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Tool life testing in gundrilling: an application of the group method of data handling (GMDH)

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Abstract

Although the known techniques of the design of experiments (DOE) allows significant improvements in the methodology of machining tests, their use in metal cutting is restricted by limited number of variables included into consideration, pre-set model, subjective pre-process decisions and uncertainties in the machining data collected experimentally. This paper introduces an application of a new powerful technique of DOE known as the group method of data handling (GMDH) to the design of tool life experiments that allows avoiding the above-mentioned disadvantages of traditional DOE. As a result of such an application, a mathematical model that correlates tool life in gundrilling of cast iron with various regime and design parameters was obtained. Special care was taken to avoid the influence of the dynamic phenomenon of the gundrilling process on the obtained experimental results. The obtained mathematical model reveals that tool life in gundrilling is a complex function of various regime and design parameters.

Keywords: Gundrilling; Tool life; Group method of data handling; Mathematical model; Drilling force; Drilling torque

1. Introduction

Although machining or material removal with cutting tools is one of the oldest methods of shaping parts, the most essential characteristics of this process such as tool life, cutting forces, integrity of the machined surface, and energy consumption can be determined only by experiments. As a result, any further improvement of the tool, machine and process design must be justified through a series of experimental studies that are very costly and time consuming. Therefore, the proper test strategy, methodology, data acquisition, and statistical model construction along with its verification are of prime concern in such studies [1].

The techniques of the design of experiments (DOE) allows significant improvements in the methodology of machining tests [2–4]. It is true, however, only if DOE is implemented properly. Probably the weakest features of implementation of traditional DOE in metal cutting studies are: a very limited number of design/process variables that can be included in the test; pre-set mathematical (statistical) model; subjective pre-process decisions and uncertainties in the machining data collected experimentally [2]. To deal with the number of variables included in the text, an additional screening DOE is often needed [4], while the other mentioned issues cannot be resolved in principle within the scope of traditional DOE. This explains rare use of this experimental technique in metal cutting studies.

Naturally, any machining test includes a great number of independent variables. In testing gundrills [4], for example, there are a number of geometry variables (rake angles, flank angles, cutting edge angles, inclination angles, etc.) and design variables (the number of and location of cutting edges, coolant hole shape and location, profile angle of the chip removal flute, shoulder dub-off shape and location, number and location of the supporting pads, back taper, etc.) that affect drill performance and tool life. However, when many factors are included in traditional DOE, the experiment becomes expensive and time consuming. Moreover, uncertainty of many included variables might affect the model adequacy and the test outcome in metal cutting

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testing [5]. Therefore, there is always a dilemma. On one hand, cost and time of testing and the adequacy of the outcome model limit the number of variables to be included into consideration. On the other hand, if even one essential factor is missed, the final statistical model may not be adequate to the process under study.

Another drawback of traditional DOE is that a 'rigid' structure of the mathematical model has to be selected at the pre-process stage. A simple model requires less test runs but its adequacy may not be justified in the subsequent statistical analysis of the experimental data obtained. If an inadequate decision is made at the pre-processing stage, it shows up only at the final stage of DOE when the corresponding statistical criteria are examined. Obviously, it is too late to correct the model, trying to add a missed factor and thus increase model complexity. Unfortunately, no objective criteria, rules, methodology are available to select the optimum model in traditional DOE.

To overcome the discussed drawbacks of the traditional DOE, the Group Method of Data Handling (GMDH) was introduced in the early 1970s as the polynomial theory of complex systems [6] and then was applied in a great variety of areas for data mining and knowledge discovery, forecasting and systems modeling, optimization and pattern recognition [7,8]. Inductive GMDH algorithms provide a possibility to find automatically interrelations in data, to select the optimal structure of model and to increase the accuracy of existing algorithms. This original self-organizing approach is substantially different from deductive methods commonly used in traditional DOE. It has an inductive nature—it finds the best solution by sorting-out all possible variants. By sorting different solutions, the inductive modeling approach aims to minimize the influence of the experimentalist on the results of modeling. The structure of the model is not pre-set as in traditional DOE [9,10]. Rather, it is determined during the course of the analysis along with the estimates for the model coefficients.

This paper discusses the application of the Group Method of Data Handling (GMDH) to tool life testing in gundrilling.

2. Background

GMDH is a set of several algorithms for different problems solution [7,8]. It consists of parametric, clusterization, analogs complexing, rebinarization and probability algorithms. This self-organizing approach is based on the sorting-out of gradually complicated models and selection of the best solution by minimum of external criterion characteristic. Not only polynomials but also non-linear, probabilistic functions or clusterizations are used as basic models.

The GMDH is a further development of inductive self-organizing methods to the solution of more complex practical problems. It solves the problem of how to handle data samples of observations. The goal is to obtain a mathematical model of the object under study (the problem of identification and pattern recognition). GMDH solves, by means of a sorting-out procedure, the multidimensional problem of model optimization

$$g = \arg\min_{g \subset G} \mathrm{CR}(g), \quad \mathrm{CR}(g) = f(P, S, z^2, T, V) \tag{1}$$

where G is set of considered models; CR is an external criterion of model g quality from this set; P is number of variables set; S is model complexity; z^2 is noise dispersion; T is number of data sample transformation; V is type of reference function. For the definite reference function, each set of variables corresponds to definite model structure $P=S$. General correlation between input and output variables are expressed by Volterra functional series, discrete analogue of which is Kolmogorov–Gabor polynomial

$$y = b_0 + \sum_{i=1}^{M} b_i x_i + \sum_{i=1}^{M}\sum_{j=1}^{M} b_{ij} x_i x_j + \sum_{i=1}^{M}\sum_{j=1}^{M}\sum_{k=1}^{M} b_{ijk} x_i x_j x_k \tag{2}$$

where $X(x_1,x_2,\ldots,x_M)$ is the input variables vector; M is the number of input variables, $A(b_1,b_2,\ldots,b_M)$ is the vector of coefficients.

Although GMDH and regression analysis use the table of test data, the regression analysis requires the prior formulation of the regression model and its complexity. This is because the row variances used in the calculations are internal criteria (a criterion is called an internal criterion if its determination is based on the same data that is used to develop the model) [2,10]. The use of any internal criterion leads to a false rule: the more complex model is more accurate. This is because the complexity of the model is determined by the number and highest power of its terms. As such, the greater the number of terms, the smaller the variance. GMDH uses external criteria. A criterion is called external if its determination is based on new information obtained using 'fresh' point of the experimental table not used in the model development. This allows the selection of the model of optimum complexity which corresponds to the minimum of the selected external criterion.

3. Tool life testing

3.1. Design matrix

As known [1,11], the metal cutting process takes place in the cutting system. This process depends on many system parameters whose complex interactions make it difficult to describe the system mathematically. The complexity of factors' interactions allows one to compare the cutting process with 'natural' processes known as 'poorly organized'. This is because the known difficulties to establish the cause-effect links between the input and output variables of the cutting process through direct observations of this process.

The preliminary gundrilling tests have shown [12] that the cutting regime (the cutting speed, v and feed, f) and the parameters of the tool geometry should be considered as the input variables. Tool life is to be considered as the output parameter. Therefore, the problem is to correlate the input variables with the output parameter using a statistical model. In other words, it is necessary to find a certain function (whether linear or not)

$$\bar{A} = F(x, \bar{B}) \tag{3}$$

that is continuous with respect to the vector of arguments $\bar{x} = (\bar{x}_1, \bar{x}_2, \ldots, \bar{x}_n)$ each of which can be varied independently in the range $[\bar{x}_{\min}, \bar{x}_{\max}]$. In Eq. (3), $\bar{B} = (\bar{b}_1, \bar{b}_2, \ldots, \bar{b}_n)$ is the vector of the estimates for the model coefficients.

The input variables vector was chosen as consisting of 11 variables ($M = 11$) which are schematically shown in Fig. 1: x_1 is the approach angle of the outer cutting edge, φ_1; x_2 is approach angle of the inner cutting edge, φ_2; x_3 is the normal flank angle of the outer cutting edge, α_1; x_4 is the normal flank angle of the inner cutting edge, α_2; x_5 is the distance c_1 between the outer cutting edge and the y-axis of the tool coordinate system; x_6 is the distance c_2 between the inner cutting edge and the y-axis of the tool coordinate system; x_7 is the location distance of the drill point with respect to the x-axis of the tool coordinate system, m_d; x_8 is the location distance of the two parts of the tool rake face with respect to the x-axis of the tool coordinate system, m_k; x_9 is the flank angle of the auxiliary flank surface, α_3; x_{10} is the cutting speed, v, m/s; x_{11} is the feed, f, mm/rev.

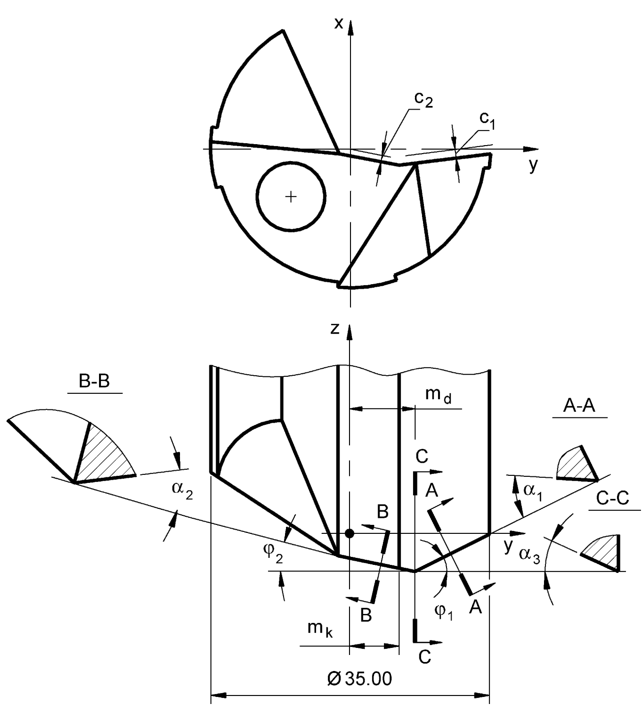

Fig. 1. Design parameters of a gundrill.

The experimental setup was mainly composed of the deep hole drilling machine, a Kistler six-component dynamometer, charge amplifiers and Kistler signal analyzer [13]. The system details are as follows:

- *Machine*—a special TBT gundrilling machine was used. The drive unit was equipped with a programmable AC converter to offer variable speed and feed rate control. The machine included a high pressure drilling fluid delivery system capable of delivering a flow rate up to 120 l/min and generating a pressure of 12 MPa. The stationary tool-rotating workpiece working method was used in the tests. The feed motion was applied to the gundrill.
- *Work material*—because special parts, calender bowls were drilled, the work material was malleable iron casting, Class 80002 having the following properties: hardness, Brinell HB 241—285 tensile strength, ultimate (Rm) 655 MPa tensile strength, yield (Rp0,2) 552 MPa, elongation at break—2%.
- *Gundrills*—specially designed gundrills of 35 mm dia. were used. The material of their tips was carbide K30. The parameters of drill geometry were kept within close tolerance of $\pm 0.2°$. The surface roughness R_a of the rake and flank faces did not exceed 0.25 μm. Each gundrill used in the tests was examined using a vision system at a magnification of $\times 25$ for visual defects such as chipping, burns and microcracks. When re-sharpening, the tips were ground back at least 2 mm beyond the wear marks.
- *Drilling fluid (coolant)*—a water soluble coolant having 7% concentration.
- *Tool life criteria*—the average width of the flank wear land $VB_{B(cr)} = 1.0$ mm was selected as the prime criterion and was measured in the tool cutting edge plane containing the cutting edge and the directional vector of prime motion according to the methodology suggested in [14]. However, excessive tool vibration and/or squeal were also used in some extreme cases as a criterion of tool life.

The design matrixes used in GMDH, $\{\bar{x}_{ij}\}$ are obtained as arguments x_i are selected randomly, as generated by a random number generator. This assures the uniform density of probability of occurring of ith argument in jth experiment, which does not depend on the other arguments in the current or previous runs. As such, the design matrix $\{\bar{x}_{ij}\}$ is considered as n realization of random vector $\bar{x}$ having the normal density of distribution of paired scalar products of all factors over the columns of the design matrix due to independence of these factors. In the algorithm of GMDH, this is accomplished using the Khomogorov criterion so the design matrix is generated using a generator of random numbers until the normal distribution is assured [7,8].

Five levels of the factors were selected for the study. The levels of the factors and intervals of factor variations are

Table 1
The levels of factors and their intervals of variation

Levels	x_1 (deg.)	x_2 (deg.)	x_3 (deg.)	x_4 (deg.)	x_5 (mm)	x_6 (mm)	x_7 (mm)	x_8 (mm)	x_9 (deg)	x_{10} (m/s)	x_{11} (mm/rev)
+2	34	24	20	16	1.50	1.50	16.0	17.5	20	53.8	0.21
+1	30	22	17	14	0.75	0.75	14.0	11.5	15	49.4	0.17
0	25	18	14	12	0.00	0.00	11.0	8.75	10	34.6	0.15
−1	22	15	11	10	−0.75	−0.75	8.75	6.0	5	24.6	0.13
−2	18	12	8	8	−1.50	1.50	6.0	3.5	0	19.8	0.11

shown in Table 1. The upper level (+2) for the cutting speed, 53.8 m/min (490 rpm), was selected as a result of the preliminary testing and was limited by the dynamic stability of the shank and strength of the tool material (including the compressive strength and TRS). As such, the critical rotational speed of the shank was determined to be 618 rpm. The experimental matrix was obtained using the algorithm described in [7]. Its fragment is shown in Table 2. At least three tests at the each point of the design matrix were carried out.

3.2. Dynamic phenomena

Before any DOE and/or optimization technique is to be applied, one has to study the influence of dynamic effects that may dramatically affect the experimental results. If a gundrill works under the condition where resonance phenomenon affects its performance, no DOE can be used because the response surface would not be smooth.

Gundrills are intended to drill deep holes and thus their shanks can be of great length. As a result, the tool has relatively low static and dynamic stiffness. This in turn leads to the process being susceptible to dynamic disturbances which results in vibrations. This is particularly true in the considered case when the properties of the work material changes along the drill diameter presenting a combination of proeutectoid white cast iron (HB429-560) and gray pearlite cast iron (HB186-220). As known [15], these dynamic disturbances lead to the torsional and flexural vibrations of the shank. In order to characterize the dynamics of the gundrilling process, the cutting force and the amplitude of the shank vibration were measured and analyzed.

For the considered case, the time of one tool revolution was $t_r = 0.19$ s (the rotational frequency of the tool $f_r = 5$ Hz, feed $f = 0.15$ mm/rev, cutting speed $v = 58$ m/min), the frequency of shank flexural vibration was $f_{fl} = 320–350$ Hz and its amplitude $A_{fl} = (38–46)\ 10^{-6}$ m, the frequency of

Table 2
Fragment of design matrix and experimental result

No.	R	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}	Tool life (min)
1	56	2	1	−1	−1	0	0	−1	0	−2	0	0	260
2	88	2	1	−1	1	−2	−1	−2	2	1	−1	2	215
3	87	1	1	−2	−2	−1	−2	−2	1	−2	1	−2	170
4	32	2	0	−2	1	−2	−1	−2	2	−1	−1	2	251
5	44	0	0	1	−1	0	0	1	0	2	−2	1	300
6	94	2	1	1	2	1	2	−2	1	−1	−2	−1	273
7	78	2	−1	2	1	−2	−1	−2	2	0	−1	−1	220
8	42	0	1	0	−1	2	1	−1	−1	−2	1	−2	123
9	4	−1	−1	1	2	1	2	−2	1	−2	−2	−1	167
10	41	2	−2	2	2	0	0	−2	0	1	0	1	160
11	54	−1	−1	1	2	1	2	−2	1	−2	1	−1	116
12	65	2	−1	−2	1	−2	−1	−1	2	0	−1	2	208
13	3	0	1	0	2	1	1	1	−2	1	1	0	79
14	11	0	−1	1	1	0	0	−1	0	1	−1	1	348
15	48	2	−1	−2	1	−2	−1	0	2	0	−1	0	173
16	43	−1	−2	0	0	1	2	−2	1	−2	−2	−1	207
17	40	1	2	1	2	1	2	−2	1	2	−1	−1	157
…	…	…	…	…	…	…	…	…	…	…	…	…	…
77	83	2	1	−1	−1	0	0	−1	0	−2	0	0	230
78	86	−1	0	1	1	2	−1	2	2	−1	1	1	32
79	90	1	1	−1	−1	2	0	0	1	−2	−1	−1	284
80	92	2	1	−1	−1	−2	0	−1	0	1	−2	2	450
81	93	−1	2	−2	−2	−2	−2	−1	0	1	0	−1	350
82	62	0	−1	0	0	2	1	2	−2	0	1	0	151
83	99	2	0	−2	−2	1	1	−2	−2	0	0	1	206
84	68	−1	2	0	0	1	1	1	−2	0	0	0	152

shank torsion vibration $f_{tr}=200$–220 Hz in machining gray cast iron and $f_{fl}=640$–770 Hz, $A_{fl}=(2$–$4)\ 10^{-6}$ m, $f_{tr}=$ 300–320 Hz in machining proeutectoid white cast iron.

The natural frequencies were $f_{nx}=18.84$ Hz and $f_{ny}=$ 23.32 Hz (the first harmonic) for the shank of length $l_{sh}=$ 780×10^{-3} m having the ratio of maximum and minimum rigidities equal to 0.67 due to the V-flute made on the shank for chip removal. As seen, these natural frequencies do not coincide with those due to the shank vibrations so there is no influence of the resonant phenomenon. This conclusion was additionally confirmed using different cutting speeds and feeds. The same conclusion was made for torsional vibrations. As such, the critical angular velocity of the shank was calculated as

$$\omega_{cr} = \sqrt{\frac{\omega_x^2\omega_y^2}{2(\omega_x^2+\omega_y^2)}} \quad (4)$$

where $\omega_{x,y}=2\pi f_{n(x,y)}$ are angular natural frequencies of the shank with respect to the x and y axes, respectively, so it was found that $\omega_{cr}=64.74\ s^{-1}$. Because the experimental points included in Table 1 are to be determined for the following range of the shank rotational frequency: $\omega_m=18.86$–$51.3\ s^{-1}$, it was concluded that there is no influence of torsional resonance on the test results.

The following can be stated to summarize these results. The frequency of chip formation causes forced vibrations of the drill. These vibrations are due to high dynamic content of the cutting forces including the cutting torque. As such, the uncut chip thickness, represented by the cutting feed per revolution, plays an important role. The influence of this parameter on the axial force is shown in Fig. 2, and on the cutting torque shown in Fig. 3. As follows from these figures, when the feed changes from 0.11 to 0.21 mm/rev, the axial force increases by 50% at the same cutting speed. Increase in the cutting speed from 0.33 to 1.15 m/s leads to approximately a 20% increase in the axial force at the same feed. As was expected, the cutting torque has the opposite variations with the cutting speed and feed.

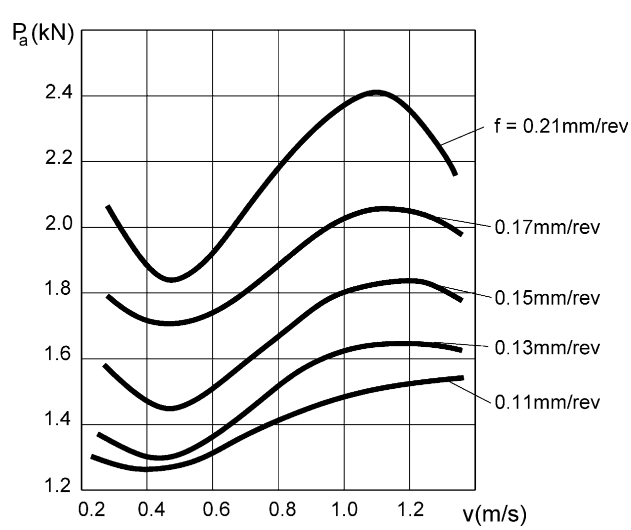

Fig. 2. Influence of the uncut chip thickness (the cutting feed, f) on the axial force, P_a under different cutting speeds, v.

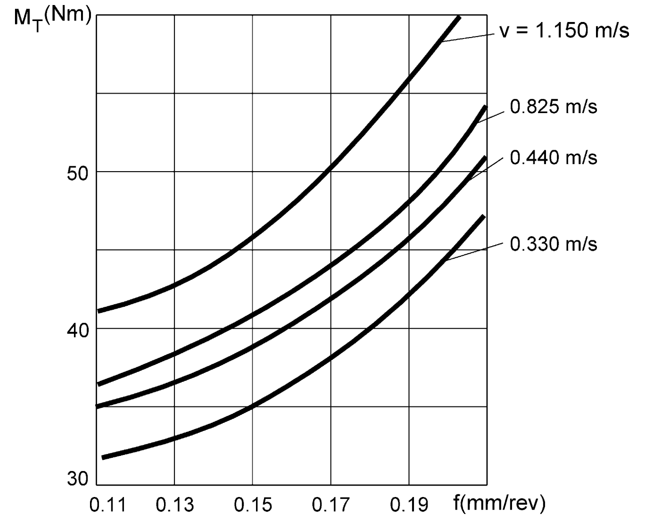

Fig. 3. Influence of the uncut chip thickness (the cutting feed, f) on the drilling torque, M_T under different cutting speeds, v.

The analysis of the records of the axial force (an example is shown in Fig. 4) and drilling torque allowed us to represent these parameters as

$$P_a(t) = P_{as} + \Delta P_a(t) + \delta P_a(t) \quad (5)$$

$$M_T(T) = M_{Ts} + \Delta M_T(t) + \delta M_T(t) \quad (6)$$

where P_{as} and M_{Ts} are static, time invariant parts of the axial force and drilling torque, respectively, $\Delta P_a(t)$ and $\Delta M_a(t)$ are time dependant parts of the axial force and drilling torque due to the variation of the properties of the work material, respectively, $\delta P_a(t)$ and $\delta M_a(t)$ are time dependant parts of the axial force and drilling torque due to the cyclic nature of chip formation [1] and interactions of the deformation and thermal waves [16].

The experiments showed that the variation of the axial force $\Delta P_a(t)$ has the frequency proportional to the rotational

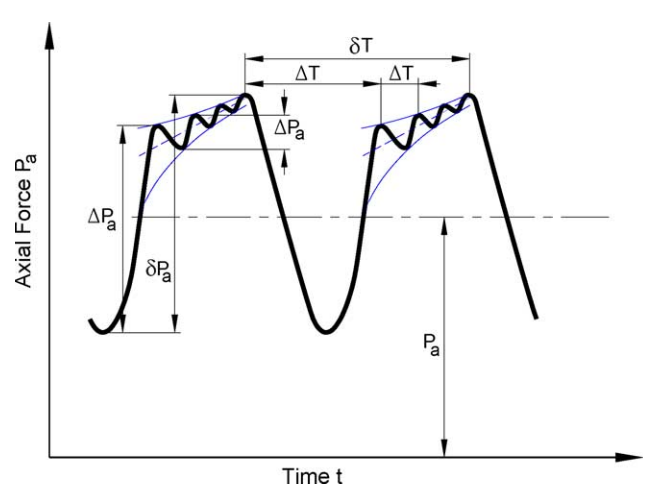

Fig. 4. A typical structure of record $P_a(t)$.

frequency of the shank. Its amplitude increases with the feed and decreases with the cutting (rotational) speed. In the considered case, the variation of $\Delta P_a(t)$ was in the range from 11 to 19% of P_a. The variation $\Delta M(t)$ of the drilling torque had smaller amplitude and was in the range from 10 to 15% of M_T in the selected ranges of the feed and speed. The variation of the axial force $\delta P_a(t)$ was in the range from 13 to 24% and that of torque $\delta M(t)$ was in the range from 13 to 24% of P_a.

The amplitude of $\delta P_a(t)$ does not vary under these given cutting conditions while that of $\Delta P_a(t)$ varies and its maximum corresponds to the beginning of period δT.

Using these results, one may conclude that the resonance phenomenon in the conducted tests did not affect drill performance significantly so that DOE can be used in the assigned ranges of feeds and speeds (Table 1).

3.3. Model

The model determination was carried out using the simplified algorithm of GMDH [7] according to which the search for the model of the process under investigation is carried out among those accepted for the processes in the considered field. Because logarithmic models are normally used for tool life tests [1], the input domain was extended by introducing variables $\ln \bar{x}$, $(\ln \bar{x})^{-1}$ to the existing $\bar{x}$ and $(\bar{x})^{-1}$. As such, the response was represented as $\ln \bar{y}$. Each vector of the input factors in this domain includes nine (first in the order) geometrical parameters and two regime parameters and their set forms the domain of input variables $\|\bar{x}\|$, i.e.

$$\bar{x} = \|x_1, \dots, x_{11}\| \tag{7}$$

$$(\bar{x})^{-1} = \|x_{12}, \dots, x_{22}\| \tag{8}$$

$$(\ln \bar{x}) = \|x_{23}, \dots, x_{33}\| \tag{9}$$

$$(\ln \bar{x})^{-1} = \|x_{34}, \dots, x_{44}\| \tag{10}$$

As such, Eq. (3) can be re-written as

$$E\{\ln \bar{y}/\|x\|\} = F(\bar{x}, (\bar{x})^{-1}, \ln \bar{x}, (\ln \bar{x})^{-1}, \bar{B}) + \bar{\Theta} \tag{11}$$

where $E\{\ln \bar{y}/\|x\|\}$ is the estimation of the response, $F(\|\bar{x}\|, \bar{B})$ is the unknown functional, $\bar{\Theta}$ is the vector of the residual errors of the model.

The basic GMDH algorithm uses an input data sample as a matrix containing N levels (points) of observations over a set of M variables. A data sample is divided into two parts. If regularity criterion AR(s) is used, then approximately two-thirds of observations forms the training subset N_A, and the remaining part of observations (e.g. every third point with same variance) forms the test subset N_B. The training subset was used to derive estimates for the coefficients of the polynomial, and the test subset was used to select the structure of the optimal model, that is one for which the regularity criterion AR(s) assumes its minimum

$$\mathrm{AR(s)} = \frac{1}{N_B} \sum_{1}^{N} [y_i - \bar{y}(B)]^2 \rightarrow \min \tag{12}$$

Experience shows [7] that better results are achieved if the cross-validation criterion RRR(s) is used because it takes into account all information in the data set and it can be computed without recalculation of the system for each test point. Thus, each point was taken successively as test subset and then the averaged value of the cross-validation criteria was used

$$\mathrm{RRR}(S) = \frac{1}{N} \sum_{1}^{N} [y_i - \bar{y}(B)]^2 \rightarrow \min$$
$$N_A = N - 1, \quad N_B = 1 \tag{13}$$

To test a model for compliance with the differential balance criterion, the input data set was divided into two equal parts. According to this criterion, the selected model must yield the same results on both subsets. The balance criterion will yield the only optimal physical model solely if the input data are noisy.

To obtain a smooth curve of criterion value, which would permit one to formulate the exhaustive-search termination rule, the full exhaustive search was performed on models classed into groups of an equal complexity. The first layer uses the information contained in every column of the set; that is the search was applied to partial descriptions of the form

$$y = a_0 + a_1 x_i, \quad i = 1, ..., M, \tag{14}$$

Non-linear members were considered as new input variables in data sampling. The output variable was specified in this algorithm in advance by the experimentalist. For each model system of Gauss normal equations was solved. At the second layer, all models–candidates of the following form were sorted

$$y = a_0 + a_1 x_i + a_2 x_j, \quad j = 1, \dots, M \tag{15}$$

The models were evaluated for compliance with the criterion, and the procedure was continued until the minimum of the criterion was found. To decrease calculation time, it is recommended to select at a certain (6–8) layer a set of the best F variables and to only use them in the full sorting-out procedure. As such, the number of input variables can be significantly increased. For extended definition of the only optimal model the discriminating criterion is recommended.

For the considered case, this algorithm allowed generating a model having RRR(s) = 14% after six rows of selection. As this stage, the further complication of the model was found unnecessary so only the estimates for the model's coefficients were taken into consideration for the further stages of selection. The model was obtained in the following form

$$y = b_0 + b_1 x_5 x_7 (x_1 \ln x_3)^{-1} - b_2 x_3 (x_2 x_6)^{-1} - b_3 x_{10} x_{11} (x_1)^{-1} - b_4 x_4 \ln x_6 (x_7)^{-1} - b_5 x_1^2 (x_6)^{-1} + b_6 \ln x_6 (x_5 x_1)^{-1} \quad (16)$$

or transforming the code variables into initial ones, one obtains

$$T = 6.7020 - 0.6518 \frac{\alpha_1}{\varphi_2 c_2} - 0.0354 \frac{\alpha_2 \ln c_2}{m_d} - 0.0005 \frac{\varphi_1^2}{c_2} + 0.0168 \frac{\ln c_2}{\varphi_1} - 2.8350 \frac{vf}{\varphi_1} - 0.5743 \frac{c_2 m_d}{\ln \alpha_1 \varphi_1} \quad (17)$$

The adequacy of the model was tested and verified using a procedure described in detail in [2,3].

The mathematical model of tool life (Eq. (17)) indicates that tool life in gundrilling is a complex function of not only of design and process variables but also of their interactions. The including of these interactions in the model brings a new level of understanding of their influence on tool life. To support the above point, one practically important particular case is considered.

It is known that the approach angle of the outer cutting edge, φ_1 is considered as the most important parameter of the tool geometry in gundrilling because it has controlling influence on tool life and on other important output parameters [17]. Traditionally, this angle along with approach angle of the inner cutting edge, φ_2 are selected depending on the properties of the work material. Although the contradictive influence of these angles has been observed [17], no one study reveals their correlations with the cutting regime as suggested by Eq. (17).

To verify the above-discussed influence, a series of additional testing was carried out using the same experimental setup. Fig. 5a and b shows an example of the obtained results. As seen, an increase in the approach angle of the outer cutting edge, φ_1 increases tool life and, simultaneously, decreases the influence of the cutting feed on drill wear. It is explained by the reduction of the uncut chip thickness a_1 (sometimes referred to as the chip load). This is illustrated with the aid of Fig. 6. Because the chip cross-sectional area should remain the same, the following equality is valid

$$fl_1 = a_1 l_2 \quad (18)$$

As follows from Fig. 6 that $l_2 = l_1/\cos\varphi_1$, hence

$$a_1 = f\cos\varphi_1 \quad (19)$$

The reduction of the uncut chip thickness results in the 'spread' of the cutting force over the wider contact surface so that, the contact stress and contact temperatures reduces that leads to an increase in tool life. Such a trend continues until the uncut chip thickness becomes small enough that the radius of the cutting edge (Section A–A in Fig. 6) starts to play a significant role affecting the tool geometry. In gundrilling, it happens when $R \geq 0.3a_1$. When this is the case, cutting with highly negative rake angle and with significant burnished layer takes place so that the contact temperatures increase dramatically and thus tool life decreases with further increase in φ_1.

It follows from Fig. 5b that tool life increases with φ_2. This is because the uncut chip thickness on the inner cutting edge decreases. As such, the axial force reduces. However, an increase of φ_2 is restricted by the strength of the drill point and by drill stability determined by the force balance.

The obtained results fully support the influence of the gundrill approach angles set by the mathematical model of tool life (Eq. (17)). These results provide further evidence that the influence of any particular design or regime

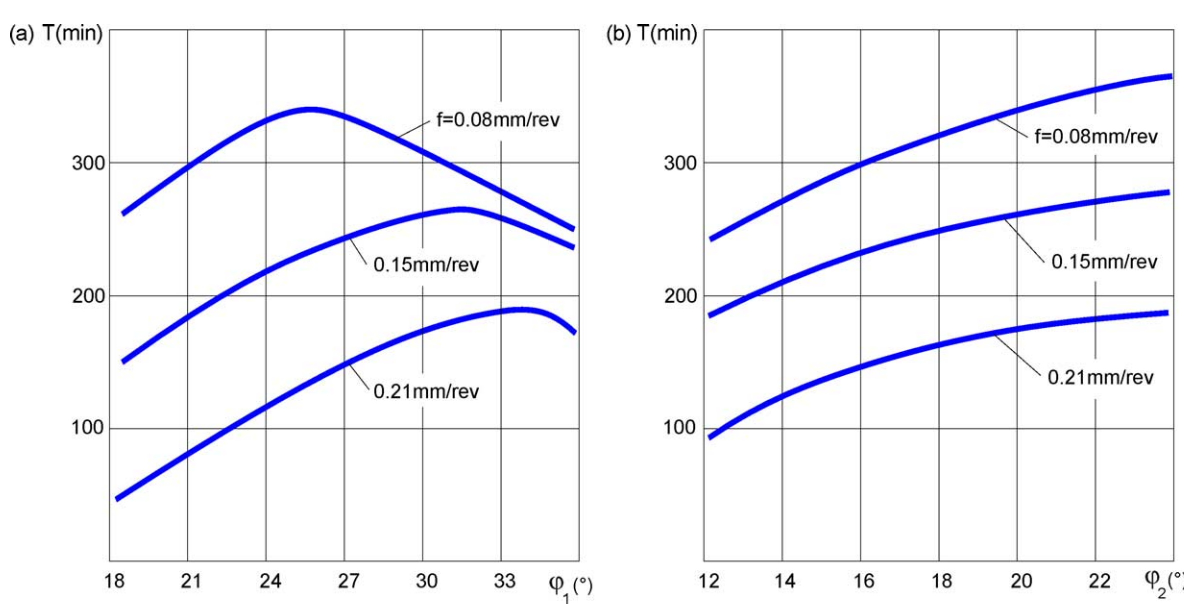

Fig. 5. Tool life T vs. (a) the approach angles of the outer cutting edge, φ_1 and (b) the approach angle of the inner cutting edge, φ_2 for different feeds.

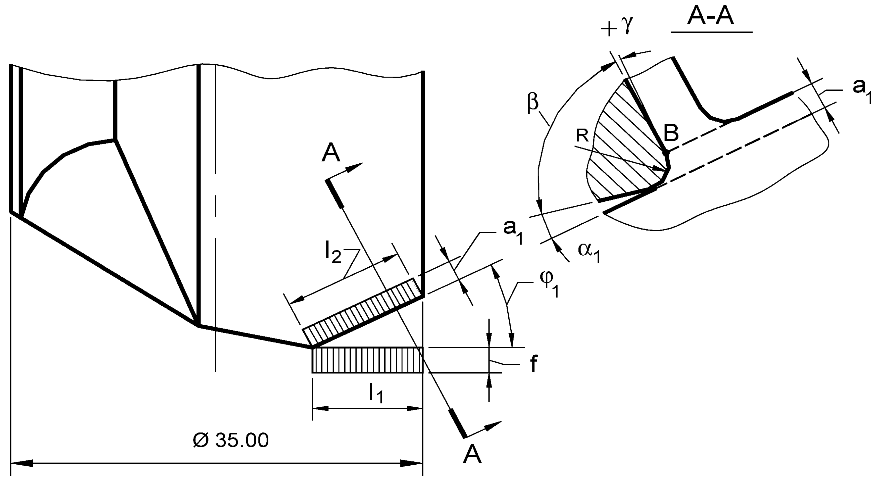

Fig. 6. Model showing influence of the approach angle of the other cutting edge φ_1 on the uncut chip thickness (the chip load) a_1.

parameter in gundrilling cannot be considered apart from other parameters.

4. Conclusions

Although the known techniques of the design of experiments (DOE) allows significant improvements in the methodology of machining tests, their use in metal cutting is restricted by limited number of variables included into consideration, pre-set model, subjective pre-process decisions and uncertainties in the machining data collected experimentally. To overcome these known difficulties, a new powerful technique of DOE known as the group method of data handling (GMDH) seems to be very useful. It is conclusively proven [8] that only this recursive method gives an optimal non-physical model whose accuracy is higher and whose structure is simpler than the structure of the usual complete statistical (traditional DOE and/or physical model for inaccurate, noisy, or short data samples (as in metal cutting). Using this method, a statistical model that correlates tool life with the regime and design parameters of gundrills is obtained (Eq. (17)).

The obtained model reveals that tool life in gundrilling is a complex function not only of many design and process variables but also of their compound interactions. This fact was first found in [3] (though in a much more simple form) where it is proven that if a test is carried out in the manner when one factor is varied at the time [18], no decisive conclusions about the influence of the combination of various parameters on tool life can be drawn.

Additional testing was carried out to verify the compound influence of the approach angles of the outer and inner cutting edges suggested by the obtained mathematical model (Eq. (17)).

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