CONTROL PROCESSES

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DESIGN OF A DECISION SUPPORT SYSTEM TO FORM OPTIMAL TECHNOLOGICAL PROCESSES FOR PARTS MACHINING BASED ON ARTIFICIAL INTELLIGENCE METHODS

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The object of this study is the process of designing a decision support system for automating the formation of technological processes (TPs) for machining parts of high-precision equipment for the aviation industry.

The task of improving the efficiency of the optimization of the process of mechanical processing of parts through the use of a decision support system (DSS) and artificial intelligence methods, which, unlike known analytical approaches, allow describing processes and phenomena that do not have strict formalization, has been solved. DSS consists of three subsystems. The first is an information subsystem for the automated formation of the structure in the technological process of machining parts of high-precision equipment. The second is an information subsystem for optimizing parameters of TP operations by cutting, taking into account the accumulation of tool wear. The third is a subsystem of control and adjustment of operating parameters.

In the process of conducting research, an approach was devised for designing optimal technological processes to machine parts of high-precision equipment. The task of designing the structure of technological processes was solved using production rules. The task of determining the optimal parameters of turning and milling operations was solved in a multi-criteria statement. The following objective functions were used: cost of the operation, specific energy consumption for the operation, and productivity of the operation. At the same time, the wear of the tool accumulated over time was taken into account. The solution was obtained by searching for the Pareto-optimal solution using genetic algorithms and artificial neural networks.

As a result of the work of DSS, an optimal technological process for machining parts of high-precision equipment for the aviation industry was formed, which made it possible to reduce the production time of one part by 5 % and reduce the total cost of production of the part by 14 %

Keywords: automation, technological process, machining, artificial intelligence, multi-criteria statement, Pareto-optimal solution

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1. Introduction

At the current stage of development of computer and production systems, competition in industry is focused on the ability to flexibly and quickly respond to changing market conditions. A modern solution to provide production efficiency and quick adaptation to new market requirements and needs is the use of decision support systems based on artificial intelligence. The task solved by these systems is the automation of the formation of technological processes for machining parts of high-precision equipment [1–5].

The task solved by the decision support system is the automated development of new TPs as the competitiveness and viability of the enterprise depend on their effectiveness. Existing approaches that we are aware of do not allow obtaining a multi-criteria solution taking into account competing technical and economic goals. Also, when calculating operational parameters, they do not take into account the wear of the tool that accumulates over time. For these reasons, they provide somewhat averaged recommendations for operational modes, which reduces the effectiveness of TP. This task is especially relevant for enterprises engaged in the production of high-precision items [1].

2. Literature review and problem statement

In work [1] it is stated that the purpose of automation of modern production is to increase its efficiency not only due to the automation of individual technological operations but also through the increase in the efficiency of the use of all technological equipment as a whole for the production of a unit of production, which requires high-quality management of it at all levels. The complexity of the control objects of modern automated production systems is constantly increasing, therefore the importance of the corresponding control information systems, which operate under conditions of a wide variety of production tasks and production situations, is also increasing. The task of managing complex objects, which are production technological processes (TPs), requires complex methodical and algorithmic support, the development of which is a separate and not always algorithmically solved problem related to logic and informatics, which allows building adequate information models with further implementation of the principles embedded in them in the form of decision support systems (DSSs).

The problem of the formation of optimal technological processes of mechanical operations related to metal treatment is directly related to the task of finding the optimal structure of the technological process for machining and finding optimal modes of equipment operation.

The task of finding the optimal structure of the technological process of machining is characterized by low formalization with multivariate solutions, multidimensionality, the presence of empirical information and hidden objective laws. There are a number of approaches to solving the tasks of synthesizing optimal structures of technological processes but the possibilities of the progressive field of scientific knowledge, artificial intelligence, are not fully utilized.

The solution to the task of finding the optimal technological process is formed in the form of a sequence of a set of operations with reference to the equipment and tool used in this process. The search criteria are a set of empirical rules that depend on many indicators, including the professionalism and experience of the technologist expert.

Next, the optimal modes of operation of the equipment are determined depending on the type of operation, taking into account technological and technical standards, allowances, tolerances, etc. The goals of optimizing the operation modes of TP machining by cutting are most often to increase productivity or reduce the cost of production or reduce energy consumption. The machining optimization task is highly non-linear and has many solutions.

A modern approach to solving such tasks is the use of artificial intelligence methods.

Thus, work [2] states that due to the complexity and uncertainty of metal machining processes, physical models are often used to predict the productivity of processing processes and their optimization. At the same time, preference is increasingly given to empirical calculations. Neural networks, fuzzy sets, and genetic algorithms are the main tools for such calculations. The application of these tools for four machining processes is considered: turning, milling, drilling, and grinding. This is due to the fact that these operations are used in the field of machining and provide the predefined accuracy of the geometric parameters of articles. The disadvantage of the cited work is that a single optimization criterion is applied – cost minimization, but in the future, it is planned to formulate a multi-criteria optimization problem. Also, the work does not consider the process to form an optimal structure of TP.

Paper [3] describes the method of structural and parametric optimization of functionally oriented metal processing products. The task is solved in a multi-criterion statement. The block diagram of the directed search algorithm for alternative and optimal parameters of the y-th technological transition of the x-th operation is shown. An algorithm for calculation and optimization of operating parameters, which are most often used in the engineering practice of metal machining, is also proposed. The algorithm used in the work takes into account the accounting of heuristic weighting factors and the calculation of normalized criteria for local optimization. The disadvantage of the work is the simplification of the task and the lack of practical results.

The author of monograph [4] emphasizes the challenges of the production environment in the 21st century and characterizes numerous factors affecting modern processing technologies. The work demonstrates comprehensive knowledge of economic considerations and possible methods for optimizing machining operations. It outlines the basics of processing economics, including costs, time, and productivity associated with typical machining operations (such as turning, milling, and drilling). The components of the processing cost and time related to the cutting speed are highlighted, and the corresponding mathematical models are given. Optimization procedures are considered, which allow choosing the optimal values of cutting speed and feed based on the criteria of tool stability and energy efficiency. Along with practical examples, an overview of advanced optimization techniques including linear programming, nonlinear programming, fuzzy optimization, and AI-based algorithms is presented.

Analysis of current intelligent technologies, including artificial neural networks, is given in work [5]. Their shortcomings and advantages were revealed. On the basis of this work, the choice of neural network architecture as an effective means of approximating experimental data was substantiated. The problem of applying artificial neural networks in the field of machining is the impossibility of obtaining a large number of experimental data families because it requires a lot of time and material costs.

In work [6], the purpose of the study is to apply the numerical solution to the problem of optimal control over fluctuations in the system of connected objects. This could make it possible to determine the optimal controls in the system of connected objects. The task was solved by classical methods of the second order. The mathematical apparatus of the Pontryagin maximum principle, the Runge-Kutta method, was used for the numerical solution of the problem.

The main limitation of the approach reported in the paper is that with the numerical solution to the problem it is impossible to vary some initial data in a wide range, it is necessary to take into account the conditions for agreement of the initial and boundary conditions. The main drawback of the cited work is significant computational difficulties in constructing and solving tasks and the control variable.

Study [7] is based on the evolutionary heron flock algorithm to find the optimal solution for the state of the object under uncertainty and in the presence of a set of various parameters. Evolving artificial neural networks are used to train the heron flock algorithm, and the improved genetic algorithm is used to select the best individuals of a flock of herons. The disadvantage of the work is the use of the term agent, instead of the generally accepted term chromosome, which causes confusion when reading the text. Also, in the work, the process of finding the optimal state of the object (heron) is carried out according to the single criterion of the size of the individual.

In work [8], the object of research is organizational and technical systems, and the subject is the decision-making process in the tasks of managing these systems. In contrast to [7], the research is based on the algorithm of a swarm of giant armadillos – for finding a solution to the state and making decisions in organizational and technical systems using artificial intelligence. The study is based on a giant armadillo swarm algorithm to find a solution to the state of organizational and technical systems. Giant Armadillo Agents (GAAs) are trained using evolving artificial neural networks, and an advanced genetic algorithm is used to select the best GAA. The disadvantage of the work is lower accuracy when searching by one parameter, loss of confidence in the obtained results compared to other assessment methods, lower accuracy compared to other assessment methods.

Work [9] solves the task of building an artificial neural network learning algorithm for intelligent decision support systems. The construction of the architecture of a multi-level neuron-fuzzy system that develops and consists of five successive layers is shown. The peculiarity of the solution is that the algorithm conducts training not only for the weight coefficients of the artificial neural network but also for the type and parameters of the membership function. If it is impossible to provide the given quality of functioning of artificial neural networks by learning parameters, the architecture of artificial neural networks is changed (retrained).

Disadvantages of the proposed algorithm include loss of informativeness during evaluation (forecasting) due to the construction of the membership function during fuzzification/defuzzification procedures of input parameters (transition from clear to fuzzy evaluation, and vice versa); lower accuracy of assessment according to a separate parameter of state assessment; loss of accuracy of results when reconfiguring the architecture of an artificial neural network.

In work [10], an ANN in the form of a four-layer associative memory with control neurons is proposed for the synthesis of optimal route maps for the production of products by methods of machining of materials. The optimal route in the graph, which is built by the ANN, is based on Dijkstra's algorithm, and is represented in the form of a sequence of many pieces of equipment for manufacturing the part. The route of manufacturing the part changes depending on the selected criterion. The disadvantage of the work is the complexity and duration of preliminary preparation of the initial data on each layer of the network.

Our review, despite the identified shortcomings, revealed the high effectiveness of artificial intelligence methods in solving the tasks of modeling decision support systems, including the modeling of technological processes of material processing. Therefore, the development in this area is promising.

Modern enterprises engaged in the production of articles using machining methods need new approaches to the automation of TP development in order to increase production efficiency. That is why our work considers the construction of DSS by setting the task of determining the optimal structure for TP and solving a multi-criteria optimization problem, as a compromise between the cost, energy consumption, and productivity of TP operations.

3. The aim and objectives of the study

The purpose of our work is to design a decision support system to form optimal technological processes related to machining of parts based on artificial intelligence methods. The system will make it possible to increase the productivity of technological processes of machining by taking into account competing optimization criteria, namely, minimizing the value of the cost price and the level of energy consumption of TP operations and maximizing the value of productivity during TP operations.

To achieve the goal, the following tasks are set:

– to design the architecture of a decision-making support system for the automation of TP development;

– to formalize the statement of the task on choosing the structure of the technological process of cutting operations;

– to investigate the method of calculating the optimal parameters of cutting operations TP, taking into account the accumulation of tool wear and competing objective functions.

4. The study materials and methods

The object of our study is the process of designing a decision support system for automating the development of TP for machining parts in high-precision equipment for the aviation industry. Application of methods and approaches of artificial intelligence systems, unlike known analytical approaches, allow describing processes and phenomena that do not have strict formalization.

The task of designing an optimal TP structure is to select such a combination of operation components that will provide for the minimum cost and energy consumption of TP operations and the maximum value of productivity during TP operations. To solve the problem, methods of decomposition and sequential hierarchical synthesis are used with the help of system analysis and production logic in the form of production rules.

In the work, the task of parametric optimization of machining by cutting TP is considered in the form of setting a multi-criteria optimization problem. The cost of operation A, the specific energy consumption of operation E, and the productivity of operation Q are chosen as the objective functions of optimization.

Also, a feature of the task statement is that when solving the task of determining the optimal parameters for machining operations by cutting, the accumulated wear on the back surface of the tool is taken into account – h_Z. This made it possible to build a mathematical model closer to real physical processes.

When choosing the architecture and software tools for the information system, the theory of information systems was used. To determine the structure and parameters of operations in the technological process of manufacturing parts for high-precision equipment, the theory of material cutting, and system analysis were applied.

In the process of building a knowledge base and processing experimental data, methods of artificial intelligence and the theory of artificial neural networks were applied.

Production logic and logical programming were used when solving the task of designing a TP structure.

When solving the problem of parametric optimization of cutting operation modes, methods for solving multi-criteria optimization problems and nonlinear programming and genetic algorithms were used.

In order to check the performance of the constructed model, computer simulation was used, which showed reasonable accuracy of the results in ANN training on a test set of experimental data. Calculations for comparison of the obtained TP structure were carried out with the basic TP and gave good results.

5. Design of a decision support system and examination of its results

5. 1. Design of the decision support system architecture

To form a machining by cutting TP, the architecture of the decision support system was designed to automate construction of technological processes for machining parts in high-precision equipment. DSS consists of three subsystems (Fig. 1). The first subsystem is an information subsystem for the automated formation of structure for the technological process of machining parts in high-precision equipment. The second subsystem is an information subsystem for optimizing the parameters of cutting operations TP, taking into account the accumulation of tool wear. The third subsystem is a subsystem of control and adjustment of operational parameters (Fig. 1).

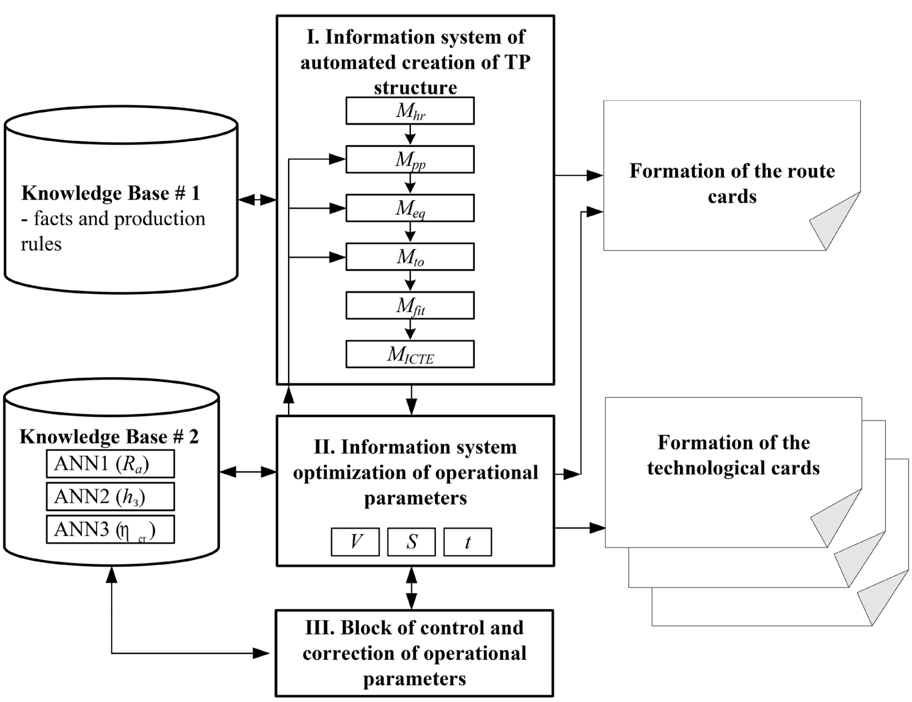

Fig. 1. Architecture of the decision support system

KB No. 1 and KB No. 2 contain weighting factors for ANN1–ANN3.

ANN1 – intended for calculating the level of roughness R_a.

ANN2 – intended for calculating the level of wear of the tool on the back surface h_Z.

ANN3 – intended for calculating the efficiency of the machine η_{ST}.

5. 2. Stating the problem of choosing the structure for the technological process of cutting operations

The task of designing an optimal TP structure is to select such a combination of operation components that will ensure the minimum cost and energy consumption of TP operations and the maximum value of productivity during TP operations. To solve the problem, methods of decomposition and sequential hierarchical synthesis are used with the help of system analysis and production logic in the form of production rules.

The structure of the technological process S_{SP} can be represented as a combination of the temporal component T_C, the functional component F_C, and the spatial component P_C:

$$S_{SP} = \{T_C,\ F_C, P_C\} \Rightarrow \begin{cases} \min\limits_k \left(\sum\limits_{i=1}^{I} A_{ki} \right), k = \overline{1, K}, \\ \min\limits_k \left(\sum\limits_{i=1}^{I} E_{ki} \right), k = \overline{1, K}, \\ \max\limits_k \left(\sum\limits_{i=1}^{I} Q_{ki} \right), k = \overline{1, K}, \end{cases} \tag{1}$$

where T_C determines the sequence of operations O_{ij} in time at each stage of workpiece processing:

$$T_{!} = \left\{ \begin{matrix} P_{11}\left(O_{11}, O_{12}, ..., O_{1j}\right), \\ P_{21}\left(O_{21}, O_{22}, ..., O_{2j}\right), ..., P_{IJ}\left(O_{I1}, O_{I2}, ..., O_{IJ}\right) \end{matrix} \right\}, \tag{2}$$

P_{ij} is the sequence of stages of machining the surfaces of the workpiece, i is the number of stages of machining the part, j is the number of the surface to be processed, the functional component F_C determines the order of transformation of the workpiece from the initial state Z_1 to the final state Z_I using the sequence of operations O_{ij}, $O_{ij}: Z_{i-1} \rightarrow Z_i$; the spatial component P_C determines the dimensional and precision relationships between the base and working surfaces, i.e. determines the scheme of installing the part in the fixture or machine; K is the number of possible TP alternatives; A_{ki} is the cost of the i-th operation on the k-th alternative TP; E_{ki} – specific energy costs of the i-th operation on the k-th alternative TP; Q_{ki} is the productivity of the i-th operation on the k-th alternative TP.

The selection of the workpiece M_{ZAG} is carried out according to the criterion of the minimum difference in the volume, size of the workpiece and the size of the part, taking into account allowances for machining:

$$M_{ZAG}=\min_{\phi_1^*}\left(\left\{M_{ZAG\phi_1}\left(V_{P\phi_1}\middle|\begin{matrix}a\geq 0, b\geq 0, c\geq 0,\\ R1\end{matrix}\right)\right\}\right),$$

$$\phi_1^*=\overline{1,\Phi_1^*},\ \phi_1=\overline{1,\Phi_1}, \quad (3)$$

$$a=X_{ZAG\phi_1}-\left(X_D+P_{OBR}\right),$$

$$b=Y_{ZAG\phi_1}-\left(Y_D+P_{OBR}\right), \quad (4)$$

$$c=Z_{ZAG\phi_1}-\left(Z_D+P_{OBR}\right),$$

$$a\geq 0,$$

$$b\geq 0,$$

$$c\geq 0, \quad (5)$$

where $M_{ZAG\phi_1}$ is the set of blanks at an enterprise of size Φ_1; $V_{P\phi_1}=V_{ZAG\phi_1}-V_D$ – the volume of material to be removed during machining, $V_{ZAG\phi_1}$ – the volume of the workpiece; *a, b, c* – the difference between the actual size of the workpiece and the size of the part with the addition of an allowance for machining along the axes *x, y, z*, mm, respectively; $X_{ZAG\phi_1}$, $Y_{ZAG\phi_1}$, $Z_{ZAG\phi_1}$ – size Φ_1 of the workpiece, mm; X_D, Y_D, Z_D – overall size of the part, mm; P_{OBR} – machining allowance, mm; $R1$ – the rule that determines the correspondence of the size of the workpiece and the part, taking into account the allowance for machining, and the correspondence of the grade of steel of the workpiece, after which the selection is made on the basis of the minimum volume of material to be removed; Φ_1^* is the number of elements of the set of blanks that correspond to rule П1.

The selection of a set of possible operations M_{OPER} for machined surfaces takes the following form:

$$M_{OPER}=\left\{M_{OPER\phi_2}\left|R2\right.\right\},\ \phi_2=\overline{1,\Phi_2}, \quad (6)$$

where Φ_2 is the number of options for operations; $R2$ is a rule that takes into account the shape of the forming surface being processed. At the same time, the possibility of switching to an alternative type of operation is taken into account. For example: the possibility of replacing a turning operation with a milling operation, milling with turning, drilling with milling, or turning, and grinding with superfinishing turning or milling. Moreover, the choice of an alternative type of operation depends on the possibility of such replacement and the type of previous operation.

The selection of the set of equipment allowed by the type of operation takes the following form:

$$M_{OBOR}=\left\{M_{OBOR\phi_3}\left|R3\right.\right\},\ \phi_3=\overline{1,\Phi_3}, \quad (7)$$

where Φ_3 is the number of equipment; $R3$ is a rule for choosing equipment based on the type of operations that can be performed on equipment M_{OBOR}, the size of the working area, the devices used on it, and the size and type of tool holders.

The selection of the set of permissible tools M_{INS} according to the type of operation is as follows:

$$M_{INS}=\left\{M_{INS\phi_4}\left|R4\right.\right\},\ \phi_4=\overline{1,\Phi_4}, \quad (8)$$

where Φ_4 is the number of tool types; $R4$ is a rule that describes the selection of a tool according to the criterion of compatibility of the dimensions of the tool and the holder, the type of operation, the size of the workpiece material, and the required quality of part machining.

Determining the device M_{PRIS} is carried out according to the criterion of rigidity of fastening, and takes the following form:

$$M_{PRIS}=\max_{\varphi_5^*}\left(\left\{M_{PRIS\phi_5}(k)\left|R5\right.\right\}\right),\ \phi_5^*=\overline{1,\Phi_5^*},\ \phi_5=\overline{1,\Phi_5}, \quad (9)$$

where Φ_5^* is the number of devices that comply with rule $R5$; *k* is a coefficient that depends on the method of fixing the part in the chuck; $R5$ – the rule that defines the device according to the criterion of rigidity of fastening and the linear size of the part that can be installed in it; Φ_5 – the number of possible options for devices.

Determination of MOTS M_{SOTS} is carried out according to the minimum cost criterion:

$$M_{SOTS}=\min_{\varphi_6^*}\left(\left\{M_{SOTS\phi_6}\left(C_{SOTS}\right)\left|R6\right.\right\}\right),$$

$$\phi_6^*=\overline{1,\Phi_6^*},\ \phi_6=\overline{1,\Phi_6}, \quad (10)$$

where Φ_6^* is the number of elements of the set MOTS that meet rule $R6$; Φ_6 – the number of possible variants of MOTS; C_{SOTS} is the cost of MOTS; $R6$ is a rule that determines the selection of MOTS according to the criterion of minimum cost, the possibility of use on the equipment selected for the operation and with the necessary workpiece material.

With this approach, the problem has a multivariate solution; the final solution on determining the necessary equipment $M_{OBORFIN}$ and tools M_{INSFIN} will be obtained after determining the optimal operational parameters, according to the following criteria:

$$M_{OBORFIN}\Rightarrow\begin{cases}\min\limits_r\left(A_r\left(M_{OBOR\ r}\right)\right), r=\overline{1,Ro},\\ \min\limits_r\left(E_r\left(M_{OBOR\ r}\right)\right), r=\overline{1,Ro},\\ \max\limits_r\left(Q_r\left(M_{OBOR\ r}\right)\right), r=\overline{1,Ro},\end{cases}$$

$$M_{INSFIN}\Rightarrow\begin{cases}\min\limits_p\left(A_p\left(M_{INST\ p}\right)\right), p=\overline{1,P},\\ \min\limits_p\left(E_p\left(M_{INST\ p}\right)\right), p=\overline{1,P},\\ \max\limits_p\left(Q_p\left(M_{INST\ p}\right)\right), p=\overline{1,P},\end{cases} \quad (11)$$

where A_r is the cost of the operation on the *r*-th equipment; *R* – volume of equipment; E_r – specific energy consumption on *r*-th equipment; Q_r is the performance of the operation on the *r*-th equipment; A_p is the cost of operation on the *p*-th tool; *P* – number of tools; E_p – specific energy consumption on the *p*-th tool; Q_p is the performance of the operation on the *p*-th tool.

For the functioning of the subsystem, two knowledge bases (KBs) were built and constructed with the help of production rules and artificial neural networks (ANNs). KBs include data on equipment, workpieces and tools, experience of expert technologists, etc. in the form of production rules. KBs also contain weighting factors for calculating the level of roughness R_a; the level of wear of the tool on the back surface h_Z; machine efficiency η_{ST}.

The Visual Prolog language was used for the software implementation of the sub-system for designing the TP structure.

5. 3. Investigating the method for calculating the optimal parameters of operations in the technological process of machining by cutting

The task of parametric optimization is to determine the optimal parameters for TP metal cutting operations, taking into account the accumulation of tool wear after each performed operation.

The optimal operating parameters for cutting operations are such a combination of depth t, feed S, and cutting speed V, at which the machining is performed most efficiently. At the same time, operations must be performed with maximum productivity, minimum energy consumption and cost of operation while meeting all requirements for accuracy and roughness, taking into account the technological capabilities of the equipment.

A model of the cutting process was built (Fig. 2), where F_X is the axial cutting force, N; F_Y – force acting in the direction of transverse feed, H; F_Z – the main cutting force, H; h_Z – wear on the back surface accumulated by the tool, μm; R_a – the actual surface roughness at the given operating parameters and actual wear of the tool, μm; T_{EF} – the time of effective operation of the tool, min; η_{ST} – coefficient of usable operation of the machine, %; $f_1, f_2, ..., f_7$ – corresponding functional dependences; f_1, f_2, f_3 and f_6 are analytical dependences.

The analytical form of the functions $R_a=f_5(V, S, t, h_Z)$, $h_Z=f_4(V, S, t)$, and $\eta_{ST}=f_7(V, S, t)$, which describes them with reasonable accuracy, is difficult to formalize and requires a large number of experiments, therefore, artificial neural networks, which are perceptrons with two hidden layers, trained on the basis of a family of limited experimental data were used to calculate R_a, h_Z and η_{ST} [7, 9, 11]. The error of the results is 1–3 %.

The peculiarity of problem statement is that when solving the task of determining the optimal parameters of machining operations by cutting, the accumulated wear on the back surface of the tool is taken into account – h_Z. This made it possible to build a mathematical model closer to real physical processes.

The goals of optimization of machining operations TP by cutting are most often to increase productivity, reduce cost, and reduce energy consumption. Therefore, the task of parametric optimization of machining by cutting TP is a multi-criteria optimization problem (MOP).

The cost of operation A (euro/min), the specific energy consumption of operation E (kW), and the productivity of operation Q (pcs/min) were chosen as the objective optimization functions:

$$A=\frac{l_Z}{S}\left(a_{RAB}+a_{EXP}+\frac{e}{T_{EF}}+\frac{q_E F_z V}{6\cdot 10^4\eta_{ST}}\right)\Rightarrow \min, \qquad (12)$$

$$E=\frac{F_z V}{6\cdot 10^4\eta_{ST}}\Rightarrow \min, \qquad (13)$$

$$Q=\frac{St}{l_Z\Delta}\Rightarrow \max, \qquad (14)$$

where l_Z is the length of the workpiece, mm; a_{RAB} – minute wage of the worker, euro/min; a_{EXP} – machine operating costs, EUR/min; e – cost of the tool, euro; q_E – cost of one kWh of electricity, euro; Δ – machining allowance, mm.

Ten constraints were selected for cutting operations:

– on the power of the electric motor driving the main movement of the machine N_{DV}, kW;

– on minimum $V_{\min}$, m/min, and maximum $V_{\max}$ cutting speed, m/min;

– on minimum $S_{\min}$, mm/min, and maximum $S_{\max}$, mm/min, feed;

– on the strength of the cutting tool $[\sigma_u]$, MPa;

– on the hardness of the cutting tool f_I, mm;

– on the hardness of the workpiece (when turning) f_Z, mm;

– on the strength of the longitudinal feed mechanism F_X, N, of the machine;

– on the required roughness of the treated surface R_a, μm.

The time of tool stability, the time of effective operation of the tool T_{EF}, is defined either as the time of the tool's serviceability after reaching the limit of wear, taking into account the variable operating parameters, or by the time until the level of the maximum allowable cost of the operation is reached. In this case, variable modes of operation of the tool are consistently taken into account, which, in turn, depend on the degree of its wear. In contrast to the classical approach, our work calculates the execution time for each individual cycle of using the tool for machining one part, taking into account the obtained optimal parameters for this cycle, after which the obtained values are summed up. The resulting value is the time of effective operation of the tool:

$$T_{EF}=\sum_{1}^{n}\tau_{o_n}\left(V_n, S_n, t_n, h_{Z_n}\right),$$

where n is the number of tool use cycles, τ_o is the operating time, min.

The task of determining the optimal parameters for turning and milling operations is solved in a multi-criteria statement by searching for a Pareto-optimal solution using genetic algorithms, in particular the FFGA method [12–14].

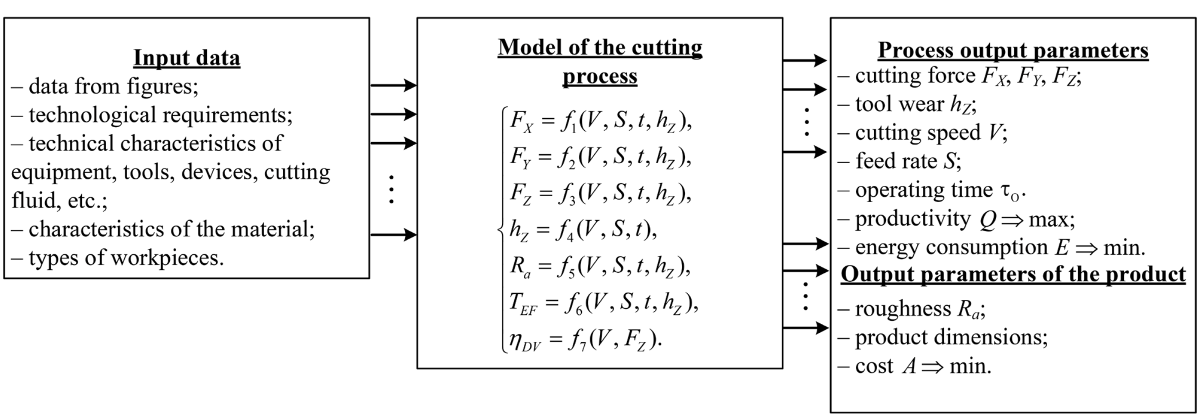

Fig. 2. Model of the cutting process and its parameters

This algorithm has a good convergence and the solutions obtained with its help do not go beyond the area of admissible solutions while the degree of coverage of the Pareto set is reasonable to solve the problem. For the operation of the genetic algorithm, fitness functions and the structure of the chromosome, which contains parameters for controlling TP operations, were developed.

For the turning operation (at t=const), the fitness functions take the following form:

$$f_8=\frac{l_Z}{S}\left(a_{RAB}+a_{EXP}+\frac{e}{T_{EF}}+\frac{q_E F_Z V}{6\cdot 10^4\eta_{ST}}\right),\quad f_9=\frac{F_Z V}{6\cdot 10^4\eta_{ST}},\quad f_{10}=\frac{St}{l_Z\Delta}. \qquad (15)$$

For the milling operation (at t=const), the fitness functions take the following form:

$$f_{11}=\frac{l_Z}{S}\left(a_{RAB}+a_{EXP}+\frac{e}{T_{EF}}+\frac{q_E F_C V}{6\cdot 10^4\eta_{ST}}\right),\quad f_{12}=\frac{F_C V}{6\cdot 10^4\eta_{ST}},\quad f_{13}=\frac{St}{l_Z\Delta}. \qquad (16)$$

The chromosome includes two parameters – feed speed S, mm/rev, its value can be in the range of $0.1\leq S\leq 3$, and cutting speed V, m/min, $1\leq V\leq 800$. The work of GA was carried out with the following parameters: the probability of mutation of one bit is 7 %; number of individuals – 500; the probability of crossing is 93 %.

The optimal structure of TP is formed by the subsystem of automated design of the structure of the technological process for machining parts in high-precision equipment. Operational parameters are calculated in the information subsystem of parametric optimization of parameters for cutting operations. On the basis of these data, the part machining route and the technological map of operations are formed. The technological map of operations contains the type of machine and tool, MOTS, as well as optimal operating modes of machining. Optimum operating modes of machining include speed, feed, depth of machining, and the number of runs. They are chosen as a result of sorting through possible alternatives based on the obtained values for the optimization criteria.

A practical test of the results of the designed decision support system was carried out. As a result of the system operation, a new TP structure and recommendations on operational parameters for turning and milling operations were obtained. To verify the results, the calculation of the optimal parameters and the values of the objective functions obtained for them for alternative machine/tool combinations was carried out. Table 1 gives a comparison of the machining modes and the values of the objective functions obtained with the help of DSS, used in the basic TP and obtained on the basis of the modes recommended by the manufacturer of the Iscar tool [15]. Table 1 demonstrates that the number of parts that were machined according to the new TP increases from 1171 pcs. to 1,468 units, which is 12 % more. At the same time, the operation cost and energy consumption are lower than when using modes in alternative TPs.

A comparison of the obtained alternative results and the result proposed by DSS confirms the efficiency of DSS for this operation. The results of our calculations are shown in Fig. 3.

Fig. 4, 5 show the time spent and the total cost of manufacturing the «Filter housing» part under different operating parameters.

To determine the efficiency of TP that was developed, the coefficient of production efficiency K_{EF_i} (pcs/EUR·min) was used:

$$K_{EF_i}=\frac{\sum_{j=1}^{J}Q_j}{\sum_{j=1}^{J}A_j\cdot\sum_{j=1}^{J}\tau_{o_j}}\Rightarrow\max, \qquad (17)$$

where $i=\overline{1,I}$, I is the number of alternative TPs; $j=\overline{1,J}$, J is the number of operations of the i-th TP. The calculation results for various TPs are shown in Fig. 6.

Table 1

Comparison of modes for finishing turning operations

Tool parameters	Cost of operation A, euro	Energy consumption E, kW	Productivity of operation Q, units/min	Feed speed of the machine S, mm/rev	Cutting speed of the machine V, m/min
Calculated modes DSS					
Sharp tool h_Z=0 mm	0.0544	1.87	10.45	0.54	112
Tool with wear h_Z=0.2 mm	0.0556	1.94	9.97	0.504	128
Tool with wear h_Z=0.4 mm	0.0636	1.99	9.35	0.46	149
Tool stability T_{EF}, min			148		
Number of machined parts based on T_{EF}, pcs.			1,468		
Modes recommended by the Iscar company guide					
Sharp tool h_Z=0 mm	0.0568	1.89	9.47	0.504	120
Tool stability T, min			144		
Number of machined parts based on T, pcs.			1,363		
Modes used in the basic technical process					
Sharp tool h_Z=0 mm	0.0584	1.91	9.01	0.53	110
Tool stability T, min			130		
Number of machined parts based on T, pcs.			1,171		

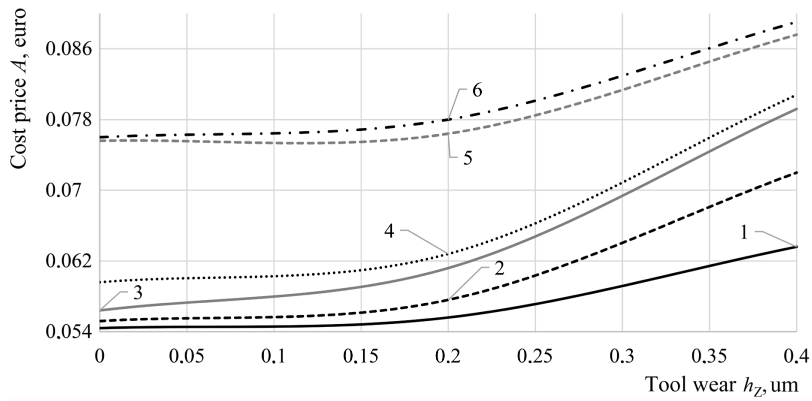

Fig. 3. Cost of the finishing turning operation with different operating parameters:
1 — machine tool and tool recommended by DSS; 2 — machine tool recommended by DSS, tool Alberg CCMW 09T308;
3 — Spinner PD/C machine tool, Iscar CCMT 09T308 tool; 4 — Spinner PD/C machine tool, Alberg CCMW 09T308 tool;
5 — SMTCL CA6150B/1000 machine tool, Iscar CCMT 09T308 tool; 6 — SMTCL CA6150B/1000T machine tool,
Alberg CCMW 09T308 tool

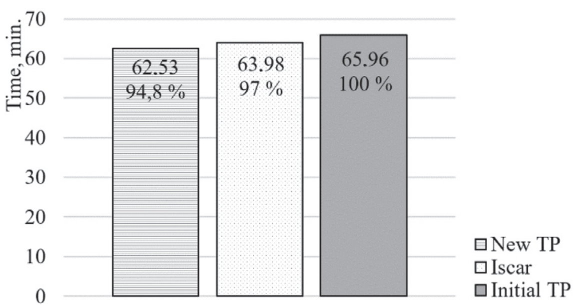

Fig. 4. Time, minutes, spent on the production of one part

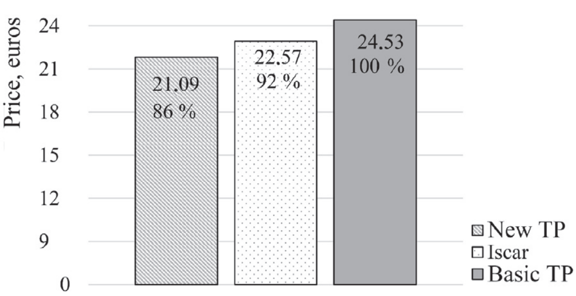

Fig. 5. The total cost of production of the part, EUR

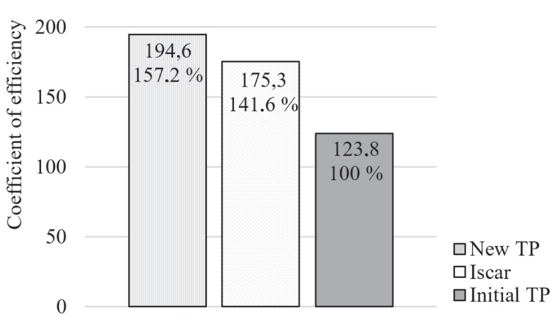

Fig. 6. Part production efficiency ratio

The time spent on the production of one part when using TP, which was obtained with the help of DSS, is 5 % less than when using the basic TP. The total production cost of the part also decreased from EUR 24.53 to EUR 21.09, which gives a saving of 14 %.

6. Discussion of results of designing a decision-making support system for the formation of optimal machining processes

The advantages of the proposed approach are as follows. The designed decision-making support system for automating the formation of technological processes for machining parts in high-precision equipment is based on artificial intelligence methods, which, unlike known analytical approaches, allow describing processes and phenomena that do not have strict formalization (Fig. 1). In the course of the work, the subsystem model for the automated construction of the optimal structure for the technological process of machining by cutting parts in high-precision equipment was improved. This became possible due to the application of production rules for logical inference, implemented using the Visual Prolog application.

In contrast to [2], in which a classical approach to surface treatment was proposed during the development of a technological process when determining the structure of the technological process, the model takes into account alternative solutions, which is the first feature of this approach. Alternative solutions are refined at the next stage of parametric optimization, which made it possible to reduce the time of obtaining solutions and increase the validity of the choice of structure (Table 1). This becomes possible owing to the optimization of the number of tool transitions and the reduction of the number of replacement operations.

The model of the parametric optimization subsystem has been improved for finding the optimal operating modes for technological cutting processes. The model, unlike well-known ones [2, 3], was set and solved in a multi-criteria statement, which made it possible to reduce the cost price and specific energy costs for operations, to increase the productivity of TP and the efficiency of operations, taking into account technological and technical requirements and limitations (Fig. 3).

The model of the information subsystem of parametric optimization of the parameters of cutting operations was also further developed [2, 3, 15]. The information subsystem, unlike known ones, when determining the optimal operational parameters, uses the mathematical model built (Fig. 2), which is closer to real physical processes as it takes into account the current wear of the tool. This made it possible to reduce the average production time of one part while the service life of the tool increased (Fig. 4, 5). Fig. 6 shows a comparison of the efficiency of various TPs for the production of a test part.

As limitations of the proposed system, it is necessary to note the increased requirements for the completeness of input data. Since the work of DSS is based on artificial neural networks, it is necessary to have an appropriate set of data for their high-quality training. Also, in fact, it is not possible to accurately determine the length of time that is required to train the ANN in the subsystem of parametric optimization of operational parameters to achieve the best result.

Also, a limitation to the use of DSS is that the system has the ability to calculate optimal operational parameters for metal cutting operations: turning, milling, and drilling.

Given that the solution to the task is obtained in the form of a Pareto-optimal solution, it should be borne in mind that there may be several such solutions. In this case, to choose the most suitable one, it is necessary to involve experts.

It is absolutely necessary to take into account that the results obtained during the operation of the system directly depend on the type of metal, tool, and equipment used. Also, the results depend on the technological requirements for a specific article.

As a disadvantage of this study, it can be noted that the accuracy of the system depends on the quality of training of artificial neural networks, which requires a significant volume of experimental data, the accumulation of which takes time. The work does not provide the development and implementation of the third subsystem – control and adjustment of operational parameters. This issue may be the subject of consideration in future works.

The further development of the research is a step towards the construction of a universal DSS. To this end, it is necessary to continue filling relevant knowledge bases with characteristics of materials, tools, equipment, MOTS, experimental data, etc.

7. Conclusion

1. An architecture of the decision-making support system to form the technological processes for machining parts in high-precision equipment has been developed. The DSS consists of three subsystems – a subsystem for automated construction of the structure for the technological process of machining parts in high-precision equipment; the optimization subsystem of the parameters for TP of cutting machining operations taking into account the accumulation of tool wear and the subsystem of control and correction of operational parameters.

2. The statement of the problem to design an optimal TP structure involves selecting such a combination of operation components that could ensure the minimum cost and energy consumption of TP operations and the maximum value of productivity during TP operations. To solve the problem, it is recommended to use methods of decomposition and sequential hierarchical synthesis with the help of system analysis and production logic in the form of production rules. At the same time, the structure of the technological process can be represented as a combination of a time component, a functional component, and a spatial component. With this approach, the problem has a multi-variant solution, the final option of which, based on the definition of the necessary equipment and tools, is found after determining the optimal operational parameters.

3. In order to build a machining by cutting TP, a decision-making support system was implemented for the formation of technological processes for machining parts in high-precision equipment, which is based on artificial intelligence methods, which, unlike known analytical approaches, allow describing processes and phenomena that do not have strict formalization. For the operation of DSS, knowledge bases were developed and constructed with the help of production rules and artificial neural networks, which include data on equipment, workpieces, and tools, technological and technical norms, experience of expert technologists, etc. Practical calculations of DSS showed high results: the time spent on the production of one part when using the TP, which was obtained with the help of DSS, is 5 % less than when using the basic TP. The method for calculating the optimal structure of TP, taking into account technical and economic goals, was studied.

A method for calculating the optimal parameters of cutting operations TP, taking into account the accumulation of tool wear, has been developed and studied. The task of determining the optimal parameters for turning and milling operations is solved in a multi-criteria statement by searching for a Pareto-optimal solution using genetic algorithms, in particular the FFGA method. It was found that this algorithm has a good convergence and the solutions obtained with its help do not go beyond the area of admissible solutions while the degree of coverage of the Pareto set is reasonable to solve the problem. For the operation of the genetic algorithm, fitness functions and the structure of the chromosome, which contains parameters for controlling TP operations, were developed.

The use of the FFGA genetic algorithm made it possible to obtain a multi-criteria solution to the optimization task taking into account competing technical and economic goals, and an artificial neural network – to obtain parameters for machining processes that are weakly formalized and cannot be calculated analytically.

Our results have made it possible to reduce the total cost of production of a part from EUR 24.53 to EUR 21.09, which gives a saving of 14 %, which confirms the effectiveness of the designed DSS.

Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study and the results reported in this paper.

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Data availability

All data are available in the main text of the manuscript.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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