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STOCHASTIC AND GENETIC MODELLING OF TOOL LIFE

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ABSTRACT
One of the prerequisites for successful and modern production is the use of high quality tools. Mathematical modelling has a great importance in the wide range of technical sciences and practice. This investigation refer to modelling and benefit analysis of TiN (PVD) technology on cutting tools application. In this works the stochastic and genetic algorithm was used for modeling of tool life for uncoated tool and TiN (PVD) coated tool.
Keywords: TiN (PVD) coatings, cutting tool, stochastic, genetic algorithm, modelling, tool life

1. INTRODUCTION
The application of modern machine tools (CNC), flexible manufacturing systems and high speed machining demand more and more quality tools which are wear resistant, stable on the high temperature and on the high cutting parameters. Also, the continuous industrial development of the new and more quality and difficult to machine materials, then increasing requirement for machining accuracy, caused the development of modern tools material and the application of wear resistant tools. At present, to increase tool life and also decreasing machining costs are used more and more tools with hard thin coatings by chemical vapour deposition (CVD) or physical vapour deposition (PVD) technology. For a successful industrial exploitation of tools and program of machine tools it was necessary to know mathematical models of tool life. Therefore, in this paper are defined and simulated two models, first one for uncoated tools and second one for tools with hard thin coatings TiN (PVD)[1-3]. In this paper is presented a comparing stochastic and genetic algorithm (GA) was used for modeling of tool life for uncoated tool and TiN (PVD) coated tool. The GA is evolutionary computation method which imitate biological evolution of living organisms [4,5]. The GA are general optimization approaches based on learning [5]. They have been successfully applied for solving different problems (see for example [6-8]).

2. EXPERIMENT AND EXPERIMENTAL RESULTS
The defined tool life models $T = T(v, f, a)$ for uncoated tool and TiN (PVD) coated tool are carried out by experimental investigations. Experimental design is $N = 2^k + n_0 = 2^3 + 6 = 14$.

Experimental conditions are: Cutting material: *conventional (WC-hard metal uncoated P30) and TiN (3-4 μm) coating (WC-hard metal + TiN (PVD) P30)*; Workpiece material: *C 45 steel*; Lubrication - cutting fluid: *SOL 40E*; Wear criterion: *VB = 0,4 mm* and NC turning machine.

Experimental results shows are in Table 1. It was selected these process variables: cutting speed (*v*), feed (*f*) and depth (*a*) presented in Figure 1.

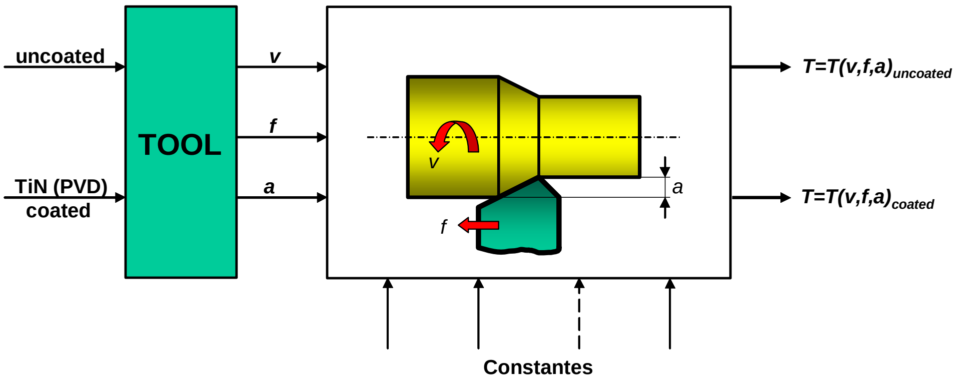

Figure 1. Schema of selected input-ouput parameters for tool life $T = T(v, f, a)$

3. STOCHASTIC MODELLING

The results of mathematical modelling are mathematical models or only the models, unless otherwise pointed out, that can be analytical, stochastical, numerical, graphic, statistical and so on [3]. The mathematical modelling is defined quantitative relation between input X_i and output Y_j variables of process, that is $Y_j = Y_j(X_i)$.

3.1. Defining and confirmation of model adequacy

Starting mathematical model with three variables has a general form:

$$Y = b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + b_{12} x_1 x_2 + b_{23} x_2 x_3 + b_{13} x_1 x_3 + b_{123} x_1 x_2 x_3 \ . \quad (1)$$

a) A model for tool life without TiN (PVD) coating.

The check of signification of model coefficients have been carried out by t – criterion, so that coded model has the form (2) and the physical model for tool life has the form(3):

$$Y = 27{,}44 - 9{,}01 X_1 - 6{,}36 X_2 - 2{,}71 X_3 \ . \quad (2)$$

$$T = 86{,}63 - 0{,}33 v - 49{,}98 f - 1{,}81 a \ . \quad (3)$$

The coefficient of multiple regression was $R = 0{,}99$, what confirm a model adequacy.

b) A model for tool life with TiN (PVD) coating.

The check of significations of model coefficients have been carried out by t – criterion, so that coded model has the form(4) and the physical model for tool life has the form(5):

$$Y = 102{,}3 - 27{,}5 X_1 - 19{,}0 X_2 - 7{,}87 X_3 - 2{,}125 X_2 X_3 \ . \quad (4)$$

$$T = 273{,}86 - 1{,}075 v - 119{,}0 f - 2{,}245 a - 11{,}0\, f\, a \ . \quad (5)$$

The model (5) adequately describes the tool life, because the coefficient of multiple regression was $R = 0{,}99$.

4. MODELLING OF TOOL LIFE BY GENETIC ALGORITHM

4.1. Method used

Genetic algorithm is evolutionary computation method where structure undergoing adaptation consists of binary coded strings, real-valued vectors, etc. Thus, the genes of which the organisms consists, are the binary numbers, real numbers, etc. Since the basic steps in evolutionary computation are well-known only brief description follows. First, the initial population *P(t)* of random organisms (solutions) is generated. The variable *t* represents the generation time. The next step is the evaluation of population *P(t)* according to fitness measure. Altering of population *P(t)* by genetic operations follows. The genetic operations alter one or more parental organism(s); thus, their offspring are created. Evaluation and altering of population take place until the termination criterion has been fulfilled. That can be the specified maximum number of generations or sufficient quality of solutions.

4.2. Organisms

In this study the prespecified second-order model for prediction of tool life was considered:

$$Y = c_0 + c_1 x_1 + c_2 x_2 + c_3 x_3 + c_4 x_1 x_2 + c_5 x_1 x_3 + c_6 x_2 x_3 + c_7 x_1 x_2 x_3 + c_8 x_1^2 + c_9 x_2^2 + c_{10} x_3^2 \quad (6)$$

where x_1 is cutting speed, x_2 is feed rate, and x_3 is dept of cut. The symbols $c_0, c_1, \cdots, c_{10}$ are coeficients. The model (6) has standard multiple linear regression form including three regressor variables and is suitable for solving many different problems [11]. Therefore, the initial random population *P(t)* consists of real-valued vectors (organisms) consist of constants $c_0, c_1, \cdots, c_{10}$. The individual vector is equal to: $\boldsymbol{c} = (c_0, c_1, \cdots, c_{10})$. The goal is to optimize the set of constants $c_0, c_1, \cdots, c_{10}$ that the deviations between predicted and the actual experimental values would be as low as possible.

4.3. Fitness measure

The absolute deviation $D(i,t)$ of individual model *i* (organism) in generation time *t* was introduced as the fitness measure. It was defined as:

$$D(i,t) = \sum_{j=1}^{n} \left| E(j) - P(i,j) \right|, \tag{7}$$

where $E(j)$ is the experimental value for measurement *j*, $P(i, j)$ is the predicted value returned by the individual model *i* for measurement *j*, and *n* is the maximum number of measurements. The Eq. 7 is standard raw fitness measure for solving regression problems proposed by Koza [10]. The aim of the optimisation task is to find such model (6) that Eq. 7 would give as low absolute deviation as possible. However, because it is not necessary that the smallest values of the above equation also means the smallest percentage deviation of this model, the average absolute percentage deviation of all measurements for individual model *i* was defined as:

$$\Delta(i) = \frac{D(i,t)}{|E(j)|\, n} \cdot 100\% \cdot \tag{8}$$

Eq. 8 was not used as the fitness measure for evaluation of population, but only to find the best organism in population after completing the run.

4.4. Genetic operations and evolutionary parameters

Altering of population *P(t)* is effected by reproduction, crossover, and mutation. For crossover operation, two parental vectors are selected randomly. Then the crossover takes place between two randomly selected parental genes having the same index. Two offspring genes are created according to extended intermediate crossover considered by Mühlenbeim and Schlierkamp-Voosen [9]. In the mutation operation, one parental vector is selected randomly. Then, the mutation takes place in one randomly selected parental gene. In both crossover and mutation the number of crossover and mutation operations performed on parental vector(s) is selected randomly.

The evolutionary parameters were: population size 100, maximum number of generations to be run 4000, probability of reproduction 0.1, probability of crossover 0.3, and probability of mutation 0.6. It is found out that in our special case more accurate solution is obtained if greater values for probability of mutation operations are used. The method of selection for all three genetic operations was tournament selection with a group size of 7.

4.5. Results and discussion

In this section, only two best models are presented: the model for toll life for uncoated tool and the model for TiN (PVD) coated tool.

Considering the evolutionary algorithm described earlier, the GA optimisation process developed the optimised vector (organism) of constants $c_0, c_1, \cdots, c_{10}$. According to the prescribed form in Eq. 6 the models are equal to:

a) The best model for uncoated tool

$$\begin{aligned} \mathrm{T} = {} & 0.650152 + 0.841047x_1 - 0.792845x_2 - 0.0630367x_3 - 0.444327x_1x_2 - 0.0613133x_1x_3 \\ & - 1.37228x_2x_3 + 0.0311605x_1x_2x_3 - 0.00341846x_1^2 + 0.399467x_2^2 + 1.1485x_3^2 \end{aligned} \tag{9}$$

The model was obtained in generation 3970 and has the average percentage deviation $\Delta(i) = 5.55\%$.

b) The best model for TiN (PVD) coated tool

$$\begin{aligned} \mathrm{T} = {} & 0.94871 + 2.30004x_1 - 0.438308x_2 + 1.53748x_3 + 0.000522091x_1x_2 - 0.0164596x_1x_3 \\ & - 0.321285x_2x_3 - 0.267969x_1x_2x_3 - 0.0113735x_1^2 - 0.851193\,x_2^2 + 1.75008x_3^2 \end{aligned} \tag{10}$$

The model was obtained in generation 3837 and has the average percentage deviation $\Delta(i) = 5.29\%$.

5. ANALYSIS OF MODELS

The calculated values based on stochastic models (3, 5) and genetic models (9, 10) are corresponded well with the experimental values are given in Table 1.

Table 1. Experimental values and calculated values based on models (3), (5), (9) and (10)

Test No	$x_1 = v$ (m/min)	$x_2 = f$ (mm/rev)	$x_3 = a$ (mm)	**Uncoated / Classic tool**			**TiN (PVD) coated tool**		
				Eksperimental	Stochastic (3)	Genetic (9)	*Eksperimental*	Stochastic (5)	Genetic (10)
1	96,0	0,145	1,20	*45,6*	45,53	38,39	*160,5*	148,80	114,80
2	150,0	0,145	1,20	*28,0*	27,71	31,24	*99,2*	90,75	84,33
3	96,0	0,40	1,20	*34,7*	32,79	27,86	*121,7*	115,09	106,61
4	150,0	0,40	1,20	*15,1*	14,97	15,11	*70,5*	57,04	71,73
5	96,0	0,145	4,20	*40,9*	40,10	39,85	*144,8*	137,28	131,69
6	150,0	0,145	4,20	*23,5*	22,28	23,50	*92,0*	79,23	92,27
7	96,0	0,40	4,20	*27,4*	27,36	30,56	*103,5*	95,15	103,58
8	150,0	0,40	4,20	*9,9*	9,54	9,89	*48,7*	37,10	48,66
9	123,0	0,270	2,70	*26,9*	27,66	27,07	*98,8*	95,42	98,80
10	123,0	0,270	2,70	*25,1*	27,66	27,07	*100,2*	95,42	98,80
11	123,0	0,270	2,70	*27,2*	27,66	27,07	*96,5*	95,42	98,80
12	123,0	0,270	2,70	*26,5*	27,66	27,07	*98,7*	95,42	98,80
13	123,0	0,270	2,70	*26,0*	27,66	27,07	*100,0*	95,42	98,80
14	123,0	0,270	2,70	*27,4*	27,66	27,07	*97,0*	95,42	98,80

6. CONCLUSION

In this paper, it has been performed modelling of tool life by means of stochastic and genetic algorithm. By applying the surface engineering technologies are considerably improved the mechanical and tribological performances of tool surface and decreased tool costs in an industrial exploitation. The tool life is increased 250-2000% by applying TiN (PVD) coated tools, depends on PVD technology, type and preparation of basic tool material. The represented example of tool life modelling at the longitudinal turning process was carried out for classic tool and tool with TiN (PVD) coating. The value of tool life in this example for classical tool without coating gotten by stochastic model (3) less negelect from experimental values than the values gotten by genetic model (9). Model (10) gotten by genetic algorithm gives the tool life results in according to stochastic model (5) for tool with TiN (PVD) coating. It shows how with relatively few experimental data can obtain stochastic and genetic model of tool life that is the base for the determining of technological parameters and the choice of optimal tool.

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