y_j^{min})}, \quad f'_j(x) = \frac{f_j(x) - y_j^{min}}{(y_j^{max} - y_j^{min})} \quad (8)$$

9 where y_j^{min}, y_j^{max} – minimal and maximal values of the partial criterion $f_j(x)$.

10 The choice of the weights of the partial criteria in the optimization function (7) can
 11 influence the result of the optimal solution and is usually set by the DM by a number
 12 of well-known methods [13]. Consider the implementation of the above approach for the
 13 example from Table 1. The complex criterion for the comparative assessment of systems
 14 is a weighted sum of three criteria. In this case, it is necessary to perform the following
 15 steps:

- 16 1. Bringing the criteria to a single range of values (normalization or scaling of the crite-
 17 ria):

$$\bar{x}_i = \frac{x_i - x_i^{min}}{x_i^{max} - x_i^{min}},$$

18 where x_i^{min} is the minimal value of i -th criterion, x_i^{max} is the maximal value of i -th
 19 criterion. For our example $x_i^{min} = 0$ for $i = 1, 2, 3$ and $x_1^{max} = 10, x_2^{max} = 10,$
 20 $x_3^{max} = 100$.

- 21 2. Selection of weight coefficients w_1, w_2, w_3 for each criterion: performance, dimen-
 22 sions and power consumption.
- 23 3. Ranking solutions according to a complex criterion $F(x) = -w_1\bar{x}_1 + w_2\bar{x}_2 + w_3\bar{x}_3,$
 24 where the value of w_1 is taken with minus sign to convert to the minimization problem
 25 according to the first criterion.

26 The minimum value of the complex criterion corresponds to the most optimal solution.
 27 The normalized values of the system parameters are presented in Table 1. Let us choose
 28 the following values of the weight coefficients $w_1 = w_2 = w_3 = 1$. Let's calculate

1 the values of the complex criterion for each of the systems $S_1 = (0, 2; 0, 4; 0, 2)$, $S_2 =$
 2 $(0, 3; 0, 1; 0, 12)$, $S_3 = (0, 5; 0, 3; 0, 1)$ and $S_4 = (0, 7; 0, 6; 0, 4)$

$$F_1(x) = -1 * 0, 2 + 1 * 0, 4 + 1 * 0, 2 = 0, 4$$

$$F_2(x) = -1 * 0, 3 + 1 * 0, 1 + 1 * 0, 12 = -0, 08$$

$$F_3(x) = -1 * 0, 5 + 1 * 0, 3 + 1 * 0, 1 = -0, 1$$

$$F_4(x) = -1 * 0, 7 + 1 * 0, 6 + 1 * 0, 4 = 0, 3.$$

3 Thus, the systems presented in Table 1 according to the complex criterion can be
 4 ranked as follows System 3, System 2, System 4 and System 1 in ascending order of the
 5 criterion value. The most optimal system is System 3.

6 The disadvantage of this ranking method is the dependence of the optimal solution on
 7 the choice of the values of the weight coefficients w_1, w_2, w_3 . For example, if the value
 of the weight $w_1 = 0.5$, then System 2 will be selected as the most optimal (Fig. 5).

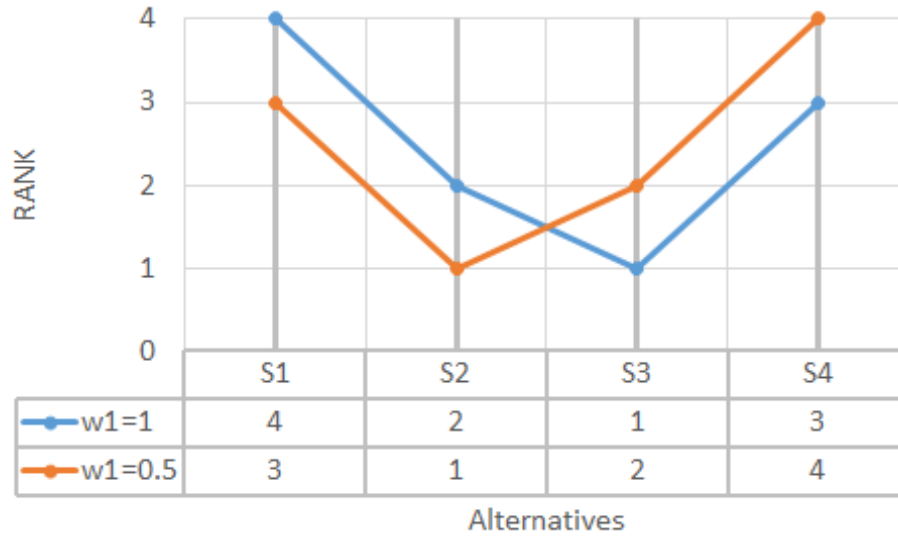


Fig. 5. Ranking of alternatives according to a complex criterion $F(x)$ with different values of weight coefficient w_1

8
 9 Another approach for solving a multicriteria problem is to search for alternatives with
 10 given characteristics. In this case, you can indicate the values of partial quality criteria
 11 $y_j^0, j = 1, \dots, k$ that are desirable for the DM or the boundaries of their change. The set
 12 of such values $y = (y_1^0, \dots, y_k^0)$ is called the reference point. Two characteristic refer-
 13 ence points are, in particular, $y^{max} = (y_1^{max}, \dots, y_k^{max})$ and $y^{min} = (y_1^{min}, \dots, y_k^{min})$,
 14 where y_i^{min} is the minimal value of i -th criterion, y_i^{max} is the maximal value of i -th
 15 criterion.

16 To solve a multicriteria optimization problem, a search is made for an alternative or
 17 technical solution that is closest to the reference point. In the multidimensional space of

1 evaluations based on partial quality criteria, a certain proximity measure $d[f(x), y^0]$ is
 2 specified between the points $f(x) = (f_1(x), f_2(x), \dots, f_k(x))$ and $y^0 = (y_1^0, \dots, y_k^0)$,
 3 where $f(x)$ is the alternative and y^0 is the reference point. Then the optimal solution is
 4 defined as

$$x^* \in \operatorname{argmin}_{x \in X^0} d[f(x), y^0] \quad (9)$$

5 Usually one of the metrics of the k -dimensional vector space (R^k, d_p) is chosen as a
 6 proximity measure, such as the weighted Euclidean metric

$$d_2[f(x), y^0] = \left[\sum_{j=1}^m w_j (f_j(x) - y_j^0)^2 \right]^{\frac{1}{2}}, \quad (10)$$

7 where w_j is the coefficient of importance of the partial criterion $f_j(x)$.

8 Setting one or another proximity measure $d[f(x), y^0]$ is another possible way of con-
 9 volving partial criteria and transforming a multicriteria problem into a single-criteria one.
 10 The disadvantage is that different metrics $d[f(x), y^0]$ may correspond to different optimal
 11 options for the technical solution x^* . Despite the disadvantage, this method for solving a
 12 multicriteria problem is widely used in practice [13].

13 One example of the implementation of multicriteria optimization taking into account
 14 reference points is the TOPSIS (Technique for Order Preference by Similarity to Ideal
 15 Solution) method proposed in [5]. The main idea of the method is as follows: after deter-
 16 mining the “ideal” or best and “ideal-negative” or worst expected states (alternatives), an
 17 attempt is made to find a solution that would allow one to get as close as possible to the
 18 “ideal” state and remain as far away from the “ideal-negative” state. The decision-making
 19 process begins with the evaluation of all alternative solutions according to all criteria. As
 20 a result, a decision matrix is formed. The method consists of six consecutive steps: 1)
 21 calculation of the normalized decision matrix; 2) calculation of a weighted normalized
 22 decision matrix; 3) definition of the “ideal” and “ideal-negative” expected state; 4) cal-
 23 culation of the metric values; 5) calculation of relative proximity to the “ideal” state; 6)
 24 ranking of alternatives.

25 Mathematical description of the TOPSIS method is as follows:

26 Step 1. Formation of a matrix of assessments or decisions $(x_{ij})_{n \times k}$, consisting of n
 27 alternatives and k criteria, where the element of the matrix x_{ij} determines the value of the
 28 j -th criterion of the i -th alternative.

29 Step 2. By normalizing the matrix $(x_{ij})_{n \times k}$ forming the matrix $R = (r_{ij})_{n \times k}$ as
 30 follows:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{t=1}^n x_{tj}^2}}, \quad i = 1, 2, \dots, n; \quad j = 1, 2, \dots, k. \quad (11)$$

31 Step 3. Calculation of the weighted normalized decision matrix:

$$t_{ij} = r_{ij} \cdot w_j, \quad i = 1, 2, \dots, n; \quad j = 1, 2, \dots, k, \quad (12)$$

32 where w_j – weight coefficient of j -th criterion, $j = 1, 2, \dots, k$ and $\sum_{j=1}^k w_j = 1$.

1 Step 4. Determination of the worst A_w and best A_b alternative:

$$\begin{aligned} A_w &= \{\langle \max(t_{ij} | i = 1, 2, \dots, n) | j \in J_- \rangle, \\ &\quad \langle \min(t_{ij} | i = 1, 2, \dots, n) | j \in J_+ \rangle\} \equiv \{t_{wj} | j = 1, 2, \dots, k\}, \\ A_b &= \{\langle \min(t_{ij} | i = 1, 2, \dots, n) | j \in J_- \rangle, \\ &\quad \langle \max(t_{ij} | i = 1, 2, \dots, n) | j \in J_+ \rangle\} \equiv \{t_{bj} | j = 1, 2, \dots, k\}, \end{aligned} \quad (13)$$

2 According to (13) the value of an individual criterion of the worst alternative A_w is
3 equal to the maximum value of this criterion for the alternatives under consideration in
4 the case of minimizing the criterion ($j \in J_-$) and equal to the minimum value of this
5 criterion for the alternatives under consideration in the case of maximizing the criterion
6 ($j \in J_+$). And the reverse reasoning applies to the best alternative A_b .

7 Step 5. Calculation of L^2 -distance between target alternative i and the worst alterna-
8 tive A_w

$$d_{iw} = \sqrt{\sum_{j=1}^k (t_{ij} - t_{wj})^2}, \quad i = 1, 2, \dots, n, \quad (14)$$

9 and the distance between i -th alternative and the best alternative A_b

$$d_{ib} = \sqrt{\sum_{j=1}^k (t_{ij} - t_{bj})^2}, \quad i = 1, 2, \dots, n, \quad (15)$$

10 where d_{iw} and d_{ib} are distances according to the L^2 -norm.

11 Step 6. Calculation of relative proximity to the ideal solution:

$$s_{iw} = \frac{d_{ib}}{d_{iw} + d_{ib}}, \quad 0 \leq s_{iw} \leq 1, \quad i = 1, 2, \dots, n. \quad (16)$$

12 The value $s_{iw} = 1$ if and only if the alternative corresponds to the best state; and $s_{iw} = 0$
13 if and only if the alternative corresponds to the worst state.

14 Step 7. Ranking alternatives by values s_{iw} ($i = 1, 2, \dots, n$).

15 Let's consider the implementation of the TOPSIS method for the example from Ta-
16 ble 1. Let us choose the following values of the weight coefficients $w_1 = w_2 = w_3 =$
17 1. According to (12) the values of the weighted normalized decision matrix t_{ij} , $i =$
18 1, 2, 3, 4; $j = 1, 2, 3$ for alternatives $S_i = t_{ij}$, $i = 1, 2, 3, 4$ are the following $S_1 =$
19 $(0, 2; 0, 4; 0, 2)$, $S_2 = (0, 3; 0, 1; 0, 12)$, $S_3 = (0, 5; 0, 3; 0, 1)$ and $S_4 = (0, 7; 0, 6; 0, 4)$.
20 According to (13) we define the best alternative as

$$A_b = (\max(0, 2; 0, 3; 0, 5; 0, 7); \min(0, 4; 0, 1; 0, 3; 0, 6); \min(0, 2; 0, 12; 0, 1; 0, 4)) = \\ (0.7; 0.1; 0.1)$$

21 and the worst alternative as

$$A_w = (\min(0, 2; 0, 3; 0, 5; 0, 7); \max(0, 4; 0, 1; 0, 3; 0, 6); \max(0, 2; 0, 12; 0, 1; 0, 4)) = \\ (0, 2; 0, 6; 0, 4).$$

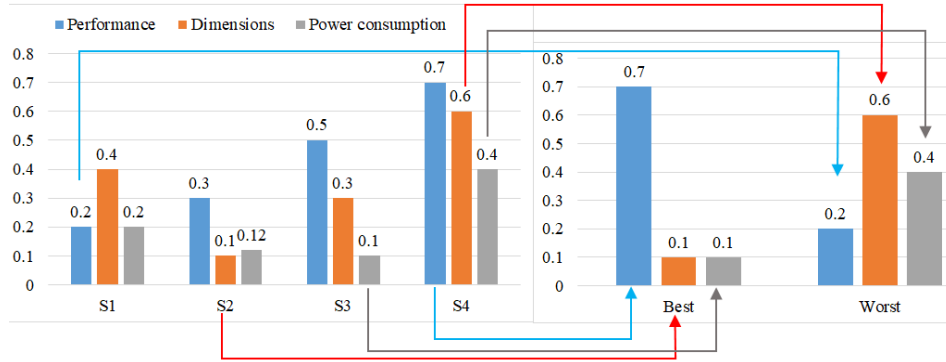


Fig. 6. Illustration of the selection of the best and worst alternatives

1 The graphical representation of the choice of the best A_b and worst A_w alternatives is
 2 shown in Fig. 6.

3 According to (14) and (15) L^2 -distances between alternatives S_i , $i = 1, 2, 3, 4$ and
 4 the worst and best alternatives A_w and A_b are

$$d_{1b} = \sqrt{(0,2 - 0,7)^2 + (0,4 - 0,1)^2 + (0,2 - 0,1)^2} = \sqrt{0,25 + 0,09 + 0,01} = \sqrt{0,35} \approx 0,2828$$

$$d_{1w} = \sqrt{(0,2 - 0,2)^2 + (0,4 - 0,6)^2 + (0,2 - 0,4)^2} = \sqrt{0 + 0,04 + 0,04} = \sqrt{0,08} \approx 0,5916$$

5

$$d_{2b} = \sqrt{(0,3 - 0,7)^2 + (0,1 - 0,1)^2 + (0,12 - 0,1)^2} = \sqrt{0,16 + 0 + 0,0004} = \sqrt{0,1604} \approx 0,4005$$

$$d_{2w} = \sqrt{(0,3 - 0,2)^2 + (0,1 - 0,6)^2 + (0,12 - 0,4)^2} = \sqrt{0,01 + 0,25 + 0,0784} = \sqrt{0,3384} \approx 0,5817$$

6

$$d_{3b} = \sqrt{(0,5 - 0,7)^2 + (0,3 - 0,1)^2 + (0,1 - 0,1)^2} = \sqrt{0,04 + 0,04 + 0} = \sqrt{0,08} \approx 0,2828$$

$$d_{3w} = \sqrt{(0,5 - 0,2)^2 + (0,3 - 0,6)^2 + (0,1 - 0,4)^2} = \sqrt{0,09 + 0,09 + 0,09} = \sqrt{0,27} \approx 0,5196$$

7

$$d_{4b} = \sqrt{(0,7 - 0,7)^2 + (0,6 - 0,1)^2 + (0,4 - 0,1)^2} = \sqrt{0 + 0,25 + 0,09} = \sqrt{0,34} \approx 0,5831$$

$$d_{4w} = \sqrt{(0,7 - 0,2)^2 + (0,6 - 0,6)^2 + (0,4 - 0,4)^2} = \sqrt{0,25 + 0 + 0} = \sqrt{0,25} \approx 0,5$$

1 After determining the distances from each alternative to the positive and negative ideal
 2 solutions, the values of relative proximity to the ideal solution s_{iw} are calculated accord-
 3 ing to (16) and presented in Table 2. According to the values of the relative similarity s_{iw}
 4 in Table 2 the systems are ranked as in the last column and the most optimal system is
 5 System 3.

Table 2. Alternatives ranking results

Alternative	d_{iw}	d_{ib}	s_{iw}	Rank
S_1	0,2828	0,5916	0,3234	4
S_2	0,5817	0,4005	0,5922	2
S_3	0,5196	0,2828	0,6475	1
S_4	0,5	0,5831	0,4616	3

6. Ranking Technical Solutions by Aggregating Ordered Ranked Lists

8 In addition to known methods in our study we consider another approach for converting
 9 a multicriteria optimization problem to a single-criteria representation when searching
 10 for technical solutions. The method is based on ranking individual alternatives for each
 11 optimization criterion separately, followed by aggregation of ordered ranked lists [2],[16].

12 Let there be n alternatives S_i , $i = 1, \dots, n$, each of which is characterized by the val-
 13 ues of k indicators (criteria) $S_i = (x_{i1}, \dots, x_{ik})$, and the indicators can be both quantita-
 14 tive and qualitative. The values of the criteria belong to the set $X^a \subseteq X = X_1 \times \dots \times X_k$
 15 of acceptable values. Heterogeneous values of indicators are usually transformed to a
 16 single measurement scale.

17 According to the method, all alternatives are initially ranked for each of the k criteria,
 18 where L_i is a list of alternatives ordered relative to the values of the i -th criterion. Thus,
 19 the following single-criteria minimization problem is formulated:

$$\delta^* = \operatorname{argmin} \Phi(\delta), \quad (17)$$

20 where $\Phi(\delta) = \sum_i d(\delta, L_i)$, d is the distance function, and minimization is carried out
 21 with respect to all possible ordered lists δ of dimension $n = |L_i|$.

22 Selecting a suitable distance function d is one of the most important steps of the
 23 method. Two options were chosen as such functions: Spearman distance and Kendall
 24 rank distance. The Spearman distance between an ordered list of alternatives L_i and any
 25 ordered list δ can be defined as

$$S(\delta, L_i) = \sum_{t \in L_i \cup \delta} |r^\delta(t) - r^{L_i}(t)|, \quad (18)$$

26 where $r^{L_i}(t)$ – rank of alternative t in the list L_i .

1 The smaller the value of the metric $S(\delta, L_i)$, the more similar the two lists. To take
 2 into account additional information about the values of the criteria for each alternative a
 3 weighted Spearman distance is determined

$$WS(\delta, L_i) = \sum_{t \in L_i \cup \delta} |M(r^\delta(t)) - M(r^{L_i}(t))| \cdot |r^\delta(t) - r^{L_i}(t)|, \quad (19)$$

4 where $M(A)$ – value of the i -th criterion of alternative A .

5 Kendall's rank distance is a metric that counts the number of pairwise divergences
 6 between two ranked sets of feature values. The greater this distance, the more different
 7 the two characteristics are, and, therefore, the less the dependence between them.

8 In the case when the number of alternatives is small, the single-criteria problem (17)
 9 can be solved by simply searching through the variants of ordered lists and choosing the
 10 alternative located at the top position of the list as the optimal solution.

11 So, for example from Table 1, we can create three ordered lists according to three
 12 optimization criteria (Table 3), where the last column presents the optimal ranking δ cor-
 responding to the minimum of the functional $\Phi(\delta) = 8$.

Table 3. Ranked lists of alternatives

Alternative	Performance	Dimensions	Power consumption	Optimal rank
S_1	4	3	3	3
S_2	3	1	2	2
S_3	2	2	1	1
S_4	1	4	4	4

13 In order to select the optimal ranking δ , we have applied the simple strategy of calculat-
 14 ing the $\Phi(\delta)$ value for all possible permutations of the rankings of alternatives S_i , $i =$
 15 1, 2, 3, 4 from Table 1. After that the ranking δ corresponding to the minimum value of the
 16 function $\Phi(\delta)$ is considered as optimal. The $\Phi(\delta)$ values for each ranking of alternatives
 17 are presented in Table 4.

18 In Table 4 the values in the column "Value" is calculated as

$$\Phi(\delta) = S(\delta, L_1) + S(\delta, L_2) + S(\delta, L_3), \quad (20)$$

20 where L_i , $i = 1, 2, 3$ are the rankings of alternatives for criteria "Performance", "Di-
 21 mensions" and "Power consumption" respectively, and $S(\delta, L_i)$ is a Spearman distance
 22 in (18). For example for ranking No. 1 in Table 4 and using single-criteria rankings in
 23 Table 3 the Spearman distances are calculated as

$$S(\delta, L_1) = |1 - 4| + |2 - 3| + |3 - 2| + |4 - 1| = 3 + 1 + 1 + 3 = 8$$

$$S(\delta, L_2) = |1 - 3| + |2 - 1| + |3 - 2| + |4 - 4| = 2 + 1 + 1 + 0 = 4$$

$$S(\delta, L_3) = |1 - 3| + |2 - 2| + |3 - 1| + |4 - 4| = 2 + 0 + 2 + 0 = 4$$

24 and the value of function in (20) is $\Phi(\delta) = 8 + 4 + 4 = 16$.

Table 4. Functional values for all possible rankings

No	Ranking	Value	No	Ranking	Value
1	(1 2 3 4)	16	13	(3 1 2 4)	8
2	(1 2 4 3)	20	14	(3 1 4 2)	16
3	(1 3 2 4)	14	15	(3 2 1 4)	8
4	(1 3 4 2)	22	16	(3 2 4 1)	16
5	(1 4 2 3)	18	17	(3 4 1 2)	14
6	(1 4 3 2)	22	18	(3 4 2 1)	14
7	(2 1 3 4)	14	19	(4 1 2 3)	10
8	(2 1 4 3)	18	20	(4 1 3 2)	14
9	(2 3 1 4)	12	21	(4 2 1 3)	10
10	(2 3 4 1)	20	22	(4 2 3 1)	14
11	(2 4 1 3)	16	23	(4 3 1 2)	12
12	(2 4 3 1)	20	24	(4 3 2 1)	12

1 In Table 4 the minimal functional value $\Phi(\delta) = 8$ corresponds to the ranking No. 15:
2 System 3, System 2, System 1 and System 4. The most optimal system is System 3. The
3 same value of functional $\Phi(\delta)$ also corresponds to the ranking No.13: System 3, System
4 1, System 2 and System 4. In case of ambiguity, it makes sense to take into account the
5 real criteria values and estimate the optimal ranking according to (19).

6 Using Multidimensional Scaling (MDS) to reduce the dimensionality of data the two-
7 dimensional representation of all possible rankings from Table 4 and single-criteria rank-
8 ings from Table 3 is shown in Fig. 7. In Fig. 7 three single-criteria rankings are marked
9 with red circles and it is clearly seen that the rankings No.15 and No.13, marked in bold
10 have a minimum total distance to three single-criteria rankings compared to other alter-
11 natives.

12 In the case of a larger number of alternatives and criteria, it is proposed to solve the
13 optimization problem (17) using a genetic algorithm (GA) [15].

14 The GA consists of the following steps:

15 Step 1. *popSize* ordered lists of dimension n (the number of alternatives) are ran-
16 domly initialized, which form the initial set of possible solutions to the problem. The size
17 of the population must be proportional to the number of alternatives and the number of
18 unique elements in the original ordered lists L_i , $i = 1, 2, \dots, k$.

19 Step 2. Depending on which distance is used, calculate the objective function for
20 each element of the population. Then randomly select individuals from the population
21 for the next generation of GA using weighted random sampling, where the weights are
22 determined according to the values of the fitness (objective) function.

23 Step 3. Carrying out crossover operations with probability p_{cross} (transition probabili-
24 ty), i.e. two randomly ordered lists can exchange their parts, which start from a random
25 position with probability p_{cross} .

26 Step 4. The crossover operation only allows the mixing of ordered lists, but to obtain
27 radically new solutions it is necessary to use mutations. Mutation operations are per-
28 formed with probability p_{mut} (mutation probability). Thus, any list in a population can
29 randomly change one or more of its elements.

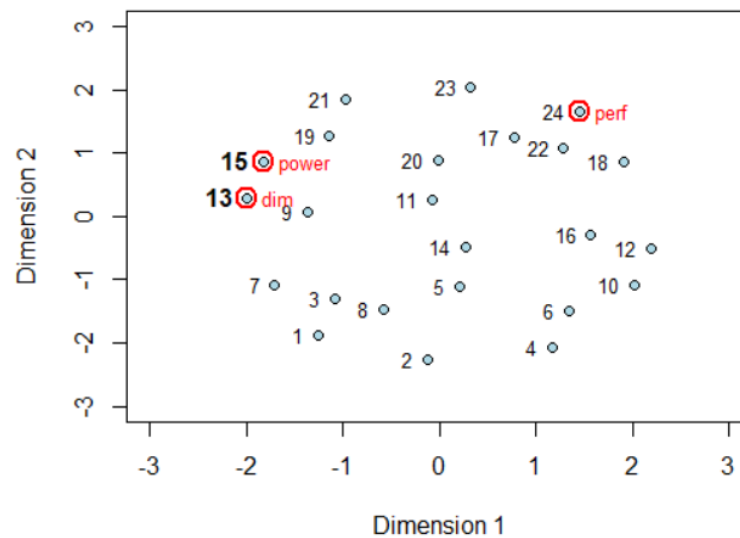


Fig. 7. Graphical representation of all alternative rankings highlighting the optimal ones

1 Step 5. The algorithm stops if the optimal list does not change for successive several
 2 generations of the GA or the maximum number of iterations (GA epochs) is reached.

3 The advantage of using the described method to solve the problem of selecting the
 4 optimal technical solution is to obtain a complete rating of technical solutions based on
 5 their effectiveness, assessed by several criteria. Any number of alternatives with arbitrary
 6 combinations of GA parameters and/or distance functions can be considered. In addition,
 7 the researcher can decide how many performance criteria to use to obtain a reliable
 8 assessment of solutions.

9 7. Conclusion

10 This paper presents the results of extended research in the field of optimization of tech-
 11 nical solutions according to many criteria. The problem statement and system design
 12 methodology are described in general terms. The problem of finding a technical solu-
 13 tion, which is characterized by various parameters or used system resources, is presented
 14 as a multicriteria optimization problem that allows one to find Pareto-optimal solutions.
 15 An approach for narrowing the solution space in order to reduce the uncertainty associ-
 16 ated with multi-criteria selection and find the optimal technical solution is described and
 17 demonstrated by example. The approaches for converting a multi-criteria selection prob-
 18 lem to a single-criteria optimization problem by criteria convolution, as well as for rank-
 19 ing solutions based on calculating distances to the ideal point are described and presented
 20 on the example. It is proposed to apply a method based on aggregating ordered ranked
 21 lists for converting a multicriteria optimization problem to a single-criteria representation
 22 when searching for technical solutions. A method is based on solving a single-criteria op-
 23 timization problem, where the optimization functional estimates the sum of the distances

1 of the searched optimal ranking of alternatives to the corresponding rankings for each of
 2 the criteria under consideration.

3 The approaches described in the paper can be used to find a compromise between
 4 various characteristics of a technical solution in order to select the optimal variant when
 5 designing multiprocessor information systems. As a result of applying methods for rank-
 6 ing solutions, it will be possible to determine not only the best solution, which is often
 7 of primary interest, but a complete rating of all solutions, which provides information for
 8 further research. The practical results of applying different approaches are demonstrated
 9 using a simple example. A further direction of research is the analysis and application of
 10 interactive methods for searching for the optimal technical solution when developing a
 11 multiprocessor information system.

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