Development a system for designing optimal technological processing parameters at machining centers

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Changes in the circulation of goods and services at the world level motivate manufacturers to fulfill the requirements of each individual customer in order to achieve a good position in the market. This phenomenon imposes increasingly strict requirements that the technological system must fulfill, so today flexible technological systems tend to become intelligent technological systems. The paper presents the development of a system for designing optimal technological processing parameters at machining centers based on biologically inspired Particle Swarm Optimization (PSO) algorithms.

Keywords: Flexible technological systems, Processing parameters, PSO algorithm

1. INTRODUCTION

The optimization of processing mode parameters is a method of knowledge implementation in the design of processing processes with the aim of their analysis, improvement and reaching higher techno-economic analysis. The basic assumption is that the costs of the processing process will be optimal if the costs of the processing process are optimal in all stages. The mathematical model of the objective function was formed by Stanić [1], and that function model was applied by Mečanin [2] on the optimization of the costs of the machining process by turning the spindle. The mathematical model of the function can be applied for all elementary operations with appropriate restrictions that are different for different operations. The objective function and constraints should contain enough influencing factors in order to have an objective impact on the machining process model.

2. MATHEMATICAL DESCRIPTION OF THE COSTS OF THE MILLING OPERATION DEPENDING ON THE PROCESSING MODE

The cost function, which, depending on the input to the processing system and the state of the processing system, mathematically describes the immediate costs of the operation, is represented in the OSVT-z trihedral surface located in the first octant and always concave because the parameters of the processing mode must have values greater than zero. Its form is:

$$T_Z = A_{1i} + A_{2i} \cdot V_i^{-1} \cdot S_i^{-1} + A_{3i} \cdot V_i^{\frac{1}{q_1}-1} \cdot S_i^{\frac{q_2}{q_1}-1} \qquad (1)$$

where $i = 1, 2, \ldots, n$ is the number of operations to be optimized. The geometric location of the points of conditional maxima on the surface of the cost function forms, in the OSV coordinate plane, a hyperbola, the arms of which, depending on the state of the input to the system, approach the coordinate axes faster or slower asymptotically. Otherwise, the set of conditional minimum points identifies the line of optimal costs along which the processing process should be managed in order to achieve the maximum effects of the system in terms of processing costs.

Optimal cost levels are located in the area $\{S_{\max}, V_{\min}\}$ ie. the highest processing effects are achieved at maximum step values and minimum cutting speed values. Conversely, $\{S_{\min}, V_{\max}\}$ the area is characterized by a relatively high level of processing costs. Exceptional cases deviate from this rule $q_2 = 1$ and $q_2 > 1$. For $q_2 = 1$ the same level of costs is achieved for the entire regime area, while in $q_2 > 1$ the case of the maximum processing effects located in the area $\{S_{\min}, V_{\max}\}$, and the minimum in the mode points $\{S_{\max}, V_{\min}\}$.

Processing outside the curve of optimal costs, unjustifiably frequent in production practice, causes relatively large losses of economy, especially in regime areas $\{S_{\max}, V_{\min}\}$ and $\{S_{\min}, V_{\max}\}$, because then high reproduction costs occur in the processing process [1].
The member A_{1i} is always constant because it represents the basic costs in the company that do not depend on the processing parameters but affect the total cost of production of the product. Members A_{2i} and A_{3i} depend on the processing mode, influence the total production costs and thus define the position of the minimum, which cannot be lower than the value

3. ALGORITAM PSO

Particle swarm optimization PSO (Figure 1) represents metaheuristic method of optimization based on agents (particles) population, which was accidentally discovered by James Kennedy and Russell Eberhart in 1995, while studying the simulation of social behavior of bird flocking [3]. Just as it is the case with all algorithms based on population, initial particle population is generated first. Position of the particle represents vector of parameters which are optimized.

$$\mathbf{x} = (x_1, x_2, \ldots, x_n) \qquad (2)$$

or potential solution. Random position in space which is explored, as well as initial velocities, is given to each particle. After that, the value of goal function of each particle is determined, and that value is added to it as the best value for the particle in question, and the initial position be-

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comes the best position of the particle $\mathbf{p}_{\mathbf{best}}$. When all the best values of particles are determined, the particle with the minimum value is searched, and its position becomes the best position for the entire swarm p_{gbest}. Afterwards, it needs to be checked whether the criteria of optimization are satisfied, and if they are, the obtained results are shown. If the criteria are not satisfied, new velocities and positions need to be calculated.

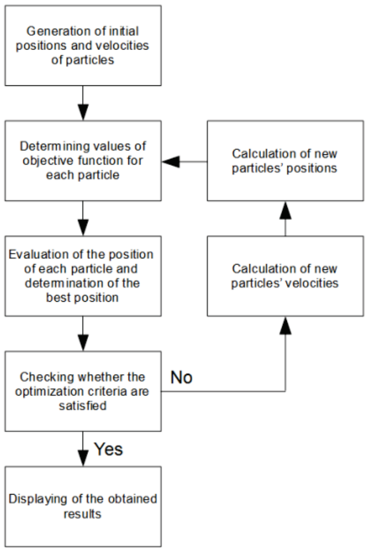

Figure1: Algorithm of the method of particle swarm optimization.

Figure 2 graphically shows how to determine new velocities and positions in two-dimensional space of search.

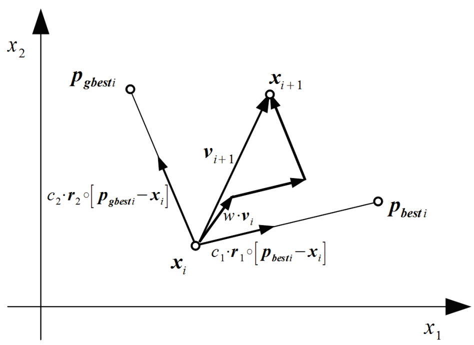

Figure 2: Updating of velocity and position of the i-th particle.

New velocity of each particle consists of three components:

1. the component which depends on instantaneous particle velocity,
2. the component which is proportional to the distance of instantaneous position of the particle and its best value,
3. the component which is proportional to the distance of instantaneous position of the particle and its best position for the entire swarm.

$$\mathbf{v}_{i+1} = w \cdot \mathbf{v}_i + c_1 \cdot \mathbf{r}_1 \circ \left(\mathbf{p}_{\mathbf{best}i} - \mathbf{x}_i\right) + c_2 \cdot \mathbf{r}_2 \circ \left(\mathbf{p}_{\mathbf{gbest}i} - \mathbf{x}_i\right) \quad (3)$$

where w represents inertia weight, c_1, c_2 are acceleration coefficients or correction factors, $\mathbf{r}_1, \mathbf{r}_2$ represent two random vectors of the length n within the limits $[0,1]$. The symbol ˚ represents Hadamard product:

$$\left(A \circ B\right)_{i,j} = \left(A\right)_{i,j} \cdot \left(B\right)_{i,j} \quad (4)$$

Inertia weight w impacts the first component, and for the values in the range of 0,9 – 1,2 [4] it gives the best results, that is, the algorithm has greater chances of finding the global minimum for a reasonable number of iterations. For coefficient values which are smaller than 0,8, if algorithm finds global minimum it will find it fast. Particles in this case move quickly and it can happen that they "fly over" some area, so it can happen that they do not find global minimum. On the other side, if inertia weight has bigger value, then particles search the solution space more thoroughly and the chances of finding global minimum are greater.

Acceleration coefficients c_1 and c_2, when multiplied by random vectors $\mathbf{r}_1$ and $\mathbf{r}_2$, stochastically manage the impact of the two other velocity components. Usually, their assumed value is approximately 2, in order for the middle value of the product of acceleration coefficient and random vector to be approximately 1. New position of the particle is determined by simple adding of the current position $\mathbf{x}_i$ and new particle velocity $\mathbf{v}_{i+1}$.

$$\mathbf{x}_{i+1} = \mathbf{x}_i + \mathbf{v}_{i+1} \quad (5)$$

The values of the goal function for new positions of the particle are determined again, and for each particle new and old values of the goal function are compared. If the new value is smaller, then it becomes new best value and the current position becomes the best position of that particle. The position of the particle with the smaller value becomes new best position for the entire swarm. Again, it needs to be checked whether the optimization criteria are satisfied; if they are, the results are shown, and if not, the entire procedure will be repeated until the criteria are satisfied.

This is the simplest version of the algorithm of particle swarm optimization. Other versions do not have constant values for the parameters w, c_1 and c_2, but they alter by specific rules during the implementation of the algorithm. In addition, other PSO algorithms also include different swarm topologies, that is, the way in which particles in the swarm communicate.

4. THEORY OF BELIEF FUNCTIONS

4.1. The basic concepts of Belief functions

Model of the belief function consists of variables, their values and the evidence, which supports the value of variables. Variables represent specific questions regarding the aspect of the problem under consideration. Given questions are answered using data originating from various sources, i.e., from context of published papers, from measurement data, from expert opinions, etc. Fully integrated support to the sought answer is called evidence.

Evidence can be represented by belief functions, which are defined as follows:

Definition1 [5, 6]. Let Θ be a finite nonempty set called the frame of discernment, or simply the frame. Mapping *Bel*: $2^{\Theta} \rightarrow [0,1]$ is called the (unnormalized) belief function if and only if a basic belief assignment (bba) *m*: $2^{\Theta} \rightarrow [0,1]$ exists, such that:

$$\sum_{A\subset\Theta} m(A) = 1 \tag{2}$$

$$Bel(A) = \sum_{B\subset A, B\neq\varnothing} m(B) \tag{3}$$

$$Bel(\varnothing) = 0 \tag{4}$$

Expression $m(A)$ can be viewed as the measure of belief which corresponds to subset A and takes values from this set.

Condition (2) means that one's entire belief, supported by evidence, can take the maximum value 1, and condition (4) refers to the fact that one's belief, corresponding to an empty set, must be equal to 0.

Value $Bel(A)$ represents the overall belief corresponding to the set A and all of its subsets.

Each subset A such that $m(A)>0$ is called a focal element.

The empty belief function is the function which satisfies $m(\Theta)=1$, and $m(A)=0$ for all subsets of $A\neq\Theta$. This function represents total ignorance about the problem under consideration.

4.2. Dempster rule of combining belief functions

Let the several independent belief function be given on the same recognition frame but with different bodies of evidence. The Dempster's combination rule (Figure 2) (5, 6) produces new belief function which represents effect resulting from the connection of the different bodies of evidence.

Let us assume that the belief functions Bel_1 and Bel_2 are created on Θ frame. Let $A_1,...,A_k$, $k<2^{|\Theta|}$ be the focal elements of function Bel_1 with corresponding m – values $m_1(A_i)$ for i=1,...,k; and let $B_1,...,B_j$, $j<2^{|\Theta|}$ be focal elements of function Bel_2 with corresponding m-values $m_2(B_i)$ for i=1,...,j [5]

Combination of these two functions is denoted as $Bel_1\oplus Bel_2$ and its focal elements are $C_1,...,C_m$ with corresponding m-values $m_3(C_k)$ for k=1,...,m, created in the following way:

$$m_3(C_k) = K\left[\sum_{\substack{i,j\\ A_i\cap B_j=C_k}} m_1(A_i)m_2(B_j)\right] \tag{5}$$

where K represents a normalization factor

$$K = \left[1-\sum_{\substack{i,j\\ A_i\cap B_j=\varnothing}} m_1(A_i)m_2(B_j)\right]^{-1} \tag{6}$$

The normalization factor K is greater than 1 whenever Bel_1 and Bel_2 contain a part of mass of some belief that correspond to the subjective probability for the decoupled (contradictory) subsets of Θ. In fact, K represents the conflict measure of the two belief functions. Whenever two or more functions are combined, the combination rule is associative and commutative. In general, $Bel\oplus Bel=Bel$. Combination of a certain number of belief functions $Bel_1\oplus\cdots\oplus Bel_n$ is denoted as $\oplus\oplus\{Bel_1,\cdots,Bel_n\}$.

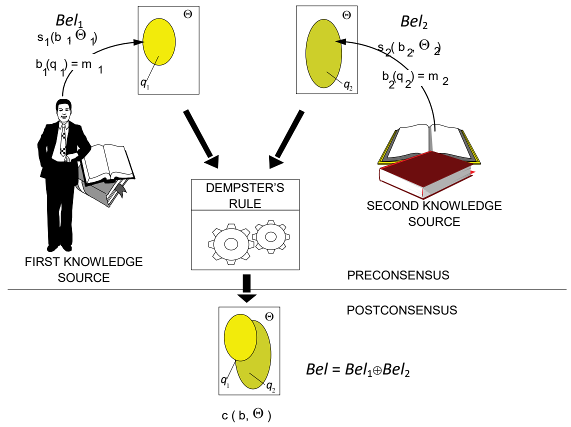

Figure 3: Graphics illustration using Dempsters rule of belief function combining [6]

4.3. What are the Evidential systems

Valuation Based Systems - VBS is an abstract framework proposed by Shenoy for representing and reasoning on the basis of uncertainty. It allows representation of uncertain knowledge in various domains, including Bayes' probability theory, Dempster-Shafer's theory of evidence which is based on belief functions and Zadeh-Dubais-Prad theory of possibility. Graphically presented VBS is called valuation network [6].

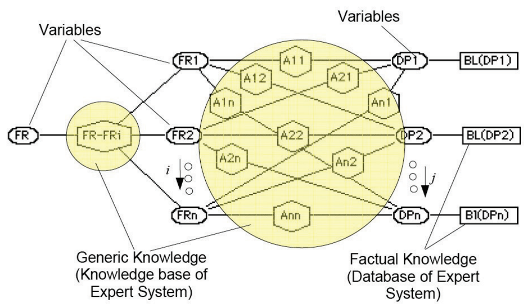

Figure 4: The concept of evidential networks

VBS consists of set of variables and set of valuations that are defined on the subsets of these variables. Set of all variables is denoted by U and represents a space covered with problem which is under consideration. Each variable represents a relevant aspect of a problem. For each variable X_i will be used ΘX_i to denote the set of possible values of variables called the frame of X_i. For a subset A (|A|>1) of U, set of valuations that are defined over ΘA represents the relationship between variables in A. Frame ΘA is a direct (Cartesian) product of all ΘX_i for X_i in A. The elements ΘA are called configurations of A.

Knowledge presented in this type of valuations is called generic or general knowledge (figure 3), which can be represented as a knowledge base in expert systems.

The VBS also defines valuations on individual variables, which represents so-called factual knowledge, and it constitutes database in expert systems (figure 3). For a problem, general-generic knowledge defines an expert. During reasoning process that knowledge won't be modified. Factual knowledge will vary in accordance with condition of a problem currently being under consideration. The VBS treats on the same way these two kinds of knowledge.

The VBS systems suited for processing uncertain knowledge described by functions of belief function theory are called Evidential Reasoning Systems or Evidential Systems, and valuation networks are now called evidential networks (EN) (figure 4).

The objective of reasoning based on the evidence is an assessment of a hypothesis, in case when the actual evidence are given (the facts). This can be accomplished by evaluating valuation networks in two steps:

- Combining all belief functions in evidential network, resulting in a so-called global belief function
- Marginalization of global belief functions in the framework of each individual variable or subsets of variables produces marginalized values for each variable or subset of variables.

Easily way of understanding the reasoning process and its graphical interpretation is the condition on which depends whether and how fast these systems will be applied in solving everyday problems. As a software support to the VBS systems application, several software tools have been developed. For evidential systems the very known are: McEvidence, Pulcinella and DELIEF.

5. GOAL AND LIMITATION FUNCTION

In this paper, 17 milling operations are optimized and in them, machining mode parameters are step $S[\text{mm/o}]$ and technological cutting speed:

$$V = \frac{\pi \cdot D \cdot n}{1000}\,[\text{m/min}] \quad (6)$$

in which the number of rotations n[o/min] is. They are directly related to the main processing time, so for optimum values of these parameters we have optimum time of duration of each operation, and therefore, the optimum processing time of machine part. Machine mode parameters that give minimum costs of machining process must be found within given limitations because there is a limitation by characteristics of tools and machine. Figure 3 shows 3D model of valve casing and section where the greatest number of different openings are located.

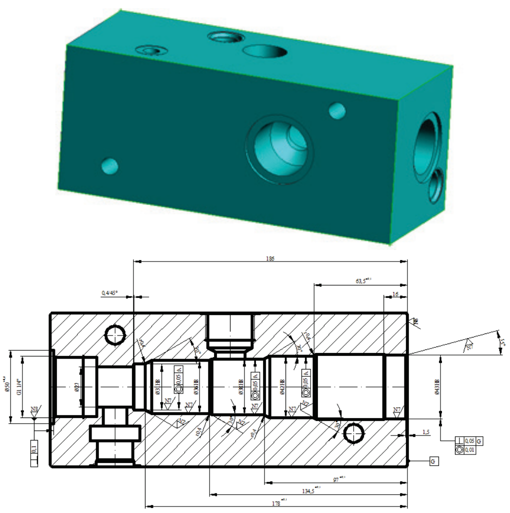

Figure5: Valve casing – a machine part whose milling operations are optimized.

Goal function which is optimized has the following form:

$$f(S_i,V_i) = \sum_{i=1}^{25} T_i = \sum_{i=1}^{25} A_{1i} + A_{2i}\cdot V_i^{-1}\cdot S_i^{-1} + A_{3i}\cdot V_i^{\frac{1}{q_1}-1}\cdot S_i^{\frac{q_2}{q_1}-1} \quad (7)$$

Values of coefficients A_1, A_2, A_3, for each of 17 goal functions, are given in Table 1 :

Table 1: Coefficient values A_1, A_2, A_3, a_i.

i	A_{1i} [min]	A_{2i} $\left[\frac{\text{din}}{\text{min}}\cdot \text{m}^2\right]$	A_{3i} $\left[\frac{\text{din}\cdot\text{min}}{\text{m}^2}\right]$	a_i [mm]
1	1707,801	828,8	0,748	0,2
2	1707,801	118,1	0,133	0,2
3	1707,801	14,76	0,019	0,2
4	1707,801	7,721	0,036	0,2
5	1707,801	1,505	0,007	0,2
6	1707,801	35,18	0,389	0,2
7	1707,801	1,535	0,010	0,05
8	1707,801	7,226	0,073	0,05
9	1707,801	46,33	0,486	0,05
10	1707,801	2,007	0,014	0,05
11	1707,801	81,46	0,713	0,05
12	1707,801	1,505	0,017	0,2
13	1707,801	19,48	0,671	0,05
14	1707,801	1,299	0,021	0,2
15	1707,801	137,0	1,157	0,05
16	1707,801	14,76	0,102	0,2
17	1707,801	1,612	0,252	0,05

6. OPTIMIZATION RESULTS

34 parameters are obtained as the results of this optimization process which represent optimum values of technological cutting speed and steps for 17 milling operations , and so the costs of these procedures have minimum value.

Optimum values of the steps ,velocity and cost price of all operations individually and collectively are given in Table 2:

Table 2: Optimum values of the steps, velocity and cost price of all operations individually

i	S_i [mm/o]	V_i [m/min]	T_i [din]
1	0,026	450,6	1708,29
2	0,238	625,3	1708,66
3	0,136	751,2	1708,57
4	0,012	325,3	1708,43
5	0,114	420,5	1708,21
6	0,023	240,5	1708,32
7	0,123	425,6	1710,47
8	0,030	350,4	1710,85
9	0,063	367,6	1709,96
10	0,026	560,8	1708,33
11	0,369	480,6	1708,87
12	0,119	375,4	1707,95
13	0,336	180,9	1707,88
14	0,887	350,6	1707,96
15	0,710	650,9	1707,97
16	0,600	850,6	1708,84
17	0,325	65,9	1708,94
		$\sum_{i=1}^{25} T_i$	29048,5

7. CONCLUSION

In this paper, the optimization of the costs of technological process of a part of a complex structure is performed by using the method pso. For instance, in optimization of the flexible technology when real processing time is less than given, optimization of machining parameters is implemented in order to decrease costs of production. In this case, we can choose cheaper tools of lower level of cutting characteristics, and by using the method pso, in a very short time, we can obtain results on which procedure allows decreasing of the machine mode and which does not, all of which can be presented in the space as in figure, for the purpose of checking of the obtained results.

ACKNOWLEDGEMENTS

This work is co-financed by the Ministry of Education, Science and Technological Development of the Republic of Serbia on the base of the contract whose record number is 451-03-47/2023-01/200108. The authors thank the Ministry of Education, Science and Technological Development of the Republic of Serbia for supporting this research.

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