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ANALYSIS OF THE IMPACT OF GENETIC ALGORITHM PARAMETERS ON THE EFFECTIVENESS OF SOLVING THE PROBLEM OF ALLOCATING LIMITED RESOURCES IN SCENARIO-BASED ECONOMIC CONDITIONS

АНАЛІЗ ВПЛИВУ ПАРАМЕТРІВ ГЕНЕТИЧНОГО АЛГОРИТМУ НА ЕФЕКТИВНІСТЬ РОЗВ'ЯЗАННЯ ЗАДАЧ РОЗПОДІЛУ ОБМЕЖЕНИХ РЕСУРСІВ У СЦЕНАРНИХ ЕКОНОМІЧНИХ УМОВАХ

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The article examines the impact of genetic algorithm parameters on the efficiency of solving the constrained resource allocation problem under scenario-based economic conditions. A discrete optimization model is considered, incorporating a set of alternatives, budget constraints, and logical dependencies between decision components. An experimental sensitivity analysis of the main algorithm parameters is conducted, including population size, crossover and mutation probabilities, elitism degree, and constraint-handling mechanisms. The study identifies the patterns of parameter influence on convergence and search performance, enabling the development of well-founded strategies for tuning evolutionary methods in complex economic environments.

Keywords: genetic algorithm, evolutionary optimization, scenario modeling, allocation of limited resources, parametric sensitivity, constraint mechanisms, strategic planning, economic efficiency.

У статті представлено комплексне дослідження впливу параметрів генетичного алгоритму на ефективність його застосування для розв'язання задач розподілу обмежених ресурсів у сценарно-орієнтованих економічних умовах. Розглянуто дискретну оптимізаційну модель, у якій рішення формуються з урахуванням бюджетних, логічних та сценарних обмежень, а функції прибутковості змінюються залежно від можливих станів економічного середовища. Основна мета дослідження полягає у виявленні закономірностей впливу окремих параметрів генетичного алгоритму на динаміку його збіжності, баланс між дослідженням простору рішень і локальним удосконаленням, а також на стабільність та якість отриманих результатів. Методологія роботи ґрунтується на використанні еволюційних принципів оптимізації, коли популяція закодованих рішень еволюціонує під дією механізмів відбору, кросовера, мутації та елітизму. Для оцінювання чутливості алгоритму проведено серію експериментів, у межах яких систематично варіювалися такі основні параметри, як розмір популяції, імовірність кросовера, імовірність мутації, частка еліти та спосіб обробки обмежень (штрафний або відновлювальний). Отримані результати засвідчили, що ключовими чинниками ефективності є імовірність мутації та обраний механізм обробки обмежень, які визначають здатність алгоритму зберігати різноманіття популяції та уникати передчасної конвергенції. Встановлено, що помірний розмір популяції забезпечує оптимальне співвідношення між якістю пошуку та обчислювальними витратами, а низький рівень елітизму сприяє підтриманню еволюційної динаміки. Аналіз також показав, що вплив параметрів має взаємозалежний і нелінійний характер. Практичне значення дослідження полягає у формуванні рекомендацій щодо вибору параметрів генетичного алгоритму для задач стратегічного планування та розподілу ресурсів у багатосценарних умовах невизначеності. Визначені параметричні закономірності можуть бути використані для підвищення ефективності систем підтримки управлінських рішень, орієнтованих на економічне прогнозування та оптимізацію інвестиційних стратегій.

Ключові слова: генетичний алгоритм, еволюційна оптимізація, сценарне моделювання, розподіл обмежених ресурсів, параметрична чутливість, механізми обмежень, стратегічне планування, економічна ефективність.

Formulation of the problem. Modern economic systems operate in a dynamic environment characterized by limited resources, uncertainty of external factors, and the need to make strategic decisions under multi-scenario conditions. In such contexts, a key challenge lies in finding the optimal allocation of limited financial, material, or intellectual resources among alternative development directions while considering potential changes in economic scenarios. Traditional methods of mathematical programming often prove inefficient due to the complexity of objective functions, the presence of logical constraints, and the nonlinear nature of interactions between the problem's parameters.

Evolutionary algorithms, particularly the genetic algorithm, have gained wide application in solving such problems due to their ability to find near-optimal solutions in complex multidimensional spaces. However, their performance strongly depends on the proper tuning of parameters such as population size, crossover and mutation probabilities, elitism degree, and the selected constraint-handling mechanism. The absence of universal guidelines for choosing these parameters complicates the use of genetic algorithms in practical economic models, where parameterization directly affects both the quality of results and the speed of convergence.

Thus, the scientific problem arises – the need for a comprehensive analysis of the impact of key genetic algorithm parameters on its performance under conditions of scenario-based economic uncertainty, which determines the relevance of the conducted research.

Analysis of recent research and publications. In modern studies of genetic algorithms, there is an intensive development of approaches related to parameter adaptation, hybridization with other evolutionary methods, and improving problem-solving efficiency under complex conditions.

In the work of Shelekhov I. and Dziuba O. [1], the influence of hybrid algorithm parameters on the efficiency of training decision support systems was analyzed. The authors demonstrated that population size, mutation probability, and waiting period significantly affect convergence and optimization accuracy, while the selection of optimal parameters enhances training speed and the quality of synthesized solutions.

Bazhan S. [2] investigates the application of stochastic processes in genetic algorithms, particularly the use of alternative encoding methods such as Elias gamma and delta codes, Golomb codes, and Rice codes. The study demonstrates that employing modified encoding techniques enhances the search for the global optimum and improves the efficiency of hybrid genetic algorithms when solving optimization problems under stochastic conditions.

In the study by K. Li et al. [3], a Two-Archive Evolutionary Algorithm (C-TAEA) for constrained multi-objective optimization was proposed. The method is based on two archives – one convergence-oriented and the other diversity-oriented – enabling a balance between convergence and exploration of the solution space. This approach proved effective for complex resource allocation problems, where accuracy and robustness are equally important. Similar results were obtained by B.-C. Wang et al. [4], who proposed a compositional differential evolution approach with adaptive combinations of mutation strategies, improving convergence stability and search efficiency in constrained optimization tasks.

F. Zaman et al. [5] focused on a hybrid approach that combines the genetic algorithm and differential evolution for dynamic economic allocation problems. Automatic switching between the methods ensures stable result quality across different model types, while the introduction of a solution "repair" mechanism enhances convergence speed and optimization accuracy.

The work of V. Kharchenko and O. Kurdenko [6] provides a fundamental approach to constructing an economic model of constrained resource allocation under conditions of scenario-based uncertainty. The authors formulated a stochastic model that integrates the profitability and risk of each alternative by introducing a risk-aversion coefficient to balance expected return and acceptable risk level. The proposed constraint structure encompasses not only resource and interval conditions but also logical and structural dependencies between alternatives, reflecting real managerial and financial limitations.

Modern studies therefore demonstrate a clear trend toward enhancing the efficiency of genetic and evolutionary algorithms through adaptive parameter tuning, hybridization of methods, the use of stochastic models, and resource-oriented strategies, as shown in works by Y. Tian et al. [7] and J. Zou et al. [8].

Highlighting previously unresolved parts of the overall problem. Despite the considerable number of studies, the relationship between genetic algorithm parameters and its performance within scenario-based economic models remains insufficiently explored. Most existing works focus on technical or continuous optimization problems, whereas discrete formulations with logical constraints and multiple environmental development scenarios have not yet been analyzed in sufficient detail [3; 7].

The issue of the combined influence of population size, crossover and mutation probabilities, elitism level, and constraint-handling mechanisms (penalty/repair) also remains insufficiently addressed. Therefore, further research is required on the comprehensive parameterization of genetic algorithms specifically for economic resource allocation problems under uncertainty.

Formulation of the article's objectives. The purpose of this article is to investigate the impact of genetic algorithm parameters on the efficiency of solving the constrained resource allocation problem under scenario-based economic conditions, where the performance of solutions depends on the variability of external factors and possible market development scenarios. The study considers a generalized economic model of strategic financial resource distribution among alternative investment directions, taking into account budgetary and logical constraints. Particular attention is paid to examining the parameters that determine the dynamics of the evolutionary search – population size, crossover and mutation probabilities, elitism level, and the constraint-handling mechanism of the “penalty” or “repair” type. The objective of the research is to identify the patterns of influence of these parameters on convergence, stability, and solution quality, as well as to determine optimal parameter ranges that ensure the best balance between search speed and accuracy.

Thus, this study is aimed at developing methodological foundations for adaptive tuning of genetic algorithms for scenario-based economic problems, where optimization efficiency depends on the interaction between population characteristics and environmental uncertainty conditions.

Summary of the main material. The genetic algorithm is one of the fundamental methods of evolutionary optimization that simulates the process of natural selection and hereditary variation. Its main idea lies in the gradual improvement of a population of potential solutions through the selection of the best individuals, recombination of their properties (crossover), and the introduction of random changes (mutation). Each solution is represented as a chromosome containing a set of genes (problem parameters) that encode the allocation of limited resources among alternative options. Owing to this structure, the algorithm can efficiently explore a vast solution space even in the presence of complex or discrete constraints.

The principle of operation is based on a step-by-step evolutionary cycle: an initial population is first generated, after which each chromosome is evaluated using a fitness function. Based on this evaluation, selection occurs – more fit solutions have a higher probability of being passed to the next generation. Next, crossover operators (with probability p_c) are applied to combine genes from two parents, and mutation operators (with probability p_m) modify individual genes to maintain diversity. Elitism ensures that a portion of the best solutions ($e\%$) is preserved unchanged, which enhances convergence stability.

The mathematical model of the problem [6] is formulated as a task of allocating a limited resource among a set of alternatives $A=\{a_1,a_2,\ldots,a_n\}$. Each alternative is characterized by the required amount of funding x_i within the permissible interval $\left[x_i^{min},x_i^{max}\right]$. The main constraint is the adherence to the budget condition: $\sum_{i=1}^{n} x_i \le B$, where B denotes the total available resource.

In addition to the budget constraint, the model accounts for two types of logical constraints: requires dependencies (the implementation of one alternative is possible only if another is present) and incompatible conditions (preventing simultaneous funding of two alternatives). Furthermore, the problem incorporates a scenario-based structure – optimistic, neutral, and crisis states of the economic environment –

which differ in their expected profitability levels [6]. For each scenario s with occurrence probability p, the profitability r_{is} of each alternative i is defined. The objective function represents the weighted average expected profit:

$$F(X) = \sum_{s=1}^{S} p_s \times \sum_{i=1}^{n} r_{is} x_i, \qquad (1)$$

which must be maximized while satisfying all constraints. To compute the fitness function, two constraint-handling mechanisms are applied: penalty and repair [3; 7]. In the penalty method, a penalty term is added to the objective function, reducing the value of $F(X)$ proportionally to the degree of constraint violation:

$$f(X) = F(X) - \lambda \times P(X), \qquad (2)$$

where λ is the penalty (risk-aversion) coefficient, and $P(X)$ is a function representing the degree of constraint violation.

The repair mechanism is used to correct infeasible individuals that violate one or more feasibility conditions, such as budget or logical constraints. Its main purpose is to restore solutions to the feasible space without completely removing them from the population, thereby preserving the accumulated evolutionary information [5].

Formally, let $X = [x_1, x_2, \ldots, x_n]$ be a potential solution satisfying the condition $\sum_{i=1}^{n} x_i \le B$. In this case, a normalization transformation is applied:

$$x_i' = x_i \times \frac{B}{\sum_{j=1}^{n} x_j}, i = 1, 2, \ldots, n, \qquad (3)$$

which proportionally reduces all elements x_i to ensure compliance with the budget constraint.

For logical constraints of the requires and incompatible types, an operational check is applied:

$$R(X) = \begin{cases} x_i' = 0, & \text{if } x_i \text{ requires } x_j \text{ but } x_j = 0, \\ x_i' = 0, & \text{if } (x_i, x_j) \text{ is an incompatible pair}. \end{cases} \qquad (4)$$

In cases where both alternatives are active and violate the incompatibility constraint, the one with the higher local fitness value ($f_i > f_j$) is retained:

$$(x_i', x_j') = \begin{cases} (x_i, 0), & f_i > f_j, \\ (0, x_j), & f_i \le f_j. \end{cases} \qquad (5)$$

If, after correction, the chromosome still does not satisfy the feasibility conditions, the procedure is repeated iteratively until the state $X' \in \Omega$ is reached, where Ω denotes the set of feasible solutions.

The general implementation structure includes population initialization, fitness function evaluation, selection, application of crossover and mutation operators, and the formation of a new population with consideration of elitism. The experimental study examines the ranges of the main parameters – population size N_{pop}, crossover probability p_c, mutation probability p_m and elitism rate e. Their combination determines the balance between search intensity, convergence speed, and the algorithm's ability to avoid local extrema.

Within the experiment [9], a scenario-based investment budget allocation problem under economic uncertainty was considered (Table 1). The total budget amounted to 100,000 monetary units, which had to be optimally distributed among ten potential projects with different funding intervals, profitability levels, and logical dependencies. The objective was to maximize the weighted average expected profit across three market development scenarios: optimistic (30%), neutral (50%), and crisis (20%).

The model includes a budget constraint as well as logical relationships: requires – the implementation of a website is possible only if a CRM system exists, and the data center upgrade is allowed only after the purchase of servers; incompatible – it is impossible to simultaneously develop an in-house AI analytics system while outsourcing, or to combine entering the EU market with logistics expansion.

To evaluate the impact of genetic algorithm parameters on problem-solving efficiency, a series of experiments was conducted in which four main characteristics were systematically varied: population size, crossover probability, mutation probability, and elitism rate. The population size was set to 30, 100, and 200 individuals, allowing a comparison of convergence speed and solution diversity in small and large populations. The crossover probability was varied within 0.2, 0.6, and 0.95 to assess the balance between the intensity of genetic material recombination and the risk of losing local stability. The mutation probability was examined at three levels – 0.01, 0.10, and 0.30 – to identify the optimal balance between global exploration and the precision of local refinement. The elitism rate was set at 1%, 5%, and 15%, enabling an analysis of how preserving the best individuals affects the stability and speed of the evolutionary process.

In addition, two approaches to constraint handling were compared: the penalty method,

Table 1

Project parameters in the scenario-based model

№	Project	min, k m.u.	max, k m.u.	Optimistic	Neutral	Crisis
1	New website	5	20	1,5	1,0	0,2
2	CRM system	8	15	1,8	1,1	0,1
3	AI analytics development	10	25	2,2	1,5	0,5
4	Analytics outsourcing	6	10	1,0	0,8	0,1
5	Entry into the EU market	7	15	1,4	1,2	0,6
6	Logistics expansion	5	10	1,6	1,0	-0,2
7	Data center upgrade	9	18	2,0	1,3	0,3
8	Server procurement	10	20	2,5	1,8	0,8
9	Marketing campaign	8	15	1,9	1,4	0,4
10	Mobile application	6	12	1,2	0,9	-0,1

Source: formed by the authors

which adjusts the objective function value according to the degree of constraint violation, and the repair method, which automatically corrects infeasible solutions to return them to the feasible domain. As a result of combining all parameters, 162 experimental scenarios were generated, each evaluated according to three criteria – the best, median, and worst values of the objective function. This approach enabled a comprehensive examination of the interdependencies among algorithm parameters, the assessment of their impact on convergence stability, and the identification of parameter combinations that deliver the best results in scenario-based resource allocation problems.

The overall convergence dynamics of the evolutionary algorithm, presented in Figure 1, reveal two characteristic phases: rapid initial adaptation followed by gradual stabilization. During the first 10-15 generations, most configurations exhibited a sharp increase in fitness values, indicating effective initial recombination of genetic material. However, after 25-30 generations, the convergence trajectories began to diverge: some runs reached local maxima and remained within them until the end of evolution, while others continued to show

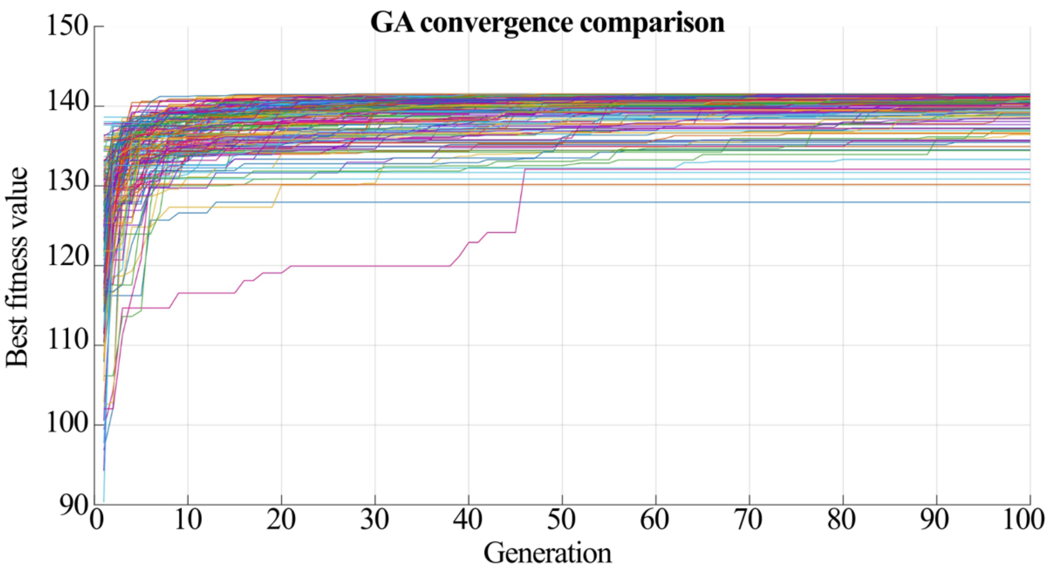

Fig. 1. GA convergence comparison

Source: formed by the authors

gradual improvement up to generations 70-90. This behavior reflects the influence of population size and mutation rate on the depth of solution space exploration – small populations with low mutation rates tend to experience premature convergence, whereas larger populations ensure broader coverage and sustain a longer phase of productive search.

The analysis of three representative convergence trajectories (Fig. 2) confirms this pattern. The best run achieved a fitness level of 141.54, resulting from a large population (200 individuals) and a moderate mutation rate (0.10), which provided a balance between stability and diversity. The median configuration, with a smaller population and higher crossover probability, demonstrated comparable quality but required more generations to stabilize. The poorest result (127.95) corresponded to a combination of low parameter values and the penalty-based constraint-handling mode, in which the algorithm discarded part of potentially viable solutions.

Further analysis showed that increasing the population size (Fig. 3) significantly reduces the variance of results and enhances convergence

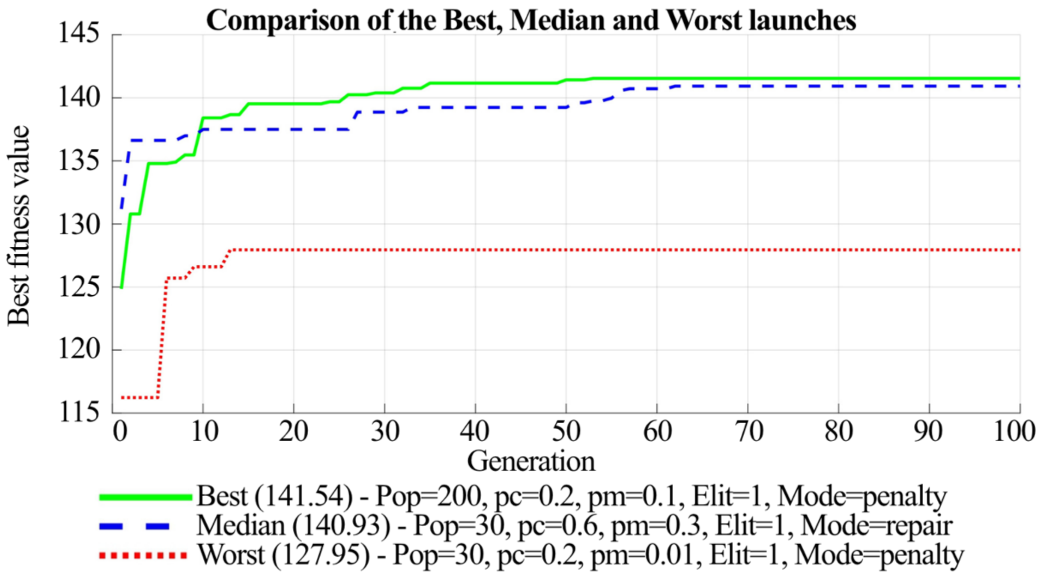

Fig. 2. Comparison of the Best, Median and Worst launches

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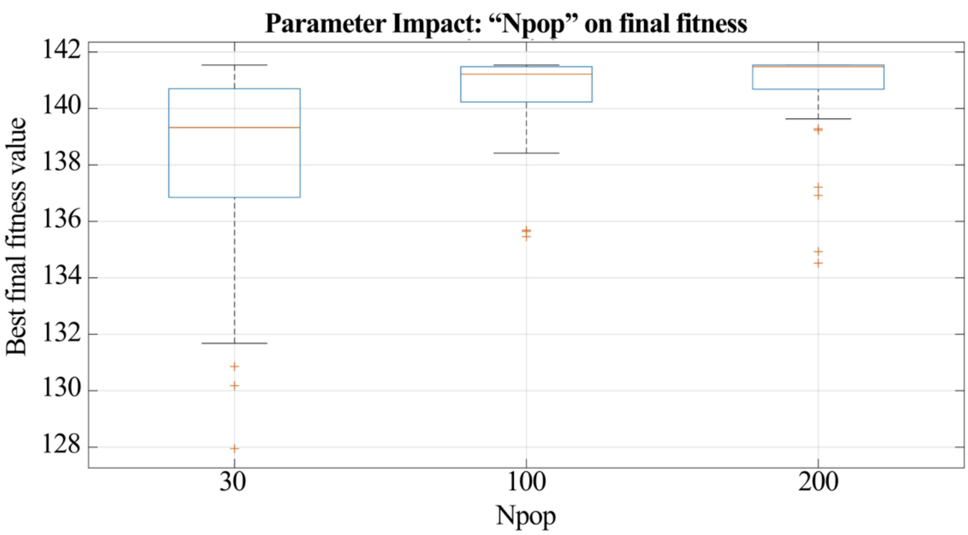

Fig. 3. Impact of population size

Source: formed by the authors

stability. Large populations establish a balance between exploration and exploitation of the solution space, whereas small ones exhibit high variability and a greater likelihood of becoming trapped in local optima. The mutation probability (Fig. 4) proved to be critical for avoiding stagnation: at $p_m = 0.01$, convergence slowed and frequent local traps were observed, while at $p_m = 0.1$, the algorithm maintained a balanced trade-off between search and stability. Excessive mutation $(p_m = 0.3)$ increased variability, which at times disrupted the process of local refinement.

The impact of crossover probability was moderate: values of 0.6 and 0.95 provided smoother and more reliable convergence compared to 0.2, where the process was highly dependent on the initial population. The elitism parameter had a secondary yet noticeable effect. Preserving 5% of the best individuals offered the best balance between stability and flexibility, whereas too small a fraction (1%) increased the risk of losing high-quality solutions, and an excessive one (15%) reduced the population's adaptation speed.

Special attention should be given to the comparison of constraint-handling mechanisms (Fig. 5). The penalty mode exhibited higher result dispersion and a tendency toward efficiency loss under high constraint density, whereas

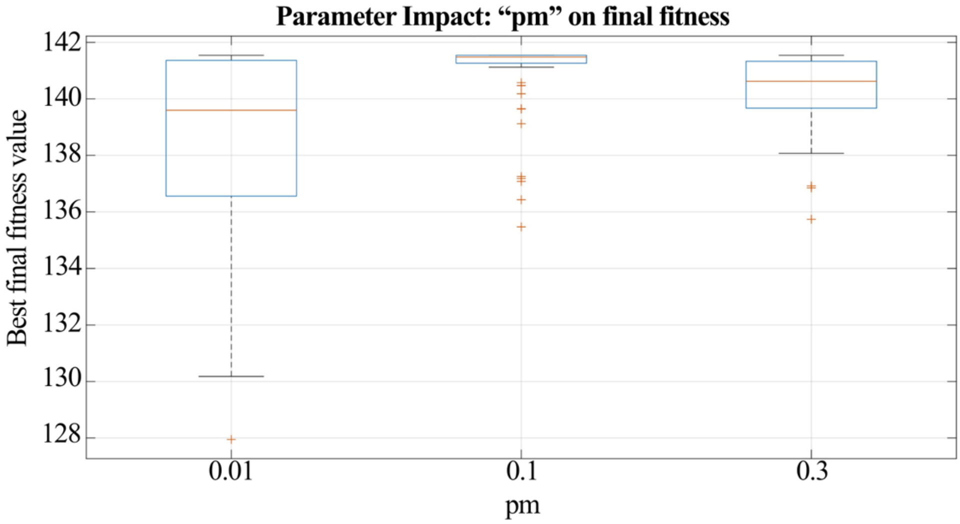

Fig. 4. Impact of mutation probability

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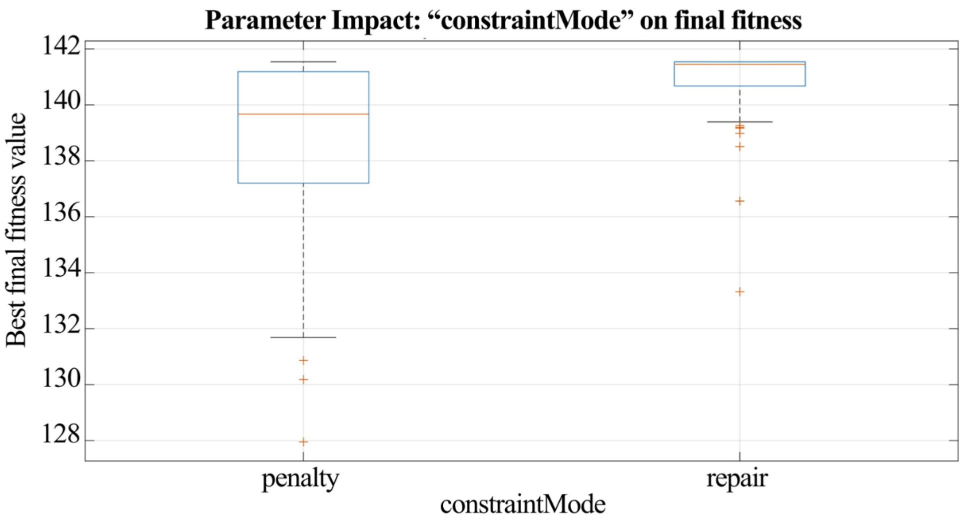

Fig. 5. Impact of constraint-handling mechanisms

Source: formed by the authors

the repair method demonstrated consistently higher performance and lower variability. This can be explained by the fact that repair directly restores solutions to the feasible region without reducing their fitness, which is particularly important in problems involving numerous logical constraints [3; 5].

On the three-dimensional surfaces (Fig. 6), a clear relationship between population size and mutation rate can be observed: in the repair mode, the region of high fitness values is broader and more stable, whereas in the penalty mode, a noticeable decline occurs for small populations and low mutation levels [7/; 8].

Summarizing the results, it can be stated that the most effective combination of parameters for the scenario-based resource allocation problem is: $N_{pop} = 200,\ p_c = 0.6, p_m = 0.1$, an elitism rate of 5%, and the repair mode. Such settings provide not only high accuracy and convergence stability but also greater resistance to local optima, which is critically important in multifactor economic scenarios.

At the final stage of optimization, the evolutionary algorithm generated a solution that satisfies all specified constraints and achieves the maximum fitness value of 141.54 thousand monetary units. The optimal portfolio includes six out of ten possible projects: № 2, № 3, № 5, № 7, № 8, and № 9. The total expenditure amounts to exactly 100 thousand monetary units, meaning the budget was fully utilized – indicating efficient allocation of available resources without exceeding financial limits.

The solution was obtained with parameters $N_{pop} = 200, p_c = 0.2, p_m = 0.1,$ $elit = 1$, using the penalty mode. Despite the application of the penalty method, the algorithm successfully satisfied all constraints. The total execution time was 83.96 seconds for all 162 runs, indicating the high computational efficiency of the implemented genetic approach with a large population size.

Thus, the obtained solution is not only formally correct but also economically sound, as it demonstrates an optimal balance between resource utilization and expected profit within the defined scenario constraints.

Conclusions. Summarizing the research results, it can be concluded that the efficiency of evolutionary methods for solving constrained resource allocation problems under scenario-based economic conditions strongly depends on the tuning of algorithm parameters. The most significant impact on the stability and accuracy of results is exerted by population size, mutation probability, and the constraint-handling mechanism. Increasing the population size improves solution reproducibility and reduces the risk of premature convergence, while the optimal mutation rate (around 0.1) ensures a balance between global exploration and local refinement. The repair mode demonstrated clear advantages over the penalty approach, as it guarantees constraint satisfaction without discarding potentially effective solutions.

The obtained results confirm that even in complex scenarios with logical dependencies

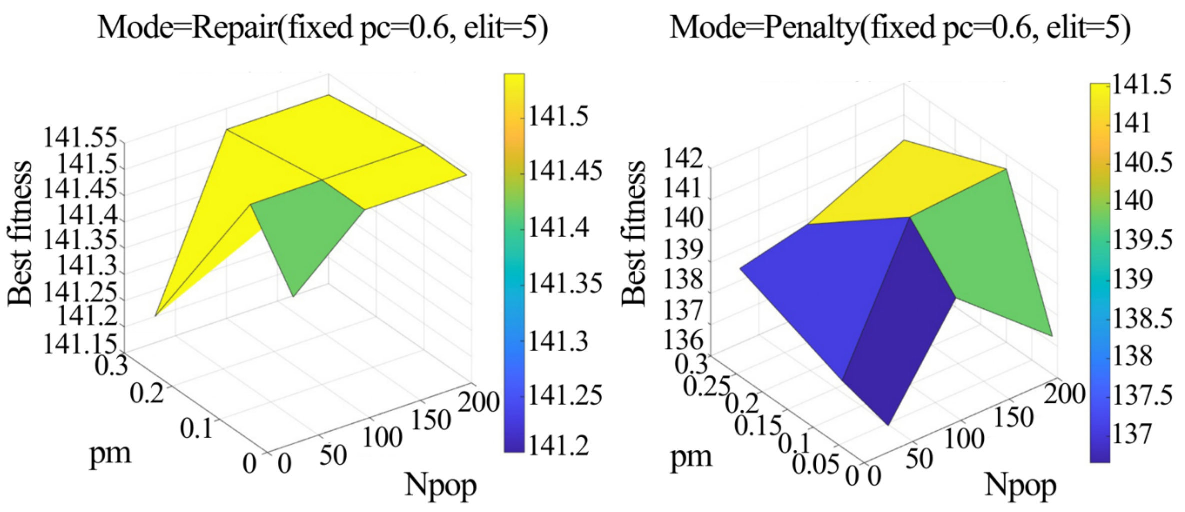

Fig. 6. Interaction between population size and mutation rate

Source: formed by the authors

and probabilistic economic conditions, the genetic algorithm is capable of generating valid and economically sound solutions by employing a flexible combination of evolutionary operators. The practical value of this study lies in identifying parmeter patterns that can be used to adapt evolutionary algorithms for strategic planning, investment analysis, and resource allocation tasks under multi-scenario uncertainty.

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