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# Decision-making Processes in Transport Organization

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**Abstract**
Transport decision-making is a complex and iterative process which requires collaboration between different stakeholders and consideration of economic, social and environmental factors. It involves balancing short-term needs with long-term sustainability to create efficient, equitable and sustainable transport systems for both the present and the future. The article discusses the main components and considerations for organising the decision-making process in the transport industry. This process is based on the search for a global optimum. The solution to this problem is associated with multi-extreme problems, which includes the issue of the problem's dimension. In addition, there is a need for dimensionality reduction and algorithmicising of multi-extreme problems, which is shown in the article.

**Keywords:** transport, decision-making, stakeholders, global optimum, stochastic, multi-extreme problems, algorithm.

## 1. KEY DECISION-MAKING FACTORS IN THE TRANSPORT SECTOR

Transport decision-making processes involve a complex interplay of factors which influence the planning, development and operation of transport systems [1-7]. The

key components and considerations for organizing a decision-making process in the transport sector are shown in

Figure 1:

- Policy and Planning: At the core of transport decision-making is the formulation of policies and long-term planning. This involves setting goals and objectives, considering social, economic and environmental factors, as well as creating strategic plans for transportation development.
- Data Analysis and Research: Utilising data analysis and research to understand transportation needs, traffic patterns, infrastructure conditions, and potential improvements. This informs decision-making on where investments and changes are most needed.
- Stakeholder Engagement: Involving various stakeholders, including government agencies, transportation authorities, local communities, businesses, and environmental groups. Their input is vital in understanding diverse perspectives and ensuring that decisions align with the needs of all parties involved.
- Financial Considerations: Assessing the financial implications of different decisions. This involves cost-benefit analyses, funding allocation, and exploring various financing models for infrastructure development and maintenance.
- Regulatory Framework: Considering the legal and regulatory framework within which transportation decisions are made. Compliance with laws, regulations, and safety standards is essential in all decision-making processes.
- Technology Integration: Embracing technological advancements for better decision-making. Utilising data analytics, modelling, simulation, and emerging technologies (such as AI, IoT, and autonomous vehicles) to improve efficiency and safety in transportation systems.
- Risk Management: Evaluating risks and uncertainties associated with different decisions. This includes assessing potential disruptions, safety concerns, and the resilience of the transportation system against various risks.
- Sustainability and Environmental Impact: Factoring in the environmental impact of transportation decisions. This involves considerations for reducing carbon emissions, promoting cleaner energy sources, and minimizing the ecological footprint of transport systems.
- Implementation and Monitoring: After decisions are made, there needs to be a structured implementation plan. Continuous monitoring and evaluation of the implemented decisions are necessary to ensure they are achieving the desired outcomes and to make adjustments as needed.

- Adaptability and Flexibility: The transportation sector is subject to rapid changes. Decision-making processes should be adaptable and flexible to accommodate evolving technology, societal needs, and unexpected events.

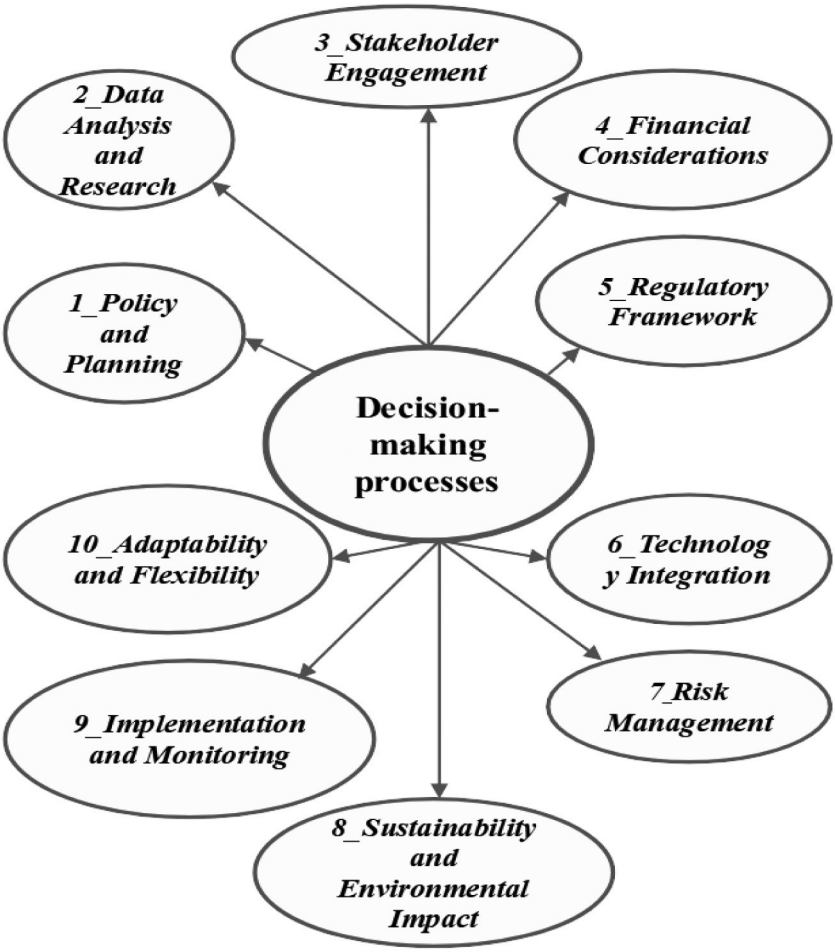



Figure 1. The main components of decision-making in transport organisation.
Source: Author.

This paper outlines the key components and considerations for organising decision-making in the transport sector to address the following challenges:

a) Transport decision-making involves a network of public authorities, transport managers, private sector actors and members of the public working together

to make informed and effective decisions that shape the present and future of transport systems.

b) It is important that public and private sector stakeholders address the following challenges: Coordinate their actions in the planning, development and delivery of transport services. These transport decisions also need to be integrated with environmental, health, energy and urban land use decisions.
c) Transport-related decisions should be made in an open and inclusive process. The public should be informed about transport options and their impact, while public participation in decision-making should be encouraged so that the needs of different communities are understood and met.
d) It is important to anticipate the environmental and social impact of transport decisions rather than to attempt reacting to them after they have occurred, i.e., proactive rather than retroactive methods should be used, as transport decisions often involve expensive, long-term infrastructure investments.
e) Both global and local social, economic and environmental impact of decisions have to be considered. Decision-making and optimization problems in transport can be solved by mathematical programming. One such approach could be as follows.

The optimisation of such a system depends on a number of factors which are ambiguous and highly variable. Therefore, the search for the transport system optimum must be solved under conditions of incomplete initial information. In fact, it is necessary to look for global, not local, extreme values of transport organisation. One possible approach to solving this problem is proposed below.

**Problems of minimization** (or maximization) of functions under various additional conditions are typical mathematical models of decision-making processes in the computer-aided design of technical devices and systems [8-10], in vehicle control, in updating dependencies based on the analysis of experimental data, etc.

The simplest type of such a problem assumes that the choice of a variant of the object to be designed (i.e., the optimization problem will be interpreted as the choice of a solution in design) is characterized by the choice of the value of the vector of design parameters $y=(y_1,\dots,y_N)$. At the same time, the conditions for the creation and operation of the vehicle impose some restrictions on the permissible values of the vector $y$. These are formally described as the requirement that the vector $y$ belongs to some valid region $Q$ in the $N$-dimensional parameter sspace $R^N$ [8] The effectiveness of an object variant which corresponds to a given value of the vector $y$

is described by the indicator $\varphi(y)$, which can be calculated based on the analysis of the mathematical model of this object. Such calculations will be called experiments. If we assume that a decrease in φ(y) corresponds to an improvement of the project, then the choice of the value of y*, which determines the best option, is reduced to an approximate solution of the minimization problem:

$$y_* = arg\ min\ \{\varphi(y): y \in Q\} \quad (1)$$

based on the results $Z_i = \varphi(y_i), 1 \leq i \leq k$ of a finite number of experiments at points $y_i \in Q$.

The selection of experimental points can be carried out sequentially, i.e., when selecting the next point $y^{i+1}$, the already known results $Z^1, \ldots, Z^i$ of the experiments at the previous points $y^1, \ldots, y^i$ can be used. It is assumed that some selected points may not belong to the region $Q$. The mathematical model of the object should contain a test to detect such cases (with a negative test result taken as the result of the experiment). Thus, the procedure for selecting points from region $Q$ can be determined indirectly – through the test for belonging to this region. It is also possible that the admissible region is empty, which corresponds to the incompatibility of the requirements for the object. Establishing this fact is also considered a solution to the problem (1).

The accuracy of the approximate solution of problem (1), which has the coordinate $y_*$ and the value $\varphi_* = \varphi(y_*)$, can be characterized by some accepted (for meaningful reasons) notion of proximity to the exact solution, for example, the estimate $||y^* - y_*||$ or the estimate $|\varphi^* - \varphi_*|$, where $\varphi^* = (\varphi) y^*$.

## 2. LIMITED DIFFERENCES IN THE ESTIMATION OF THE OPTIMUM

Any possibility of a reliable estimate of the global optimum in a multi-objective problem is fundamentally based on the availability of certain a priori information which allows for relating the possible values of the minimization function to the known values at points where measurements have already been made.

Let us assume that the valid domain Q in accordance with problem (1) coincides with the search domain $D$ (i.e., there are no constraints) [8].

We will use the fact that, in many applied problems, a change in the parameter vector $\boldsymbol{y}$ leads to a change in the characteristics of the object, limited to a certain degree of change in $\boldsymbol{y}$. This fact can be interpreted as a reflection of the capacity constraint which generates changes. Of course, there are situations when opposite phenomena occur (shock effects, resonance phenomena, etc.), which should be modelled as discontinuities in characteristics.

A formal model which describes the above property of boundedness of changes for the considered problem with one characteristic $\varphi\ (y)$ can be, for example, the following system of inequalities:

$$|\varphi(y')-y'')|\leq K\rho(y',y''),y',y''\in D, \tag{2}$$

where $\rho\ (y',\ y'')$ is a certain distance function in the parameter space, and K is a given constant. In the case when in (2)

$$\rho(y',y'')=(||y'-y''||)^{1/N}, \tag{3}$$

where the function $||\cdot||$ corresponds to the Euclidean metric, we say that the function $\varphi$ satisfies the uniform condition with exponent $\frac{1}{N}$ and coefficient $K$.

When $N = 1$, this condition is called the Lipschitz condition with constant $K$. We will consider this case to explain the main ideas, and for the sake of clarity, let us assume that the problem is one-dimensional, and, therefore, the search domain $D$ is some segment $[a, b]$ of the real $y$ -axis.

So, let the function $\varphi\ (y)$, $y \in [a, b]$ satisfy the condition with a given constant $K$, i.e:

$$|\ \varphi(y')\ -\ \varphi(y'')|\leq K\,|\ y'\ -\ y\ ''|,\ y',y''\in\ [a,b], \tag{4}$$

and let the experiments be carried out at points $y^1, \ldots, y^k$ in the interval $[a, b]$. Renumber the points $y^i$ using the lower indices in ascending order of coordinate values, i.e:

and denote the values of the function calculated in them as

Figure 2 illustrates the point.

$$a\leq y_1< \ldots < y_i < \ldots < y_k \leq b,$$

Let us enter the functions:

$$\varphi_i(y)=z_i-K|y-y_i|, y\in D, 1\le i\le k, \quad (5)$$

for which, in accordance with (4), the following applies:

$$\varphi_i(y)=z_i-K|y-y_i|, y\in D, 1\le i\le k,$$

or

$$\varphi(y)\ge\psi(y)=max\{\psi_i(y):1\le i\le k\},\ y\in D, \quad (6)$$

that is, the experimental results and condition (4) allow us to construct the minorant $\varphi(y^*)$ from (6) of the minimized function $\varphi(y^*)$ in the search domain. At the same time, the desired minimum value of $\varphi(y^*)$ is estimated:

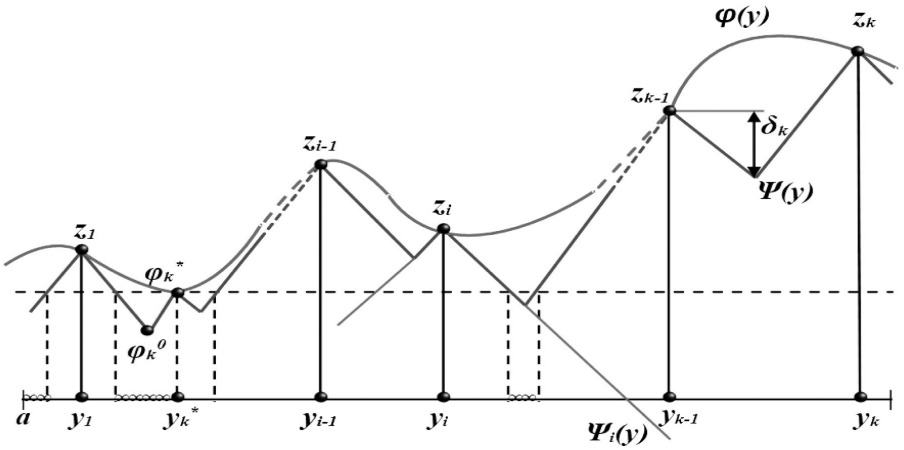



Figure 2. Conduct experiments at points $(y', y^k)$ on the interval $[a, b]$.

$$\varphi k^\circ\le\varphi(y*)\le\varphi k*, \quad (7)$$

where

$$\varphi_{k^\circ}=min\{\psi(y):y\in D\},$$

. bb $\varphi k*=min\{zi:1\le i\le k\}$, (8)

and the upper estimate of $\varphi^*_k$ corresponds to the point$y\ k^*$, at which it is reached, i.e., $\varphi^*_k = \varphi\ (y^*_k\ )$. The lower bound $y^o_k$ can be calculated quite simply. If we denote

$$\varphi ki^\circ = min\{\psi(y): y \in [y_{i-1}, y_i]\}, 1 \le i \le k+1, \tag{9}$$

where

$y_0 = a$ and $y_{k+1} = b$ , then according to (8),

$$\varphi k^\circ = \varphi kt^\circ = min\{\varphi ki^\circ: 1 \le i \le k+1\ \}, \tag{10}$$

and in accordance with (5), (6), (8)

$$\varphi ki^\circ = (zi + zi - 1 - K\delta i)/2,\ 1 < i \le k, \tag{11}$$

$$\varphi k1^\circ = z1 - K\delta 1, \varphi k,k+1^\circ = zk - K\delta k + 1, \tag{12}$$

where

$\delta_i = y_i - y_{i-1}, 1 \le i \le k+1.$

The search method. It follows from (9), (11), (12) that

$$\delta i = min(zi - 1, zi) - \varphi ki^\circ \le K\delta i)/2, 1 < i \le k \tag{13}$$

$$\delta i = z1 - \varphi k1^\circ = K\delta 1, \delta k+1 = zk - \varphi k, k+1^\circ = K\delta k + 1. \tag{14}$$

Because, at the same time:

$$\varphi k* - \varphi k^\circ min\{\delta i\colon\ 1 \le i \le k+1\},$$

then the uniform arrangement of test points $y_i, 1 \le i \le k$, at which $\Delta_i = 2\delta/K, 1 \le i \le k, \delta_1 = \delta_{k+1} = \delta/K$, provides an estimate of (7) with an accuracy of $\delta$, since, according to (13) – (14):

$$\varphi k* - \varphi k^\circ \le \delta. . \tag{15}$$

This method of finding an optimal solution is called the uniform grid search method.

### *2.1 Search on an uneven grid*

To obtain an estimate of (15) by the search method, it is necessary to perform $k=K(b-a)/2\delta$ experiments. This estimate can be achieved with a much smaller number of experiments, given that the desired solution $y_*$ can only belong to a set:

$$D_k=\{y\in D:\psi(y)\}\leq\varphi_{k*} \tag{16}$$

In Fig. 2, the corresponding set is indicated by shading. Thus, it is possible to perform the search on a coarse grid, which corresponds to an accuracy of $\delta' > \delta$ and requires a small number of experiments $k'$. At the next stage of the search, the search is performed only in a subset of $D_k$ for a higher accuracy $\delta'' < \delta'$, and so on (until the required accuracy $\delta$ is reached). By increasing the number of stages and decreasing the number of experiments at each stage, a fully sequential method can be constructed in which exactly one experiment is performed at each stage.

One such method which consistently generates a non-uniform mesh is that each subsequent $k + 1$ iteration (next experiment) is performed at a point:

$$y^{k+1}=(y_t + y_{t-1})/2-(z_t + z_{t-1})/2K,$$

at which the minimum of the minorant $\psi(y)$ is achieved, i.e., the lower estimate of $\varphi_k^\circ$ from (8), (10) is achieved.

The expediency of conducting the next experiment at the point of minimum of the minorant $\psi$ can be (informally) motivated by the fact that obtaining a small value of the minimized function $\psi$ at this point will lead to an improvement in the upper estimate ($\varphi^*_{k+1}<\varphi^*_k$), and obtaining a large value will lead to an improvement in the lower estimate ($\varphi^\circ_{k+1}>\varphi_k^\circ$), if the latter was achieved at a single point. In this case, each experiment improves the estimate (7). The starting points for the experiments can be, for example, $y_1 = a$, $y^2 = b$.

## 3. ESTIMATION OF THE CONSTANT AND STOCHASTIC MODEL

The previous discussion was based on the assumption that the constant $K$ in conditions (2) or (4) is given. A rough upper bound estimate which can be obtained in applied problems leads, as can be seen from (15), to the need to use significantly

denser networks (uniform or non-uniform), the nodes of which are used for experiments. With an underestimation of the value of the constant, inequalities (4) and the entire scheme for estimating the optimum based on them lose their validity [9].

A possible solution is as follows [8]. Instead of condition (4), which implies reliable boundedness of the differences of the function, the assumption is made that the differences $\varphi(y') - \varphi(y'')$ are interpreted as random variables with an absolute value of the mathematical expected value equal to $L/y'-y''/$ if the minimum point does not lie between the points $y'$, $y''$. In this case, it is possible to build current estimates of the unknown constant L based on the results of the experiments, i.e., based on the observed values of the relative differences of the function.

This approach leads to the fact that the estimates of the desired optimum based on the results of experiments are also stochastic in nature. At the same time, both estimates using probability distributions and precise estimates, such as maximum likelihood estimates for the global minimum point, can be entered, which allows for building a sequential search method, according to which each subsequent experiment is carried out at the current point of maximum likelihood.

### *3.1 Maximum likelihood algorithm.*

The first experiment is performed at an arbitrary point $y_1 \in (a,b)$.. The point of any subsequent $k+1$-th experiment is determined by the expression:

$$y^{k+1} = \frac{y_t + y_{t-1}}{2} - \begin{cases} (z_t - z_{t-1})/2r\mu, & 1 < t \le k, \\ 0, t = 1, & t = k+1, \end{cases} \quad (17)$$

where the number is determined from the condition:

$$R(t) = \max\{R(i): 1 \le i \le k+1\}, \quad (18)$$

where for $1 < i \le k$

$$, \quad R(i) = \delta_i + (z_i - z_{i-1})^2/\mu^2\delta_i - 2(z_i + z_{i-1})/r\mu, \quad (19)$$

$$R(1) = 2\delta_1 - 4z_1/r\mu, R(k+1) = 2\delta_{k+1} - 4z_k/r\mu \quad (20)$$

$$\mu = max\{|z_i - z_{i-1}| / \delta_i : 1 < i \le k\}. \quad (21)$$

If expression (21) is equal to zero, as well as when $k = 1$ , it is assumed that $\mu = 1$. The number $r$ from (17), (19), (20) is a parameter of the method, and the inequality $r > 1$ must be satisfied.

### *3.2 Conditions of convergence*

The method (17) – (21), as already mentioned, sequentially iterates at the points which are most likely to contain the global minimum, evaluating their location by means of an appropriate interpretation of the experimental results within a certain stochastic model. However, the rules (17) – (21) for selecting iterations can be investigated beyond the initial assumptions. If this algorithm is used to minimize (with a constant $K$) the function $\varphi$, then for any boundary point $y'$, the sequence $\{y^k\}$, generated by it is valid [8]:

1. a point $y'$ is at least a locally optimal point of the function $\varphi$ if this function has a finite number of local minima.
2. if there is another boundary point $y''$ of the sequence $\{y_k\}$, then $(y') = \varphi(y)$, which means that simultaneous convergence to different values of the function is impossible; and, therefore, the method generates an uneven mesh when minimizing functions other than a constant.
3. $z^k = \varphi(yk) \geq \varphi(y')$, $k = 1,2,\ldots$, i.e., the algorithm cannot generate convergence to points where the function value exceeds the result of any experiment.
4. if at some stage the condition

$$r\mu > 2K, \tag{22}$$

then $y'$ is a point of global minimum of the function $\varphi$, and, moreover, the set of all boundary points of the sequence $\{y^k\}$ coincides with the set of points of global minimum of the function $\varphi$.

It is important to note that this algorithm, which does not require an a priori setting of the Lipschitz constant, has proven to be effective in solving many specific applied problems.

### *3.3 The influence of dimensionality*

The considered scheme for estimating the global optimum based on the test results and the a priori assumption (1.2.11.2), which characterizes the limitation of the

differences in the values of the minimized function to some extent of the differences in the corresponding argument values, remains true in multidimensional problems, i.e., when N>1. However, the computational complexity of the evaluation increases significantly.

**Exponential increase in the complexity of the search**

Let us assume that the minimized function φ satisfies the condition (with constant K) in the admissible domain Q=D from (4). Similarly, to (5), we introduce a family of minorants ψ_i, i.e:

$$\varphi(y) \geq \psi\_i\,(y)\; z^i\text{-}K\|\|y\text{-}yi\;|, y\in D, \quad 1\leq i\leq k, \tag{23}$$

where $y^1$ and $z^i$ $\varphi(y^i)$ denote the points and experimental results, respectively. It follows from (23) that in the closed ε-neighbourhood $U(y^i)$ of the point $y^i$, there is an estimate:

$$z^i\text{-}min\ \{\varphi(y)\text{:}y\ \in\ D\cap U(y^i)\}\leq\delta,$$

if ε=δ/K. By selecting test points so that they form an ε-network in the search domain D, we obtain an estimate of the desired solution:

$$\varphi_{k*}-\varphi(y_*)\leq\delta \tag{24}$$

where

$$\varphi_{k*}=min\,\{z_i\text{:}\ 1\leq i\leq k\}, \tag{25}$$

since, for the solution point $y_*$ and the coverage of the domain $D$ by the neighbourhoods of $U(y^i)$, it is true that:

$$\varphi(y_*)=min_{1\leq i\leq k}(min\,\{\varphi(y)\text{:}\ y\in D\cap U(y')\}).$$

A uniform ε-network in a multidimensional domain D from equation (1.4) can be effectively constructed in various ways. In this case, the total number of nodes of such a uniform network exceeds $(b_1-a_1\cdot\ldots\cdot(b_N-a_N)/\varepsilon_N,$, i.e., grows exponentially with increasing dimension $N$.

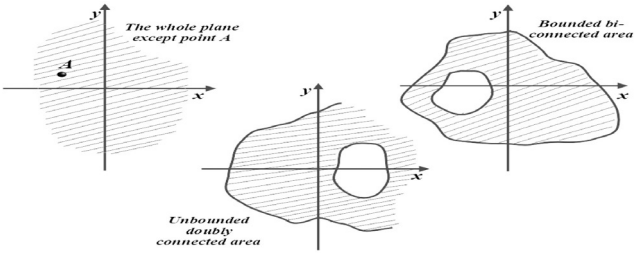
**Difficulty in constructing non-uniform grids consistently**

Similarly to the one-dimensional case, it is possible to reduce the number of measurements required to obtain an estimate of (24) using the brute force method by first performing a low-fidelity search on a coarse mesh containing $k$ nodes and, based on the measurement results, constructing the set $D_k$ from (16), where $\psi(y)$ is the upper envelope of (6) of the minorants $\psi i$ from (23) and $\varphi^*_k$ from (25). The set $D_k$ should contain the desired solution $y^*$, and further search (with greater accuracy) should be performed in this set, and so on.

When $N = 1$, the set (16) is a set of segments on the real number axis. When $N>1$, the constructive task of this set becomes much more complicated. To illustrate the difficulties, consider a specific example for the case of $N= 2$ and $k = 4$ shown in Fig. 3, where in the rectangular area $D$ the points of the four measurements are marked (by small black circles) and the values of the minimized function at these points are indicated, along with the lines of a constant level of the minorant $\psi(y)$. The outline of the non-contour region $D_k$ is highlighted (shading).

The difficulty of determining the region $D_{k,}$ which should include a uniform grid corresponding to a higher accuracy, is removed if we switch to a fully sequential search scheme, when at each $k + 1$ step in the corresponding region $D_k$ exactly one measurement is performed, as discussed for the one-dimensional case. In this case, the point $y^{k+1}$ of the next measurement which improves the estimate of (7) can be used, for example, as the point at which the minorant $\psi(y)$ reaches the absolute minimum of (8). This point, of course, belongs to the domain $D_k$, but it can be determined by minimizing $\psi$ in a simpler domain $D$.

The problem lies in the nature of the domain $D$, which can vary from single-connected to multi-connected (Figure 3). It depends on the set of parameters of transport organisation and the nature of their stochasticity [10].



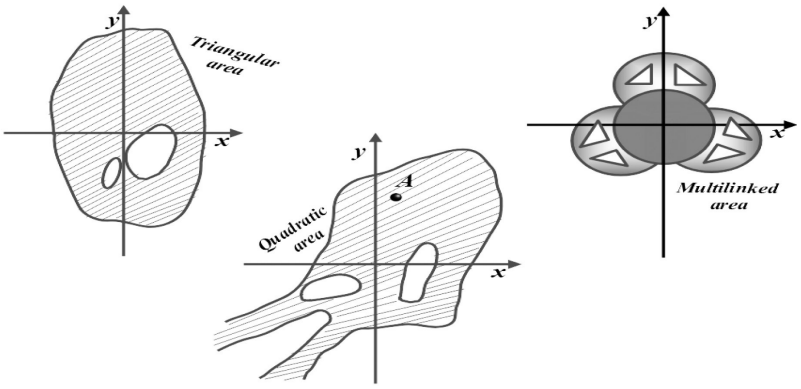



Fig. 3. Possible areas of search for the optimum in different types of sets of two variables.

In the one-dimensional case, according to (9) – (12), minimizing $\psi$ is quite simple and reduces to choosing the minimum of $k + 1$ values (10), each of them constituting the minimum value of (9) of the minor of $\psi$ in the corresponding subinterval $[y_{i-1}, y_i]$, $1 \le i \le k + 1$. This simplicity follows from the fact that for $N > 1$, each measurement point falls into at most two intervals $[y_{i-1}, y_i]$, $[y_i, y_{i+1}]$, and the minimum value of in each such interval does not depend on the results of measurements in other intervals (and can be found analytically as a function of the coordinates of the endpoints of the interval and the values of the minimized function at these endpoints). When $N > 1$, the relationship between the measurement results and the minimum point is minor:

$$y^{k+1} = \arg\min\{\psi(y; y^1, \ldots, yk; z^1, \ldots, z^k) : y \in D\} \quad (26)$$

The multidimensional function $\psi$ is an essentially multi-extreme condition (the points of local minima corresponding to the example shown in Figure 4 are marked with large dark circles).

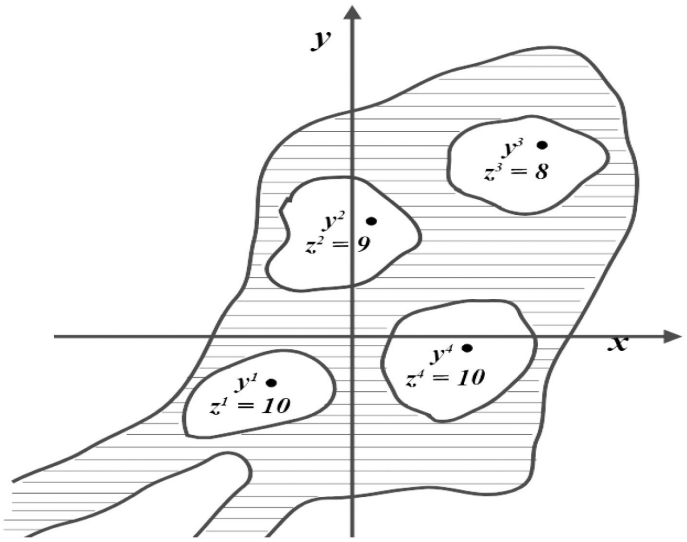



Fig. 4. Points of local minima of the multi-connected domain D.

In fact, rule (26) for selecting the next measurement point itself includes a minimization problem like the original problem (1). The values of the function $\psi$ from (6), (23) are usually much easier to calculate than the values of the object characteristic $\varphi$ from (1), which must be minimized, obtained by analysing a complex mathematical model of this optimization object. However, problem (26) has to be solved at each iteration of problem (1). Note that this difficulty remains unchanged for approaches according to which the next iteration is carried out not at the point of minimum of the minority $\varphi$, but at the point of maximum likelihood or at the point of minimum of the expected value of the function $\varphi$ (both of these rules are based on probabilistic analogues of model (2), similar to the model for the case $N$=1 discussed above), or by using another rule which ensures consistent improvement of the estimates (7) at each (or almost each) step by performing iterations at the point (26) which provides an extremum to some current estimate $\varphi$ of the desired solution.

Let us summarize some conclusions. Solving multidimensional problems using a simple search method on a uniform grid requires a significant number of iterations and is actually possible only for small values of $N$ and low solution accuracy. The use of economical sequential methods which create a non-uniform grid requires solving an additional multi-extreme problem of type (26) at each iteration, which also needs to be solved by search methods (e.g., the brute force method), which dramatically increases the computational complexity of the iteration.

In turn, when $N$=1, simple sequential search methods can be constructed for a multi-extreme problem, based either on a given value of a constant or on estimates calculated during the solution process, and create an economical non-uniform grid whose nodes are used for measurements. In this regard, it is worth considering the possibility of reducing multidimensional, multi-extreme problems to some equivalent one-dimensional problems.

## CONCLUSION

In conclusion, it should be noted that a targeted search for solutions to multi-extreme problems based on a priori assumptions such as (2) about bounded differences generally requires more measurements than a local search for solutions to unimodal problems, since in the first case measurements are made at the nodes of a (non-uniform) grid in a multidimensional search area, and in the second case - at nodes located on some one-dimensional descent path. This ratio can change under certain conditions, complementing model (2).

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