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GROWING TREE METHOD FOR OPTIMISATION OF MULTIFACTORIAL EXPERIMENTS

Koshovyi M. D. – Dr. Sc., Professor, Professor of the Department of Intelligent Measuring Systems and Quality Engineering, National Aerospace University M. E. Zhukovsky "Kharkiv Aviation Institute", Kharkiv, Ukraine.

Pylypenko O. T. – Post-graduate student of the Department of Intelligent Measuring Systems and Quality Engineering, National Aerospace University M. E. Zhukovsky "Kharkiv Aviation Institute", Kharkiv, Ukraine.

Ilyina I. V. – PhD, Associate Professor, Associate Professor of the Department of Electronic Computing, Kharkiv National University of Radio Electronics, Kharkiv, Ukraine.

Tokarev V. V. – PhD, Associate Professor, Associate Professor of the Department of Electronic Computing, Kharkiv National University of Radio Electronics, Kharkiv, Ukraine.

ABSTRACT

Context. The task of planning multifactorial experiments is important in science and industrial production. In the context of competition, rising costs, and increasing efficiency, it is necessary to optimize plans for multifactorial experiments in terms of cost and time. To solve this problem, there are a number of approaches and methods, the choice of which for a competitive technical task is an important and difficult task. In this regard, there is a need to develop new methods for optimizing the cost (time) of multifactorial experiment plans, compare them with existing methods, and give recommendations for practical application in the study of real objects.

Objective. The purpose of the study is to develop and test the method of growing trees, to evaluate its effectiveness in comparison with other methods. The following tasks has been solved to achieve this goal: the proposed method of growing trees has been implemented in the form of software; the method has been used to optimize plans for multifactorial experiments in the study of real objects; its effectiveness has been evaluated in comparison with other methods; recommendations for its use were given.

Method. The proposed method of growing trees is based on the application of graph theory. The advantage of the method is the reduction of time for solving optimization problems related to the construction of optimal plans for multifactorial experiments in terms of cost (time) expenses. Another characteristic feature is the high accuracy of solving optimization problems.

Results. The results of experiments and comparisons with other optimization methods confirm the efficiency and effectiveness of the proposed method and allow us to recommend it for the study of objects with the number of significant factors $k \le 7$. It is promising to further expand the range of scientific and industrial objects for their study using this method.

Conclusions. A growing tree method has been developed for the optimization of multifactorial experimental plans in terms of cost and time expenditures, along with software that implements it using the Angular framework and the TypeScript programming language.

The effectiveness of the growing tree method is shown in comparison with the following methods: complete and limited enumeration, monkey search, modified Gray code application, and bacterial optimization. The growing tree method is faster than complete enumeration and can be applied to optimize multifactorial experimental plans in terms of cost (time) expenses for objects with a number of factors k ≤ 7. In solving optimization problems, the method of growing trees gives better results compared to monkey search, limited enumeration and bacterial optimization.

KEYWORDS: growing tree method, algorithm, multifactorial experiment, software, comparison.

NOMENCLATURE

X_{IE} is a matrix of the initial plan of the multifactorial experiment;

X_i^j is a value of the *i*-th factor of the process under study in the j-th experiment;

k is a number of factors of the research object;

N is a number of experiments in the experiment planning matrix;

S_{tl} is a matrix of transition costs of factor levels;

$S^i_{(+1)(-1)}, S^i_{(-1)(+1)}$ is a value of the cost of level transitions for the *i*-th factor;

t_{tl} – matrix of transition durations of factor levels;

$t^i_{(+1)(-1)}, t^i_{(-1)(+1)}$ is a value of the duration of level transitions for the *i*-th factor;

X_{opt} is a matrix of the optimal or near-optimal experiment plan;

S_t is a total cost of the experiment;

$S_{i,j}$ is a cost of installing the *i*-th factor in the *j*-th experiment;

t_t is total time of the experiment;

$t_{i,j}$ is a duration of the installation of the *i*-th factor in the *j*-th experiment.

INTRODUCTION

Saving resources and time is an important issue in industrial production and scientific research. Due to global inflation, the cost of resources is increasing, which leads to the need to optimize technological processes, production, etc. By optimizing, a company reduces the amount of raw materials required, shortens production time, and increases its potential and efficiency. Therefore, the issue of optimizing plans for multifactorial experiments in terms of cost and time is relevant.

The object of study: the process of optimizing plans for multifactorial experiments in terms of cost and time.

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The subject of study: the method of growing trees for optimization of multifactorial experimental plans in terms of cost and time and the software that implements it.

The purpose of the work: development of the growing tree method and the software that implements it; application of the method to optimize the plans of multifactorial experiments; comparison with other optimization methods and evaluation of its effectiveness.

1 PROBLEM STATEMENT

For a given matrix X_{IE} of the initial plan of a multifactorial experiment

$$X_{IE}=\begin{vmatrix} X_1^1 & X_2^1 & \dots & X_i^1 & \dots & X_k^1 \\ X_2^1 & X_2^2 & \dots & X_i^2 & \dots & X_k^2 \\ \dots & \dots & \dots & \dots & \dots & \dots \\ X_1^j & X_2^j & \dots & X_i^j & \dots & X_k^j \\ X_1^N & X_2^N & \dots & X_k^N & \dots & X_k^N \end{vmatrix} \quad (1)$$

and a matrix of transition costs of factor levels S_{tl}, or a matrix of transition durations of factor levels ttl

$$S_{tl}=\begin{vmatrix} S^1_{(+1)(-1)} & S^1_{(-1)(-1)} \\ S^2_{(+1)(-1)} & S^2_{(-1)(+1)} \\ \dots\dots & \dots\dots \\ S^i_{(+1)(-1)} & S^i_{(-1)(+1)} \\ \dots\dots & \dots\dots \\ S^k_{(+1)(-1)} & S^k_{(-1)(+1)} \end{vmatrix},$$

$$t_{tl}=\begin{vmatrix} t^1_{(+1)(-1)} & t^1_{(-1)(-1)} \\ t^2_{(+1)(-1)} & t^2_{(-1)(+1)} \\ \dots\dots & \dots\dots \\ t^i_{(+1)(-1)} & t^i_{(-1)(+1)} \\ \dots\dots & \dots\dots \\ t^k_{(+1)(-1)} & t^k_{(-1)(+1)} \end{vmatrix} \quad (2)$$

it is necessary to find the optimal or near-optimal experiment plan X_{opt}, for which the total cost or duration of the experiment is minimized, i. e.

$$S_t=\sum_{j=2}^{N}\sum_{i=1}^{k} S_{i,j} \to \min;$$

$$t_t=\sum_{j=2}^{N}\sum_{i=1}^{k} t_{i,j} \to \min. \quad (3)$$

2 REVIEW OF THE LITERATURE

The following optimization methods can be applied to solve the problem of constructing optimal plans for multifactorial experiments in terms of cost (time) expenses: lion [1], black hole [2], grey wolf [3], artificial algae algorithm [4], firefly algorithm [5], hunting search [6], water cycle algorithm [7], bat algorithm [8], binary dragonfly algorithm [9], binary butterfly algorithm [10], cat swarm optimization [11], cuckoo search [12], dolphin echolocation algorithm [13], flower pollination algorithm [14], honey bee mating optimization [15], fish migration optimization [16], immune algorithm [17], tumbleweed algorithm [18], ant lion optimization [19].

Currently, the following methods have been developed and tested to optimize experimental plans in terms of cost (time): permutation analysis [20], complete enumeration [20, 21], particle swarm [20, 22, 23], genetic algorithm [20, 24], jumping frogs [20, 25], application of Gray code [20, 26], branch and bound [20, 21], monkey search [20, 27], fish school search [20, 28], ant algorithm [20], sequential approximation [20], greedy algorithm [20], nearest neighbor [20], tabu search [20, 23], simulated annealing [20, 29], nested partitions [20], combinatorial graph [20], based on serial sequences [20, 21], and simplex method [20].

Each of them has its own advantages and disadvantages [20]. When studying a variety of objects, each task of constructing optimal experimental plans has a technical task with its own priorities and conditions. Some objects require high optimization accuracy, while others require fast calculation. There are also difficulties with the fact that when using the method, you need to calculate many steps that are irrational, which leads to a large time spent on finding the optimal experiment plan. Therefore, the usefulness of a particular optimization method depends on the specific technical task.

In this regard, there is a need to develop and investigate the method of growing trees for optimizing multifactorial experimental plans in terms of cost (time) in order to assess its effectiveness.

3 MATERIALS AND METHODS

The growing tree optimization method is based on the use of tree graphs.

A tree is a connected acyclic graph in which one vertex has a zero in-degree and the other vertices have an in-degree of 1. The vertex with zero in-degree is called the root of the tree, and the vertices with zero out-degree are referred to as terminal vertices or leaves [30]. Figure 1 shows the standard representation of a tree graph, illustrating that there is only one path between any pair of vertices.

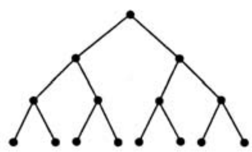

Figure 1 – Tree graph

The application of graph theory for analyzing plans of multifactorial experiment is considered on the example of the study of non-contact direct current and density meters [21]. Table 1 shows an experiment plan for the study of such meters.

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Table 1 – Experimental plan for the study of non-contact direct current and density meters

Number	X_1	X_2
1	–1	–1
2	–1	+1
3	+1	–1
4	+1	+1

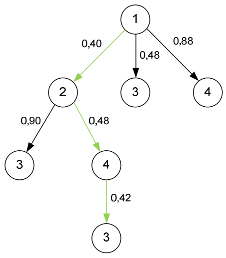
The cost of changing factor levels is shown in Table 2.

Table 2 – Cost of changing factors

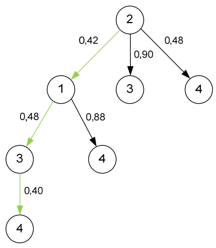
Changing factors	X_1	X_2
From “–1” to “+1”	0.48	0.40
from “+1” to “–1”	0.50	0.42

After analyzing the experiment plan. we have four initial vertices for graph construction.

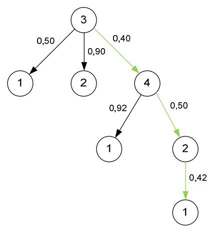
We optimized the experiment plan in terms of cost by constructing graphs for each of the four initial vertices (Fig. 2).



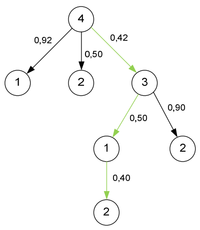
a



b



c



d

Figure 2 – Graph construction for each of the *i*-th vertices: a – $i = 1$; b – $i = 2$; c – $i = 3$; d – $i = 4$

After constructing the graphs for each of the possible vertices. we calculate the costs of implementing the experiment plans. which are shown in Table 3.

Table 3 – Cost of implementing the experimental plans

Vertex	Cost
1	1.30
2	1.30
3	1.32
4	1.32

Based on the calculation. we can conclude that the best performance is achieved with experiment plans represented by graphs with initial vertices 1 and 2. with a cost of 1.30 u. m.. compared to the initial plan’s cost of 1.70 u. m.

Thus. the gain in the cost of implementing the optimal plans compared to the initial plan is 1.31 times.

The algorithm for optimizing the cost (time) of a multifactorial experiment plan using the growing tree method is as follows.

Step 1. Select the number of factors.

Step 2. Input the transition costs values for each factor.

Step 3.1. Generate the initial plan matrix based on the number of factors.

Step 3.2. Determining the sequence of matrix calculations.

Step 4. Calculate the cost of the initial matrix.

Step 5.1. Inserting a row at the beginning of the matrix.

Step 5.1.1. Calculate the cost of the transition between the selected row and the next.

Step 5.1.2. Search for the minimum difference in the transition cost between the selected row and the row that has not yet been used in the matrix.

Step 5.1.3. All rows in the matrix have been used.

Step 5.1.4. Replace the initial row of the matrix with the next unused. and perform the calculation.

Step 5.2. All rows of the matrix have been substituted at its beginning and calculations have been performed according to the above scheme.

Step 6.1. Calculate the costs of all obtained matrices.

Step 6.2. Compare the costs of the obtained matrices.

Step 7. Select the matrix with the minimum total cost Based on the results.

Step 8. Compare and analyze the initial matrix with the optimal one calculated using the growing trees method.

Step 9. Display the results on the screen.

The algorithm diagram implementing the method of growing trees is presented in Figure 3.

The software implementation of the algorithm was performed using the Angular framework in the TypeScript development language [31]. which is an add-on to the JavaScript programming language. The advantage of using Angular is that it is built on the basic principles of object-oriented programming (OOP). OOP includes three main principles: encapsulation. inheritance. and polymorphism. These principles enable the creation of more modular and scalable programs that are easier to maintain and evolve. As a result. the number of input factors can be increased seamlessly.

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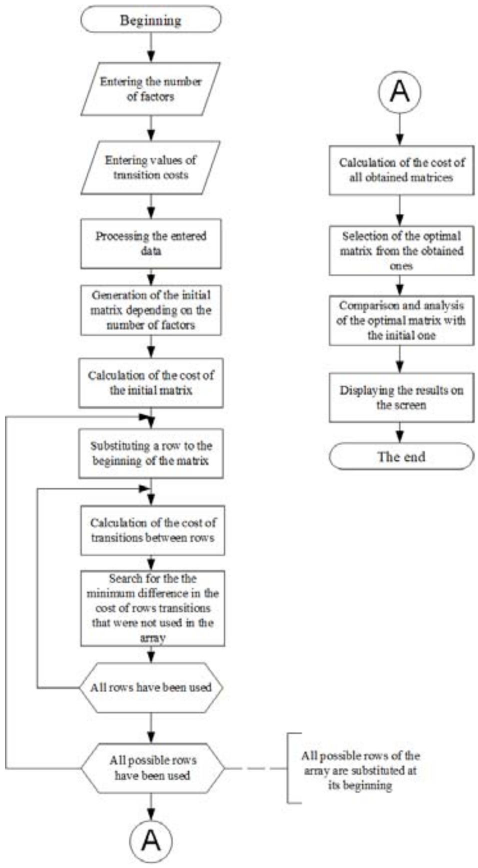

Figure 3 – Diagram of the algorithm for implementing the growing trees method

4 EXPERIMENTS

Optimization of multifactorial experiment plans was carried out using the method of growing trees. and a comparative analysis of the obtained experimental plans was performed with plans obtained using the following methods: monkey search. complete enumeration. limited enumeration. modified Gray code. bacterial optimization.

Optimization based on the cost expenses of the experiment plan has been conducted for the investigation of the technological process of welding thin plates. The factors considered: X_1 – capacitor capacity. μF; X_2 – conversion coefficient. X_3 – electrode force. N. The cost of changing the values of the factor levels is presented in Table 4.

The initial and optimal plans for conducting a multifactorial experiment for the investigation of the technological process of welding thin plates are provided in Tables 5 and 6 respectively.

Table 4 – Cost of changing the values of the factor levels

Factor	Costs of changes in the values of factor levels. u. m.	
	from “–1” to “+1”	from “+1” to “–1”
X_1	2.5	3
X_2	2	2.5
X_3	1.5	2

Table 5 – Initial plan of a multifactorial experiment

Experiment number	Factors		
	X_1	X_2	X_3
1	–1	–1	–1
2	+1	–1	–1
3	–1	+1	–1
4	+1	+1	–1
5	–1	–1	+1
6	+1	–1	+1
7	–1	+1	+1
8	+1	+1	+1

Table 6 – Optimal plan of a multifactorial experiment obtained by the growing tree method

Experiment number	Factors		
	X_1	X_2	X_3
1	–1	–1	–1
2	–1	–1	+1
3	–1	+1	+1
4	–1	+1	–1
5	+1	+1	–1
6	+1	+1	+1
7	+1	–1	+1
8	+1	–1	–1

The cost of the initial experiment plan is 27 u. m.. and the cost of the plans obtained by the growing tree method and full search is 14 u. m. The cost of the plan obtained by the monkey search method is 14.5 u. m. [32].

During the investigation of the accuracy of a device for measuring material humidity. the following factors were selected as dominant: X_1 – power supply voltage;

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X_2 – resistance value connected to the output of the operational amplifier; X_3 – number of turns W in the main winding of the magnetostrictive transducer; X_4 – number of turns W1 in the additional winding 3 or 4 [21]. The cost of changing the levels of factor values is presented in Table 7.

The initial plan of a full factorial experiment for studying the accuracy of the material moisture meter is presented in Table 8.

As a result of applying the growing tree method. an optimal plan for a multifactorial experiment was obtained. as shown in Table 9.

Table 7 – Costs of changing factor level values

Factor	Costs of changing factor level values. u. m.	
	from “–1” to “+1”	from “+1” to “–1”
X_1	0.52	0.51
X_2	0.72	0.71
X_3	5.5	1.4
X_4	6.7	2.4

Table 8 – Initial plan of a multifactorial experiment

Experiment number	Factors			
	X_1	X_2	X_3	X_4
1	–1	–1	–1	–1
2	+1	–1	–1	–1
3	–1	+1	–1	–1
4	+1	+1	–1	–1
5	–1	–1	+1	–1
6	+1	–1	+1	–1
7	–1	+1	+1	–1
8	+1	+1	+1	–1
9	–1	–1	–1	+1
10	+1	–1	–1	+1
11	–1	+1	–1	+1
12	+1	+1	–1	+1
13	–1	–1	+1	+1
14	+1	–1	+1	+1
15	–1	+1	+1	+1
16	+1	+1	+1	+1

Table 9 – Initial plan of a multifactor experiment

Experiment number	Factors			
	X_1	X_2	X_3	X_4
1	+1	+1	+1	+1
2	–1	+1	+1	+1
3	–1	–1	+1	+1
4	+1	–1	+1	+1
5	+1	–1	–1	+1
6	–1	–1	–1	+1
7	–1	+1	–1	+1
8	+1	+1	–1	+1
9	+1	+1	–1	–1
10	–1	+1	–1	–1
11	–1	–1	–1	–1
12	+1	–1	–1	–1
13	+1	–1	+1	–1
14	–1	–1	+1	–1
15	–1	+1	+1	–1
16	+1	+1	+1	–1

The cost of the initial experiment plan is 31.84 u. m.. the cost of the plans obtained by the growing trees method and the method based on the use of the modified Gray code [33] is 16.28 u. m.

When investigating a section of the machine-building workshop [21]. the overall working time of computer numerically controlled (CNC) machines was chosen as the optimization criterion. The dominant factors affecting this metric were selected as follows: X_1 – maintenance time t_m. hours; X_2 – number of CNC machines y_m; X_3 – machine working time within a day t_d. hours; X_4 – maintenance periodicity t_0. The time for changing the levels of these factors is presented in Table 10. The initial and optimal plans for conducting the experiment on the CNC machine section are provided in Tables 11 and 12. respectively.

Table 10 – Time changes in factor levels

Factor	Time changes in factor levels. hours.	
	from “–1” to “+1”	from “+1” to “–1”
X_1	7	3
X_2	6	2
X_3	16	12
X_4	100	50

Table 11 – Initial pan of a multifactorial experiment

Experiment number	Factors			
	X_1	X_2	X_3	X_4
1	–1	–1	–1	–1
2	+1	–1	–1	–1
3	–1	+1	–1	–1
4	+1	+1	–1	–1
5	–1	–1	+1	–1
6	+1	–1	+1	–1
7	–1	+1	+1	–1
8	+1	+1	+1	–1
9	–1	–1	–1	+1
10	+1	–1	–1	+1
11	–1	+1	–1	+1
12	+1	+1	–1	+1
13	–1	–1	+1	+1
14	+1	–1	+1	+1
15	–1	+1	+1	+1
16	+1	+1	+1	+1

Table 12 – Optimal plan of a multifactor experiment obtained by the growing trees method

Experiment number	Factors			
	X_1	X_2	X_3	X_4
1	–1	+1	–1	+1
2	–1	–1	–1	+1
3	+1	–1	–1	+1
4	+1	+1	–1	+1
5	+1	+1	+1	+1
6	+1	–1	+1	+1
7	–1	–1	+1	+1
8	–1	+1	+1	+1
9	–1	+1	+1	–1
10	–1	–1	+1	–1
11	+1	–1	+1	–1
12	+1	+1	+1	–1
13	+1	+1	–1	–1
14	+1	–1	–1	–1
15	–1	–1	–1	–1
16	–1	+1	–1	–1

The time required to implement the initial experiment plan is 251 hours [21]. while the optimal plan takes 130 hours.

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5 RESULTS

The results of the conducted experiment. presented in Table 13. demonstrate gains in the implementation of experiment plans obtained using the recalculated methods compared to the cost of conducting the initial plan for the study of the technological process of welding thin plates.

Table 13 – Comparison of costs for implementing experimental plans for the investigation of the technological process of welding thin plates

Optimization method	Cost. standard u. m.	Gain
Method of constructing the initial plan	27	1
Complete enumeration	14	1.93
Monkey search method	14.5	1.86
Growing tree method	14	1.93

Table 14 presents the gains in implementing the experimental plans obtained using mentioned methods compared to the cost of the initial plan for the study of the accuracy of the humidity meter for materials.

Table 14 – Comparison of implementation costs for experimental plans investigating the accuracy of the moisture meter

Optimization method	Cost. u. m.	Gain
Method of constructing the initial plan	31.84	1
Modified Gray code	16.28	1.96
Growing trees method	16.28	1.96

The time expenditures for implementing the experiment plans obtained by different methods [32]. along with the time savings compared to the time of conducting the initial plan for the study of the numerical program-controlled machine shop area. are presented in Table 15.

Table 15 – Comparison of optimization methods for experiment plans in the study of the machining workshop with numerical program control

Optimization method	Plan implementation time. hours	Gain
Method of constructing the initial plan	251	1
Monkey search method	180	1.39
Limited enumeration method	214.5	1.17
Bacterial method	181	1.39
Growing trees method	130	1.93

6 DISCUSSION

Based on the comparison of methods. the following conclusions can be drawn. When optimizing plans for multifactorial experiments in the study of technological processes using the growing trees method. we obtain plans with cost expenditures that coincide with those obtained through complete enumeration and the application of modified Gray code. This confirms the effectiveness and efficiency of the growing tree method.

In comparison to methods such as monkey search. limited enumeration. and bacterial optimization. the growing tree method yields better results.

The growing tree method has faster performance than complete enumeration and can be applied for optimizing plans of multifactorial experiments in terms of cost (time) expenditures for objects with up to $k \leq 7$ factors.

CONCLUSIONS

The growing tree method has been developed for optimizing plans of multifactorial experiments in terms of cost and time expenditures. along with the corresponding software implementation.

The scientific novelty of the obtained results lies in the development of the growing tree method that allows for obtaining optimal or near-optimal plans of multifactor experiments with high speed in terms of cost and time expenditures.

The practical value of the research results is that the developed software. implementing the growing tree method. enables the generation of optimal or near-optimal plans of multifactor experiments for a wide range of objects with up to $k \leq 7$ factors.

The prospects for further research lie in the application of the growing tree method to a wide range of scientific and industrial objects. such as capacitance moisture meters [34].

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МЕТОД ЗРОСТАЮЧИХ ДЕРЕВ ДЛЯ ОПТИМІЗАЦІЇ ПЛАНІВ БАГАТОФАКТОРНИХ ЕКСПЕРИМЕНТІВ

Кошовий М. Д. – д-р техн. наук. професор. професор кафедри інтелектуальних вимірювальних систем та інженерії якості. Національний аерокосмічний університет ім. М. Є. Жуковського «Харківський авіаційний інститут». Харків. Україна.

Пилипенко О. Т. – аспірант кафедри інтелектуальних вимірювальних систем та інженерії якості. Національний аерокосмічний університет ім. М. Є. Жуковського «Харківський авіаційний інститут». Харків. Україна.

Ільїна І. В. – канд. техн. наук. доцент. доцент кафедри електронних обчислювальних машин. Харківський національний університет радіоелектроніки. Харків. Україна.

Токарєв В. В. – канд. техн. наук. доцент. доцент кафедри електронних обчислювальних машин. Харківський національний університет радіоелектроніки. Харків. Україна.

АНОТАЦІЯ

Актуальність. Задача планування багатофакторних експериментів займає важливе місце в науці та промисловому виробництві. При цьому в умовах конкуренції. зростання витрат. підвищення ефективності необхідна оптимізація планів багатофакторних експериментів за вартісними та часовими витратами. Для вирішення цієї задачі існує ряд підходів та методів. вибір яких для конкретного технічного завдання є важливою та складною задачею. У зв’язку з цим виникає необхідність в розробці нових методів оптимізації за вартісними (часовими) витратами планів багатофакторних експериментів. порівнянні їх з уже існуючими методами та видачі рекомендацій по практичному застосуванні при дослідженні реальних об’єктів.

Мета. Мета роботи полягає у розробці та апробації методу зростаючих дерев. оцінки його ефективності у порівнянні з іншими методами. При цьому для дослідження мети вирішені наступні завдання: запропонований метод зростаючих дерев реалізований у вигляді програмного забезпечення; метод застосований для оптимізації планів багатофакторних експериментів при дослідженні реальних об’єктів; проведена оцінка його ефективності у порівнянні з іншими методами; видані рекомендації по його використанню.

Метод. Запропонований метод зростаючих дерев заснований на застосуванні теорії графів. Перевагою методу є скорочення часу вирішення оптимізаційних задач. пов’язаних з побудовою оптимальних за вартісними (часовими) витратами планів багатофакторних експериментів. Характерною рисою є також висока точність вирішення оптимізаційних задач.

Результати. Результати експериментів та порівняння з іншими методами оптимізації підтверджують працездатність та ефективність запропонованого методу та дозволяють рекомендувати його для дослідження об’єктів із числом суттєвих факторів $k \leq 7$. Перспективним є подальше розширення кола об’єктів наукового та промислового призначення для їх дослідження цим методом.

Висновки. Розроблено метод зростаючих дерев для оптимізації за вартісними та часовими витратами планів багатофакторних експериментів та програмне забезпечення. що його реалізує за допомогою framework Angular на мові розробки TypeScript.

Показана ефективність методу зростаючих дерев у порівнянні з наступними методами: повний та обмежений перебір. мавпячий пошук. застосування модифікованого коду Грея. бактеріальна оптимізація. Метод зростаючих дерев має більшу швидкодію ніж повний перебір та може застосовуватися для оптимізації планів багатофакторних експериментів за вартісними (часовими) витратами для об’єктів з кількістю факторів $k \leq 7$. При рішенні оптимізаційних задач метод зростаючих дерев дає кращі результати у порівнянні з мавпячим пошуком. обмеженим перебором та бактеріальною оптимізацією.

КЛЮЧОВІ СЛОВА: метод зростаючих дерев, алгоритм, багатофакторний експеримент, програмне забезпечення, порівняння.

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