Application of the Pareto front for risk control in the transport system

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Abstract. The article describes the developed model of controlling the process of means of transport operation, in which the choice of control strategy is carried out using non-deterministic methods. The model presented in the paper allows one to evaluate the quality of the transport system operation from the point of view of selected evaluation criteria: the risk of occurrence of undesired events and the availability of means of transport. The article presents a description of the method for determining the optimal (quasi-optimal) strategy for controlling the process of the use of means of transport taking into account the semi-Markov decision-making processes. The selection of the optimal (quasi-optimal) solution is carried out using the genetic algorithm and the simulated annealing algorithm. As a result of numerical calculations, for the criterion functions used, a set of quasi-optimal solutions is obtained in the form of the so-called Pareto front. This applies to the selection of possible decision variants, such a strategy for controlling the operation process, for which the functions constituting the evaluation criteria achieve values belonging to the Pareto-optimal solutions set.

1 Introduction

The issues discussed in the article concern the problem of controlling the process of operation of technical objects. In complex systems of the use of technical objects, the choice of rational control decisions from among the possible decision-making variants should be implemented using appropriate scientific methods, not only in an "intuitive" manner, based solely on the knowledge and experience of the system decision-makers. Due to the considerable complexity of the modeled processes and technical systems, it is necessary to use various types and mathematical tools that ensure effective implementation of the research and the analysis of the results obtained. Depending on the type of the discussed research problems, appropriate methods for determining optimal or quasi-optimal solutions are used, eg: [3, 6, 8, 9, 10, 11, 16]. The use of appropriate mathematical methods to control the operation process facilitates the selection of rational control decisions in a way that ensures correct and effective implementation of the tasks assigned to the system. One of the methods of assessing the possibility of proper implementation of the assigned task is to determine the values of the characteristics describing the safety and efficiency of the system of the use of technical objects.

The article describes the method for determining the optimal (quasi-optimal) strategy for controlling the operation of technical objects using decision-making semi-Markov processes, in which the evaluation criteria include the risk of undesired events and availability in the transport system operation. Moreover, paper [11] in which the selection of the optimal strategy was carried out using genetic algorithm, contains the semi-Markov decision-making model of availability control. On the other hand, paper [3] discusses the

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issues regarding the safety and risk evaluation, also analyzing the marine safety control model developed using decision-making semi-Markov processes as well as the Howard algorithm. Additionally, in paper [10] the semi-Markov model of risk evaluation in the transport system was developed. In this paper, two multi-criteria algorithms (genetic and simulated annealing) belonging to the group of non-deterministic methods were used to determine rational control strategies, the use of which makes it possible to obtain a result in the form of a set of optimal solutions in the Pareto sense (set of solutions belonging to the so-called Pareto Front). The application of these methods made obtaining simple and quick solutions in complex issues of multi-criteria optimization possible.

Genetic algorithm belongs to the group of methods in which the determination of the optimal solution is obtained as a result of determining successive solutions as random modifications of previous solutions dependent on them in a significant way. The basic assumption of using genetic algorithm to search for the optimal solution is the fact taken from the theory of evolution that the highest probability of modification concerns solutions with the highest degree of adaptation, determined by the value of the adaptation function (the function of the optimization task). The concept of a single-criterion genetic algorithm was developed by Holland in the 1960s [5]. The first genetic algorithm used to solve multi-criteria optimization problems was presented by Schaffer in 1985 and was called Vector Evaluated Genetic Algorithm (VEGA) [13]. The most important out of the numerous methods of this type include [7]: Multi-objective Genetic Algorithm (MOGA), Niche Pareto Genetic Algorithm (NPGA), Weight-Based Genetic Algorithm (WPGA), Random Weighted Genetic Algorithm (RWGA), Non-dominated Sorting Genetic Algorithm (NSGA), Strength Pareto Evolutionary Algorithm (SPEA), Pareto-Archived Evolution Strategy (PAES), Pareto Envelope-based Selection Algorithm (PESA).

The simulated annealing algorithm belongs to the group of heuristic methods in which the optimal solution is obtained as a result of searching for better and better solutions in subsequent iterations. Such algorithms are used to search for solutions close to optimal solutions in large optimization tasks, and the way they work is similar to the annealing process used in metallurgy. In the literature on the subject, many studies can be found concerning both theoretical description and examples of practical applications of the simulated annealing algorithm for searching for the optimal solution, eg: [1, 4, 12, 14, 15, 17]. The most important methods of this kind include: the MOSA multicriteria algorithm of simulated annealing with the acceptance criterion based on Pareto dominance and the AMOSA archived algorithm of simulated annealing.

In the case of risk related to the operation of technical systems, many methods are used to evaluate and analyze threats or levels of security, including qualitative, analytical, graphic, as well as quantitative methods. Although these methods allow to assess, control and reduce the risk values to acceptable levels, they do not take into account or only take into account, to a limited extent, the impact of significant parameters of the operation process of technical objects. There is no link between the risk assessment and the completion of the criteria for ensuring the correct implementation of the assigned tasks, eg taking into account the required level of availability, reliability and the value of economic indicators in the technical objects operation system. Such an approach requires taking into account, in addition to the risk, an additional criterion for evaluating the operation of the technical system. The paper presents the results of research of the decision model, the use of which allows to determine a rational strategy for controlling the operation process based on the evaluation of the risk of undesired events, while taking into account the requirements for technical objects for the implementation of assigned transport tasks.

2 Decision-making model for determining control strategies

Due to the random nature of factors affecting the process of operation of technical objects (eg. means of transport), stochastic processes are most often used for mathematical modeling of the operation process. Among the random processes, the Markov and semi-Markov processes were widely used in modeling the process of exploitation of technical objects, while in the case of issues related to the control of complex operation processes - Markov and semi-Markov decision-making processes.

Assuming that the analyzed model of the process of means of transport operation is a stochastic process $\{X(t): t \geq 0\}$ with finite number of process states $i \in S = \{1, 2, \dots, m\}$, then

$$D_i = \{d_i^{(1)}(t_n), d_i^{(2)}(t_n), \dots, d_i^{(k)}(t_n)\} \quad (1)$$

means a set of all possible decisions that can be applied in the i -th state of the process at the moment t_n , where $d_i^{(k)}(t_n)$ means the k -th controlling decision made at the i -th process state at the moment t_n .

In the case where the optimization task consists of choosing the optimal strategy for controlling the operation process from among the acceptable strategies, then the δ strategy is to be understood as a sequence expressed by vectors, made up of decisions $d_i^{(k)}(t_n)$ made at moments t_n of changes of states of the modeled technical object operation process

$$\delta = \{[d_1^{(k)}(t_n), d_2^{(k)}(t_n), \dots, d_m^{(k)}(t_n)]: n = 0, 1, 2, \dots\} \quad (2)$$

In the case when decisions made at successive states of the process do not depend on the moment t_n at which they are taken, that is $d_i^{(k)}(t_n) = d_i^{(k)}$, the strategy δ is called the stationary strategy. Then the formula (2) takes the following form

$$\delta = [d_1^{(k)}, d_2^{(k)}, \dots, d_m^{(k)}] \quad (3)$$

In order to determine the optimal control strategy (decision sequence) it is possible to apply decision-making semi-Markov processes. The decision-making semi-Markov process is a stochastic process $X(t)$, $t \geq 0$ the implementation of which depends on the decisions made at the initial process moment t_0 and in the moments of process changes $t_1, t_2, \dots, t_n, \dots$. In the case of using semi-Markov decision-making processes, making the k -th control decision at the moment t_n of the i -th state of the process means the selection of the i -th line of the process kernel from the set

$$\left\{ Q_{ij}^{(k)}(t): t \geq 0, d_i^{(k)}(t_n) \in D_i, i, j \in S \right\} \quad (4)$$

where

$$Q_{ij}^{(k)}(t) = p_{ij}^{(k)} \cdot F_{ij}^{(k)}(t) \quad (5)$$

The selection of the i -th line of the process kernel determines the probabilistic mechanism of the process evolution in the time interval $< t_n, t_{n+1}$. This means that for the semi-Markov process, if the process state changes from any given one to the i -th (entry into the i -th state of the process) at the moment t_n , decision $d_i^{(k)}(t_n) \in D_i$ is made; moreover, according to the distribution $(p_{ij}^{(k)}: j \in S)$, the j -th process state is generated, transition into which takes place at the moment t_{n+1} . At the same time, according to the distribution defined by the distribution function $F_{ij}^{(k)}(t)$, the length of the time interval $< t_n, t_{n+1}$ for remaining at the i -th state of the process is generated, when the next state is j -th state.

In the paper, for the developed decision-making model two criteria functions were used: unit risk of occurrence of an undesired event $r(\delta)$ [PLN/h] and availability of a single technical object $G(\delta)$:

$$f_{C_1}(\delta) = r(\delta) = \sum_{i \in S_N} c_i(\delta) \cdot p_i^*(\delta) = \frac{\sum_{i \in S_N} c_i(\delta) \cdot \pi_i \cdot \Theta_i(\delta)}{\sum_i \pi_i \cdot \Theta_i(\delta)} \quad (6)$$

$$f_{C_2}(\delta) = G(\delta) = \sum_{i \in S_G} p_i^*(\delta) = \frac{\sum_{i \in S_G} \pi_i \cdot \Theta_i(\delta)}{\sum_{i \in S} \pi_i \cdot \Theta_i(\delta)} \quad (7)$$

where:

$S_N \subset S$ – set of undesirable states of the modeled operation process,

$S_G \subset S$ – set of availability states of the modeled operation process,

$c_i(\delta)$ – unit revenue generated at process states $X(t)$,

$p_i^*(\delta)$ – border probabilities for remaining at the states of the analyzed process $X(t)$, determined on the basis of border theorem for semi-Markov processes [2]

$$p_i^*(\delta) = \frac{\pi_i \cdot \Theta_i(\delta)}{\sum_{i \in S} \pi_i \cdot \Theta_i(\delta)} \quad (8)$$

where:

$\Theta_i(\delta)$ – mean values for unconditional time lengths of process states,

π_i – probabilities of stationary distribution of the embedded Markov chain completing the system of linear equations

$$\sum_{i \in S} \pi_i \cdot p_{ij} = \pi_j, \quad j \in S, \quad \sum_{i \in S} \pi_i = 1 \quad (9)$$

where:

p_{ij} – conditional probabilities of transition from state i to state j , according to the dependence:

$$p_{ij} = \lim_{t \rightarrow \infty} p_{ij}(t) \quad (10)$$

$$p_{ij}(t) = P\{X(t) = j | X(0) = i\} \quad (11)$$

In the semi-Markov decision-making model, the choice of rational control strategy δ referred to as optimal strategy δ^* applies to the situation when the function (functions) constituting the criterion for selecting the optimal strategy assumes the extreme value (minimum or maximum)

$$f_C(\delta^*) = \min_{\delta} [f_C(\delta)] \quad \text{or} \quad f_C(\delta^*) = \max_{\delta} [f_C(\delta)] \quad (12)$$

then, in the decision model presented in the paper, the selection of the rational (optimal) strategy δ^* is made on the basis of the following criteria:

$$r(\delta^*) = \min_{\delta} [r(\delta)] \quad (13)$$

$$G(\delta^*) = \max_{\delta} [G(\delta)] \quad (14)$$

In the developed decision-making model, the genetic algorithm and the simulated annealing algorithm were used to select the strategy to control the process of means of transport operation. In the case of using this type of mathematical tools to determine the strategy of optimal δ^* control of the operation process, the following assumptions should be made:

- the examined model of the process of means of transport operation is an m -state stochastic process,

- at each state of the operating model, you can use one of the two possible decisions $D = \{0, 1\}$,
- if the decisions are marked as 0 and 1, then the number of possible control strategies for the m -state model of the operation process amounts to 2^m ,
- set of control strategies is a set of the function $\delta : S \rightarrow D$.

Based on the above assumptions, every possible control strategy can be presented as a m -positioned sequence consisting of 0 and 1, then a typical control strategy for a 19-state model is defined as follows: $\delta = [1, 0, 0, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 0, 1, 0, 1, 0, 1]$.

3 Defining rational control strategy

The model of the operation process was built on the basis of the analysis of the state space as well as operational events concerning city buses operating in the analyzed transport system. Due to the analyzed evaluation criteria: the risk of occurrence of undesired events and the availability of technical objects, based on the identification of the running multi-state process of operation of technical objects, significant operational states of this process were determined and possible transitions between the distinguished states. The following list contains the states of the modeled operation process and a probabilities matrix of transitions between these states:

1 – carrying out of transport task, **2** – supply, **3** – servicing on day of operation OC, **4** – periodical technical service OT, **5** – stoppage at the depot yard, **6** – stoppage at route due to damage, **7** – diagnostics performed by emergency service PT, **8** – repair by emergency service PT without missing a ride, **9** – repair by emergency service PT with a missed ride, **10** – waiting for completion of the transport task after repair by technical service PT, **11** – emergency exit, **12** – diagnostics before repair at service station SO, **13** – repair at service station SO, **14** – diagnostics after repair at service station SO, **15** – stoppage caused by an accident or collision, **16** – intervention and rescue operation after an accident or collision, **17** – repair after an accident or collision, **18** – vehicle replacement, **19** – diagnostics after post-accident repair.

$$P = \begin{bmatrix} 0 & p_{1,2} & 0 & 0 & 0 & p_{1,6} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & p_{1,15} & 0 & 0 & 0 & 0 \\ 0 & 0 & p_{2,3} & p_{2,4} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & p_{3,5} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & p_{3,13} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & p_{4,5} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & p_{4,13} & 0 & 0 & 0 & 0 & 0 & 0 \\ p_{5,1} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & p_{6,7} & 0 & 0 & 0 & p_{6,11} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & p_{7,8} & p_{7,9} & 0 & p_{7,11} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ p_{8,1} & 0 \\ p_{9,1} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & p_{9,10} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ p_{10,1} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & p_{11,12} & p_{11,13} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & p_{12,13} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & p_{13,2} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & p_{13,14} & 0 & 0 & 0 & 0 & 0 \\ 0 & p_{14,2} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & p_{15,16} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & p_{16,17} & 0 & p_{16,19} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & p_{17,18} & 0 & 0 \\ 0 & p_{18,2} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & p_{19,2} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Controlling the process of city buses operation is possible as a result of making appropriate decisions in the decision-making states of the process. For the model of the urban bus operation process in question, based on operational data, the values of probability transition matrix elements P were estimated, possible decisions at the decision-making states of the process (Table 1) as well as unconditional dates and unit revenues generated at the states of the analyzed process were determined (Table 2).

Table 1. Decision at decision-making states of the analysed process.

Process state	Decision “0”	Decision “1”
1	Route with “light” conditions for completing the transport task	Route with “heavy” conditions for completing the transport task
3	OC servicing – “standard”	OC servicing – “intense”
4	OT servicing – “standard”	OT servicing – “intense”
7	PT diagnostics – “standard”	PT diagnostics – “intense”
8	PT repair without missing a ride – “standard”	PT repair without missing a ride – “intense”
9	PT repair with a missed ride – “standard”	PT repair with a missed ride – “intense”
11	Emergency exit – no assistance	Emergency exit – towing
12	Diagnostics before repair at SO – “standard”	Diagnostics before repair at SO – “intense”
13	Repair at SO – “standard”	Repair at SO – “intense”
14	Post-repair diagnostics at SO – “standard”	Post-repair diagnostics at SO – “intense”
16	Post-collision intervention – “standard”	Post collision intervention – “intense”
17	Post-repair or post-collision repair – “standard”	Post-repair or post-collision repair – “intense”
18	Post-accident repair diagnostics – “standard”	Post-accident repair diagnostics – “intense”

Table 2. Mean lengths of time and unit revenues at the states of the analyzed process depending on decision.

Process state	$\theta_i^{(0)}$ [h]	$\theta_i^{(1)}$ [h]	$c_i^{(0)}$ [PLN/h]	$c_i^{(1)}$ [PLN/h]
1	8.9	7.8	28.5	33.5
2	0.1	0.1	-23	-23
3	0.15	0.11	-215	-250
4	3.9	2.9	-210	-235
5	5.7	5.7	-6.8	-6.8
6	0.055	0.055	-24.5	-24.5
7	0.25	0.19	-55	-70
8	0.10	0.06	-70	-97
9	0.55	0.45	-102	-132
11	0.45	0.45	-24.5	-24.5
12	0.41	0.35	-110	-140
13	0.42	0.38	-83.5	-110
14	3.4	2.7	-117	-136
15	0.42	0.38	-83.5	-110
16	0.4	0.4	-245	-245

17	2.2	1.7	-400	-540
18	120	100	-100	-200
19	0.8	0.6	-55	-84

The presented example has been developed on the basis of operational data obtained from the tests of the actual system of operation of means of transport (city transport buses). 160 city buses are used in the analyzed transport system, and service and repair processes are carried out at technical support stations and by technical emergency units.

In the presented model of the operation process of city buses, states between 6 and 19 are undesirable states (they influence the value of the risk of occurrence of undesirable events), while states 1, 5, 8 and 10 are states of the availability of the technical object to carry out the transport tasks. To add, the calculations were made using an operational computer program using the simulated annealing algorithm and the genetic algorithm. The computer program was developed by R Development Core Team (2018). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0. On the basis of the above calculations, the optimal criteria (quasi-optimal) control strategies for the operation process carried out in the analyzed transport system were determined for the adopted criteria. The results of calculations are shown in Figures 1 and 2 and in Tables 3 and 4.

Fig. 1. The Pareto front of optimal solutions determined using simulated annealing algorithm [Availability/Risk].

Fig. 2. The Pareto front of optimal solutions determined using genetic algorithm [Availability/Risk].

Table 3. Optimal control strategies δ^* and values of criterion functions determined using simulated annealing algorithm.

Strategy δ^*	$r(\delta^*)$ [PLN/h]	$G(\delta^*)$
[0,0,0,0,0,0,1,1,1,1,1,0,0,0,1,0,0,0,0]	5.9553	0.9027
[0,0,0,0,1,1,0,0,0,1,1,0,0,0,0,0,1,1,0,1,0]	5.9562	0.9024
[0,1,0,1,1,0,1,1,0,0,1,1,0,1,1,0,0,0,0,0]	5.9575	0.9031
[0,0,1,0,1,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0]	5.9716	0.9051
[0,1,1,1,0,1,0,0,0,1,1,0,1,0,0,1,0,0,0,0]	5.9742	0.9055
[0,1,1,1,0,0,1,0,1,0,0,0,0,0,0,1,1,0,1,0]	5.9804	0.9060
[0,0,0,0,1,0,0,1,0,0,1,0,1,1,1,1,0,0,0]	6.0229	0.9126
[0,0,0,0,1,0,0,0,1,1,0,0,1,0,0,1,0,1,0]	6.0230	0.9125
[0,1,0,1,0,1,0,0,1,0,0,1,1,1,0,1,0,0,0]	6.0260	0.9130
[0,1,1,0,0,0,1,1,1,1,0,0,1,0,0,0,0,0,0]	6.0435	0.9161

Table 4. Optimal control strategies δ^* and values of criterion functions determined using genetic algorithm.

Strategy δ^*	$r(\delta^*)$ [PLN/h]	$G(\delta^*)$
[0,0,0,0,1,0,0,1,0,1,0,1,0,0,1,0,0,1,0]	5.9507	0.9020
[0,1,0,0,0,1,0,0,0,1,0,0,0,1,1,0,0,1,0]	5.9521	0.9021

[0,0,0,0,0,1,0,1,1,0,0,0,0,1,1,1,0,1,0]	5.9553	0.9023
[0,1,0,1,0,1,1,1,0,0,1,1,0,1,0,0,0,0,0]	5.9575	0.9031
[0,1,0,0,0,1,1,0,1,0,0,1,0,0,0,1,0,0,0]	5.9578	0.9026
[0,1,0,0,1,1,0,1,0,1,1,1,1,0,1,0,0,0,0]	6.0193	0.9124
[0,1,0,1,1,0,0,1,1,0,0,0,1,1,0,0,0,0,0]	6.0225	0.9129
[0,0,0,0,1,1,0,1,0,0,0,0,1,1,1,1,0,1,0]	6.0226	0.9125
[0,0,1,1,1,1,1,0,1,0,0,1,1,1,0,0,1,0]	6.0462	0.9165
[0,1,1,1,0,0,1,1,1,1,0,1,1,1,1,0,0,0,0]	6.0470	0.9166
[0,1,1,1,0,0,1,1,1,0,1,1,1,1,0,1,0,0,0]	6.0505	0.9168
[0,1,1,1,0,0,1,1,1,0,1,0,1,1,0,1,1,0,0]	6.7679	0.9168

4 Summary

Paper [11] discusses the model of the process of operation of means of transport, the use of which enables the designation of control strategies with the help of a single criterion (availability of technical objects). The method presented in the article, however, applies to multi-criteria analysis (eg. using two evaluation criteria such as risk and availability). On the basis of the results obtained, it can be noticed that increasing the availability of means of transport is associated with an increased risk of undesired events. This may be due to the fact that in the developed model the increase in the level of availability of technical objects does not reduce the probability of undesired events, but only causes the necessity of incurring additional costs related to the removal of the effects of these events. This is due to the need to provide additional actions and measures for the treatment of technical objects. This is accomplished by increasing the intensity of service and repairs performed, e.g. using more efficient equipment and tools, and a larger number of employees.

Analyzing the obtained results, it can be noticed that both in the case of simulated annealing algorithm and genetic algorithm, the values of the criterion functions are included in similar ranges for the designated control strategy sets. The risk values for undesired events are relevant from 5.9553 to 6.0435 [PLN/h], with the availability of technical objects ranging from 0.9027 to 0.9161 for simulated annealing algorithm and from 5.9507 to 6.0505 [PLN/h], with the availability of technical objects ranging from 0.9020 to 0.9168 for genetic algorithm. Only in the case of genetic algorithm, for one of the designated control strategies a higher value of the risk of undesired events amounted to 6.7679 [PLN/h], however, without increasing the level of availability of technical objects.

For the determined values of the criterion functions, the corresponding rational control strategies have been developed as sets of optimal solutions in the Pareto sense. The optimal set in the Pareto sense is a set of non-dominated solutions of the entire permissible search space. Optimal solutions in the Pareto sense create the so-called Pareto front. Then, based on the results obtained, one may select a single solution from among the set of optimal solutions located on the Pareto front. Such selection is usually made by the decider (team of deciders) of the system, based on additional premises regarding both the specific decision-making situation and the current conditions in which the operating system operates.

Depending on the demands, the developed algorithms (simulated annealing or genetic), along with the decision-making model of the operation process can be applied to the mathematical formulation and solving of a wide range of problems related to the control of complex technical systems. This applies mainly to the economic analysis, risk and security management as well as to the availability and reliability of the technical objects under operation.

The model presented in the article is a partial result of the conducted research the aim of which is to develop a comprehensive method of controlling the operation of means of transport.

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