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Preface

Nowadays, it is the trend to report production engineering as a combination of manufacturing technology with applied management science. This book covers design of experiments (DoE) applied in production engineering. DoE is a statistical methodology used to establish statistical correlation between a set of input variables with a chosen outcome of the system/process. DoE is a systematic approach to investigation of a system/process. In general, DoE analysing and interpreting sets of experiments without incurring a too high cost or taking too much time.

The purpose of this book is to present a collection of examples illustrating DoE applied in production engineering. The first chapter is "Screening (Sieve) Design of Experiments in Metal Cutting". The second chapter is "Modelling and Optimisation of Machining with the Use of Statistical Methods and Soft Computing". The third chapter is "Design of Experiments—Statistical and Artificial Intelligence Analysis for the Improvement of Machining Processes: A Review". The fourth chapter is "A Systematic Approach to Design of Experiments in Waterjet Machining of High Performance Ceramics". The fifth chapter is "Response Surface Modeling of Fractal Dimension in WEDM". The sixth chapter is "Thrust Force and Torque Mathematical Models in Drilling of Al7075 Using the Response Surface Methodology". The seventh chapter is "Design of Experiments in Titanium Metal Cutting Research". Finally, the eighth chapter is "Parametric Optimization of Submerged Arc Welding Using Taguchi Method".

This book can be used as a research book for a final undergraduate engineering course or as a topic on DoE in production engineering at the postgraduate level. Also, this book can serve as a valuable reference for academics, engineers, researchers, professionals in production engineering and related subjects. The scientific interest in this book is obvious for many important centres of research and universities as well as industry. Therefore, it is expected that this book will motivate others to undertake research in DoE in production engineering.

The Editor acknowledges Springer for this opportunity and for their enthusiastic and professional support. Finally, I would like to thank all the chapter authors for their availability for this work.

Aveiro, Portugal J. Paulo Davim
October 2015

Contents

Nomenclature

AI	Artificial Intelligence
AISI	American Iron and Steel Institute
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
BN	Bayesian Networks
CAM	Computer Aided Manufacturing
CNC	Computer Numerical Control
DoE	Design of Experiments
EDM	Electrical Discharge Machining
FFD	Full Factorial Design
FL	Fuzzy Logic
GA	Genetic Algorithm
MRPD	Multivariate Robust Parameter Design approach
OA	Orthogonal Array
rpm	Revolutions per minute
RSM	Response Surface Methodology
SSA	Singular Spectrum Analysis

Screening (Sieve) Design of Experiments in Metal Cutting

Viktor P. Astakhov

This chapter discuses particularities of the use of DOE in experimental studies of metal cutting. It argues that although the cost of testing in metal cutting is high, there is no drive to improve or generalize the experimental results. It explains that full factorial design of experiments and the most advanced group method of data handling (known as GMDH) method allow accurate estimation of all factors involved and their interactions. The cost and time needed for such tests increase with the number of factors considered. To reduce these cost and time, two-stage DOE procedure to be used in metal cutting experimental studies is suggested: screening DOE in the first stage and full factorial DOE in the second stage. The Plackett and Burman DOE is found to be very useful in screening tests in metal cutting studies.

1 Introduction

Although machining is one of the oldest manufacturing processes, most essential characteristics and outcomes of this process such as tool life, cutting forces, integrity of the machined surface, and energy consumption can only be determined experimentally. As a result, new improvements in the tool, machine and process design/optimization, and implementation of improved cutting tool materials are justified through a series of experimental studies. Unfortunately, experimental studies in metal cutting are very costly and time-consuming requiring sophisticated equipment and experienced personnel. Therefore, the proper test strategy, methodology, data acquisition, statistical model construction, and verification are of prime concern in such studies.

Metal cutting tests have been carried out in systematic fashion over at least 150 years, in tremendously increasing volume. However, most of the tests carried out so far have been conducted using a vast variety of cutting conditions and test

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methods having little in common with each other. It is understood that test results are meaningless if the test conditions have not been specified in such a way that the different factors, which affect the test results, will be under a reasonable and practical degree of control. Though this sounds simple and logical, the main problem is to define and/or determine these essential factors.

Unfortunately, there is lack of information dealing with test methodology and data evaluation in metal cutting tests. Some information about setup and test conditions can be found in most of the reported experimental studies. On the contrary, it is rather difficult to find corresponding information about test methodology and answers to the questions of why the reported test conditions or design parameters of the setup were selected at the reported levels, what method(s) was (were) used for experimental data evaluation, etc.

Although the cost of testing in metal cutting is high, there is no drive to improve or generalize the experimental results in the published experimental works and even up to the level of national and international standards. For example, the standard ANSI/ASME Tool Life Testing with Single-Point Turning Tools (B94.55M-1985) suggests conducting the one-variable-at-a-time test. When it comes to acquisition of test results, the only calculation of the confidence interval limits is required to carry out and, thus report. As a result, only the influence of cutting speed on the tool life can be distinguished for a given machine (static and dynamic stiffness, spindle runout, accuracy of motions, etc.), workpiece parameters (metallurgical state, dimensions, holding method, etc.), cutting tool material and cutting tool design, the accuracy of the cutting tool setting in the tool holder, and in the machine spindle (for round tools).

The design of experiments (DOEs) technique allows a significant improvement in the methodology of machining tests. DOE is the process of planning of an experiment so that appropriate data will be collected, which are suitable for further statistical analyses resulting in valid and objective conclusions. Because there are a number of different methodologies of DOE, one is always challenged to select the appropriate methodology depending on the objective of the test and the resources available.

Reading this, a logical question, "what seems to be the problem?" is frequently asked. In other words, why does another chapter or even a book on DOE in machining needed? Indeed, the theory of DOE is fully covered in many fundamental books, e.g. [1–3]; its application to machining studies is discussed by many researches including the author [4–7]. Moreover, there are many commercial DOE software packages as, for example, Minitab by Minitab, Inc., SAS by SAS Institute, Inc., S-Plus by Mathsoft, Inc., Design-Expert by Stat-Ease, Inc., STATISTICA/StatSoft by Dell Software, with detailed online manuals (e.g. http://www.statsoft.com/textbook/experimental-design#general). A great body of the available literature and online sources combined are readily available as commercial software packages that apparently make DOE almost effortless. In the author's opinion, however, the simplicity of DOE is really pseudo-simplicity or masked complexity. That is, when it comes to machining, the available DOE sources represent only the tip of the iceberg, i.e., a much greater, in terms of size and complicity, part is often hidden underwater in dark.

This chapter aims to discuss an important but rarely discussed issue of accounting for factors' numbers and their interactions in DOE machining tests. It argues that including such interactions into the consideration in DOE in metal cutting makes experimental studies not only effective but also efficient. In this context, the term "effectiveness" is understood as doing the right things, i.e. the use of DOE, whereas the term "efficiency" is understood as doing things right, i.e., accounting for the relevant number of factors and their interactions. The latter allows optimization of not only parameters of the machining regime but even intricate parameters of the cutting tool including tool geometry, material, setting, etc.

2 Basic Terminology

DOE is one of the most powerful, and thus widely used statistical methods in machining tests. The outcomes of machining are affected by many factors as shown in Fig. 1a. In order to design a new process or to improve the existing machining process, the relationship between the inputs and outputs should be established. DOE is a statistical formal methodology allowing an experimentalist to establish statistical correlation between a set of inputs (input variables) with chosen outcomes of the system/process under certain uncertainties, called environmental influence. An input factor in a process is determined as a source of variability in the output of the process. Once the process input variables for a process are determined they are often termed as the key process input variables (known as KIPV in the literature). Thus, a statistically-based experiment can be designed so that optimal values for each factor to achieve the desired output quality can be revealed. In this respect, DOE is the process of determine the correlations of KPIVs with the output of the process. A key point of the DOE process is that it changes several variables at once. This allows the statistics behind the process to identify interactions between the KPIVs in terms of their influence on the output.

The visualization of this definition as it used in DOE is shown in Fig. 1b, where (x_1, x_2, … x_n) are n KPIVs selected for the analysis; (y_1, y_2, … y_m) are m possible system/process outputs from which one should be selected for the analysis; and (z_1, z_2, … z_p) are p uncontrollable (the experimentalist has no influence) inputs (often referred to as noise). The system/process is designated in Fig. 1b as a black box,[1] i.e., it is a device, system, or object that can be viewed solely in terms of its input,

[1]The modern term "black box" seems to have entered the English language around 1945. The process of network synthesis from the transfer functions of black boxes can be traced to Wilhelm Cauer who published his ideas in their most developed form in 1941. Although Cauer did not himself use the term, others who followed him certainly did describe the method as black-box analysis.

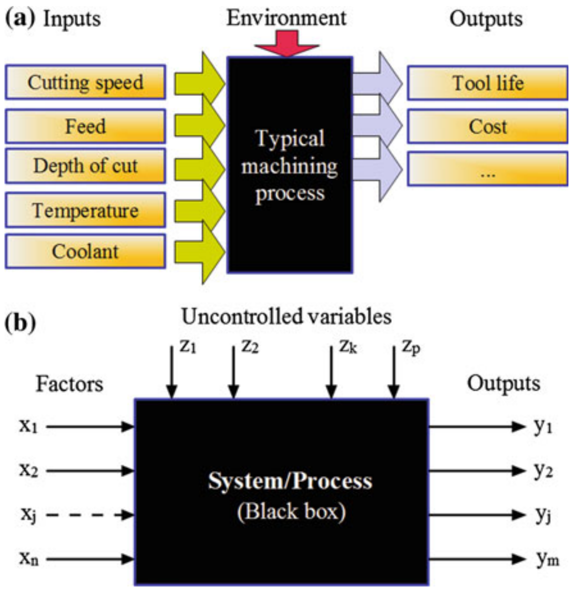

Fig. 1 Visualization of: **a** DOE intent, and **b** formal definition of DOE

output, and transfer (correlation) characteristics without any knowledge of its internal workings, that is, its implementation is "opaque" (black).

The first stage of DOE requires the formulation of clear objective(s) of the study. The statistical model selection in DOE requires the quantitative formulation of the objective(s). Such an objective is called the response, which is the result of the process under study or its output as presented in Fig. 1. The process under study may be characterized by several important output parameters but only one of them should be selected as the response.

The response must satisfy certain requirements. First, the response should be the effective output in terms of reaching the final aim of the study. Second, the response should be easily measurable, preferably quantitatively. Third, the response should be a single-valued function of the chosen parameters.

The proper selection of KPIVs cannot be overstated. In DOE, it is necessary to take all the essential factors into consideration. Unconsidered factors change arbitrarily, and thus increase the error of the tests. Even when a factor does not change arbitrarily but is fixed at a certain level, a false idea about the optimum can be obtained because there is no guarantee that the fixed level is the optimum one.

The factors can be quantitative or qualitative but both should be controllable. Practically, it means that the chosen level of any factor can be set up and maintained during the tests with certain accuracy. The factors selected should affect the response directly and should not be a function of other factors. For example, the cutting temperature cannot be selected as a factor because it is not a controllable parameter. Rather, it depends on other process parameters as the cutting speed, feed, depth of cut, etc.

The factor combinations should be compatible, i.e., all the required combinations of the factors should be physically realizable on the setup used in the study. For example, if a combination of cutting speed and feed results in drill breakage, then this combination cannot be included in the test. Often, chatter occurs at high cutting regimes that limits the combinations of the regime parameters.

3 Factor Interactions

The famous UCLA Coach John Wooden used to say: "A player who makes a team great is much more valuable than a great player." When the Brazilian soccer team led by Pele, reportedly the best player in the soccer history, came to the 1966 World Cup final in England, almost no one had a doubt that this competition was only a formality for this team. Brazil assembled a "dream team" from the ranks of the top FIFA superstars. The expectation was that this high-powered assembly of top talent would walk all over their competition. However, Brazil lost in the group matches to Hungary and then to Portugal. Brazil returned home early, without getting past the first stage of the cup. For the disorganization and for the bad results, this is considered the worst performance of Brazil in a World Cup.

How could this have happened, particular the devastating lost to Hungary? Clearly the individual Brazilian players were superior to their Hungarian counterparts. But the Hungarian squad had trained together and was used to playing by the slightly different rules of World Cup soccer. By contrast, the Brazilian team was assembled shortly before the games and had not practiced very much. They had not "jelled" as a team. Similarly, some of the parameters of metal cutting regime or tool that one may be testing may be superstars individually, i.e., the tool cutting edge angle and cutting feed. But one should be looking for the combination of variables that performs best when presented together.

What is a variable interaction? Simply put, it is when the setting for one variable in your test positively or negatively influences the setting of another variable. If they have no effect on each other, they are said to be independent. In a positive interaction, two (or more) variables create a synergistic effect (yielding results that are greater than the sum of the parts). In a negative interaction, two (or more) variables undercut each other and cancel out some of the individual effects.

In metal cutting, we want to know interactions. We want to use factors interaction to achieve the maximum effect, i.e., to optimize the process using the selected criteria (criteria) of optimization. We want to detect any parts of the tool geometry that are working at cross-purposes and undercutting the performance of the machining regime. Our goal should be to find the best-performing group of machining process elements.

Some DOEs (such as A-B split testing and many forms of fractional factorial parametric testing widely used in metal cutting testing [2, 8]) assume that there are absolutely no interactions among process variables and that these variables are completely independent of each other.

In the author's opinion, this is an absurd assumption in metal cutting testing. Very strong interaction effects (often involving more than two variables) definitely exist although admitted rarely. This should not be a surprise to anyone, because the optimization of metal cutting is intentionally trying to create a combination of the process parameters that are greater than the sum of their parts. In doing such an optimization, one should be looking for synergies among all of machining elements and trying to eliminate combinations of variable values that undermine the desired outcome.

Although one may be able to get some positive results by ignoring interactions, he or she will not get the best results. So where can you look for interactions? In general, there is no way to guarantee that any subset of your testing elements does not interact. However, you should consider elements that are in physical proximity, or that are otherwise confounded with each other. For example, if a new tool material prone to chipping (e.g., CVD diamond) is used in face milling, extremely sharp cutting edges should be honed to prevent their chipping due to shock loading. To balance the negative effect of the edge radius, r_{ed}, the uncut chip thickness (h_D) should be increased to keep the ratio $h_D/r_{\text{ed}} > 6$ to maximize the tool life [4]. In turn, the uncut chip thickness depends on the cutting feed per tooth, f_z and tool cutting edge angle, κ_r. As follows, a strong correlation of three parameters of face milling, namely the edge radius, r_{ed}, the cutting feed per tooth, f_z, and tool cutting edge angle, κ_r are clearly established.

Therefore, possible variable interactions should not be ignored in metal cutting tests because interactions exist and can be very strong.

4 Examples of Variable Interaction in Metal Cutting Testing

The common statistical representation of the results of metal cutting test for tool life and the cutting force are

$$T = C_T v_c^{x_T} f^{y_T} a_p^{z_T} \tag{1}$$

$$F = C_F v_c^{x_T} f^{y_F} a_p^{z_F}, \tag{2}$$

where C_T, C_F, x_T, y_T, z_T, x_F, y_F, z_F are initially assumed as constants.

Therefore, even the initial structure of these statistical equations assumes that there are no interactions among the included factors. One can argues, however, that the possible interactions as hidden (distributed) in the corresponding constants and the intervals of factors variation are chosen to avoid, or at least, to reduce the possible interactions. In the author's opinion, these arguments are not valid because if the former is the case then the experimentalist deliberately decreases the range of factors variation, and thus significantly reduces the value of the obtained results.

Moreover, as the factors interactions are not known before testing, there is no way to take some purposeful measures to reduce these integrating at the stage of test planning.

This section provides some examples of factors interaction detected in the proper-planned and statistically-evaluated metal cutting tests.

Example 1 This example relates to the experiments on longitudinal turning [9]. Test samples were carbon steel bars DIN Ck45 (steel ANSI 1045) 100 mm in diameter and 380 mm in length. The cutting tool included a holder DDJNL 3225P15 with coated inserts DNMG 150608-PM4025. The tool geometry was with rake angle 17°, clearance angle 5°, tool cutting edge angle 93°, and nose radius 0.8 mm. The experiments were carried out using the rotatable central composite design with five levels (coded by: −1.6817; −1; 0; +1 and +1.6817) of three cutting parameters (Table 1). The cutting force was chosen to be the response.

The required number of experimental points is $N = 2^3 + 6 + 6 = 20$ [2]. There are eight factorial experiments (3 factors on two levels, 23) with added 6 star points and center point (average level) repeated 6 times reduce test error. The test result is represented as

$$F_c = 187.937 - 1970.77f + 10.418a_p + 1598fa_p + 40.6765f^2 + 40.953a_p^2 \quad (3)$$

As can be seen, the factors affecting F_c, are cutting feed f, depth of cut a_p, square of feed f^2 (which can be conditionally termed as ‘self-interaction’), square of depth of cut, a_p^2 (self-interaction), and the interaction of feed and depth of cut $f \cdot a_p$. Therefore, two main and three interaction effects were revealed.

Example 2 As discussed by Astakhov [4], the cutting temperature θ_{ct}, understood as the mean integral temperature at the tool–chip and tool–workpiece interfaces as measured by a tool-work thermocouple, is the most important parameter to correlate the tribological conditions at the discussed interfaces with tool wear. Moreover, for a given combination of the tool and work materials, there is the cutting temperature, referred to as the optimal cutting temperature, at which the combination of minimum tool wear rate, minimum stabilized cutting force, and highest quality of the machined surface is achieved. This temperature is invariant to the way it has been achieved (whether the workpiece was cooled, pre-heated, etc.).

Table 1 Physical and coded values of factors in Test 1

Factors/levels	Lowest	Low	Center	High	Highest
Coding	−1.6817	−1	0	+1	+1.6817
Cutting speed (m/min) $X_1 = v_c$	266	300	350	400	434
Cutting feed (mm/rev) $X_2 = f$	0.23	0.30	0.40	0.50	0.57
Depth of cut (mm) $X_3 = a_p$	1.0	1.5	2.25	3.0	3.5

The objective of the considered test is to establish the correlation of this temperature with parameters of the cutting system. The following correlation equation was used:

$$\theta_{\mathrm{ct}} = C_{\theta} v_c^{x_{\theta}} f^{y_{\theta}} a_p^{z_{\theta}}, \tag{4}$$

where C_{θ} is constant which depends on the properties of the work material, x_{θ}, $y_{\theta,}$ and z_{θ} are powers to be determined in DOE.

The longitudinal turning tests were carried out. Test samples were carbon steel bars made of steel ANSI 1020 of 50 mm in diameter and 260 mm in length. The cutting tool was made of T15 high speed steel. The tool geometry was: rake angle 10°, clearance angle 10°, tool cutting edge angle 45°, and nose radius 0.2 mm. The experiments were carried out using the rotatable central composite design with five levels (coded by: −1.6817; −1; 0; +1 and +1.6817) of three cutting parameters (Table 2). The cutting temperature measured in millimeters of millivolt meter tape was chosen to be the response.

Analogous to the previous example, the required number of experimental points is $N = 2^3 + 6 + 6 = 20$. There are eight factorial experiments (3 factors on two levels, 23) with added 6 star points and center point (average level) repeated 6 times reduce test error. The result DOE is represented as

$$\theta_{\mathrm{ct}} = 26.8 v_c^{(1.58-0.34 \ln v_c)} f^{(0.46-023 \ln f)} a_p^{(0.44-0.15 \ln a_p)} \tag{5}$$

As follows from Eq. (5), the powers x_{θ}, y_{θ} and z_{θ} are not constants as routinely assumed in metal cutting experimental studies; rather, a complicated self-interaction of each factor is revealed by DOE.

Example 3 The third example is the use of DOE in the experimental study of the influence of three parameters: cutting speed, v_c, feed f, and the cutting fluid flow rate Q on the roughness Δ_{sf} and roundness Δ_R of the machined hole in gundrilling [4]. A 2^3 DOE, complete block is used.

The test conditions were as follows:

– Work material: hot rolled medium carbon steel AISI 1040 was used. The test bars, after being cut to length (40 mm diameter, 700 mm length), were normalized to a hardness of HB 200.

Table 2 Physical and coded values of factors in Test 2

Factors/levels	Lowest	Low	Center	High	Highest
Coding	−1.6817	−1	0	+1	+1.6817
Cutting speed (m/s) $X_1 = v_c$	0.072	0.115	0.229	0.454	0.725
Cutting feed (mm/rev) $X_2 = f$	0.082	0.110	0.170	0.260	0.463
Depth of cut (mm) $X_3 = a_p$	0.25	0.36	0.61	1.04	1.49

Table 3 The levels of factors and their intervals of variation

Level of factors	Code	v_c (m/min)	f (mm/rev)	Q (l/min)
Basic	0	100	0.07	60
Interval of variation	Δx_i	15	0.02	20
Upper	+1	115	0.09	80
Lower	−1	85	0.05	40

– Cutting tool: gundrills of 12.1 mm diameter were used. The material of their tips was carbide M 30. The parameters of drill geometry were as discussed in [4].

The levels of the factors and intervals of factor variations are shown in Table 3. At each point of the design matrix, the tests were replicated thrice. The sequence of the tests was arranged using a generator of random numbers.

The results DOE are represented as

Surface roughness

$$\Delta_{\mathrm{sf}} = 2.7446 - 0.0198v - 33.9583f + 0.2833vf \tag{6}$$

Roundness of drilled holes

$$\begin{aligned}\Delta R(\mu\mathrm{m}) = {} & -20.044 + 0.238v + 396f + 0.462Q \\ & - 3.960vf - 0.005vQ - 6.600fQ + 0.066vfQ\end{aligned} \tag{7}$$

Equation (6) reveals that for the selected upper and lower limits of the factors, the surface roughness in gundrilling depends not only on the cutting speed and feed singly, but also on their interaction as follows from Eq. (7). Therefore, although the cutting speed, feed, and cutting fluid flow rate have significant influence of roundness, they cannot be judged individually due to their strong interactions.

Reading these examples, one can wonder what seems to be a problem with factors' interactions? The factors and their interaction are accounted for in the models obtained by full factorial DOEs in the discussed examples. The problem, however, is in the number of factors included in these DOE. For example, in Example 3, the surface roughness and roundness in gundrilling strongly depend not only on the considered factors but also on the many parameters of the gundrill geometry (e.g., the point angles of the outer and inner cutting edges, backtaper, margin width [10]) not included as factors in the test.

Full factorial DOE allows accurate estimation of all factors involved and their interactions. However, the cost and time need for such a test increase with the number of factors considered. Normally, any manufacturing test includes a great number of independent variables. In the testing of drills, for example, there are a number of tool geometry variables (the number of cutting edges, rake angles, flank angles, cutting edge angles, inclination angles, side cutting edge back taper angle, etc.) and design variables (web diameter, cutting fluid holes shape, their cross-sectional area and location, profile angle of the chip removal flute, length of the cutting tip, the shank length and diameter, etc.) that affect drill performance.

Table 4 shows the number of runs needed for the full factorial DOE where the two levels of factors variation are considered (as that used in Example 3). If one runs more accurate DOE discussed in Examples 1 and 2, i.e., using the rotatable central composite design with five levels, the number of tests will be even greater.

The time and cost constraints on such DOE are definitely important in the DOE planning stage. In metal cutting tests, however, other constraints should be considered as they can be decisive. The major problem is with a great number of cutting tools and a significant amount of the work material needed to carry out the tests. It is difficult to keep the parameters of these tools and properties of the work material within limits needed to obtain statistically reliable results when the test program is too large. If the variations of these parameters and properties are also included in DOE, a virtually infinite number of runs would be needed to complete the study.

One may further argue that omitting the influence of the interactions is the price to pay to keep DOE within the reasonable number of runs, and thus within reasonable cost. To understand what can be missed in the test results, let us consider a comparison of the result of tool life DOEs.

The first test is a 2^3 DOE, complete block with the test conditions as in Example 3. The following result, presented as a correlation equation was achieved:

$$T = \frac{e^{9.55} d_w^{0.19}}{v_c^{1.37} f^{0.14}} \tag{8}$$

The second test used to carry out the tool life test in gundrilling is the Group Method of Data Handling (hereafter, GMDH) [11]. This kind of DOE is more complicated than the above-discussed DOEs, but it has a number of advantages in terms of the number of variables included in the test and objectivity of statistical evaluation of the test results [12].

Eleven input factors were selected for the test. They are: x_1 is the approach angle of the outer cutting edge (φ_1); x_2 is the approach angle of the inner cutting edge (φ_2); x_3 is the normal clearance angle of the outer cutting edge (α_1); x_4 is the normal clearance angle of the outer cutting edge (α_2); x_5 is the location distance of the outer cutting edge (c_1); x_6 is the location distance of the outer cutting edge (c_2); x_7 is the location distance of the drill point with respect to the drill axis (m_d); x_8 is the location distance of the two parts of the tool rake face with respect to drill axis (m_k); x_9 is the clearance angle of the auxiliary flank surface (α_3); x_{10} is the cutting speed (v_c); x_{11} is the cutting feed (f). The design matrix is shown in Table 5.

The following result was obtained with GDMT DOE

Table 4 Two-level designs: minimum number of runs as a function of number of factors for full factorial DOE

Number of factors	Number of runs	Number of runs	Number of repetitions	
			3	5
1	2	2	6	10
2	$4 = 2^2$	$4 = 2^2$	12	20
3	$8 = 2^3$	$8 = 2^3$	24	40
4	$16 = 2^4$	$16 = 2^4$	48	80
5	$32 = 2^5$	$32 = 2^5$	96	160
6	$64 = 2^6$	$64 = 2^6$	192	320
7	$128 = 2^7$	$128 = 2^7$	384	640
8	$256 = 2^8$	$256 = 2^8$	768	1280
9	$512 = 2^9$	$512 = 2^9$	1536	2560
10	$1024 = 2^{10}$	$1024 = 2^{10}$	3072	5120

Table 5 The levels of factors and their intervals of variation used in GMDH DOE

Levels	x_1 (°)	x_2 (°)	x_3 (°)	x_4 (°)	x_5 (mm)	x_6 (mm)	x_7 (mm)	x_8 (mm)	x_9 (°)	x_{10} (mm)	x_{11} (mm)
+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

$$
\begin{aligned}
T = 6.7020 &- 0.6518\frac{\alpha_1}{\varphi_2 c_2} - 0.0354\frac{\alpha_2 \ln c_2}{m_d} - 0.0005\frac{\varphi_1^2}{c_2} \\
&+ 0.0168\frac{\ln c_2}{\varphi_1} - 2.8350\frac{vf}{\varphi_1} - 0.5743\frac{c_2 m_d}{\ln \alpha_1 \varphi_1}
\end{aligned} \tag{9}
$$

The statistical model of tool life (Eq. 9) indicates that tool life in gundrilling is a complex function of not only design and process variables but also of their interactions. The inclusion of these interactions in the model brings a new level of understanding about their influence on tool life. For example, 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 [13]. Traditionally, this angle along with approach angle of the inner cutting edge (φ_2) is selected depending on the properties of the work material. Although the contradictive influence of these angles has been observed in practice, none of the studies reveals their correlations with the cutting regime as suggested by Eq. (9). Moreover, three- and four-factor interaction terms are found to be significant.

5 Need for a Screening Test

It is discussed above that although a full factorial DOE and GMDH methods allow accurate estimation of all factors involved and their interactions, the cost and time needed for such tests increase with the number of factors considered. Therefore, the pre-process stage in a full factoring DOE is considered to be of high importance in metal cutting studies [4] because pre-process decisions to be made at this stage are crucial to the test, whereas they are not nearly formalized. Among them, the proper selection of KPIVs is probably the most important.

The major problem in pre-process decision is the selection of KPIVs justifying two important rules:

1. The number of factors should be kept to a possible minimum defined by adequate time, resources, or budget to carry out the study. This is an obvious rule.
2. The second rule pointed out explicitly in the classical paper by Box and Hunter [14] includes the assumptions that the observations are uncorrelated and have equal variance. Note that this is next to impossible to verify the latter in practice.

Often, pre-process decisions rely on experience, available information, and expert opinions and thus they are highly subjective. Even a small inaccuracy in the preprocess decisions may affect the output results dramatically. Therefore, the pre-process stage of full factorial DOE should be more formalized.

As discussed above, any machining test includes a great number of independent variables. However, when many factors are used in DOE, the experiment becomes expensive and time-consuming. Therefore, there is always a dilemma. On one hand, it is desirable to take into consideration only a limited number of KPIVs carefully selected by the experts. On the other hand, even if one essential factor is missed, the final statistical model may not be adequate to the process under study.

Unfortunately, there is no simple and feasible way to justify the decisions made at the pre-process stage about the number of KPIVs prior to the tests. If a mistake is made at this stage, it may show up only at the final stage of DOE when the corresponding statistical criteria are examined. Obviously, it is too late then to correct the test results by adding the missed factor or interaction. However, being of great importance, this problem is not the principal one.

The principal ‘silent’ problem of all experimental studies in metal cutting including DOE studies is that the results obtained in the test are valid only for the set of conditions used in the test, i.e., DOE studies in metal cutting are not efficient (see Sect. 1). To explain this statement consider the common statistical representation of the results of metal cutting test for tool life and for the cutting force defined by Eqs. (1) and (2). The use of these equations in a simple DOE-assisted turning test implies that the cutting force and tool life depend only on the parameters of the machining regime under the fixed work material (kind, grade, and mechanical properties), dimensions of the workpiece (diameter and length) [15], tool geometry parameters (the tool cutting edge angles of the major and minor cutting edges, the rake, clearance, and inclination angles, nose and cutting edge radii, etc.), tool material, particularities of the tool holder, system runout, test setup rigidity, etc. If one or more of the listed parameters is changed, the test results may not be valid for the new machining conditions.

Another dimension of the discussed problem is that a certain (out of the listed) parameter can be not important for one test condition, while for others it is of chief importance. For example, the radius of the cutting edge does not have a significant influence on rough turning of carbon steel where great cutting feeds are used. It, however, becomes important in finish turning with shallow feeds. Moreover, it is of crucial importance in turning of titanium alloys. Another example is backtaper. Backtaper applied to a drill might not be a significant factor in drilling soft materials or cast irons, but it is highly significant in machining titanium and aluminum alloys having low elasticity modulus [10].

The theory of DOE offers a few ways to deal with such a problem [2]. The first relies on the collective experience of the experimentalist(s) and the research team in the determination of KPIVs. However, the more experience such a team has, the more factors they recommend to include in DOE.

A second way is to use screening DOE [16]. This method appears to be more promising in terms of its objectivity. Various screening DOEs are used when a great number of factors are to be investigated using a relatively small number of tests [17]. This kind of test is conducted to identify the significant factors and factors' interactions for further analysis. In other words, the whole project is divided into two stages. In the first stage, the important factors and interaction are determined. These are used in a full factorial DOE in the second stage. In the author's opinion, this is the only feasible way to deal with the above-discussed principal problem.

For the further discussion on the selection of the adequate screening DOE, the notion of the DOE resolution should be briefly introduced.

6 Resolution Level

In general, a particular kind of the statistical model which correlates the factors and factor interactions with the chosen output is initially unknown due to insufficient knowledge of the considered phenomenon. Thus, a certain approximation for this model is needed. Experience shows [18] that a power series or polynomial (Taylor series approximations to the unknown true functional form of the response variable) can be selected as an approximation

Table 6 Resolution levels and their meaning

Resolution level	Meaning
II	Main effects are confounded with others. In other words, main effects are linearly combined with each other ($\beta_i + \beta_j$)
III	Can estimate main effects, but they may be confounded by two variable interactions. In other words, main effects are linearly combined with two-way interactions ($\beta_i + \beta_{jk}$)
IV	Can estimate main effects unconfounded by two variable interactions. Can estimate two variable interactions, but they may be confounded by other two variable interactions. It means that main effects are linearly combined with three-way interactions ($\beta_i + \beta_{jkl}$) and two-way interactions with each other ($\beta_{ij} + \beta_{kl}$)
V	Can estimate main effects unconfounded by three (or lower) variable interactions. Main effects and two-way interactions are not linearly combined except with higher-order interactions ($\beta_i + \beta_{jklm}$) and ($\beta_{ij} + \beta_{klm}$)

$$y = \beta_0 + \sum_{\substack{i=1}}^{p} \sum_{\substack{j=1 \\ i \neq j}}^{p} \beta_{ij} x_i x_j + \sum_{i=1}^{p} \sum_{\substack{j=1 \\ i \neq j \neq k}}^{p} \sum_{k=1}^{p} \beta_{ijk} \, x_i x_j x_k + \cdots, \tag{10}$$

where β_0 is the overall mean response, β_i is the main effect of the factor ($i = 1,2, \ldots, p$), β_{ij} is the two-way interaction effect between the ith and jth factors, and β_{ijk} is the three-way interaction effect between the ith, jth, and kth factors.

Experimental designs can be categorized by their resolution level. A design with a higher resolution level can fit higher-order terms in Eq. (10) than a design with a lower resolution level. If a high enough resolution level design is not used, only the linear combination of several terms can be estimated, not the terms separately. The word “resolution” was borrowed from the term used in optics. Resolution levels are usually denoted by Roman numerals, with III, IV, and V being the most commonly used. To resolve all of the two-way interactions, the resolution level must be at least V [19]. Four resolution levels and their meanings are given in Table 6.

7 Using Fractional Factorial DOEs for Factors Screening

A type of orthogonal array design which allows experimenters to study the main effects and some desired interaction effects in a minimum number of trials or experimental runs is called a fractional factorial design [2]. These fractional factorial designs are the most widely and commonly used types of design in industry.

In the introduction of this type of DOE, the following rationale is provided. In theory, it is possible that every variable that is tested has interactions with every specific value of every other variable. In practice, this is usually not the case.

During tests, one may discover that many or even most of the elements that have been decided to include do not impact performance at all. They simply do not affect the output variable. It is also common that strong interactions between two variables exist but that higher-order interactions (among three or more variables) are insignificant. In such cases, the behavior of the output variable can be described by looking at the main effects and a few low-order interactions (involving two variables). Unfortunately, not much attention is paid to the described limitation. In other words, no effort is made to verify that these limitations are applicable in a particular test.

The mentioned basic idea of the fractional factorial design arises as a consequence of three empirical principles commonly accepted in the testing community:

1. *Hierarchical Ordering Principle*. Lower-order effects are more likely to be important than higher-order effects. Effects of the same order are equally likely to be important. This principle suggests that when resources are scarce (i.e., the data collection rate low), priority should be given to estimating main effects and lower-order interactions.
2. *Effect Sparsity Principle*. The numbers of relatively important effects in a factorial experiment are small. This is another formulation of the 80/20 rule. Only a few variables combine to produce the biggest effects, and all of the rest will not matter nearly as much.
3. *Effect Heredity Principle*. In order for an interaction to be significant, at least one of its parent factors should be significant. This is another application of common sense. If a variable does not produce any big effects of its own (i.e., it is benign or negligible), it is unlikely to do so when combined with something else. It may be that a big interaction effect is produced by variables that do not show the largest main effects, but at least one of the variables involved in an interaction will usually show some main effect.

The underlying rationale behind fractional factorial design is that one can collect data on a fraction of the recipes needed for an equivalent full factorial design and still maximize the model's predictive value.

Fractional factorial designs are expressed using the notation l^{k-p} (l is the common branching factor for all variables (the number of levels of factors) in the test; k is the number of variables (factors) investigated, and p describes the size of the fraction of the full factorial search space used. $1/2^p$ represents the fraction of the full factorial 2 k [20]. For example, $2^{(5-2)}$ is a 1/4th fraction of a 2^5 full factorial DOE. This means that one may be able to study 5 factors at 2 levels in just 8 experimental trials instead of 32 trials. In mathematical terms, p is the number of generators (elements in your model that are confounded and cannot be estimated independently of each other). In other words, when p is increased, some of the input variables are not independent and can be explained by some combination of the other input variables or their interactions.

Creating a proper fractional factorial design is beyond the scope of this chapter. The basic steps are as follows:

- Based on the generators (see above) of the chosen design, one can determine the defining relation.
- The defining relation specifies the alias structure.
- A fractional factorial experiment is created from a full factorial experiment by using the chosen alias structure.

One common constraint on fractional factorial tests is that the branching factor is two for all variables (i.e. $l = 2$). The methods for creating custom test designs outside of this constraint are complex. Many testers simply copy “standard” designs from statistical texts or use standard DOE software packages, and thus restrict themselves to a choice of variables and branching factors that fit the model.

7.1 Short Overview of Common Fractional Factorial Methods

Although there is some difference in common fractional factorial methods, their basic predictive power, required data sample size, and underlying assumptions are pretty similar. The main difference lies in the shape of the search spaces that each can be used for. So if one is going to use any of the methods below, the final decision should be based on one’s familiarity with each and the number and branching factor of the variables included in the test.

In the following sections, the sparsest fractional factorial approaches are described in detail:

- Plackett–Burman,
- Latin squares,
- Taguchi method.

There is no reason to prefer the Taguchi method over Plackett–Burman or Latin squares. All three fractional factorial methods suffer from the same fundamental issues. These problems are a direct consequence of their origins in manufacturing. Let us take a look at some of the characteristics of this original environment:

1. *Expensive prototypes*. The underlying assumption is that creating alternative recipes is difficult, time-consuming, or expensive. When applications involve physical processes or manufacturing technology, this is indeed the case. So the goal is to minimize the required number of recipes (also called “prototypes” or “experimental treatments”) in the experiment.
2. *Small test sizes*. A direct consequence of the expensive prototypes is that one needs to keep the number of elements that he or she tests to an absolute minimum, and focus only on the most critical variables.
3. *No interactions*. As another consequence of the expensive prototypes, one can only measure the main effects created by the included variables. The small test

size and expensive data collection force one to assume very sparse fractional factorial models that cannot accurately estimate even two variable interactions.
4. *High yields*. In most cases, the process or outcome that one is measuring had a high probability of success.
5. *Continuous variables*. Many of the input variables involved in the tests were continuous (e.g., temperature, cutting force). Although one had to pick specific levels of the variable for the test, he or she could often interpolate between them to estimate what would happen at non-sampled settings of the variable.

These approaches were transplanted to the manufacturing tests (and machining tests in particular) because of their relative simplicity and familiarity. Unfortunately, the assumptions that accompanied them came along for the ride, even though they were not applicable to the new environment where factors' interactions may play a significant role.

All three listed fractional factorial methods are resolution III designs. It implies that they can only estimate the main effects in the model. In other words, they cannot capture all possible two-variable interactions (or any higher-order interactions). Some of them explicitly assume that there are no interactions. They use this radical assumption to dramatically lower the number of sampled recipes and the amount of data required to estimate the main effects. An important additional requirement for all of these approaches is that the data collection is balanced across all possible values of a variable.

Let us assume that one wants to collect data for each of the variable main effects in the examples that follow. He or she can construct a series of increasingly larger tests and see how to achieve the desired results with only a few recipes. The simplest case is an A-B split test containing two recipes, *a* and *b* [2, 8]. He or she needs to split the traffic 50/50 between *a* and *b*. Therefore, two recipes are needed to measure the two values of variable *V*1. These two recipes represent the entire search space.

Now imagine that one has two variables, each with a branching factor of two. This results in four possible recipes: *aa*, *ab*, *ba*, and *bb*. Assume further that one chooses to sample only from recipes *aa*, and *bb* (still only two recipes as in the previous example). Note that half the data collected involves *V*1*a* (from recipe *aa*), while the other half involves *V*1*b* (from recipe *bb*). Similarly, half the data covers *V*2*a* (from recipe *aa*), while the other half involves *V*2*b* (from recipe *bb*). As you can see, equal amounts of data on each main effect are collected, which was done by sampling only half of the total search space (two out of four recipes).

Let us extend the considered example to three variables, each with a branching factor of two. This results in eight possible recipes: *aaa*, *aab*, *aba*, *abb*, *baa*, *bab*, *bba*, and *bbb*. Assume that one chooses to sample only from recipes *aaa* and *bbb* (still only two recipes). Note that half the data that one collects involves *V*1*a* (from recipe *aaa*), while the other half involves *V*1*b* (from recipe *bbb*). Similarly, half the data collected covers *V*2*a* (from recipe *aaa*), while the other half involves *V*2*b* (from recipe *bbb*). A half of the collected data will also cover *V*3*a* (from recipe *aaa*), while the other half will cover *V*3*b* (from recipe *bbb*). As can be seen, equal amounts of data have been collected again on each main effect, and have done it by sampling only a quarter of the total search space (two out of eight recipes).

Of course one cannot continue to sample just two recipes and still cover all main effects at larger test sizes. But by clever test construction, one can keep the number of unique recipes surprisingly small (especially when considered as a proportion of the total search space).

Underlying the use of fractional factorial methods is the assumption that creating a test run is difficult or time-consuming. Therefore, one needs to keep the number of recipes that he or she samples as low as possible. This may have been true in the manufacturing setting. For practical data collection purposes, it does not matter how many unique recipes one has in the test. When recipe construction is expensive and time-consuming, a heavy price is paid during data gathering. By sampling very limited recipes, one can significantly reduce the cost of testing. In doing so, however, he or she destroys the ability to do a comprehensive analysis and find variable interactions later.

7.1.1 Plackett–Burman DOE

The idea and principles of the DOE was published by R.L. Plackett and J. P. Burman in their paper "The Design of Optimal Multifactorial Experiments" in 1946 [21]. In it, they describe a very efficient and economical method for constructing test designs. The requirements for a Plackett–Burman (PB) design are a branching factor of two on all variables, and the number of recipes sampled must be a multiple of four. PB designs exist for 12, 20, 24, 28, and larger sizes. Each PB design can estimate the main effects of one fewer variable than the size of the design (e.g., the PB design with 24 recipes may be used for an experiment containing up to 23 two-value variables).

PB designs are all resolution III and are known as saturated main effect designs because all degrees of freedom in the model are used to estimate the main effects. PB designs are also known as nongeometric designs. Because of their construction, they do not have a defining relationship (since interactions are not identically equal to main effects). They are efficient at detecting large main effects (assuming that all interactions are relatively small). It was discovered in the 1990s that PB designs have an additional interesting property of being "3-projectible." This means that one can find important interactions involving any subset of three variables in the design. The use of this remarkable property will be discussed further.

7.1.2 Latin Squares

Latin squares were first described by Euler in 1782 [22]. They are used for a number of applications (including the popular Sudoku puzzles) and have extensive mathematical literature describing them.

Latin squares are square arrangements of numbers and can be of different sizes (2×2, 3×3, etc.). Each position in the Latin square contains one of the numbers (from 1 to n) arranged in such a way that no orthogonal (row or column) contains the same number twice.

The two possible Latin squares of size 2×2 shown here are

$$\begin{bmatrix} 1 & 2 \\ 2 & 1 \end{bmatrix} \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix} \tag{11}$$

The 12 possible Latin squares of size 3×3 shown here are

$$\begin{matrix} \begin{bmatrix} 1 & 2 & 3 \\ 2 & 3 & 1 \\ 3 & 1 & 2 \end{bmatrix} & \begin{bmatrix} 1 & 2 & 3 \\ 3 & 1 & 2 \\ 2 & 3 & 1 \end{bmatrix} & \begin{bmatrix} 1 & 3 & 2 \\ 3 & 1 & 2 \\ 2 & 3 & 1 \end{bmatrix} & \begin{bmatrix} 1 & 3 & 3 \\ 2 & 1 & 1 \\ 3 & 1 & 2 \end{bmatrix} & \begin{bmatrix} 1 & 2 & 3 \\ 2 & 3 & 1 \\ 3 & 1 & 2 \end{bmatrix} & \begin{bmatrix} 1 & 2 & 3 \\ 2 & 3 & 1 \\ 3 & 1 & 2 \end{bmatrix} \\ \begin{bmatrix} 1 & 2 & 3 \\ 2 & 3 & 1 \\ 3 & 1 & 2 \end{bmatrix} & \begin{bmatrix} 1 & 2 & 3 \\ 2 & 3 & 1 \\ 3 & 1 & 2 \end{bmatrix} & \begin{bmatrix} 1 & 2 & 3 \\ 2 & 3 & 1 \\ 3 & 1 & 2 \end{bmatrix} & \begin{bmatrix} 1 & 2 & 3 \\ 2 & 3 & 1 \\ 3 & 1 & 2 \end{bmatrix} & \begin{bmatrix} 1 & 2 & 3 \\ 2 & 3 & 1 \\ 3 & 1 & 2 \end{bmatrix} & \begin{bmatrix} 1 & 2 & 3 \\ 2 & 3 & 1 \\ 3 & 1 & 2 \end{bmatrix} \end{matrix} \tag{12}$$

The number of possible Latin squares grows very quickly with the size (576 at size 4×4, 161,280 at size 5×5, etc.)

Latin squares are used in experimental designs when input variables of interest have a branching factor of greater than two, and there are assumed to be no interactions among the input variables. The combination of the row and columns labels with the cell contents in the Latin square defines a recipe in the experimental design. For example, let us assume that one wants to understand the effect of four different Co contents (%) in the carbide tool material on the radial accuracy (wear) of a single-point cutter. If he or she has four tool holders and four operators available, then a full factorial design (for a total of 64 recipes) can be employed.

However, if he or she is not really interested in which tool holder is better or which operator is more productive, nor any minor interaction effects between tool holders and operators and tool holders and machine tools, then other type of DOE can be used. In other words, the major concern is to estimate the main effects. As such, it is desirable to make sure that the main effects for tool holders and machine tools do not bias the obtained estimates for the cobalt content. Hence, one can randomize across all tool holders and operators by using the following 4×4 Latin square design, illustrated in Table 7, where each letter represents one of the cobalt contents being tested.

As can be seen, each operator will try cutting inserts of every cobalt content and each machine tool will be run using inserts of every cobalt content. The assumption that all variables are independent allows one to complete the study by sampling only 16 recipes (instead of the full 64).

Table 7 Design matrix

	Machine tool				
Operator		1	2	3	4
	1	A	B	C	D
	2	B	A	D	C
	3	C	D	A	B
	4	D	C	B	A

7.1.3 Taguchi Method

Genichi Taguchi was a Japanese mathematician and a proponent of manufacturing quality engineering. He focused on methods to improve the quality of manufactured goods through both statistical process control and specific business management techniques. Taguchi developed many of his key concepts outside of the traditional Design of Experiments (DOE) framework and only learned of it later. His main focus was on robustness—how to develop a system that performed reliably even in the presence of significant noise or variation [23]. In traditional DOE, the goal is to model the best-performing recipe. In other words, the higher the value of the output variable (e.g., tool life), the better. So the goal is to find the highest mean. When taking repeated samples, any variation is considered a problem or a nuisance.

Taguchi had a different perspective. He felt that manufacturing quality should be measured by the amount of deviation from the desired value. In other words, he was concerned not only with the mean, but also with the amount of variation or "noise" produced by changing the input variables. Hence optimization from the Taguchi perspective means finding the best settings for the input variables, defined as the ones producing the highest signal-to-noise ratio (the highest mean with the least amount of variation). An important consideration is how to keep the noise in the output low even in the face of noisy inputs.

The numbers of variables (factors) and alternative values for each variable (levels) is arbitrary in metal cutting optimization tests. One can easily find additional variables to test, or come up with alternative values for each variable. Unfortunately, basic Taguchi arrays exist only for the following experimental designs: L4: Three two-level factors; L8: Seven two-level factors; L9: Four three-level factors; L12: Eleven two-level factors; L16: Fifteen two-level factors; L16b: Five four-level factors; L18: One two-level and seven three-level factors; L25: Six five-level factors; L27: Thirteen three-level factors; L32—Thirty-two two-level factors; L32b: One two-level factor and nine four-level factors; L36: Eleven two-level factors and twelve three-level factors; L36b: Three two-level and twelve three-level factors; L50: One two-level factor and eleven five-level factors; L54: One two-level factor and twenty-five three-level factors; L64: Twenty-one four-level factors; L81: Forty three-level factors.

Orthogonal arrays are particularly popular in applications Taguchi methods in technological experiments and manufacturing. An extensive discussion is given in [24–26]. For simplest experiments, the Taguchi experiments are the same as the fractional factorial experiments in the classical DOE. Even for common experiments used in the industry for problem solving and design improvements, the main attractions of the Taguchi approach are standardized methods for experiment designs and analyses of results. To use the Taguchi approach for modest experimental studies, one does not need to be an expert in statistical science. This allows working engineers on the design and production floor to confidently apply the technique.

While there is not much difference between different types of fractional factorial methods for simpler experiment designs, for mixed level factor designs and building robustness in products and processes, the Taguchi approach offers some revolutionary concepts that were not known even to the expert experimenters. These include standard *method for array modifications*, experiment designs to include *noise factors in the outer array*, *signal-to-noise ratios* for analysis of results, *loss function* to quantify design improvements in terms of dollars, treatment of systems with *dynamic characteristics*, etc. [23].

Although the Taguchi method was developed as a powerful statistical method for shop floor quality improvement, a way too many researchers have been using this method as a research and even optimization method in manufacturing, and thus in metal cutting studies (for example, [27–31]).

Unfortunately, it became popular to consider the use of only a fraction of the number of test combinations needed for a full factorial design. That interest spread because many practitioners do not take the time to find out the "price" paid when one uses fractional factorial DOEs including the Taguchi method: (1) Certain interaction effects lose their contrast so knowledge of their existence is gone; (2) Significant main effects and important interactions have aliases—other 'confounding' interaction names. Thus wrong answers can, and often do come from the time, money, and effort of the experiment.

Books on DOE written by "statistical" specialists add confusion to the matter claiming that interactions (three-factor or higher order) would be too difficult to explain, nor could they be important. The author wishes to remind to many statisticians that the ideal gas law (1834 by Emil Clapeyron), known from high-school physics as

$$PV = nRT \tag{13}$$

(where P is the pressure of the confined gas, V is the volume of the confined gas, n is the number of moles of gas, R is gas constant, T is the temperature) plots as a simple graph. It depicts a three-factor interaction affecting y (response) as pressure, or as volume. The authors of these statistical books/papers may have forgotten their course in high-school physics.

The problem is that the ability of the Taguchi method is greatly overstated by its promoters, who described Taguchi orthogonal tables as Japan's "secret super weapon," which is the real reason for developing an international reputation for quality. The major claim is that a large number of variables could now be handled with practical efficiency in a single DOE. As later details became available, many professionals realized that these arrays were fractional factorials, and that Taguchi went to greater extremes that other statisticians in the degree of fractionating. According to the Taguchi method, the design is often filled with as many single factors for which it has room. The design becomes “saturated” so no degrees of freedom are left for its proper statistical analysis. The growing interest in the Taguchi method in the research and optimization studies in manufacturing attests to the fact that manufacturing researches either are not aware of the above-mentioned “price” paid for apparent simplicity or know of no other way to handle more and more variables at one time.

7.2 Two-Stage DOE in Metal Cutting Tests

By now, readers have probably determined the author’s preference for full factorial over fractional factorial data collection in metal cutting studies. There is no efficiency disadvantage to full factorial designs during the data collection stage and significant advantages during the analysis stage. As discussed above, the major limitation is in the number of factors included as the cost, time, and test accuracy depend on this number. This problem can, and in the author’s opinion, should be resolved by using two-stage approach to testing. Ideally, the first, simple, and relatively inexpensive stage of DOEs in metal cutting should provide a help in determining the significant factors and interactions to be included in any kind of full factorial DOE to be used in the second stage of the study. Therefore, a closer look at various fractional factorial DOEs should be taken to find which one can justify the above-mentioned requirements.

Most Taguchi method test arrays are resolution III design, and thus can only estimate the main effects in the model. In other words, they cannot capture all possible two-variable interactions (or any higher-order interactions). Some of them explicitly assume that there are no interactions. They use this radical assumption to dramatically lower the number of sampled recipes and amount of data required to estimate the main effects. An important additional requirement for all of these approaches is that data collection is balanced across all possible values of a variable (i.e., you cannot use uneven data sampling, or it may complicate or throw off your use of standard data analysis).

8 The Use of Plackett and Burman DOE as a Sieve DOE in Metal Cutting

As discussed above, Plackett and Burman [21] developed a special class of fractional factorial experiments that includes interactions. When PB DOE is conducted properly using a completely randomized sequence, its distinctive feature is high resolution.

Despite a number of disadvantages (for example, mixed estimation of regression coefficients), this method utilizes high-contrast diagrams for the factors included in the test as well as for their interactions of any order. This advantage of PB DOE is useful in screening tests in metal cutting studies [32].

The method has its foundation in the Plackett–Burman design ideas, an over-saturated design matrix and the method of random balance. PB DOE allows the experimentalist to include as many factors (impute variables) as needed at the first phase of the experimental study and then to sieve out the nonessential factors and interactions by conducting a relatively small number of tests. It is understood that no statistical model can be produced in this stage. Instead, this method allows the experimentalist to determine the most essential factors and their interactions to be used at the second stage of DOE (full factorial or RSM DOE).

PB DOE includes the method of random balance. This method utilizes over-saturated design plans where the number of tests is fewer than the number of factors and thus has a negative number of degrees of freedom [33]. It is postulated that if the effects (factors and their interactions) taken into consideration are arranged as a decaying sequence (in the order of their impact on the variance of the response), this will approximate a ranged exponential-decay series. Using a limited number of tests, the experimentalist determines the coefficients of this series and then, using the regression analysis, estimates the significant effects and any of their interactions that have a high contrast in the noise field formed by the insignificant effects.

The initial linear mathematical model, which includes k number of factors (effects), has the following form:

$$y = a_0 + a_1x_1 + \cdots + a_kx_k + a_{12}x_1x_2 + \cdots + a_{k-1,k}x_{k-1}x_k + \delta, \tag{14}$$

where a_0 is the absolute term often called the main effect, a_i (i = 1, k) are the coefficients of linear terms, a_{ij} (i = 1, …, k − 1; j = i + 1, …, k, $i \neq j$) are the coefficients of interaction terms, and δ is the residual error of the model.

The complete model represented by Eq. (14) can be rearranged as a split of a linear form considering that some x_i designate the iterations terms as

$$\begin{aligned} y &= a_0 + a_1x_1 + \cdots + a_{k-l,k}x_{k-l} + b_1z_1 + b_2z_2 + \cdots b_lz_l + \delta \\ &= a_0 + a_1x_1 + \cdots + a_{k-l,k}x_{k-l} + \Delta \end{aligned}, \tag{15}$$

where

$$\Delta = b_1z_1 + b_2z_2 + \cdots b_lz_l + \delta \tag{16}$$

and

$$\sigma^2\{\Delta\} = b_1^2\sigma^2\{z_1\} + b_2^2\sigma^2\{z_2\} \cdots + b_l^2\sigma^2\{z_l\} + \sigma^2\{\delta\} \tag{17}$$

In the construction of the split model represented by Eq. (15), *(k − l)* significant effects were distinguished and l effects were assigned to the noise field. Naturally, the residual variance $\sigma^2\{\Delta\}$ is greater than the tests variance $\sigma^2\{\delta\}$ so that the regression coefficients in Eq. (15) will be estimated with greater errors and, moreover, the estimates of the coefficients of this model are mixed. Therefore, the sensitivity of the random balance method is low so that the resultant model has a little significance, and thus should not be used as a valid statistical model. However, this method is characterized by the great contrast of essential effects, which could be distinguished easily on the noisy fields formed by other effects. The latter makes this method the simplest yet highly reliable screening method that can be used at the first stage of testing to distinguish the significant factors and interaction to be used in the full factoring DOE including RSM.

The step-by-step methodology of the discussed test was presented by the author earlier using a tool life test of the gundrill as an example [31]. The test was carried out using eight parameters of the gundrill geometry as the input variables. The test result shows two linear effects and one interaction having the strongest effects on tool life. As was expected (well known from the practice of gundrilling [10]), the strongest influence on tool life has the drill point offset m_d. The second strongest effect was found to be the approach angle of the outer cutting edge, φ_1. This result is also expected. What was not expected is a strong influence of the interaction term "shoulder dub-off location—the approach angle of the outer cutting edge." This distinguished interaction has never been considered before in any known studies of gundrilling. Using this factor and results of the full factorial DOE, a new pioneering geometry of gundrills has been developed (for example US Patent 7147411).

Another implementation of this DOE is considered in this chapter. It deals with sieve test to reveal significant factors of the tool geometry of 5 mm drill that affect tool life. The parameters chosen for the test and their levels are shown in Table 8. The construction of this table is based on the manufacturing practice and preliminary observations of the performance of this drill type in machining of a medium-carbon steel of HB 149 hardness.

The design matrix was constructed as follows. All the selected factors were separated into two groups. The first group contained factors x_1, x_2, x_3, x_4, form a half-replica 2^{4-1} with the defining relation $I = x_1x_2x_3x_4$. In this half-replica, the factors' effects and the effects of their interactions are not mixed. The second half-replica was constructed using the same criteria. A design matrix was constructed using the first half-replica of the complete matrix and adding to each row of this replica a randomly selected row from the second half-replica. Three more rows were added to this matrix to assure proper mixing and these rows were randomly selected from the first and second half-replicas. Table 9 shows the constructed design matrix.

As soon as the design matrix is completed, its suitability should be examined using two simple rules. First, a design matrix is suitable if it does not contain two identical columns having the same or alternate signs. Second, a design matrix should not contain columns whose scalar products with any other column result in a column of the same ("+" or "−") signs. The design matrix shown in Table 9 was found suitable as it meets the requirements set by these rules.

Table 8 The levels of the factors selected for the sieve DOE

Factors	Length of working part, w (mm)	Clearance angle, α_n (°)	Point angle, φ_p (°)	Web diameter, d_w (mm)	Length of the chisel edge (mm)	Margin width, b_m (mm)	Surface roughness the rake and flank faces (μm)	Hardness HRC
Code designation	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8
Upper level (+)	58.7	20	136	0.91	1.5	0.7	0.81	65.4
Lower level (−)	56.6	10	118	0.81	0.2	0.5	0.57	64.2

Table 9 Design matrix

Run	Factors								Average tool life (min)	Corrections	
	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	$\bar{y}$	$\bar{y}_{c1}$	$\bar{y}_{c2}$
1	+1	+1	−1	−1	+1	−1	+1	−1	10.80	16.80	13.60
2	+1	+1	+1	+1	−1	+1	+1	−1	17.20	10.08	6.83
3	−1	+1	−1	−1	+1	+1	−1	+1	9.09	9.09	2.64
4	−1	−1	+1	+1	+1	−1	−1	+1	42.00	28.26	21.81
5	+1	−1	−1	+1	−1	−1	+1	−1	16.91	9.17	9.17
6	+1	−1	+1	−1	+1	+1	−1	−1	19.46	25.46	19.01
7	−1	−1	−1	−1	−1	+1	−1	+1	10.21	10.21	10.21
8	−1	+1	−1	+1	−1	−1	+1	+1	27.31	13.57	13.57
9	+1	−1	−1	−1	−1	+1	−1	+1	4.54	10.54	10.54
10	−1	+1	+1	+1	−1	+1	−1	−1	36.00	22.26	19.01
11	+1	−1	+1	−1	−1	−1	+1	−1	12.20	18.20	14.95

The results of the first round of the tests are shown in Table 9 as the responses $\bar{y}_i$ i … 11. They are the average tool life calculated over three independent tests replicas (3 replicas were used) obtained under the indicated test conditions. Analysis of these results begins with the construction of a correlation (scatter) diagram shown in Fig. 2. Its structure is self-evident. Each factor is represented by a vertical bar having on its left side values (as dots) of the response obtained when this factor was positive (the upper value), while the values of the response corresponding to lower lever of the considered factor (i.e., when this factor is negative) are represented by dots on the right side of the bar. As such, the scale makes sense only along the vertical axis.

Each factor included in the experiment is estimated independently. The simplest way to do this is to calculate the distance between means on the left and right side of each bar. These distances are shown on the correlation diagram in Fig. 2. Another way is to take into account the number of points in the upper and lower part of the scatter diagram. For example, there are three dots for factor x_4 (Fig. 2) at the (+) level that have resonances greater than the greatest response on the (−) level. Similarly, there are four dots at the (−) level that have responses smaller than the smallest response at the (+) level. The total number of distinguishing points for factor x_4 is seven. In Fig. 2, a large group of such dots is signified by braces. The greater the number of distinguishing points, the stranger effect the corresponding factor has.

As seen in Fig. 2, factors x_1 and x_4 can be easily distinguished after the first sieve. Thus these two factors are selected for analysis. The effects of factors are calculated using special correlation tables. A correlation table (Table 10) was constructed to analyze the considered two factors. Using the correlation table, the effect of each selected factor can be estimated as

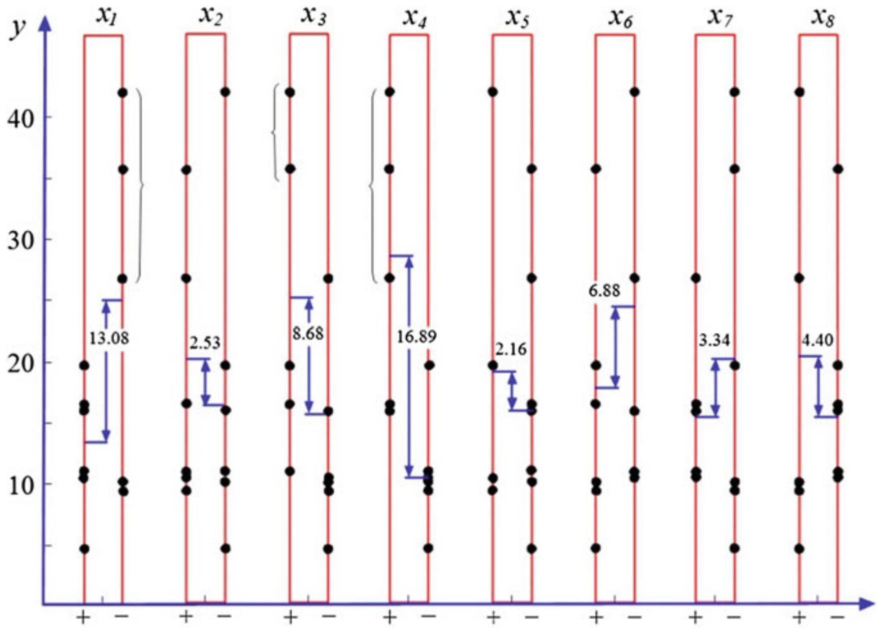

Fig. 2 Correlation diagram (original data)

$$X_i = \frac{\bar{y}_1 + \bar{y}_3 + \cdots + \bar{y}_n}{m} - \frac{\bar{y}_2 + \bar{y}_4 + \cdots + \bar{y}_{n-1}}{m}, \tag{18}$$

where m is the number of $\bar{y}$ in Table 10 for the considered factor assigned to the same sign ("+" or "−"). It follows from Table 10 that $m = 2$.

The effects of the selected factors were estimated using data in Table 10 and Eq. (18) as

$$X_1 = \frac{\bar{y}_{1-1} + \bar{y}_{1-3}}{2} - \frac{\bar{y}_{1-2} + \bar{y}_{1-4}}{2} = \frac{17.37 + 11.75}{2} - \frac{31.5 + 9.65}{2} = -6.00 \tag{19}$$

$$X_4 = \frac{\bar{y}_{1-1} + \bar{y}_{1-2}}{2} - \frac{\bar{y}_{1-3} + \bar{y}_{1-4}}{2} = \frac{17.37 + 31.50}{2} - \frac{11.75 + 9.65}{2} = 13.74 \tag{20}$$

The significance of the selected factors is examined using the Student's t-criterion, calculated as

$$t = \frac{\left(\bar{y}_{1-1} + \bar{y}_{1-3} + \cdots + \bar{y}_{1-n}\right) - \left(\bar{y}_{1-2} + \bar{y}_{1-4} + \cdots + \bar{y}_{1-(n-1)}\right)}{\sqrt{\sum_i \frac{s_i^2}{n_i}}}, \tag{21}$$

where s_i is the standard deviation of ith cell of the correlation table defined as

Table 10 Correlation table (original data)

Estimated factor	$+x_1$	$-x_1$	Estimated factor	$+x_1$	$-x_1$
$+x_4$	17.82 16.91 $\sum y_{1-1} = 34.73$ $\bar{y}_{1-1} = 17.37$	36.00 42.00 27.31 $\sum y_{1-2} = 105.31$ $\bar{y}_{1-2} = 31.50$	$-x_4$	10.80 19.46 4.54 12.20 $\sum y_{1-3} = 47.00$ $\bar{y}_{1-3} = 11.75$	9.09 10.21 $\sum y_{1-4} = 19.30$ $\bar{y}_{1-4} = 9.65$

$$s_i = \sqrt{\frac{\sum_i y_i^2}{n_i - 1} - \frac{\left(\sum_i y_i\right)^2}{n_i(n_i - 1)}}, \tag{22}$$

where n_i is the number of terms in the considered cell.

For the considered case, the Student's criteria, calculated using Eqs. (21) and (22), are $t_{X_1} = -2.37$ and $t_{X_4} = 5.18$. A factor is considered to be significant if $t_{X_i} > t_{\text{cr}}$ where the critical value, t_{cr} for the Student's criterion in found in a statistical table for the following number of degrees of freedom

$$f_r = \sum_i n_i - k = 11 - 4 = 7, \tag{23}$$

where k is the number of cells in the correlation table.

For the considered case, $t_{0.05} = 2.365$ and $t_{0.10} = 1.895$ (Table 5.7 in [34]) so that the considered factors are significant with a 95 % confidence level.

The discussed procedure is the first stage in the proposed sieve DOE. This first stage allows the detection of the strongest factors, i.e., those factors that have the strongest influence on the response. After these strong linear effects are detected, the size of "the screen" to be used in the consecutive sieves is reduced to distinguish less strong effects and their interactions. Such a correction is carried out by adding the effects (with the reverse signs) of the selected factors (Eqs. 19 and 20) to column $\bar{y}$ of Table 9, namely by adding +6.00 to all results at level "$+x_1$" and −13.74 to all results at level "$+x_4$." The corrected results are shown in column $\bar{y}_{c1}$ of Table 9.

Following the procedure presented by the author earlier [7] and using the results shown in column $\bar{y}_{c1}$ of Table 9, one can construct a new correlation diagram shown in Fig. 3, where for simplicity, only a few interactions are shown although all possible interactions have been analyzed through constructing a new correlation table. Evaluation of the effects obtained and the subsequent corrections of the results are carried out till the remaining effects are found insignificant as having less than 10 % significance level. In the considered case, the sieve procedure was stopped after the second sieve (the corrected results are shown in column $\bar{y}_{c2}$ of Table 9). Aftereffects X_7 and X_8 of the corresponding factors were found

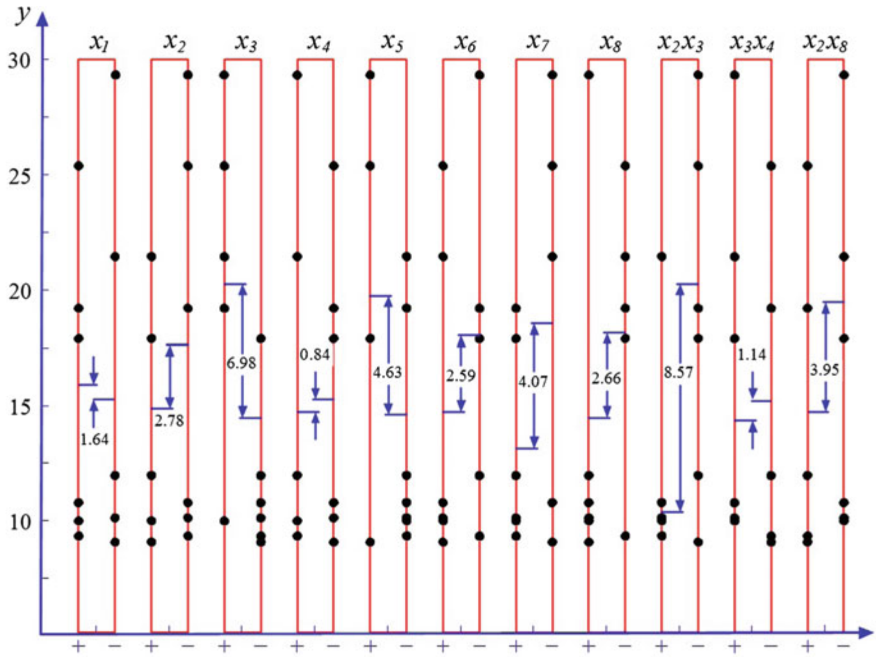

Fig. 3 Correlation diagram (first sieve)

insignificant because the calculated student's coefficients for these factors are $t_7 = 0.79$ and $t_8 = 0.87$, whereas the critical value, $t_{cr(0.10)} = 1.865$.

A scatter diagram was constructed (Fig. 4) to visualize the screening effects. As can be seen, the scatter of the factors reduces after each screening. The results of factors screening are shown in Table 11. Figure 5 shows the significance of the distinguished effects in terms of their influence on tool life. As seen, four linear effects and one interaction were distinguished.

The analysis of the obtained results shows that the web diameter has the strongest effect on tool life. This result was expected by the known experience [10]. What was not expected is the second strongest effect of the interaction of the clearance angle with the point angle, particularly the negative sign of this interaction. The meaning of the negative sign of x_2x_3 and x_1 is that tool life decreases when these parameters increase. The obtained effect of factors x_3, x_1, and x_5 are known from drilling practice.

Consider another example of the use of PB DOE in face milling of a gray cast iron pump cover with a face milling tool equipped with PCBN cartridges. Twelve input factors, including machining regime and tool geometry parameters, were included in DOE, namely x_1 is the cutting speed (m/min); x_2 is the cutting feed (mm/rev); x_3 is the depth of cut (mm); x_4 is the length of the chamfer cutting edge (mm); x_5 is the normal rake angle (°); x_6 is the normal clearance angle of the major cutting edge (°); x_7 is the normal clearance angle of the minor cutting edge (°); x_8 is

Fig. 4 Scatter diagram

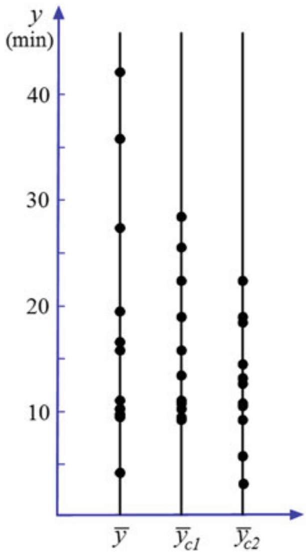

Table 11 Summary of the screening test

Stage of analysis	Effects	Value of effects	Calculated t-criteria
Initial data	X_1	−6.00	2.37
First sieve	X_4	13.74	5.18
	X_3	6.36	2.38
	X_5	3.20	1.91
	X_2^{a}	–	–
Second sieve	X_7	2.71	0.87
	X_8	2.03	0.79

[a]Factor is distinguished due to its interaction with factor x_3 with effect −7.65 (t_{23} = 1.97)

Fig. 5 Significance of the effects distinguished by the sieve DOE (Pareto analysis)

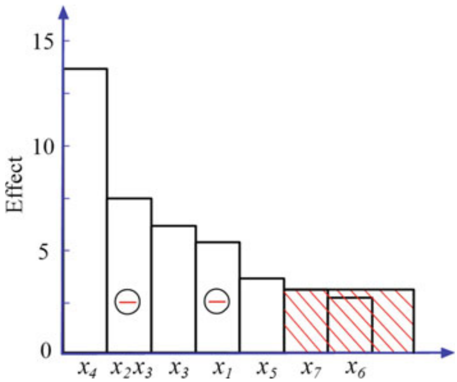

Table 12 The levels of factors selected for the sieve DOE

Factors	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}	x_{12}
+1	1580	0.25	0.50	2.0	+5	20	20	20	0.2	60	30	10
−1	700	0.05	0.05	0.5	−15	5	5	5	0	30	10	0
0	1180	0.75	0.275	1.25	−5	12.5	12.5	12.5	0.1	45	20	5

the normal clearance angle of the chamfered part of the cutting edge (°); x_9 is the edge preparation parameter (mm); x_{10} is the tool cutting edge angle of the major cutting edge (°); x_{11} is the tool cutting edge angle of the minor cutting edge (°); x_{12} is the inclination (in the tool-in-holder system [35]) angle of the major cutting edge (°). The levels of factors are shown in Table 12. Experience shows that these include parameters may affect tool life; some of them significantly whereas other might have much less significant effect depending on the machining conditions, setting level of factors, and other test particularities.

The tool life, T measured by the operating time over which the roughness of the milled surface remains less than or equal to Ra = 1.25 microns was chosen as the response (the test output). Pre-DOE experience shows that the flank wear is the predominant wear mode under the test conditions. As such, the average flank wear VB_B = 0.3–0.5 mm was observed at the end of tool life. Moreover, it particular value in this range depends on the test conditions (Table 12).

The design matrix was constructed by random mixing of four one-fourth replicas the matrix of the full factorial DOE. All the selected factors were separated into two groups. Factors x_1, x_2, x_3, x_4, x_5, x_6 are gathered in the first group used to contract a one-fourth replica of the full factorial DOE 2^{6-2} with defining contrast $1 = x_1\, x_2\, x_3\, x_5$. In this replica, the effects of the factors are not mixed. The same way is used to construct replica for the other half of the factors. A design matrix was constructed using the first half-replica of the complete matrix and adding to each row of this replica a randomly selected row from the second replica. Table 13 shows the constructed design matrix. As before, the suitability of the constructed design matrix was analyzed and the constructed matrix is proven to be suitable.

In Table 13, the responses $\overline{T}_i\; i\; \ldots\; 11$ are the average tool life calculated over three independent tests replicas obtained under the indicated test conditions.

Analysis of the result of sieve DOE begins with the construction of a correlation (scatter) diagram shown in Fig. 6. Its structure is self-evident [4]. Each factor is represented by a vertical bar having on its left side values (as dots) of the response obtained when this factor was positive (the upper value), while the values of the response corresponding to lower lever of the considered factor (i.e., when this factor is negative) are represented by dots on the right side of the bar. As such, the scale makes sense only along the vertical axis.

Each factor included in the experiment is estimated independently. The simplest way to do this is to calculate the distance between the means on the left and right side of each bar. These distances are shown on the correlation diagram in Fig. 6. As

Table 13 Design matrix

Number of test	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}	x_{12}	Average tool life, $\overline{T}$ (min)	Correction, T_c
1	+	–	–	+	–	–	+	+	–	–	+	–	1163.5	1162.5
2	+	–	+	–	–	+	–	–	+	–	–	+	106	26.0
3	–	+	–	–	–	+	+	–	–	+	+	+	10	423.75
4	+	+	+	+	+	+	+	+	+	+	+	+	0.05	423.80
5	+	+	–	–	+	–	–	–	–	+	–	–	50	582.18
6	–	+	+	+	–	–	–	+	+	+	–	–	0.0	542.18
7	+	–	+	+	+	–	–	–	–	+	–	+	400	430.00
8	–	–	–	–	+	+	+	+	+	+	–	–	645	510.67
9	–	–	+	–	+	–	+	–	+	–	+	–	770	770.00
10	–	–	–	+	+	+	–	+	–	–	–	+	1155	1020.57
11	–	+	+	–	–	–	+	+	–	–	–	+	10	552.10
12	–	–	+	–	–	+	+	–	–	+	–	–	5	134.40
13	–	–	–	–	–	–	–	+	+	+	+	+	270	270.00
14	+	+	+	–	+	–	–	+	–	–	+	–	25	433.75
15	+	+	–	+	–	+	–	–	+	–	+	–	20	487.75
16	–	+	–	+	+	–	+	–	+	–	–	+	88	924.18
17	0	0	0	0	0	0	0	0	0	0	0	0	245	924.18

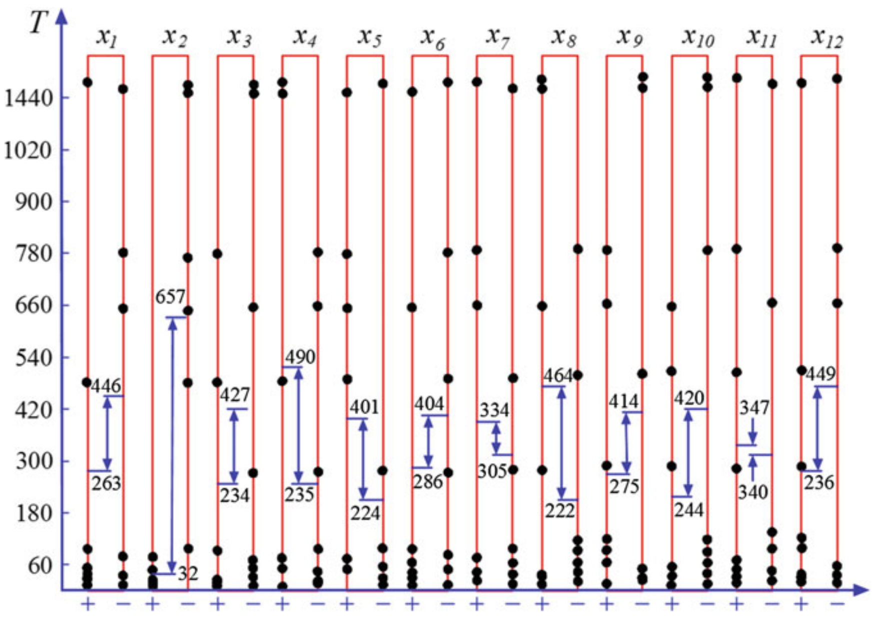

Fig. 6 Correlation diagram (original data)

Table 14 Correlation table (original data)

Estimated factor	$+x_2$	$-x_2$
$+x_4$	0.05 0.05 80 82 $\overline{T}_1 = 40.1$	1162.5 498 1155 0 $\overline{T}_2 = 701.87$
$-x_4$	16 50 10 25 $\overline{T}_3 = 25.25$	108 645 770 270 $\overline{T}_4 = 448.25$

can be seen, these are the greatest for factors x_2 (the cutting feed) and x_4 (the length of the chamfer cutting edge), and thus these two factors are selected for analysis.

The effects of factors are calculated using a correlation table shown in Table 14. As can be seen, the effects for the considered case are $X_2 = -524.18$ and $X_4 = 134.63$.

The Student's criteria for the selected factors were calculated to be $t_2 = 6.87$ and $t_4 = 5.24$. The critical value of the Student's criterion, t_{cr} is found in a statistical table for the following number of degrees of freedom:

$$f_r = \sum_i n_i - k = 12, \tag{24}$$

where k is the number of cells in the correlation table.

For the considered case, $t_{0.05} = 2.18$ (Table 5.7 in [34]). Therefore, the considered factors are significant with a 95 % confidence level as $t_2 > t_4 > t_{0.05}$, i.e., they have a significant influence on tool life.

The discussed procedure concludes the first stage of the sieve. The corrected results of the first sieve results are presented in column T_c of Table 13. Using the data of this table, a new correlation diagram is constructed as shown in Fig. 7. As can be seen in this figure, the scatter of the analyzed data reduces significantly after each sieve.

An analysis of Fig. 7 allowed to distinguish three factors, namely x_3 (the depth of cut), x_8 (the normal clearance angle of the chamfered part of the cutting edge), and x_{10} (the tool cutting edge angle of the major cutting edge) for further analysis.

A new correlation table (Table 15) was constructed to analyze the considered factors. The effects of factors were calculated using this table: $X_3 = -127.50$, $X_8 = 105.40$, and $X_{10} = 110.1$. The Student's criteria for the selected factors were calculated to be $t_3 = 5.01$, $t_8 = 4.42$, and $t_{10} = 4.91$. For the considered case, $t_{0.05} = 2.18$ (Table 5.7 in [34]). Therefore, the considered factors are significant with a 95 % confidence level as $t_2 > t_4 > t_{0.05}$, i.e., they have a significant influence on tool life. The critical value of the Student's criterion, t_{cr} is found in a statistical table

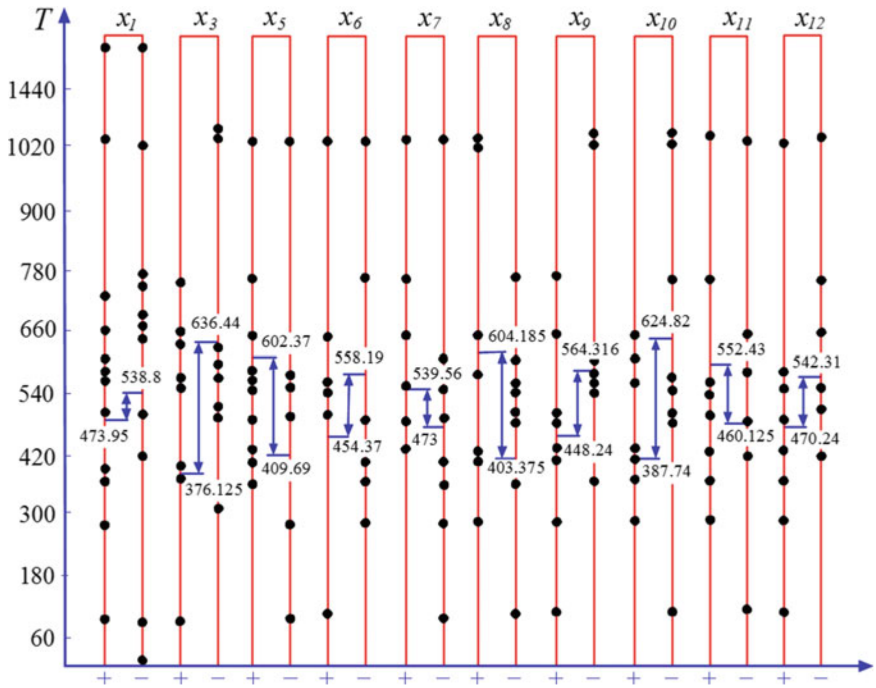

Fig. 7 Correlation diagram (first sieve)

Table 15 Correlation table (first sieve)

Estimated factor	$+x_3$		$-x_3$	
$+x_{10}$	$+x_8$	$-x_8$	$+x_8$	$-x_8$
	423.80 542.13	430.00 −134.43	510.57 270.00	423.75 542.18
$-x_{10}$	552.18 432.75	−26.00 770.00	1162.50 1020.60	487.75 624.18

for the number of degrees of freedom $f_r = \sum_i n_i - k = 16 - 2 = 8$ at 95 % significance level to be $t_{0.05} = 2.306$ (Table 5.7 in [34]).

The results of factors screening are shown in Table 16. Figure 8 shows the significance of the distinguished effects in terms of their influence on tool life. The analysis of the obtained results shows that five factors out of twelve included in the test are found to be significant, and thus should be included in the full factorial test.

As expected, the cutting feed (factor x_2) has the strongest effect on tool life under the selected tool life criterion. The second strongest effect has the length of the chamfer of the cutting edge (factor x_4). This was not obvious before testing.

Table 16 Summary of the screening test

Stage of analysis	Effects	Value of effects	Calculated *t*-criteria
Initial data	X_2	−524.0	6.87
	X_4	134.4	5.24
First sieve	X_3	−127.5	5.01
	X_{10}	119.1	4.91
	X_8	10.4	4.42

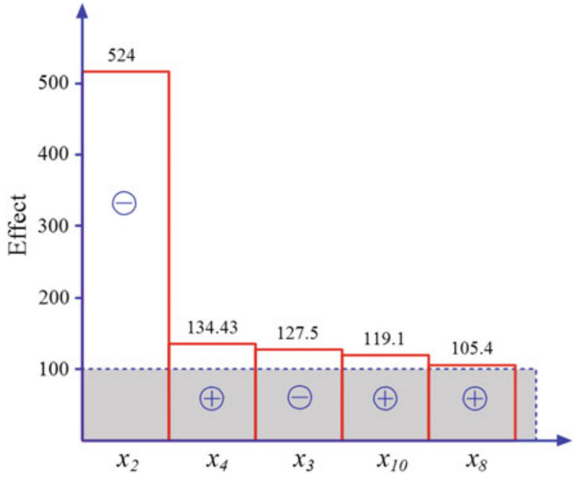

Fig. 8 Significance of the effects distinguished by the sieve DOE (Pareto analysis)

Influences of the depth of cut (factor x_3) and the tool cutting edge angle of the major cutting edge are common for metal machining in terms of their signs and effects. The most interesting finding is the effect of the normal clearance angle of the chamfered part of the cutting edge (factor x_8). Using the result of the subsequent full factorial DOE, and further optimization of this factor allowed an increase in tool life by factor 5 while solving a long-standing problem in the automotive industry.

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Modelling and Optimization of Machining with the Use of Statistical Methods and Soft Computing

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Abstract This book chapter pertains to the use of statistical methods and soft computing techniques that can be used in the modelling and optimization of machining processes. More specifically, the factorial design method, Taguchi method, response surface methodology (RSM), analysis of variance, grey relational analysis (GRA), statistical regression methods, artificial neural networks (ANN), fuzzy logic and genetic algorithms are thoroughly examined. As part of the design of experiments (DOE) the aforementioned methods and techniques have proven to be very powerful and reliable tools. Especially in machining, a plethora of works have already been published indicating the importance of these methods.

1 Introduction

A model can be defined as an abstract system, equivalent to the real system it represents in respect to its properties and characteristics. It can be used for calculations, analysis and predictions which would otherwise be expensive or in some cases impossible to be carried out. The process of optimization is defined generally as a process or methodology of making something as fully perfect, functional or effective as possible.

Specifically, in common engineering practice, optimization involves a suitable mathematical procedure which can provide through a well-ordered way the optimum set of characteristics that is related to the optimum performance of a system. More specifically, an optimization problem consists of a function, termed the objective function that describes the goal of the process which needs to be

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minimized or maximized; a set of input variables termed the design variables, whose optimum combination is required and a set of constraints that may be related to the configuration of the problem and its physical characteristics. Then, by using suitable heuristic algorithms, the area of possible solutions is searched in order to determine the region when the optimum point lies in an ordered and efficient way. Essentially using numerical optimization methods, the mathematical problem of optimization, which consists of finding the extreme points of a function, is transformed into a numerical procedure and considering the great amount of computational power available nowadays, a powerful tool for many applications is created. It is worth noting that in real-life engineering problems, the evaluation of each set of possible solutions is much more difficult than in cases of the optimization of mathematical functions. Specifically, it can involve the numerical modelling and simulation of a process and its duration can vary from seconds to hours in very demanding problems. Thus, the optimization procedure has to be able to determine the optimum with the less possible number of iterations in order to be efficient and finish within a reasonable period of time.

Machining processes are examples of complicated systems in which modelling and optimization have already found extended applications [1]. In the next paragraphs the most commonly used statistical and soft computing methods used for the modelling and optimization of machining processes are presented. For each method discussed, the most important features are analysed. Furthermore, at the end of each section, a list of references involving the application of the specific method in machining is given. Finally, at the end of the book chapter, for the presentation of an optimization procedure in a machining problem, a case study is examined.

2 Factorial Design Method

The factorial design method is a general family of statistical methods, employed for the design of a scientific experiment. When an experiment is conducted using the factorial design method, the effect of various factors on one or more response variables can be successfully investigated. Each factor is generally considered as an independent variable and is studied at various discrete subdivisions or levels, namely discrete values that lie within a predefined range, appropriate for each experiment. In early works, the importance and effectiveness of conducting complex, multi-factor experiments were considered important and the basis for the factorial design methods were set [2]. Fisher was the first to introduce the term "factorial" in his work [3].

Commonly, the factorial design methods are categorized into full factorial and fractional factorial designs. Using a full factorial design, the experiment is conducted by assuming the combinations of each factor with all the other factors at all levels. Thus, in these cases all the possible experiments are conducted. Usually, two or three levels are considered for each factor and the factorial design is then named after the number of factors according to the number of levels for each factor, e.g. a

2×2 or a 2^2 factorial design. A similar notation is employed in cases with factors with different number of levels, e.g. $3^5 2$ denotes that there are 5 factors with 3 levels each and one factor with 2 levels, i.e. total $3^5 \times 2 = 486$ experiments. It is evident, however, that such a design can easily lead to an unfeasible amount of experiments to be conducted, resulting in a considerably large amount of work or additional cost.

On the contrary, fractional factorial design involves a certain subset or fraction of the total number of experimental runs that would occur as a result of a full factorial design. This subset is carefully chosen using proper statistical processes in order to study a subset of the original problem which contains as much information about the process as possible. When referring to fractional factorial design, a notation relevant to the full factorial design is employed, e.g. a 2^{4-2} design means that only the ¼ of the $2^4 = 16$ experiments originally required will be conducted. In Fig. 1 a schematic of the trial points in a 2^2 design is presented.

Apart from the two main categories, other types of multi-factor designs are: randomized block designs (RBD), Plankett–Burman designs, Taguchi designs and designs related to the response surface methodology (RSM). The two latter methods will be discussed separately in the following sections of this book chapter. As for all families of DOE methods, there is a considerable amount of theoretic work concerning the mathematic foundations of factorial design method. The reader, who is interested in the mathematical foundations of DOE, should consider studying the relevant literature; references [4–12] are proposed.

2.1 Description of Factorial Design Method

Factorial designs have common characteristics when they are applied to experimental design. The first fundamental step consists of the choice of factors and their levels. This step should not be underestimated in any case, as it depends both on theoretical understanding of the problem parameters and experience on similar problems. Afterwards, the selection of the suitable response variables, that can provide adequate information about the process, is required. This selection, however, depends on the existing equipment of each lab and the level of difficulty for the conduction of the measurements. When the fundamental choices for the

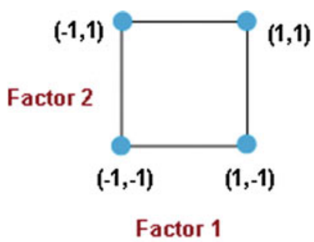


Fig. 1 Trial points of the 2^2 design

experiment are performed, the choice of the details of the experimental design is made. The number of runs required for each design scheme has to be taken seriously into consideration as well as the actual levels of each factor. It is often preferable to use a small number of levels, e.g. two, when a thorough study is not required. After the choice of the experimental design scheme and details has been completed, the array describing the parameters used in every run is produced. It is a common practice to code the actual values of experimental factors to levels denoted as −1 and 1, as it can be also seen in Fig. 1 or with the "+" and "−" signs. Examples of factorial designs using both notations are presented in Tables 1 and 2 for the case of a 2^3 full factorial design, i.e. 3 factors at 2 levels each.

The next step is the conduction of the experiment according to the defined set of runs. It is important to monitor the process during all stages, as errors in this stage produce irrelevant output and actually cancel the advantages offered by the experimental design method concerning the scientific validity of the experiment. If the experiment is carried out successfully, the statistical analysis of the results can provide a solid way to determine the effect of each factor to the response or the effect of the interaction between various factors and whether the results are affected by experimental errors. Using the factorial design method, the first stage of analysis comprises of response plots such as histograms, box plots, etc. and main effects and interaction plots with a view to visualize the experimental outcome and evaluate the characteristics of the basic findings. Then, regression models can be employed to determine the relationship between the various experimental factors and statistical

Table 1 Factorial design 2^3 where the level values are represented by −1 and 1

Trial	Factor 1	Factor 2	Factor 3
1	1	−1	−1
2	1	−1	1
3	1	1	1
4	1	1	−1
5	−1	−1	−1
6	−1	−1	1
7	−1	1	1
8	−1	1	−1

Table 2 Factorial design 2^3 where the level values are represented by − and +

Trial	Factor 1	Factor 2	Factor 3
1	+	−	−
2	+	−	+
3	+	+	+
4	+	+	−
5	−	−	−
6	−	−	+
7	−	+	+
8	−	+	−

analysis methods such as analysis of variance (ANOVA) can be applied for a more detailed analysis of the results. In specific, the ANOVA method is discussed in the following section.

Furthermore, after the analysis of results is performed, soft computing and optimization methods can be applied to the experimental results in order to create models that describe the behaviour of a studied system and investigate its performance in various ranges of operating parameters. Usually, the experimental design using factorial designs is carried out using suitable statistical and experimental software such as Minitab, Design-Expert and SPSS. These software packages provide users with sufficient guiding on the conduction of the whole process and are highly reliable.

2.2 Applications of Factorial Design Method in Machining

There are numerous examples of applications of the factorial design method in scientific experiments. Specifically in machining experiments, a wide range of processes are designed using factorial design. Studies generally on machining [13–18], milling [19–21], drilling [22], laser-assisted machining [23], electrodischarge machining (EDM) [24–26], ultrasonic machining [27] and abrasive waterjet machining [28] have been conducted using these design schemes. The main advantages of this method are proven to be its reliability in creating a well-structured experimental process and its easiness to combine with various statistical, soft computing and optimization methods and subsequently increase their effectiveness and accuracy.

3 Taguchi Method

The Taguchi method is one of the most frequently employed DOE methods. Essentially, this category of DOE methods can be considered as a special category of fractional factorial designs. Although Taguchi methods derive from factorial designs, their development introduced several new concepts on the design and evaluation of experiments, which provide valuable help both to scientific and industrial applications. As with the other fractional factorial designs, the Taguchi method was developed in order to overcome the large number of experiments associated with multi-factor, full factorial designs. The reduction of the number of experiments required for a study is usually performed by ignoring some of the interactions between the parameters of the problem, an assumption also employed in Plackett–Burman designs. Taguchi method is often employed as first step of an optimization process, in which the factors studied in the experiment are also used as design variables for the optimization of a system or a process.

Taguchi methods allow for a strict guideline and a well-defined methodology for the determination of the choice of a sufficient subset of the total number of experiments to be conducted using the full factorial method. Using Taguchi method, orthogonal arrays are created and employed with a view to reduce significantly the number of experiments even when a large number of variables are studied. Taguchi designs can be performed at two or more levels for each factor and it is even possible to choose mixed configurations. Once the appropriate Taguchi orthogonal array is selected, the experiments are carried out using the predefined values, in a random sequence.

3.1 Description of the Method

The Taguchi design method can be applied at certain distinct steps, similar to the other experimental design methods. After the independent variables of the experiment, i.e. factors, are carefully chosen, the selection of the appropriate number of levels for each factor must be determined. This is a crucial part of the Taguchi method, as it is related to the type of orthogonal array and determines the number of experimental runs. Examples of two cases of different orthogonal arrays, namely the L9 orthogonal array and the L27 orthogonal array, can be seen in Tables 3 and 4. The next step consists of the encoding of the actual values of each factor level by assigning to them a specific value such as: −1, 0 and 1 which represents the minimum, centre and maximum level of a factor, respectively. When these steps are completed, the experiment can take place.

After the experiments are conducted in the ordered way, data analysis for the experimental results is performed. Traditionally, the Taguchi method employs the calculation of the signal-to-noise ratio (S/N ratio) as a means to determine the effect of each factor to the final output of the process. The S/N ratio is associated with one of the basic goals of the Taguchi method, the reduction of variability by minimizing

Table 3 Taguchi L9 orthogonal array

No. of experiment	Factor 1	Factor 2	Factor 3	Factor 4
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

Table 4 Taguchi L27 orthogonal array

No.	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13
1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	2	2	2	2	2	2	2	2	2
3	1	1	1	1	3	3	3	3	3	3	3	3	3
4	1	2	2	2	1	1	1	2	2	2	3	3	3
5	1	2	2	2	2	2	2	3	3	3	1	1	1
6	1	2	2	2	3	3	3	1	1	1	2	2	2
7	1	3	3	3	1	1	1	3	3	3	2	2	2
8	1	3	3	3	2	2	2	1	1	1	3	3	3
9	1	3	3	3	3	3	3	2	2	2	1	1	1
10	2	1	2	3	1	2	3	1	2	3	1	2	3
11	2	1	2	3	2	3	1	2	3	1	2	3	1
12	2	1	2	3	3	1	2	3	1	2	3	1	2
13	2	2	3	1	1	2	3	2	3	1	3	1	2
14	2	2	3	1	2	3	1	3	1	2	1	2	3
15	2	2	3	1	3	1	2	1	2	3	2	3	1
16	2	3	1	2	1	2	3	3	1	2	2	3	1
17	2	3	1	2	2	3	1	1	2	3	3	1	2
18	2	3	1	2	3	1	2	2	3	1	1	2	3
19	3	1	3	2	1	3	2	1	3	2	1	3	2
20	3	1	3	2	2	1	3	2	1	3	2	1	3
21	3	1	3	2	3	2	1	3	2	1	3	2	1
22	3	2	1	3	1	3	2	2	1	3	3	2	1
23	3	2	1	3	2	1	3	3	2	1	1	3	2
24	3	2	1	3	3	2	1	1	3	2	2	1	3
25	3	3	2	1	1	3	2	3	2	1	2	1	3
26	3	3	2	1	2	1	3	1	3	2	3	2	1
27	3	3	2	1	3	2	1	2	1	3	1	3	2

the effect induced by noise factors in the experiment and it is generally defined as follows:

$$\mathrm{SNR} = \frac{\mu}{\sigma} \tag{1}$$

where μ is the signal mean or the expected value and σ is the standard deviation of the noise. In some cases, the S/N ratio can be defined as the square of the above fraction.

More specifically, using the Taguchi method, optimization methods can be categorized into two distinct groups: the static and the dynamic problems. The static problems are related to the determination of the best control factor levels for a process so that the output has a desired value, while the dynamic problems involve the determination of the best control factor levels so that the ratio of an input signal and its output is closest to a desired value. In static problems the signal (input) factor has a fixed value, while in the dynamic problems a relationship between the input and output signal is required.

In the case of static problems, the S/N ratio can be defined in three different ways according to the optimization target of the process in the study. More specifically, these ratios are defined as follows:

- **Smaller-the-better** (often abbreviated as STB or SN_s):

$$\eta = -10\ \log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \tag{2}$$

  where the quantity inside the summation symbol represents the mean of sum of squares of measured data. This ratio is usually employed when the value of the "noisy" characteristic should ideally have a value of zero or when the desired value is defined as a difference of the current value and the optimal one.
- **Larger-the-better** (often abbreviated as LTB):

$$\eta = -10\ \log\left(\frac{1}{n}\sum_{i=1}^{n} \frac{1}{y_i^2}\right) \tag{3}$$

- **Nominal-the-best** (NTB):

$$\eta = 10\ \log\left(\frac{\mu^2}{\sigma}\right) \tag{4}$$

This ratio is often employed when the desired value does not appear in an expression that requires minimization or maximization.

In the case of dynamic problems, a desired type of relationship between an input and an output signal is required to be attained. Two ratios are generally considered, namely the slope of the input/output characteristics and the linearity of the input/output characteristics. The slope of the input/output characteristics should have a certain value and has two alternative definitions, the one based on a LTB ratio and the second one based on a STB ratio:

$$\eta = 10\ \log\left(\beta^2\right) \tag{5}$$

$$\eta = -10\ \log\left(\beta^2\right) \tag{6}$$

where β^2 represents the square of slope of the input/output relationship.

The linearity is often considered as a LTB ratio and is related to deviations from a purely linear relationship between input and output:

$$\eta = 10\ \log\left(\frac{\beta^2}{\sigma}\right) \tag{7}$$

Furthermore, other statistical analysis tools such as ANOVA are often employed for the analysis of results. Using the analysis results and by determining the effects between the factors of the experiments, the optimization process can be effectively conducted.

3.2 Application of Taguchi Method in Machining

The Taguchi method was successfully applied in a wide range of machining processes and experiments. Both conventional machining including turning [29–40], milling [41–43], drilling [44, 45] and non-conventional machining processes such as EDM [46–54], laser-assisted machining [55, 56], abrasive jet polishing [57], ultrasonic machining [58], high-pressure jet machining [59] and micromachining [60] are designed using Taguchi method with a view to optimize the parameters of these processes and determine the effect of various parameters to their outcome.

4 Response Surface Methodology

RSM is a group of mathematical and statistical techniques, often employed in engineering studies with regard to model problems, whose underlying structure is unknown and also optimize the desired output of these problems. The term Response Surface is employed to describe the surface that represents the output of a process when input parameter values vary within specified ranges. This method is of great importance specifically for machining problems, as it can be seen from the considerable amount of scientific works employing this method in the literature [61–88].

The first step for the RSM method is to determine a suitable function that represents the relationship between input and output variable and is, in general, unknown. If the response of the examined system can be sufficiently modelled using a linear function of the input variables, a so-called first-order model can be employed. If the response is more complex, a second-order model is usually employed or even a combination of a first-order model and a second-order model.

The parameters in the approximation models are determined using the least square method, as it also happens in the case of statistic regression models. The goodness of fit of the response surfaces indicates the validity of the study of the modelled system. More accurate estimation of the model parameters is achieved only if the corresponding experiment was conducted using a suitable DOE method. For most RSM studies, a special case of factorial design, the central composite design (CCD) method, is employed; however, Taguchi orthogonal arrays can also be applied. In Sect. 11 an actual example of the application of RSM method to a machining problem is presented as a case study in order to further clarify the procedure.

4.1 Description of Response Surface Methodology

The optimization process using the RSM method is a sequential procedure. The start point is often a point of the response surface, which is far from the optimum point and corresponds to the existing operating conditions of a system. Subsequently, the optimization procedure leads to the determination of the vicinity of the optimum point and then a higher order model is applied in this area. After further analysis the optimum point is determined. For simplicity reasons the initial optimization procedure is conducted using a first-order model, as it is assumed that the start point is far from the optimum point. A suitable method for the rapid convergence to the optimum point is the method of steepest descent, in case of minimization problems or steepest descent, in case of maximization problems. This method consists of a numerical procedure of moving along the path of steepest descent/ascent that leads to the area around the optimum point. The next step of the optimization process is to fit a second-order model in the experimental results. The experimenter may need to conduct additional experiments, in order to improve the accuracy of the second-order model. The optimum point in a second-order surface is called the stationary point; in this point all partial derivatives are zero. However, it must be determined whether this point is actually a point of maximum, a point of minimum response or a saddle point.

Using a DOE method for the experiment is necessary in order to apply the RSM method. This leads to a better distribution of points, reduces the error and results to a more accurate estimation of the coefficients of the regression function. Orthogonal first-order designs are often used when first-order models are considered and CCD method is used in the case of second-order design. The CCD method is a special case of fractional factorial designs that includes also centre and axial points in the design, as it can be seen in Fig. 2. More specifically, a CCD involves three sets of experiments: a factorial design set, a set of centre points and a set of axial points. The centre points have values equal to medians of value used in the factorial design set and allow for an improvement of the precision of the experiment, while the axial points set involve points outside the range of factorial design points for all factors. An example of a CCD is presented in Table 5. Thus, using the CCD method two parameters must be specified: the distance of the axial runs, i.e. the proposed experiments, from the design centre and the number of centre points. These two parameters should be selected in such a way that they ensure rotatability of the

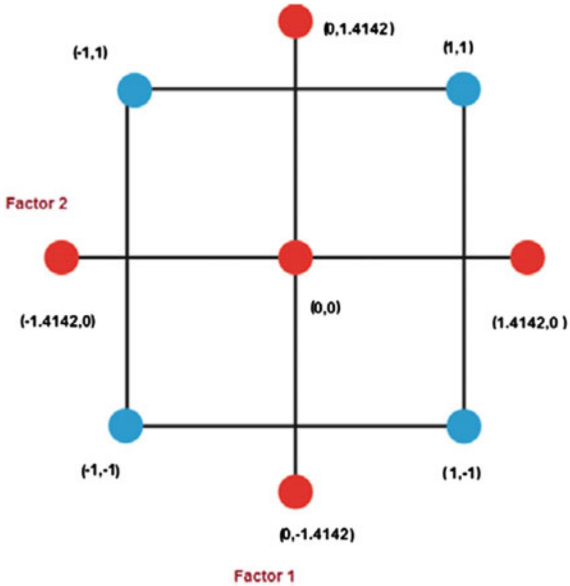


Fig. 2 A schematic of the trial points used in a two-factor central composite design

Table 5 An example of central composite design for a two-factor experiment

Trial	Factor 1	Factor 2
1	−1	−1
2	−1	1
3	1	−1
4	1	1
5	−1.4142	0
6	1.4142	0
7	0	−1.4142
8	0	1.4142
9	0	0
10	0	0
11	0	0
12	0	0
13	0	0
14	0	0

composite design. A rotatable design is defined as a design that provides the same variance of predicted response for points that lie at the same distance from the design centre. The Box–Behnken design can be employed as an alternative to the CCD method. The difference of the Box–Behnken design is that corner points and out-of-boundary points are omitted in the design. However, the mid-points of edges of the experimental space are employed in the design, as it can be seen in Fig. 3. Box–Behnken design involves fewer points than the CCD, but at least three factors

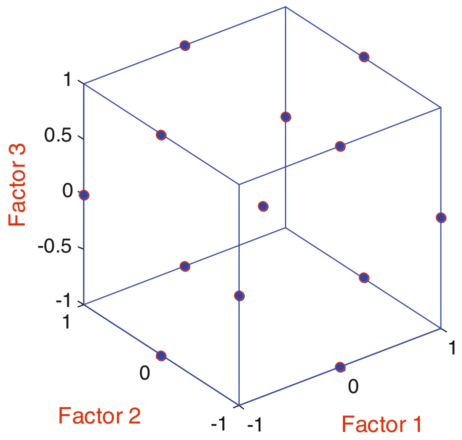


Fig. 3 A schematic of the trial points in a three-factor Box–Behnken design

Table 6 Box–Behnken parameters for a three-factor experiment

Trial	Factor 1	Factor 2	Factor 3
1	−1	−1	0
2	−1	1	0
3	1	−1	0
4	1	1	0
5	−1	0	−1
6	−1	0	1
7	1	0	−1
8	1	0	1
9	0	−1	−1
10	0	−1	1
11	0	1	−1
12	0	1	1
13	0	0	0
14	0	0	0
15	0	0	0

should be used in this method. For example, for a three-factor experiment, CCD would require 20 trial points, while Box–Behnken design would require 15 trial points. The latter method has a smaller cost but should be employed only if the experimental boundaries are supposed to be known. An example of the Box–Benhken design is given in Table 6.

The RSM method can be also applied to multi-response problems. In this case, the regions of optimum results are found by considering the optimum regions of each response and then the area that contains together all these optimum points. This problem is also considered as a constrained optimization problem or desirability functions are employed in order to determine the optimum using a single function.

4.2 Application of RSM to Machining

As mentioned before, the RSM method has been applied to a wide range of machining processes. In specific, RSM method has been applied to the following processes: turning [61–71], milling [72–78], EDM [79–85], abrasive waterjet turning [86], abrasive assisted electrochemical machining [87] and wire electrochemical micromachining [88]. In these investigations several parameters concerning the machining processes have been successfully analysed and simulated using the RSM method, such as surface roughness [61, 69, 73, 74, 79, 88], tool geometry optimization [65, 75], tool performance [62], tool wear [66, 67] and tool life prediction [72], optimal machining parameters selection [68, 71, 76, 86], energy consumption in turning [71] and cutting forces prediction [67, 77].

5 Analysis of Variance

ANOVA is an important analysis tool for scientific experiments and it is also one of the most widely used statistical analysis methods. It is often used as a supplementary means of studying the variability of the means of experimental observations or to examine the significance of factors in a multi-factor experiment.

The simplest case of ANOVA test is called the one-way ANOVA test and is related to one factor experiment, where multiple experiments are conducted for each factor level. For a problem of one factor at various levels, the observations can be expressed using a suitable model. Two of the most common methods are the means model and the effects model. The means model considers each observation as the sum of the mean of the corresponding factor level and a random error component that includes all other sources of variability that appear in the experiment. The effects model considers each experimental observation as the sum of the overall mean of all observations and a parameter associated with effects due to each factor level. In cases that it is desired to test hypotheses about the level means, concerning only the factor levels that appear in the analysis, a fixed effects model is employed. Thus, for a fixed effects model statistical tests for the equality of level means are conducted.

In order to conduct the ANOVA test, at first, the total variance can be decomposed into terms: a term related to each factor level and a term related to errors. The statistic test for the ANOVA is an *F*-test. *F*-test is a statistical test in which the test statistic is considered to follow an F-distribution under the null hypothesis. A schematic of the *F*-distribution is presented in Fig. 4. This test is usually used in order to determine which model fits more accurately the population from which the data from an experiment were sampled. In fact ANOVA is the best known case of an *F*-test.

Beginning with the two terms of variance (sum-of-squares terms), the mean squares of these terms according to the degrees of freedom are calculated and then

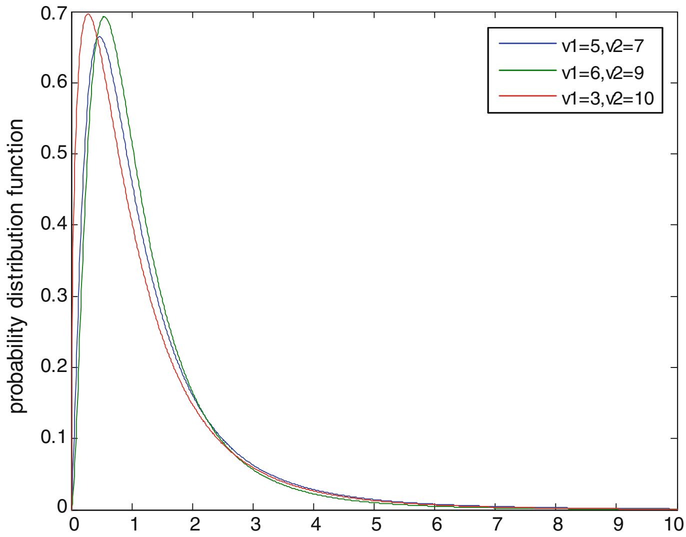


Fig. 4 The *F*-distribution in various cases (*v1* degrees of freedom of nominator, *v2* degrees of freedom of denominator)

Table 7 A typical table for analysis of variance results

Source of variation	Sum of squares	Degrees of freedom	Mean square	F_0	*P*-value
A	20.52	2	10.26	41.58	0.00006
B	12.30	4	3.075	12.46	0.0016
Error	1.97	8	0.24675		
Total	34.79	14			

the value for the *F*-test is obtained by the ratio between them to determine if the null hypothesis is rejected or not. In case of rejection of the null hypothesis the mean values for each level are found to differ significantly. An example for a problem concerning two parameters is shown in Table 7. The ANOVA test can be generalized to a two-way test or an *N*-way test that involves *N* factors. In these cases, the interaction effect between various factors can be examined. Furthermore, ANOVA tests are widely employed as a means of identifying the significance of parameters of a regression equation or other soft computing methods.

5.1 Application of ANOVA to Machining Problems

Although ANOVA is performed in almost every experimental results analysis and numerous applications of this method can be found in the literature of this chapter, a brief selection of several notable cases was made. ANOVA method is applied to analyse results from machining [89–95], milling [96], drilling [97], EDM [98–101], high-pressure jet assisted turning [102], laser micro-turning [103] and water abrasive jet machining [104].

6 Grey Relational Analysis

The grey system theory has been applied successfully in many scientific fields, such as finance, engineering and even social sciences. Grey relational analysis (GRA) is derived from grey system theory and is proven to be an efficient statistic tool for the analysis of experimental results and system optimization [105–108]. Although GRA is not a method for experimental design, it can be easily combined with one of the available experimental design methods to form a powerful experimental analysis tool.

Grey theory is related to the concept of information. A system for which no available information exists is considered as a "black" system, while a system whose parameters are completely known is considered as a "white" system. In fact, as these two extreme conditions are almost unlikely to happen, the real-system systems are classified according to the level that their properties are known and they are assigned a value corresponding to a certain level of "grey" such as the values assigned to pixels in greyscale images.

6.1 Presentation of the Method

GRA is performed at various steps. At first, a suitable pre-processing of the input data is required in order to modify them according to the grey theory. For this reason, several methods exist, such as: higher-the-better, lower-is-better and transformation using a desired value, similar to those presented for S/N ratio. However, sometimes a simple normalization process is applied. In fact, using the grey analysis method, the input is at first transformed using relevant formulas so that it can be more easily compared to other experimental results. This pre-processing step is called grey relational generating and is conducted using one of the three aforementioned methods:

- **Higher-is-better**:

$$x_{ij}^{*} = \frac{x_{ij}^{(0)} - \min x_{ij}^{(0)}}{\max x_{ij}^{(0)} - \min x_{ij}^{(0)}} \tag{8}$$

- **Lower-is-better**:

$$x_{ij}^{*} = \frac{\max x_{ij}^{(0)} - x_{ij}^{(0)}}{\max x_{ij}^{(0)} - \min x_{ij}^{(0)}} \tag{9}$$

- **Desired value $x^{(0)}$**:

$$x_{ij}^{*} = 1 - \frac{\left|x_{ij}^{(0)} - x^{(0)}\right|}{\max x_{ij}^{(0)} - x^{(0)}} \tag{10}$$

where x_{ij}^{*} is the generated value of GRA and x_{ij} are in general experimental results from a given set; i denotes a group of experimental results and j an experiment.

In the next step, the grey relational coefficient is calculated using the pre-processed values from the following formula:

$$\delta_{ij} = \frac{\min_i \min_j \left|x_i^0 - x_{ij}^{*}\right| + \xi \max_i \max_j \left|x_i^0 - x_{ij}^{*}\right|}{\left|x_i^0 - x_{ij}^{*}\right| + \xi \max_i \max_j \left|x_i^0 - x_{ij}^{*}\right|} \tag{11}$$

where ξ is the so-called distinguishing coefficient and is defined in the range of 0–1 and x_i^0 is the ideal value for the ith performance characteristic.

Then, the grey relational grade is calculated as the average of the grey relational coefficient. If this value is equal to 1, two sequences are considered identical. The formula for the calculation of the grey relational grade for each experiment j is the following:

$$a_j = \frac{1}{m} \sum_{i=1}^{m} \delta_{ij} \tag{12}$$

where m is the number of performance characteristics considered.

The grey relational grade also denotes the significance of the influence of a sequence to another sequence. This is one of the most significant advantages of the GRA method, as multiple responses are transformed in a single measure and the optimization of multiple criteria is reduced to the optimization of a single quantity. Moreover, by grouping the relational grades for each factor and experimental level, grey relational grade graphs can easily be obtained and the correlations between the studied variables, as well as the optimum parameters for a process can be determined.

6.2 Application of GRA to Machining Problems

The GRA is applied in various machining processes studies, usually as a part of a general experimental design and optimization study. More specifically, GRA was employed in studies pertaining to turning [109–115], milling [116–119], drilling [120–124], EDM [125–131], laser machining and micro-machining [132–135] and electrochemical machining and polishing [136, 137].

7 Statistical Regression Methods

Regression analysis is a general statistical process for the determination of relationships among various variables studied in a particular problem. Regression analysis provides information about how the values of a dependent variable change when the value of one or different independent variables change by estimating their relationship by means of a function called generally the regression function. The variation of the dependent variable around the computed regression function is often estimated using a suitable probability distribution. Moreover regression analysis can be employed as a predictive tool in order to predict the behaviour of a system in conditions for which no experimental data are available. The most widely employed method for data fitting into regression models is the method of least squares.

Based on the kind of regression function employed, regression methods can be categorized into linear regression methods and nonlinear regression methods. In linear regression, it is required for the dependent variable to be a linear combination of the parameters of the regression function. However, the dependent variables can be a nonlinear combination of the independent variable; that means that $f(x) = b_3x^3 + b_2x^2 + b_1x + b_0$ is still a linear regression function as the relationship between $f(x)$ and the parameters b_i is linear. Linear regression in case of a single independent variable is termed simple linear regression, whereas in case of multiple independent variables, this process is termed as multiple linear regressions. In order to fit experimental results into linear regression models, the least square or other minimizing approaches are employed. Various linear regression models have been developed with a view to extend the capabilities of the method, such as: general linear models, where the response variable is generally considered as a vector, generalized linear models, where the response variable is assumed to be bounded or discrete and hierarchical linear models, where the regression model consists of various levels.

Nonlinear regression models involve a modelling function which is a nonlinear combination of the model parameters. Generally, this category of regression models is more preferable in cases where there is physical evidence that dictates the use of a function that describes a nonlinear relationship of unknown parameters. For example, in biology, that is the case of the famous Michaelis–Menten model for enzyme kinetics. As it can be seen in the following formulas, this model can be written in the form of a nonlinear function as the unknown parameters exist both in the nominator and the denominator of the fraction:

$$v = \frac{V_{\max}[S]}{K_m + [S]} \tag{13}$$

$$f(x, \alpha) = \frac{\alpha_1 x}{\alpha_2 + x} \tag{14}$$

where the parameters $V_{\max}$ and K_{m} have been substituted by α_1 and α_2 respectively.

Some types of nonlinear functions used in nonlinear regression are: exponential functions, logarithmic functions, power functions, trigonometric functions. In some cases, the Gaussian function, Lorenz curves or other probability distributions, e.g. Weibull, can also be employed, as it can be seen in Fig. 5. It is noteworthy that some of these functions can be properly linearized using different variables and then the linear regression model can be employed on this transformed function. Iterative methods are often employed for the fitting process such as Newton–Raphson or Gauss methods. Moreover, the fit of models is assessed by similar statistical tests as in the case of linear regression models but measures such as R^2 are argued to be inadequate in the case of nonlinear regression.

After the process of fitting has finished, the regression function should be tested using various measures in order to determine the validity of the fitting process. Some general measures usually employed in various applications are the multiple correlation coefficient R, the coefficient of determination R^2, the adjusted R^2 and the root-mean-squared error (RMSE). The coefficient of determination is defined from the following formulas.

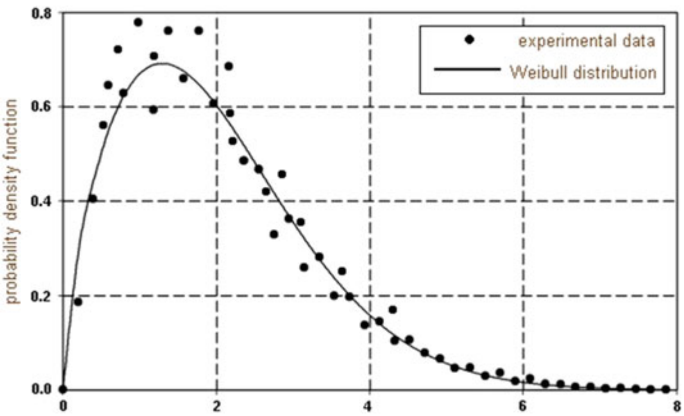


Fig. 5 Experimental data fitted into Weibull distribution

If $\bar{y}$ denotes the mean of the observed data in an experiment, then:

$$\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i \tag{15}$$

Then, the total sum of squares, related to the variance of the experimental data, is defined as:

$$\mathrm{SS}_{\mathrm{tot}} = \sum_{i=1}^{n} (y_i - \bar{y})^2 \tag{16}$$

And the sum of squares of residuals can be defined as:

$$\mathrm{SS}_{\mathrm{res}} = \sum_{i=1}^{n} (y_i - f_i)^2 \tag{17}$$

Based on the previous definitions, the coefficient of determination can be defined as:

$$R^2 = 1 - \frac{\mathrm{SS}_{\mathrm{res}}}{\mathrm{SS}_{\mathrm{tot}}} \tag{18}$$

The adjusted R^2, denoted also as $\bar{R}^2$, can then be defined as:

$$\bar{R}^2 = 1 - \left(1 - R^2\right)\frac{n-1}{n-p-1} \tag{19}$$

where p is the total number of regressors in the model and n is the size of the sample.

Furthermore, the RMSE can be defined as:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (\hat{y}_i - y_i)^2}{n}} \tag{20}$$

where $\hat{y}_i$ denotes a predicted value, y_i an experimental value and n is the size of the sample.

Generally, a value of R indicates the correlation between the predicted and observed values, R^2 indicates the fraction of the variability of the results obtained by the regression model, the adjusted R^2 alters the R^2 value when extra explanatory variables are added to the model and the RMSE indicates the standard deviation of data about the regression model. Regression methods can be easily coupled with various statistical methods such as ANOVA in order to perform a more detailed statistical analysis of the results and to check the validity of the regression model.

7.1 Applications of Statistical Regression Methods in Machining

Regression methods are among the first methods to be applied to the modelling of machining processes [138]. Several machining processes, namely turning [139–151], milling [152–155], boring [156] and EDM [157] are investigated with these methods. Furthermore, various aspects such as tool wear and tool condition monitoring [138, 140, 141, 145–147, 151, 156], machinability [139], surface roughness [142, 144, 148–150, 153–155, 157] and process cost estimation [152] are analysed. In several of these studies [140–144, 152], the efficiency of a regression model is compared to that of soft computing methods, such as artificial neural networks (ANN). From the aforementioned studies it was concluded that, although regression methods exhibit their mathematical background and possess a clear explanatory value, it is generally proven that regression models can perform well when the relationships are almost linear [141], while the ANN give more accurate predictions also in complex, nonlinear cases with a large number of variables [140, 141, 144].

8 Artificial Neural Networks

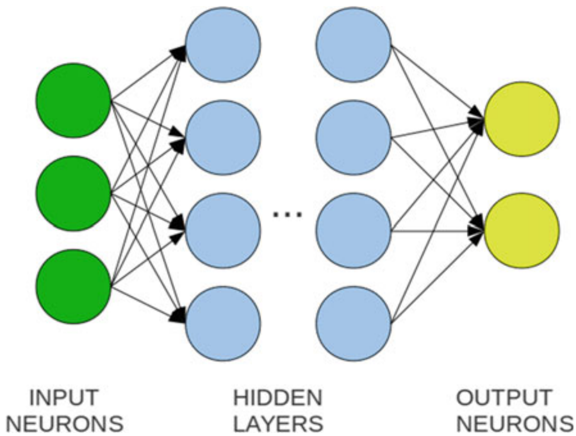
ANN are a group of machine learning algorithms, originating from the concept of biological neural networks. Essentially, they constitute one of the most widely used soft-computing algorithms, as they can easily be used in many scientific fields. More specifically, this method is of particular interest in engineering simulations and optimization problems as it involves the determination of outputs of an unknown system without the need to have absolute knowledge of its physics or the exact relations between different its parameters, but considers it only as a "black box". A system of layers of interconnected neurons that convey information from inputs to outputs and adequate learning algorithms are employed for ANN simulation, following the example of an information processing system, which involves a number of interconnected processing elements, that are working combined to solve a complex problem and gain knowledge by studying an adequate amount of relevant examples.

8.1 Description of Artificial Neural Networks

As mentioned before, some of the basic characteristics of a simple ANN are the layers, the neurons and the learning algorithms. When employing ANN as a means of simulating a system using experimental data, the collection of a sufficient amount of experimental data is needed at first. Then, the neural network is constructed using a suitable architecture. The term architecture is employed to describe the configuration of neurons and layers and the interconnections between neurons of different layers. In a multi-layer configuration usually an input layer, an output layer and one or more middle layers, called hidden layers constitute the neural network. In a feedforward ANN, as it will be discussed afterwards, the input layer is associated directly to the information that is fed into the network, the behaviour of the hidden layers is determined by the activities of the input neurons and the interconnections with them and finally the behaviour of the output layer is determined by the activity in the hidden layer and the interconnection with it. Various parameters concerning the components of the neural networks must be taken into consideration from this early step, such as: the number of inputs, the number of outputs, the number of hidden levels, the neurons in each hidden level and the interconnections between neurons. In most cases these parameters are experimentally calculated by conducting several runs with different values but there are also specific rules that indicate a better choice of these parameters. However, this choice depends on each problem and so it is difficult to create rules that apply to every case. Often, when the inputs have not been obtained by measurements or calculation as in the case of pattern recognition, the inputs and the outputs need to be normalized in the range 0–1.

The most common network is a feedforward network. The architecture of a feedforward network is depicted in Fig. 6. Each artificial neuron, according to its position in the network receives some inputs and produces some outputs. A weight is associated with each input into the neuron. This weight can be a real number and it will be adjusted to a desirable value after the learning process. Each input is multiplied by the weight of the relevant neuron before entering the neuron and all input values are summed to compute the total activation value that enters the neuron. Usually, an additional weight referred as bias is employed as a threshold value and is added to the total output of the neuron. Then, a special function called the activation function is used to transform the input values to the neuron's output. This function can be a linear, step or a sigmoid-like function. Various sigmoid-like

Fig. 6 The architecture of a feedforward ANN



functions can be employed as activation functions provided that they produce output values in the range 0–1, in a way similar to the step or threshold function. This is often done in most engineering applications in order to have a smoothed response and allow for a continuous output variable, something that resembles closely to the function of real neurons. In a feedforward network, as it is expected, the neurons in each level feed their output forward to the next layers up to the output layer; no loops, involving a backward movement, exist in the network.

The next step involves the initialization of the neural network using random weights. Then, the training process can start. During this stage of the algorithm, the network is fed with a series of inputs obtained by experiments, i.e. the training set. Each training set represents a certain pattern or combination of inputs along with the relevant outputs. Subsequently, by observing the output of the network, the weights of each neuron should be accordingly altered in order to produce the desired result; this is the so-called supervised learning. Thus, supervised learning is a learning method that involves the use of an external means of learning that indicates to the output units the desired output to specific inputs. On the other hand, unsupervised learning involves no external supervision of the learning process, and this process is entirely based on local information, so that the network is trained in a self-organized way.

There are many ways of adjusting the weights and the most common is the backpropagation method, which is related to the computation of the error derivative of each weight. In every step or epoch a better approximation of the actual desired value is obtained. A suitable method is used to monitor the error convergence between the computed and desired output values, e.g. the least mean square (LMS) method, the mean square error (MSE) method, etc. The MSE can be defined as:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{y}_i - y_i\right)^2 \tag{21}$$

The backpropagation algorithm first computes the error between the actual and the desired output in the output layers. Then, using the weights between the hidden and the output level, the error of the output level is propagated back to the hidden level. Accordingly, the error propagates back to the input level and subsequently the error derivative for each neuron can be calculated.

A set of validation data, originating from experimental results is used to measure the level of network generalization, which is one of the basic requirements for a neural network in order to avoid the problem of overfitting; that is when the network has great performance near well-known values but poor performance otherwise. Often, these sets of results constitute a small percentage of the original result set. When generalization stops improving the training process is stopped and adjustments are made. An additional step is the testing step, in which another set of results is used not to train the network but to provide another way to measure its performance.

After the network has been trained and its accuracy has been tested, the network can be used in similar problems as a predictive tool or in conjunction to other soft computing or optimization techniques. Nowadays numerous specialized software packages for ANN are also incorporated into toolboxes of numerical analysis software such as MATLAB, as they are applied in various scientific fields.

8.2 Applications of ANN in Machining

ANN have been extensively used in modelling of machining processes within the last few decades. More specifically, a variety of machining processes, have been investigated using ANN, such as turning [158–164], milling [165], drilling [166], EDM [167–172], ultrasonic machining [173], abrasive flow machining [174–176] and abrasive waterjet machining [177, 178]. Furthermore, ANN are combined with several soft computing and optimization methods such as fuzzy logic [164], genetic algorithms [170] and simulated annealing method [171, 178]. Finally, another important application of ANN is online monitoring of machining processes [158].

9 Fuzzy Logic

Fuzzy logic is an alternative form of logic that involves not only two possible states, i.e. true or false, but the logic variables can have a value that ranges between 0 and 1. While the traditional binary or bivalent logic deals with discrete logic states, in fuzzy logic an approximate value for the logic state such as 0.65 or 0.1 can exist, thus extending the concept of truth/falsity to the concept of partial truth/partial falsity state. Fuzzy logic, as most soft computing methods, has a wide range of applications, extending from artificial intelligence and robotics to machining.

Fuzzy logic originates from the fuzzy set theory developed by Zadeh [179]. In mathematics, a “set” is defined as a collection of distinct objects which can be considered as a single object. So, in the classical sense an object can belong or not to a second set. On the contrary, using the concept of a “fuzzy set”, an object can belong to a set partially, fully or not, according to its membership function, an important element of the fuzzy set theory. Using the membership function, each member of a fuzzy set is assigned to a membership degree that denotes how much this member belongs to the specific set. The membership function can have various shapes as long as its values range from 0 to 1. Another important aspect of fuzzy logic is the fuzzy operators such as equality, subset, union, etc. which can be defined in a similar way like operators on classical sets. These operators combine to form complex events and sets of rules that describe various possible activities. The fuzzy sets and fuzzy rules constitute finally the knowledge base of the fuzzy system.

After the fuzzy system is implemented, three others stages are observed in fuzzy systems, namely fuzzification, inferencing and defuzzification. During the

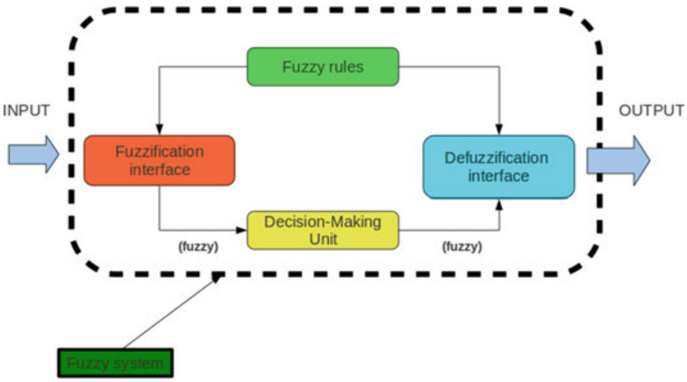


Fig. 7 Configuration of a fuzzy logic system

fuzzification stage, input values are transformed into objects of fuzzy sets, or they are fuzzified as this procedure is usually called in the relevant terminology, using membership functions. During the inference stage, the fuzzified inputs are transformed into fuzzified outputs taking into consideration the fuzzy rules of the system. The inference step is essentially the main step of this method. Defuzzification constitutes the last stage of the process, where the fuzzified outputs of the inference stage are converted into scalar or general non-fuzzy values. In Fig. 7, the configuration of a fuzzy logic system can be seen.

9.1 Description of Fuzzy Logic Method

When modelling a problem using the fuzzy logic method, the whole process can be divided into discrete steps. The first step consists of the determination of the degree of membership of each input to each of the defined fuzzy sets using the membership function; various types of membership functions can be seen in Fig. 8. The input is usually an actual numerical value and the output a value in the range 0–1 called fuzzy degree of membership. The determination of this output depends on the membership function and the fuzzification process is required to be conducted for all the linguistic sets that appear in the fuzzy rules. The next stage of the process involves the evaluation of fuzzy rules. If the input or antecedent for a rule involves more than one part, a suitable fuzzy operator must be applied to the antecedent. The implementation of the various fuzzy logic operators, such as AND and OR can be conducted in various ways. For example, two simple methods for implementing AND are minimum and product (of multiplication).

When this operation is performed, a single truth value is obtained for the antecedents of each rule. Afterwards, an optional further step consists of applying a specific weight in the range 0–1 to each rule, which is performed by applying that

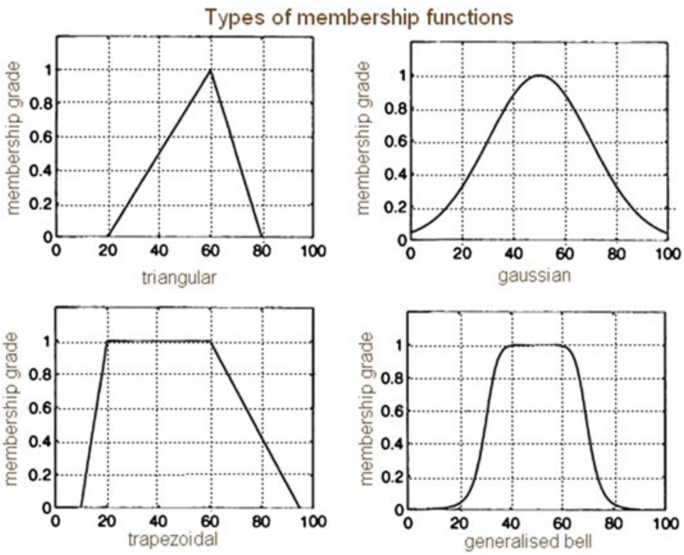


Fig. 8 Various types of membership functions

value to the output of the antecedent of each rule. Essentially, this is performed when it is desired for certain rules to have more contribution to the result. Thereafter, an implication method is applied to obtain the fuzzified output for each rule, based on the result of the previous step. As with the fuzzy operators, there are various operators for the implication process, such as min, which truncates the output, product, which scales the output, etc. Subsequently, all the fuzzy outputs for each rule are required to be summed, in order to obtain an aggregate final result and thus make the appropriate decision. The aggregation process provides a fuzzy set for each output variable. Various aggregation methods can be employed, such as max or sum of the fuzzy outputs and then the results are placed together to form a polygon shape. In the last step of the overall process, the fuzzy aggregated output is defuzzified, with a view to obtain a single number representing the actual desired output in a way that it can be easily understood. The defuzzification process is often conducted using the centroid method; that means that the centroid of the polygon obtained in the precedent step is calculated and this numerical value is actually the defuzzified output.

9.2 Applications of Fuzzy Logic Method in Machining

The application of the fuzzy logic method in machining has proven to be very important [180, 181] with applications in turning [182–193], milling [194–198], grinding [199–202], EDM [203–205], abrasive waterjet machining [206] and assisted abrasive finishing [207]. As it can be deduced by examining the relevant literature, the use of the fuzzy logic method can be invaluable for a wide range of applications such as control of chip form [182], prediction and control of cutting forces [187, 197], design of operation and selection of cutting parameters [183–186, 201, 206, 208–210], surface roughness prediction and improvement [193, 207], residual stresses prediction [199], development of a tool breakage detection system [194], decision-making tools for machining processes [211–213]. Furthermore, the fuzzy logic method can be combined with other methods such as Taguchi method [191, 198], genetic algorithms [201] or GRA [204] to compose a complex predictive and decision-making software.

10 Other Optimization Techniques

In general, optimization algorithms are divided into two categories: stochastic and deterministic algorithms. More specifically, stochastic optimization algorithms involve stochastic process in several parts of the process, not only in order to select the initial solution and often can make a more extensive search of the area of possible solutions. These algorithms are generally more suitable to determine the global optimum for a given system, in spite of their relatively high computational cost when the system is complex or has a great number of local minima/maxima. Another important advantage of the stochastic optimization method is that no knowledge of the exact mathematical description is required and closed-source proprietary software can be used in the solution evaluation process without problems. So it is a process that considers the system as a "black box" and does not require complex mathematical computations from the user, e.g. computation of derivatives. On the other hand, algorithms such as the gradient descent or the conjugate gradient method are considered non-stochastic methods in the sense that they do not involve process related to randomized values. These algorithms require the calculation of derivative of the objective function, are capable to determine the optimum point with significantly smaller computational cost but they are more prone to reach a locally optimum point rather than the globally optimum.

A common characteristic of many stochastic optimization algorithms is that their creation was inspired by natural processes such as the evolution of species, the behaviour of animals or the characteristics of insect colonies which are shown to exhibit features that lead to the optimal design of a process. Although it may seem to be quite irrelevant to engineering and machining processes, these algorithms perform sufficiently well in a great variety of cases [214]. Some of these algorithms are examined in the following part.

10.1 Genetic Algorithms

The genetic algorithms are essentially a subcategory of evolutionary algorithms. Using this method, the possible solutions are termed as individual atoms of a general population, which are comprised of chromosomes. The first step is the creation of the initial population, which are the initial candidate solutions. In this step the various solutions are generated through a random number generator with values within a predefined range. In the second step, a proportion of the initial population is employed in order to create the next generation. The individual solutions which will be employed in this step are chosen according to the value of objective function associated to them. Several processes related to the improvement of solution, which are termed operators, exist such as crossover and mutation, which are employed in order to determine the next-generation atoms. The crossover process consists of an exchange of chromosomes between two atoms, namely the exchange of parameters values between two possible solutions. The mutation process consists of the alteration of some chromosomes of atoms, namely a possible change of value of some parameters for several solutions. Both processes are performed with a certain degree of possibility, defined at the beginning of the algorithm, e.g. there is 95 % possibility of conducting crossover between 2 atoms, 0.4 % possibility for a mutation to happen in an atom, etc. Sometimes, a selection of several solutions that exhibit objective function values near to the optimum one are kept unchangeable with a view to match with other similar atoms and produce better offspring. This process is termed as "elitism" and the related solutions as "elite" atoms.

It is important to note that all the parameters employed in the optimization process need to be chosen carefully according to the characteristics of each problem. Accordingly, parametric studies need to be conducted in order to determine the appropriate crossover and mutation possibilities that produce the optimum solution at the lower computational cost. Finally, the optimization algorithm stops when a termination criterion is reached. Some of these criteria are: a fixed total function of generations, a certain number of iterations where no better results are produced, etc. After the algorithm is stopped, several measures can be used to indicate the efficiency of the optimization process, e.g. the convergence plot. In multi-objective cases, the optimal value is determined from a Pareto chart.

10.2 Applications of Genetic Algorithms in Machining

In the last three decades, genetic algorithms have been employed in many cases of machining experiments. A considerable amount of work concerning genetic algorithms and machining processes has been conducted, some of which are studies on turning [215–219], milling [220–225], drilling [226], grinding [227, 228], EDM [229, 230], electrochemical machining [231] and abrasive waterjet machining [232, 233].

As it can be seen in the aforementioned literature, genetic algorithms can easily be combined with other soft computing methods and DOE methods in order to form general analysis tools. Specifically, genetic algorithms can be combined with the Taguchi method [223], RSM method [223, 225, 228], ANN [222, 229, 230], simulated annealing method [232] and fuzzy logic method [233].

10.3 Other Stochastic Algorithms

Apart from the well-established method of genetic algorithms, other stochastic algorithms have been successfully employed for machining optimization problems, namely artificial bee colony method [234, 235], artificial ant colony [236–238], particle swarm optimization method [239–242] and simulated annealing method [243–245]. Despite the fact that these algorithms seem exotic for a machining process optimization problem, they are proven to be robust and efficient methods. The increasing interest in the development and application of these methods is observed also by the amount of scientific work carried out in these areas within the last decade.

11 A Case Study

This case study presents an example of using the RSM method for the modelling of end milling process of titanium alloy Ti6Al4V and the analysis of results with ANOVA. For the presented implementation of DOE technique, Design-Expert 8.0.7 software was employed. Obtaining the appropriate functional equations between the effects of the cutting process and adjustable parameters usually requires a large number of tests for different tool–workpiece configurations. The large number of experimental studies significantly increases the cost of the experiment which is particularly important in relation to the difficult-to-cut alloys, such as titanium alloys. A solution of this problem is mathematical and statistical tools for DOE. Choosing the right tool remains at the knowledge of researcher, who must be aware of the benefits and limitations that arise from each potential method of approximation.

Among conventional DOE techniques RSM is widely used for machining processes. Experiments based on RSM technique relate to the determination of response surface based on the general equation:

$$y = b_0 + b_1 \cdot x_1 + \cdots + b_k \cdot x_k + b_{12} \cdot x_1 \cdot x_2 + b_{13} \cdot x_1 \cdot x_3 + \cdots \\ + b_{k-1,k} \cdot x_{k-1} \cdot x_k + b_{11} \cdot x_1^2 + \cdots + b_{kk} \cdot x_k^2 \tag{22}$$

where b_0, b_i, b_{ii}, b_{ij} are regression coefficients for intercept, linear, quadratic and interaction coefficients, respectively, and x_i are independent input variables. RSM requires a quantitative response affected by continuous factors. It works best with only a handful of critical factors, namely those that survive the screening phases of the experimental programme. RSM produces an empirical polynomial model which gives an approximation of the true response surface over a factor region.

Many input variables may affect the measured response of the process; it is practically impossible to identify and control a small contribution from each one. Therefore, it is necessary to select those variables with major effects. Screening designs should be carried out to determine which of the numerous experimental variables and their interactions present statistically significant effects. Full or fractional two-level factorial designs may be used for this objective.

11.1 Definition of the Input Variables and the Output Responses

In the case study, the effects of three cutting parameters, namely cutting speed v_c, depth of cut a_p and feed rate f have been experimentally sought upon three performance responses: temperature in cutting zone T and two components of total cutting force—tangential force F_t and radial force F_r. The levels for each factor are tabulated in Table 8.

The temperature measurements were carried out with the use of a thermal imaging camera. Tangent F_t and radial F_r components of cutting force were calculated based on measurement results obtained from a dynamometer measuring F_X, F_Y, F_Z force components and geometric relationship presented in Fig. 9.

11.2 DOE and Response Data Implementation

For the experiment design CCD-Rotatable was selected, in which standard error remains the same at all the points which are equidistant from the centre of the region. The upper and lower limits and their levels of the parameters are given in Fig. 10, as they are entered to the software.

Table 8 Factors for response surface study

Factor	Unit	Low level (−1)	High level (+1)
Cutting speed v_c	m/min	60	80
Depth of cut a_p	mm	1	2.5
Feed f	mm/tooth	0.1	0.15

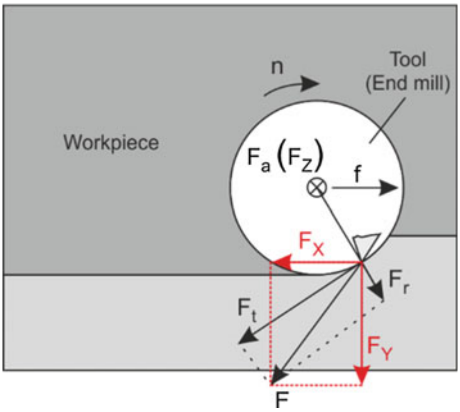


Fig. 9 The relationships between the components of cutting forces

	Name	Units	Low	High	-alpha	+alpha
A [Numeric]	Cutting speed vc	m/min	60	80	53.1821	86.8179
B [Numeric]	Depth of cut ap	mm	1	2.5	0.488655	3.01134
C [Numeric]	Feed f	mm/tooth	0.1	0.15	0.0829552	0.167045

Fig. 10 Definition of cutting condition as numeric factors in Design-Expert

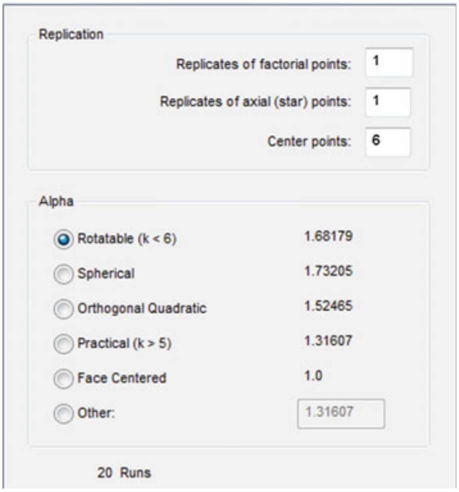


Fig. 11 The dialog box for definition replication points and “alpha” parameter

CCD is composed of a core factorial that forms a cube with sides that are two coded units in length, from −1 to +1. The distance out of the cube, designated as distance “Alpha” and measured in terms of coded factor levels, is a matter for much discussion between statisticians. Design-Expert software offers a variety of options for Alpha, as it can be seen in Fig. 11.

Table 9 The CCD-Rotatable matrix with entered results of experiment

Std	Run	Factor 1 cutting speed vc (m/min)	Factor 2 depth of cut a_p (mm)	Factor 3 cutting speed v_c (m/min)	Response 1 temp. T (°C)	Response 2 tangent force F_t (N)	Response 3 radial force F_r (N)
9	1	53.18	1.75	0.125	721	551.2	396
13	2	70	1.75	0.08	768	408.8	292.3
11	3	70	0.48	0.125	685	159.5	153.3
18	4	70	1.75	0.125	775	491.7	414.5
20	5	70	1.75	0.125	766	499	379.4
6	6	80	1	0.15	723	301.8	260.2
15	7	70	1.75	0.125	762	489.4	389.6
14	8	70	1.75	0.167	730	558.3	434.7
2	9	80	1	0.1	741	189.2	162.4
12	10	70	3.01	0.125	785	843.9	619.7
19	11	70	1.75	0.125	769	486	392.1
8	12	80	2.5	0.15	798	701.7	501.4
10	13	86.82	1.75	0.125	803	441.7	392.7
1	14	60	1	0.1	717	293.5	173.1
4	15	80	2.5	0.1	785	670.3	453.8
17	16	70	1.75	0.125	776	521.8	400.8
3	17	60	2.5	0.1	759	759.7	436.3
5	18	60	1	0.15	674	347.1	270.8
16	19	70	1.75	0.125	772	512.3	424.1
7	20	60	2.5	0.15	758	813.6	495.4

The CCD-Rotatable matrix is given in Table 9.

11.3 Analysis of Results and Diagnostics of the Statistical Properties of the Model

ANOVA is commonly used to summarize the test for significance of the regression model and test for significance on individual model coefficients. The models summary statistics are shown in Table 10. In this case, coefficient of determination, "Adjusted R-Squared" and "Predicted R-squared" values are higher for "Quadratic" model. This model is suggested for analysis.

The analysis of the experimental data was performed to identify statistical significance of the parameters cutting speed v_c, depth of cut a_p and feed f on the measured response temperature T. The model was developed for 95 % confidence level and the results are summarized in Table 11.

Table 10 Models summary statistics

Source	Sequential p-value	Lack of fit p-value	Adjusted R-Squared	Predicted R-Squared	
Linear	<0.0001	0.0051	0.7753	0.7070	
2FI	0.4064	0.0044	0.7771	0.5790	
Quadratic	<0.0001	0.2265	0.9641	0.8939	Suggested
Cubic	0.1721	0.3670	0.9765	0.7218	Aliased

Table 11 ANOVA for response surface quadratic model for temperature T

ANOVA for response surface quadratic model						
Source	Sum of squares	df	Mean square	F-value	p-value prob > F	
Model	23,050.87	9	2561.21	57.73	<0.0001	Significant
A-v_c	5614.58	1	5614.58	126.55	<0.0001	
B-a_p	12,500.47	1	12,500.47	281.75	<0.0001	
C-f	933.47	1	933.47	21.04	0.0010	
AB	6.13	1	6.13	0.14	0.7180	
AC	190.13	1	190.13	4.29	0.0653	
BC	666.13	1	666.13	15.01	0.0031	
A^2	172.62	1	172.62	3.89	0.0768	
B^2	2438.11	1	2438.11	54.95	<0.0001	
C^2	935.56	1	935.56	21.09	0.0010	
Residual	443.68	10	44.37			
Lack of fit	297.68	5	59.54	2.04	0.2265	Not significant
Pure error	146.00	5	29.20			
Cor total	23,494.55	19				

Model "F-value" of 57.73 implies that the model is significant. There is only a 0.01 % chance that a model "F-value" this large could occur due to noise. Values of "Prob > F" less than 0.05 indicate that model terms are significant; in this case A, B, C, BC, B^2, C^2 are significant model terms. Values greater than 0.10 indicate the model terms are not significant. If there are many insignificant model terms, excluding those required to support hierarchy, model reduction may improve the model. The "Lack of Fit" "F-value" of 2.04 implies the "Lack of Fit" is not significant relative to the pure error. There is a 22.65 % chance that a "Lack of Fit" "F-value" this large could occur due to noise; non-significant lack of fit is desired. Next step is the reduction of the model to only significant terms by backward selection, after the p-value of the model terms. The results are presented in Table 12.

Table 12 ANOVA for response surface reduced quadratic model for temperature T

ANOVA for response surface quadratic model						
Source	Sum of squares	df	Mean square	F-value	p-value prob > F	
Model	22,682.00	6	3780.33	60.48	<0.0001	Significant
A-v_c	5614.58	1	5614.58	89.83	<0.0001	
B-a_p	12,500.47	1	12,500.47	199.99	<0.0001	
C-f	933.47	1	933.47	14.93	0.0020	
BC	666.13	1	666.13	10.66	0.0062	
B^2	2333.98	1	2333.98	37.34	<0.0001	
C^2	865.99	1	865.99	13.85	0.0026	
Residual	812.55	13	62.50			
Lack of fit	666.55	8	83.32	2.85	0.1316	Not significant
Pure error	146.00	5	29.20			
Cor total	23,494.55	19				

Table 13 Regression statistics for adopted reduced quadratic model

Std. Dev.	7.91	R-Squared	0.9654
Mean	753.35	Adj R-Squared	0.9495
C.V. %	1.05	Pred R-Squared	0.9045
PRESS	2242.79	Adeq precision	26.169

Table 13 shows the regression statistics. The coefficient of determination is high and close to 1, namely R-Squared equals to 0.9654, which is desirable. “Pred R-Squared” of 0.9045 is in reasonable agreement with the “Adj R-Squared” of 0.9495. “Adeq Precision” measures the S/N ratio. A ratio greater than 4 is desirable. In this case the ratio of 26.169 indicates an adequate signal. This model can be used to navigate the design space.

The adequacy of the model should be checked by the examination of residuals. Residual analysis is necessary to confirm that the assumptions for the ANOVA are met. Other diagnostic plots may provide interesting information in some situations. The residuals are examined using the normal probability plots of the residuals and the plot of the residuals versus the predicted response. Normal plot of residuals, shown in Fig. 12, should be in a straight line. The residuals generally fall on a straight line implying that the errors are distributed normally. Nonlinear patterns, such as an S-shaped curve, indicate non-normality in the error term, which may be corrected by a transformation.

Residuals versus predicted response should be randomly scattered without pattern or “megaphone” shape, as shown in Fig. 13.

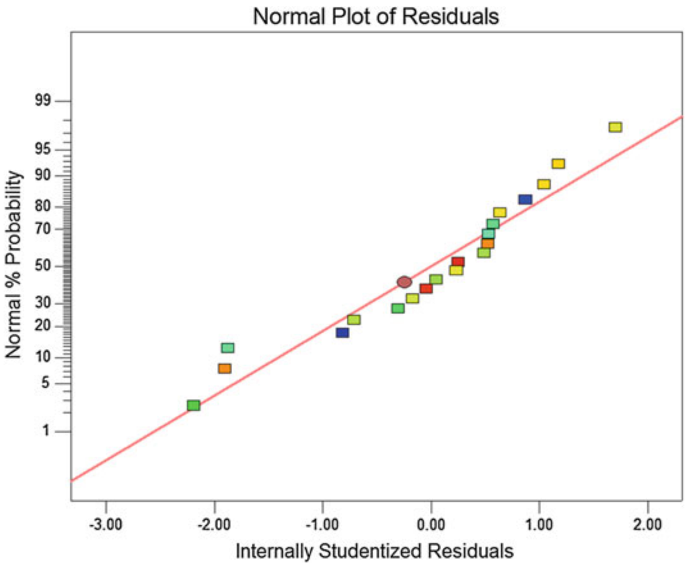


Fig. 12 Normal probability plot of residuals for temperature T

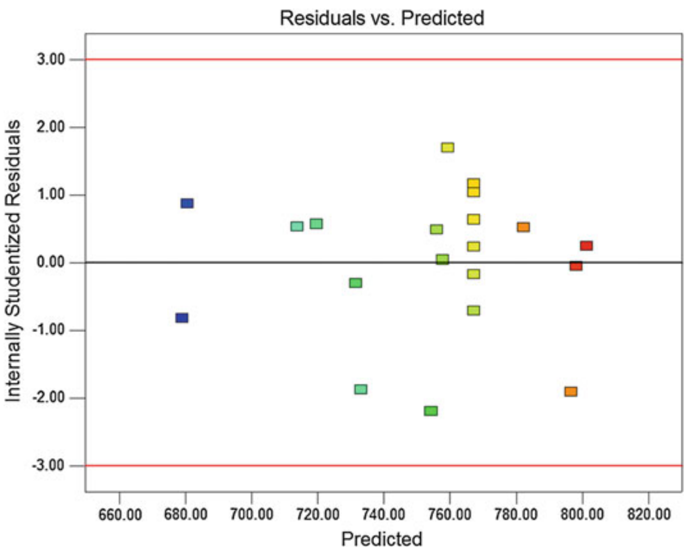


Fig. 13 Residuals versus predicted response for temperature T

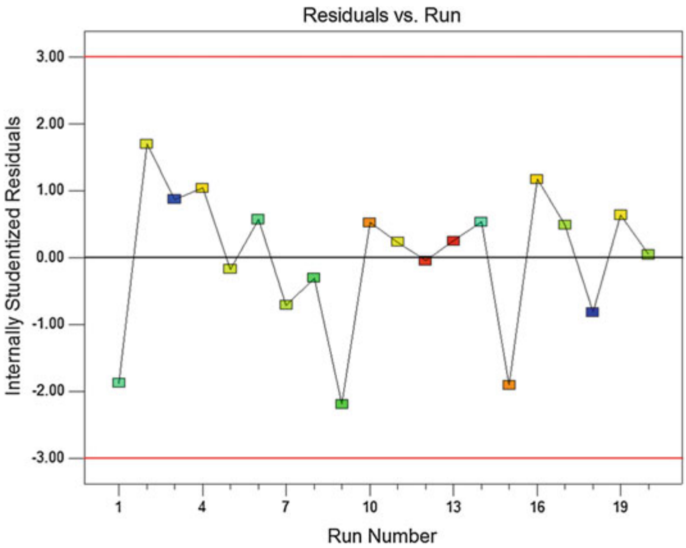


Fig. 14 Residuals versus run for temperature T

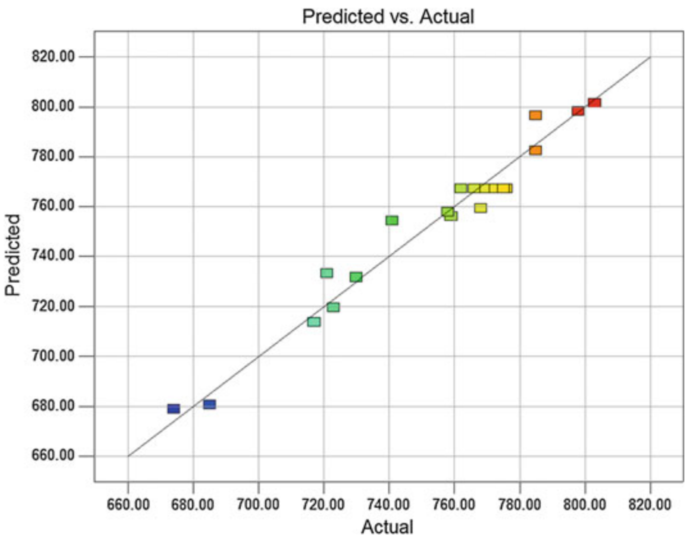


Fig. 15 Predicted response versus actual for temperature T

Residuals versus run tests should be randomly scattered without trend, see Fig. 14.

In order to determine the quality of the adopted model, it needs to be checked whether points of predicted response versus actual values are randomly scattered along the 45° line like in Fig. 15.

This implies that the proposed model is adequate and there is no reason to suspect any violation of the independence or constant variance assumptions.

11.4 Final Equations and Models Graphs

For the analysed example the final equation in terms of actual factors was determined, which determines the temperature T from the input factors, namely the cutting parameters:

$$T = 440.75 + 2.03 \cdot v_c + 58.30 \cdot a_p + 1903.04 \cdot f + 486.67 \cdot a_p \cdot f - 22.51 \cdot a_p^2 - 12341.64 \cdot f^2 \tag{23}$$

Figures 16 and 17 show the response surfaces describing the temperature T dependence on the depth of cut and cutting speed for this case study.

Next, the final equations and examples of response surfaces for the remaining measured responses are shown. The analysis was performed in analogy to the temperature T. To approximate the result for tangential force F_t, the linear model

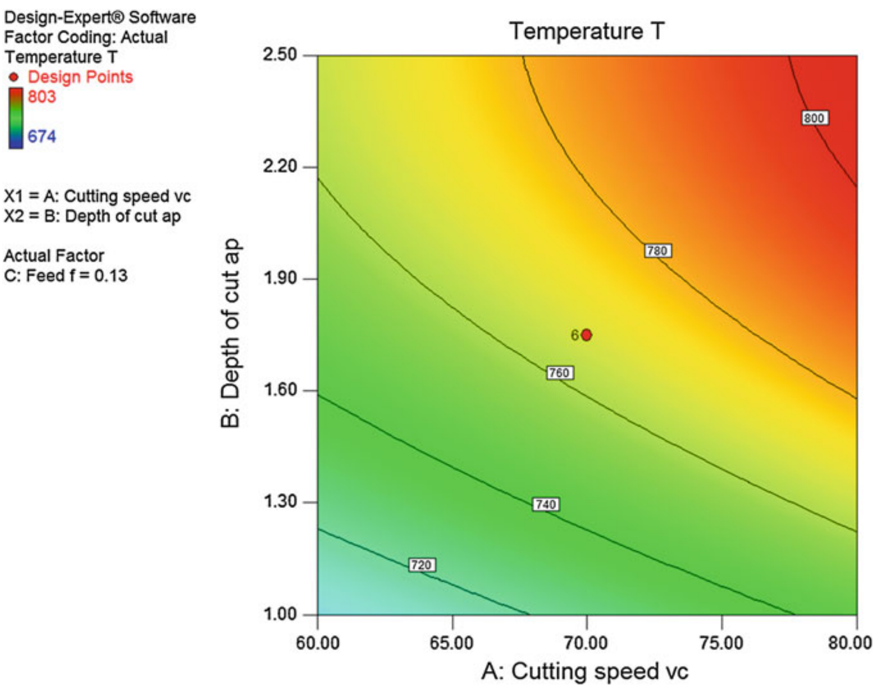


Fig. 16 Response surface contour plot representing the temperature T dependence on the depth of cut a_p and cutting speed v_c for feed $f = 0.13$ mm/tooth

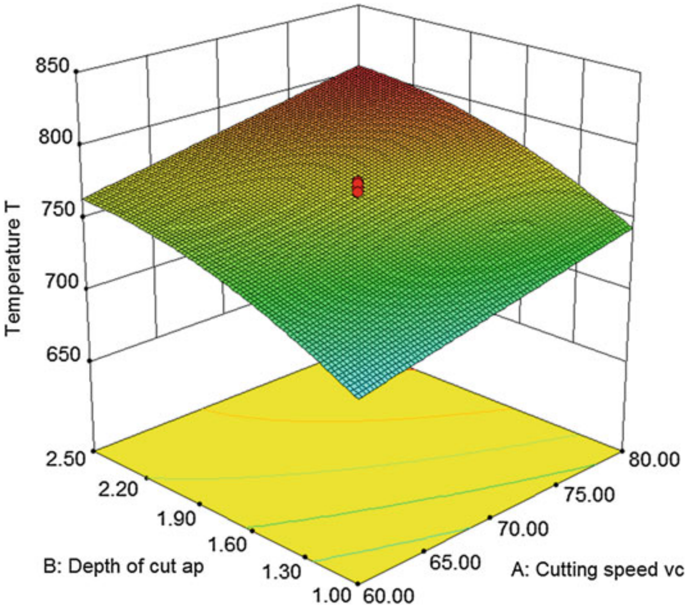


Fig. 17 Response surface 3D representing the temperature T dependence on the depth of cut a_{p} and cutting speed v_{c} for feed $f = 0.13$ mm/tooth

was chosen and an ANOVA followed. The final model of tangential force F_{t} is the next function of adjustable parameters of the process:

$$> F_t = 85.61 - 3.92 \cdot v_{\mathrm{c}} + 289.44 \cdot a_{\mathrm{p}} + 1472.84 \cdot f \tag{24}$$

Figure 18 contains the 3D response surface representing the effect of cutting parameters on tangential force F_{t}.

Similarly, to approximate the result for radial force F_{r}, the reduced quadratic model was chosen. The final model of radial force F_{r} is:

$$F_r = -586.04 - 176.20 \cdot a_{\mathrm{p}} + 9013.28 \cdot f - 29{,}706.86 \cdot f^2 \tag{25}$$

Figure 19 depicts the 3D response surface representing the effect of cutting parameters on radial force F_{r}.

Furthermore, based on the data from multifactor RSM it is possible to obtain the numerical optimization of the process, i.e. the optimum cutting conditions. Design-Expert allows setting criteria for all variables, including factors and propagation of error. The programme restricts factor ranges to factorial levels, plus one to minus one in coded values, the region for which this experimental design provides the most precise predictions.

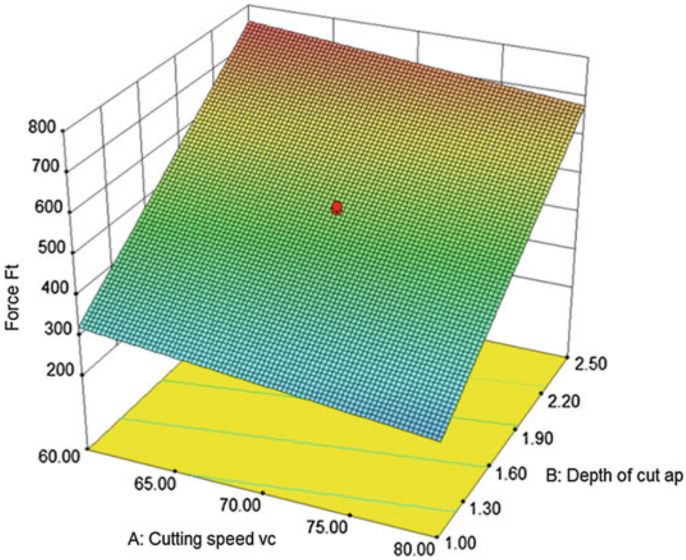


Fig. 18 Response surface 3D representing the tangential force F_t dependence on the depth of cut a_p and cutting speed v_c for feed $f = 0.13$ mm/tooth

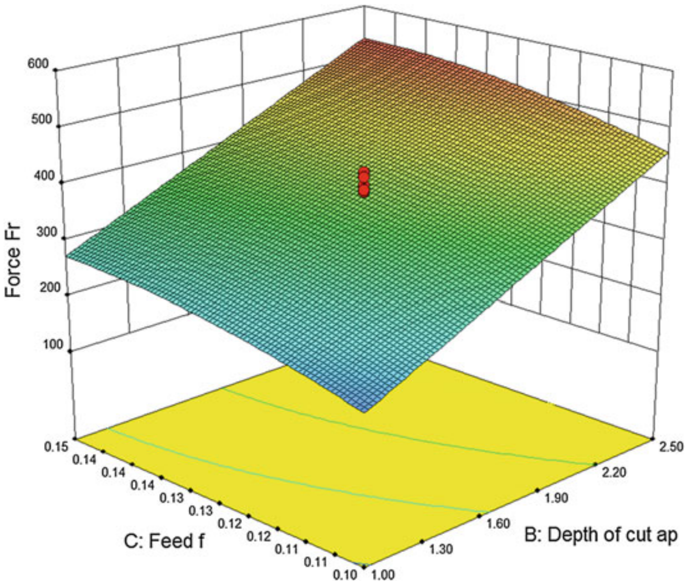


Fig. 19 Response surface 3D representing the radial force F_r dependence on the depth of cut a_p and feed f

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Design of Experiments—Statistical and Artificial Intelligence Analysis for the Improvement of Machining Processes: A Review

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Abstract The modern industry needs that its manufacture process to be fast, efficient, low cost, ecologic, and other. It occurs because many consumers require that the products have great quality and a fair price. Furthermore, in sometimes, the industry has the sale price imposes by client. Thus, the industry develops news techniques, process, tools, and other to attain this goal. However, these new developments require great studies to obtain the best condition and avoid that become more a waste. The Statistical or Artificial Intelligence (AI) Analysis are great ways to understand the new developments and obtain the best conditions. This review chapter presents the techniques (Statistical and AI) that were applied to plan and analyse the machining processes. Aim of this chapter is to argue the planning and analysis importance in researches, as well as help researchers to choose a technique and define their machining experiments, optimising the time, material and other means.

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1 Introduction

Nowadays it is common to find many investigators using the statistical and/or Artificial Intelligence (AI) analysis in their papers. These methods help to understand the importance of parameter appointed or to define the ideal condition. To obtain a controlled cutting process through the parameter optimisation, a manufacturer should find points in the process that offer the balance of cost and quality [1]. Asiltürk and Akkuş [2] highlighted that a high number of the cutting variables require a high numbers of experiments, besides, the variables should be studied under controlled conditions.

The usage of these techniques in investigating machinability had the goal of estimating the effects of feed rate, cutting velocity and depth of cut on power consumption and surface finish [3]. According to Makadia and Nanavati [4], in most publications the effect of cutting parameters on surface roughness applying few number of tests was studied. However, they suggested also analyse effect of cutting geometry on surface roughness.

To predict the surface quality, the AI methods (artificial neural network, genetic algorithm (GA), and others) has been employed. Its main advantages are models that present most realistic and accurate, a highest level of integration with computers, and an approach that can be used with conventional methods [5].

Paiva et al. [6] used the multivariate robust parameter design (MRPD) approach to optimise the turning of AISI 52100 using wiper tools due to the moderate to high degree of correlation obtained by multiple responses. The authors observed that MRPD approach showed better results that the individual optimisation routines and minimal variance for each surface roughness profile. Subramanian et al. [7] applied a second-order quadratic model to optimise the milling of Al7075-T6 aluminium alloy with high-speed steel end mill cutting tool that the deviation is well within the limit of 95 % confidence level.

Generally, modelling and monitoring with statistical methods employ regression-based and time-domain techniques [8]. To understand the machinability of tungsten-copper (WCu25) alloy with cemented carbide tool, Gaitonde et al. [9] planned their experiments as per full factorial design (FFD). The adequacy of the quadratic models was verified using the analysis of variance (ANOVA) and the analyses used the Response Surface Methodology (RSM).

The trade-offs between energy, production rate and quality were weighed up in a multi-objective optimisation problem by Yan and Li [10] using grey relational analysis and RSM-based method. This approach allowed a reducing of the cutting energy consumption by 18.1 % when compared with traditional objective optimisation, satisfying the requirement for sustainable machining. Wang et al. [11] used multi-objective (energy, cost and machining quality) to optimise the turning of AISI 1045 steel applying non-dominated sorting genetic algorithm II (NSGA-II).

The present work presents a review of the state of the art on statistical, mathematical and computational techniques applied to machining process planning and analyse. First, statistical methods for design and analyse of experiments are addressed. Subsequently, AI approaches are referenced with focus on machining parameters optimisation. Several papers were covered providing a wide view of methodologies applied to achieve the best results on machining processes.

2 Design of Experiments (DoE)

Design of experiments (DoE) comprises a set of statistical techniques to process improvement and planning. Using DoE the experimenter can adjust the optimum parameter levels to achieve the best output levels and a robust process, that is, a process which has minimum variability.

The DoE strategies can be separated into classical DoE, RSM and Taguchi approaches. These methods are commonly jointly applied or with another mathematical and/or computational techniques. There are several statistical packages to apply DoE in machining analysis and planning, facilitating the process improvement.

According to Montgomery [12] the first statistical concepts to design experiments were based on factorial design and ANOVA. These techniques summarise the classical DoE. Mandal et al. [13] affirmed that the RSM embraces mathematical and statistical techniques to model and analyse the problems in which the objective is to optimise a response that is influenced by the variables.

The Taguchi method is a DoE technique, which is useful to reduce the number of experiments and to minimise effects of the not controlled factors, the time of experiments, and costs, besides to present the significant factors in a shorter time. This technique is focused on determining the parameter settings which produces the best levels of a quality characteristic with minimum variation [2].

Abellan-Nebot and Subirón [14] affirmed that performing a correct DoE can provide an adjustment of the regression model relatively fine for the machining parameters. In their investigation on turning of AISI 304 stainless steel, Mahdavinejad and Saeedy [15] used the DoE with full factorial method to analyse the effects of all levels of the parameters.

Krimpenis et al. [16] mentioned that DoE is applied in the manufacturing field to identify the significant parameters that affect the process or product and determine the near-optimum parameter values that increase productivity and machine efficiency. It defines the significant parameters and the ideal values based on the quality characteristics. These authors [16] suggested a series of steps to improve knowledge of the obtained results:

- Choice of parameter levels: each significant parameter has a value out of an extensive field that should be well studied to define the value that is expressive;
- Orthogonal array (OA) issues: is represented by Latin L and number of the array's lines that can be two-level, three-level and mixed-level factors. In this step is chosen the number of parameters and interactions, their levels and desired experiment resolution between 1 (lowest) and 4 (highest);

- Experiment conduction according to an OA and analysis of results: In this step is applied the statistical analysis. ANOVA is used to define the high influence parameters and draw generic conclusions.

Soshi et al. [17] applied DoE in their investigation to find the best combination of parameters to achieve a smooth surface since there are several important parameters to be considered to produce a high-quality surface in milling operations. In the dry turning of Al 7075-O aluminium alloy study, Agustina et al. [18] used the DoE (24 with 2 replications) to analyse the influence of the cutting parameters on cutting forces in dry turning of an aluminium alloy.

In the investigation of turning of SS202 stainless steel applying cryogenic cooling, Kumar and Choudhury [19] used the central rotatable composite DoE to plan their experiments. This design type allows generating second-order models. The total number of experiments using this design is defined by Eq. (1).

$$n_{\mathrm{exp}} = 2^k + 2K + n_{\mathrm{c}} \tag{1}$$

where

n_{exp} number of experiments to perform;
K number of input variables;
n_{c} number of central runs.

Studying the turning of AISI 1045, Hwang and Lee [20] employed a fractional factorial design with resolution V, widely used in the industry, to analyse the significant effect and two-factor interactions. In this method, generally the significant effects are disconcerted with four factor interactions, and two-factor interactions are disconcerted with three-factor interactions, ignoring interactions higher than three factor.

In the electrical discharge machining of AISI D2, Prabhu et al. [21] applied a FFD using three parameters (pulse current, pulse duration and pulse voltage) with three levels, amounting to 27 experiments that helped them to found a designed model with 99.7 % accuracy.

To find the high influence parameters of the characteristic values in the beginning of the experiment, Park et al. [22], used four factors defined by the FFD and, posteriorly, used the central composite circumscribed design and RSM to optimise the process. They observed that the spindle speed, feed rate, depth of cut and interval of lubricating oil application presented strong influences in the machinability in ultra-high-speed machining.

2.1 Classical DoE

The influence of some machining parameter can be determined by ANOVA from a series of results of experiments by the design of experiment approach. ANOVA is the predominant statistical method used to interpret the data [23].

In the 1930s, Sir Ronald Fisher developed the ANOVA method to understand the results of experiments in the agricultural. He used the sum of the squared deviations from the total mean signal-to-noise ratio, separating its total variability into contributions by each of the design parameters and the error. This method shows the significance of all important factors and their interactions by comparing the mean square against an estimate of the experimental errors at specific confidence levels [24].

According to Muthukrishnan and Davim [25], ANOVA is a technique of portioning variability into identifiable sources of variation and the associated degree of freedom in an experiment. The quality characteristics from the significant effects of the parameters is analysed by Fisher test (*F*-test). The influence on the result was indicated by the "percent" contribution (*P*) of each factor.

For some machining processes, especially, when the experimenter do not know the factors (controllable or not) affect the outputs, it is necessary to draw a set of screening experiments using fractional factorial designs. Born and Goodman [26], affirmed that the objective of screening experiments is to diminish a high number of potentially parameters to those that are strong significant since it is not economically practical to perform every possible combination of machining parameters. They studied the tool wear, which observed that the track length, chip size, tool rake angle and cutting speed had significantly affected in the tested ranges.

In many studies, researchers commonly consider admissible a confidence of 95 %, i.e. they use a significance level (α) of 0.05. In Table 1 is exhibited some studies that used ANOVA method and the significance level chosen. In the

Table 1 Significance values used in machining researches

Researcher	Process	Material	Factors	Significance (%)
Muthukrishnan and Davim [25]	Turning	Composite	Cutting speed, feed rate, depth of cut	5
Gopalsamy et al. [23]	Milling	AISI P20 (55 HR_C)	Cutting speed, feed, depth of cut, width of cut	5
Babu and Chetty [28]	Waterjet	Al 6063-T6 aluminium alloy	Depth of cut, top kerf width, bottom kerf width, kerf taper, surface roughness	10
Bagci and Ozcelik [24]	Drilling	Al 7075-T651 aluminium alloy	Spindle speed, feed rate	5
Carvalho et al. [29]	Tapping	AM60 magnesium alloy	Forming speed, hole diameter, type of tool	5
Lin et al. [30]	EDM	AISI H13	Machining polarity, peak current, auxiliary current with high voltage, pulse duration, no-load voltage, servo reference voltage	5

mathematical models developed in turning of AISI 1040, Neşeli et al. [27] applied ANOVA and the prediction of surface roughness offered a 96 % confident interval.

In the turning AISI 4340 steel with Zirconia Toughened Alumina (ZTA) insert, Mandal et al. [13] used the ANOVA to develop mathematical model that was verified with excellent results. Yu et al. [31] applied ANOVA to find the ideal values of cutting parameters and obtain the better machinability (accuracy and efficiency).

In the Pareto ANOVA the sum of squares of differences (S) for each controlled parameter is calculated as the percentage of sum of squares of differences for each parameter to the total sum of the squares of differences and a Pareto diagram is plotted using the contribution ratio and the cumulative contribution [32]. Hamdan et al. [33] used Pareto ANOVA method, a very simple alternative to analyse the optimisation exhibiting the influence (percentage) each parameter. This method provided an improvement of cutting forces (25.5 %) and surface roughness (41.3 %).

2.1.1 Multiple Comparisons Methods

When the ANOVA indicates that the average levels of a source of variation differ, it is necessary to identify which factor levels or combination of the factors levels are specifically different. There are various procedures of multiple comparisons in the literature, for example, Tukey, Fisher, Dunnett, Bonferroni, Scheffé, Dunnett, HSU, Scott-Knott and others.

Pereira et al. [34] used the multiple comparison method of Scott-Knott to identify which factor levels or combinations of the factors levels are specifically different and this method which is a method of grouping means that categorises results without ambiguity. The methodology proposed was effective and essential to analyse of surface roughness and cutting force and to determine the best machining conditions and chip breaker for the response factors in turning AISI 1045 steel with grooved tools.

2.2 Response Surface Methodology (RSM)

The Response Surface Methodology (RSM) is method to optimise and model (empirical approach) a problem to define the relationship between several parameters and the responses with the several desired criteria. For example, this method conjugated with the factorial DoE can predict surface roughness using a small number of experiments [35].

Mandal et al. [13] used RSM to model the surface roughness in turning of AISI 4340 and optimized it through desirability function. They optimised the performance of the cutting tool in 92.3 % with a combination of cutting parameter, cutting speed (high), feed rate (high) and depth of cut (low). Habib [36] applied the RSM in the EDM process to determine the relations between the parameters (material removal rate, electrode wear ratio, gap size and the surface finish) for developing mathematical models, in a manner very simple, powerful and flexible.

In the study of turning on the AISI 410 steel, Makadia and Nanavati [4] applied the RSM and found a quadratic model to analyse the influence of cutting parameters in Ra that presented an error value of 6 %. They affirmed that 3D surface counter plots allows in determining the ideal combination to optimise the surface roughness. Neşeli et al. [27] mentioned that in RSM shall have at least three levels for each factor to avoid uncertainties due to estimated values for the combinations of not tested factor.

In the drilling of composites, Rajamurugan et al. [37] used RSM to find the optimal parameters set (feed rate, spindle speed, drill diameter and fibre orientation angle) to optimise thrust force. Valarmathi et al. [38] applied the RSM in drilling of medium density fibreboards (MDF) and developed a mathematical model to optimise the process for reducing thrust force.

2.3 Taguchi

Taguchi is a technique widely used in engineering design and take the DoE from the exclusive world of the statistician and bring it more fully into the world of manufacturing [3]. Hamdan et al. [33] cited that Taguchi has great success for optimising industrial processes. They observed the efficiency of method for optimising surface roughness in high-speed machining of stainless steel; and suggest the following steps to prepare an experiment:

- Selecting the OA according to the numbers of controllable factors;
- Running experiments based on the OA;
- Analysing data;
- Identifying the optimum condition;
- Conducting confirmation runs with the optimal levels of all the parameters.

Tzeng and Chen [39] used Taguchi design on high-speed EDM process. The authors assure that it separates the control factors from the noises, minimising the noise effects. It can be minimised and generates unintended effects by using inner, which assigns the control factors, and outer arrays, which arranges the noise factors coupled with signal factors for exposing the process to varying noise conditions.

In the investigation of the effects of drilling on the Al 7075-T651 aluminium alloy, Bagci and Ozcelik [24] observed that Taguchi method was useful to analyse it using smaller number of tests than the FFD. Furthermore, it provides a systematic and efficient methodology to optimise the process that would be required lower effect than other techniques.

Bissey-Breton et al. [40] used two levels for eight factors (cutting speed, feed, tool nose radii, depth of cut, tool holders, tool life and machine tools) and an orthogonal plan designed according to the Taguchi's method was considered to observe surface and subsurface characteristics in the finishing turning of pure copper.

In their study, Kirby et al. [41] presented an efficient method, applied using a specific set of control and noise parameters, and a response variable of surface roughness, for determining the optimal parameters for surface finish using Taguchi design with L_9 (34) OA.

According to Rao et al. [42], Taguchi method is generally used due to it be powerful tool to analyse the machining parameters. They designed especially OA to analyse the influence of the machining parameters using few number of tests that require a smaller experimental time.

2.4 Other

The singular spectrum analysis (SSA) that consists a nonparametric technique of time series analysis based on the principles of multivariate statistics was used by Salgado et al. [43]. This technique projects the original time series onto a vector basis obtained from the series itself, following the procedure of principal component analysis. The set of series resulting from the decomposition may be interpreted as a slowly.

Gopalsamy et al. [23] used the grey relational analysis that is an effective technique to analyse many factors with few data, providing a solution to uncertainty in multi-input and discrete data problems and to optimise the multi-response processes through the setting of process parameters. They integrated Taguchi L_{18} OA with grey relational to study the rough and finish machining individually by varying of cutting parameters.

3 Artificial Intelligence Analysis (AI)

AI is to related intelligent machines, especially intelligent computer programs that use similar to the human intelligence. It is more used in the engineering to resolve problems normally requiring human intelligence due to a number of powerful tools, such as Ant colony optimisation (ACO), Artificial Neural Network (ANN), Expert System (ES), Fuzzy Logic (FL), Genetic Algorithm (GA), Particle Swarm Optimisation (PSO), Simulated Annealing (SA), and various swarm intelligence [44].

Ramesh et al. [45] cited in their paper the usage of AI techniques to develop a thermal error compensation module using temperature values at different locations of the machine. They developed a positioning accuracy measured and surface finish automatically controlled by adjusting the operating parameters using AI-based regression techniques to build the prediction model between vibration and surface finish.

According to Abellan-Nebot and Subirón [14], AI technique had been applied to monitoring systems due to need for consistent models that can learn complex non-linear relationships between variables and its adequate selection is crucial to

Table 2 Frequency of usage, drawbacks and advantages of AI in machining researches [14]

	Usage	Drawbacks	Advantages
Neural networks	59 %	No clear guidelines on how to design neural nets; lack of physical meaning; low extrapolation capability; trial and error procedures to find neural network parameters	Model can be obtained without previous knowledge; ANN can learn patterns in a noisy environment or with incomplete data; good generalisation capability
Fuzzy logic	15 %	Do not have much learning capability; generalisation capability is poor compared with ANN; no standard methods to transform human knowledge into fuzzy models; inputs limited	Tolerant of imprecise data; easy to understand since it is based on natural language; models can be built on top of the experience of experts; good extrapolation capability
ANFIS	10 %	Drawbacks: many parameters to be learnt or defined by the user; usual contradictory learnt rules; inputs limited	Combines fuzzy systems and ANN It can be applied with or without previous process knowledge; tolerant of imprecise data; good extrapolation and generalization capability
Bayesian networks	4 %	High quantity of experimental data is required; high computational cost; variable discretisation is required and depends on network reliability and accuracy	Adequate for modelling stochastic systems; the model presents the causal relationships between variables; let fuse prior knowledge by fixing well-known causal relationships

Frequency of usage of AI approaches in intelligent machining systems according to the references found in the research platform ISI-Web of knowledge from 2002 to 2007. The remainder, 12 %, corresponds to others methods

develop reliable machining models. Several AI techniques, mainly ANN, FL systems and the Adaptive neuro-fuzzy inference system (ANFIS), have been widely used for monitoring machining systems and modelling (surface roughness and tool wear). These authors mentioned that although AI is gaining popularity in recent works, it has been less widely used; and some drawbacks and advantages that may facilitate the selection of a particular, as can be seen in Table 2.

3.1 Fuzzy Logic (FL)

The Fuzzy system is based on fuzzy set theory and associated techniques that contain the ideas of modelling and controlling very complex cases. This technique tries to reproduce two extraordinary human capabilities, capability to converse, reason and make rational choices in an environment of imperfect data; developing several tasks without the use of measurements or computations. This method also is denominated of fuzzy-rule-based system, fuzzy ES, FL controller, fuzzy model, fuzzy associative memory and simply (and ambiguously) fuzzy system [44]. FL is a set without a crisp, clearly defined boundary that may contain elements with a partial degree of membership, commonly 0–1. To predict the machining performance, this technique provides relevancy and importance [46].

In the study of turning on carbon fibre reinforced polymer using CBN cutting tool, Rajasekaran et al. [47] used of fuzzy-rule modelling to predict the surface roughness that when compared to results of experiments were highly satisfactory. Zhang et al. [48] studied the adaptive fuzzy control system of servomechanism for EDM combined with ultrasonic vibration that affirmed that an appropriate selection of input and output variables and the establishment of the membership functions of these variables meet the actual control requirements very well.

Liu et al. [49] used a method called grey-fuzzy logic that has been applied for requests of several machining responses and can be modified to optimise a single grey-fuzzy reasoning grade. It used OA to obtain the optimisation of multi-response characteristics during the process. This technique can simplify the optimisation of complex multiple response.

3.2 Artificial Neural Network (ANN)

The Artificial Neural Networks (ANN) imitates the human brain to implement the functions of association, self-organisation and other. This technique has the capacity to estimate functions accurately, thus it is useful to model highly non-linear processes [50]. In study of end milling, Zain et al. [51] employed the ANN to predict the surface roughness and present a table highlighting some researchers that used this technique in machining researches (milling, turning and drilling) for modelling Ra. They affirmed that the ANN may predict accurately values using a small number of training samples that is not the significant issue in obtaining a good prediction. However, it will be influenced by how the number of layers and nodes is altered in the hidden.

The ANN models developed by Özel et al. [52] were useful in the prediction of tool wear and surface roughness for a range of cutting parameters and develop an intelligent hard turning. To predict in the surface roughness in the EDM of various steel, Markopoulos et al. [53] used two discrete programs to develop the ANNs and the modelling of EDM that were proven to perform well, providing reliable predictions and a possible way to avoid time-and money consuming experiments.

According to Korkut et al. [54], the back-propagation of ANN with Levenberg-Marquardt has strong acceptance and has been used in different fields. They proposed a variation of the standard back-propagation to train the ANN and obtain model that was useful to predict the tool-chip interface temperature. Furthermore, these models could be used for an efficient analysis of experiment that can contribute for the optimisation of time and cost.

3.3 Adaptive Neuro-Fuzzy Inference System (ANFIS)

The ANFIS is a technique to develop membership functions that can use neural networks method to develop membership functions. This provides the advantages of both fuzzy and neural networks modelling plus it do not need a mathematical description, i.e. neuro-fuzzy modelling improves convergence rate and approximation accuracy [55]. The authors used Sugeno fuzzy system and hybrid algorithm was employed to train neural networks and affirmed that ANFIS is a more accurate modelling method in comparison with ANN and multiple linear regression.

In the dry wire electrical discharge machining (WEDM) study, Fard et al. [56] used the ANFIS technique to correlate input variable (discharge current, gap voltage, pulse on time and off time, wire tension and feed) and main outputs (cutting velocity and surface roughness). They observed that obtained ANFIS surfaces it could be found combination of input variable and the model could predict the cutting velocity and surface roughness as well due to low values of root mean squared error (RMSE) in testing.

Neto et al. [57] applied ANFIS in their investigation about drilling of composed of Al 2024-T3 aluminium alloy and upper portion of Ti-6Al-4V titanium alloy, which observed that ANFIS proved to produce very precise predictions. Studying the wear in the turning of stainless steel 304L study using uncoated carbide inserts, Liu et al. [58] applied ANFIS in the online measurements to detect the tool wear. They concluded that ANFIS can predict the tool wear very accurately, finding a success rate of 96.67 %.

To monitor the tool wear in the turning, Gajate et al. [59] applied the dynamic evolving neural-fuzzy inference system (DENFIS) and of the transductive-weighted neuro-fuzzy inference system (TWNFIS) to model the tool wear using four input (acoustic emissions, cutting forces, time and vibrations) and one output (tool wear rate). The TWNFIS was modified to normalise the data procedure and cluster the algorithm, which shows results were better than DENFIS and ANFIS due to it provides smaller errors.

Dynamic evolving neural-fuzzy Inference System (DENFIS) is suitable for online adaptive systems. This model was developed depending on the position of the input vector in the input space a fuzzy inference system for calculating the output is formed dynamically bases on m fuzzy rules that had been created during the past learning process [60]. According to Gajate et al. [59], the transductive-weighted neuro-fuzzy inference system (TWNFIS) consists of a dynamic neuro-fuzzy inference system with local generalisation that is elaborated with three important characteristics:

- Fuzzy: semantic transparency, capacity to simulate the human thought presenting a best result with uncertainty and imprecision.
- Neural: exhibit a high learning capability that is excellent to model non-linear function.
- Transductive: estimate the model a single input/output set of the space, using only data associated with the set.

3.4 Bayesian Networks (BN)

The Bayesian Network (BN) is a probabilistic graphical model that has a directed acyclic graph representing a set of variables (nodes) that can represent any kind of variable and their probabilistic conditional independencies (encoded in its arcs). The facility of the interpretation offers clear and extensive advantage to the operator, when compared with other AI technique [61].

Dey and Stori [8] cited that BN, which had been employed for monitoring and diagnostic in the manufacturing, provides a flexible structure to model and evaluate the uncertainty. They applied the Bayesian belief network in their study (which the interest variables were the dimensional and hardness variation and tool wear) that concluded that seems to be a great technique for explicitly addressing uncertainty and using data from various bases.

Dong and Yang [62] developed a drilling model using dynamic bayesian network (DBN) inference procedures and particle filtering algorithms that can be established. In the study of the milling of AISI P20, Dong et al. [63] compared the Bayesian multilayer perceptron (BMLP) and Bayesian support vector machines for regression (BSVR) networks. The results show that the BSVR was more precise than BMLP to predict the flank wear, although it required higher computational efforts. The BMLP can be a useful to solution in online implementation when do not have access to high-performance computer.

Correa et al. [61] compared BN with ANN that observed better results for the BN to predict problem of quality in high-speed milling. Furthermore, the BN offers better result than ANN in the computational time of models, requiring 0.08 and 12.69 CPU seconds, thus, the employed of BN can be easy and fast.

3.5 Genetic Algorithms (GA)

The Genetic Algorithm (GA) can be considered an optimisation technique, indifferently of physical substance, used to resolver a complex problem similar to Darwinian theories of evolution. Its principle is optimising an objective function in complex multi-modal space that occurs indifferently of the nature of the phenomenon [64].

According to Wang et al. [65], the GA is based in the theory of biological evolution that includes the natural selection. The survival of the fittest uses the parameters, rules, and switches of the problem that are represented by binary combination. This combination is called chromosome that optimises an objective function through the following step:

- Designing of the parents;
- Designing of the hereditary chromosome;
- Gene crossover;
- Gene mutation;
- Creation of the subsequent generation.

In the temperature milling study of Al-6063 aluminium alloy, Sivasakthivel and Sudhakaran [66] applied GA to optimise the machining parameters to obtain the minimum temperature rise. They found a result that optimised the helix angle, spindle speed, feed rate, axial and radial depth of cut. Rao et al. [67] studied a relationship between the input parameters and surface roughness using GA, which was observed a significant decrease in mean square error when GA is used to optimise an ANN.

4 Modelling and Optimisation for Machining Process

In the literature, several paper employed models to understand, predict or optimise the parameters or events that occur in the machining processes. Campos et al. [68] affirmed that the modelling and optimisation are employed by researchers due to it has an important influence in the total cost of the product. It is need due to increase the number of cutting parameters that require high number of tests, consuming several means. These authors [68] suggest the employ of the following methods to model bellow:

- Taguchi and ANOVA: efficient techniques to control the effect on tool wear and surface roughness.
- RMS: to optimise the relationship between the several inputs and outputs.
- ANFIS: to provide or optimise the cutting parameter and phenomenon such as surface roughness and tool wear.
- Artificial neural networks (ANN): to predict the phenomenon such as the surface roughness, tool wear.
- GA: to find the factors of a model and optimise the outputs.

Akkuş and Asilturk [69] affirmed that time, material and labour work may be saved by predicting surface roughness without experimental testing for intermediate values. They developed accurate models to predict the surface roughness in the turning of AISI 4140 applying ANN, FL and statistically multi-regression methods for the used input parameters, cutting speed, feed rate and depth of cut.

Hessainia et al. [35] classified the surface roughness (R_a) modelling techniques into three groups: experimental; analytical; and AI models. They proposed a model using the RSM for the hard turning of AISI 4140 (56 HR_C), which found a quadratic model of RMS with correlation coefficient of 99.9 and 96.4 % for models R_a and R_t, respectively.

According to Upadhyay et al. [70], to predict the surface roughness using machining parameters was useful only to define the parameters for finishing due to the vibrations/cutting forces. They developed this model using multiple regression method as a function of vibration in radial, axial and tangential directions. They tested the prediction using an ANN model that was trained with the Levenberg-Marquardt. These developed models can be effect to predict the surface roughness with average error of 4.11 % and maximum error of 6.42 %.

Lopes et al. [71] presented a model considering the multivariate uncertainty as weighting matrix for the principal components. In the study of turning of AISI 52100 hardened steel with wiper tools was implemented a central composite design using three factors, cutting parameters, for a set of five correlated metrics, different surface roughness profile. The results showed that the developed technique presented an excellent predictability.

5 Conclusions

The objective of the manufacturers is obtaining a production that is economic, ecological, efficient and reliable. Thus, in the machining sector, there are several developments in tools (example the geometry, material and coatings) and machines (example power, spindle speed and accuracy). However, the definition of the cutting parameters is more important to obtain a condition that result in desired objectives. The users can be several parameters as outputs, as the tool wear, chip removal volume, cutting forces, vibration and others. After, the users should analyse the outputs and define the cutting parameters to obtain the desired objective, as the maximum production, low time, or quality of product and others.

Meantime, the machining processes are composed of several operations, as turning, milling, drilling, broaching and others, that have variables, as cutting speed, feed rate, depth of cutting, cooling system and others. Sometimes, the users ignore or forget that some variable can be influence the process, as the brands, room temperature, material structure and others. Thus, the users should realise randomly all tests at least twice (repeat and replications), to reduce the influence of the not assigned variables and the randomness of responses. Furthermore, the analysis will be more reliable and easily to comprehend the influence of the parameters.

The analysis of the outputs using Statistical and/or Artificial Intelligence methods provides results about the cutting parameter and their interaction that facilitate the comprehension of machining phenomena. These methods employed to model the process can indicate the best cutting parameter combination to obtain a product with maximum quality, minimum losses (time, material and others) among the tested condition. The usage of the one or both methods will depend of the user's goal, i.e. if the user wants an analysis simplest, the statistical analysis using the ANOVA can be the ideal method. However, if the research employs the several factors, levels, and other or the previse results, the usage of the artificial intelligence analysis, as the ANN, can be the ideal method. Furthermore, the planning of experiments is more important in the research because it can reduce the cost and the time need to execute the experimental.

Thus, although the machining processes are increasingly evolved, the planning and the analysis (Statistical and/or Artificial Intelligence) always will be necessary in the academic investigation or industrial application to optimise the means and avoid error or waste. For example, an industry that desires to buy the tool machine. Will the new technical characteristics be significant in the production to return the investment? Other example, this industry desires chance the tool supplier. Will the cost variation between suppliers compensate the production variation?

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A Systematic Approach to Design of Experiments in Waterjet Machining of High Performance Ceramics

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Abstract The main objective of this chapter is to highlight the strategic role that a systematic and sequential approach of experimentation plays in order to achieve competitive advantage and technological innovation. The efficacy of this approach is demonstrated by describing an application where the appropriate use of statistical knowledge, along with technological knowledge, has allowed to characterize manufacturing processes, to catalyze the innovation process and to promote the technological transfer. Moreover this approach, based on the use of customized pre-design guide sheets, allows to put into action a virtuous cycle of sequential learning and helps to overcome the gap between practitioners and statisticians in effective application of Design of Experiments (DoE).

1 Statistics for Innovation: Design of Experiments

Today, the improvement of manufacturing processes and process innovations are some of the strategic activities carried out in research and development departments of manufacturing industry and in research centres.

Finding the best solution often requires extensive testing; in order to obtain these results as efficiently as possible is fundamental to adopt adequate experimental procedures and effective data analysis.

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According to Czitrom [1], many engineers and scientists typically perform One-Factor-At-a-Time (OFAT) experiments, which vary only one factor or variable at a time while keeping others fixed. They will continue to do so until they understand the advantages of different approach over OFAT experiments, and until they learn to recognize OFAT experiments so they can avoid them.

The Design of Experiments (DoE) is a methodology for systematically applying statistics to the experimentation process; in many cases it is the best way to establish which variables are important in a process and the conditions under which these variables should work to optimize such process. It is the only tool to perform efficient analysis of a process determined by numerous parameters.

The DoE was introduced in the 1920s by Sir Ronald A. Fisher in the field of agricultural research [2]. Since then much has been published about the theoretical aspect of DoE, such as Wu and Hamada [3], Montgomery [4], Box et al. [5] and today there is sufficient awareness that OFAT experiments are always less useful than statistically designed experiments.

Using some real examples Czitrom [1] illustrates the advantages of DoE and shows that the experimental results cannot take into account the interactions between factors when only one factor at a time varies while keeping all the other ones fixed. Otherwise in DoE all factors are varied together and it is the only way to discover interactions between variables. For these and many other reasons Montgomery [4] says that DoE is a critically important tool for engineers to improve the performance of manufacturing processes. He also says that the application of experimental design techniques early in the process development can result in:

- Improved process yields;
- Reduced variability and closer conformance to nominal or target requirements;
- Minimized development time;
- Saved overall cost.

However, as Ilzarbe et al. [6] deduce, after a review of 77 articles about practical DoE application in the field of engineering, the DoE is a methodology that has been applied for many years in industry to improve quality, but it is still not used as it should be.

These statistical techniques are commonly found in statistics and quality literature but, as pointed out by Tanco et al. [7], they are hardly used in European industry; there is still a significant gap between theoretical development of DoE and its effective application in industry. Why? On the one hand Costa et al. [8] show that DoE is not an easy technique to be applied due to limitations in technical knowledge of the product and technologies involved. On the other hand Montgomery [9] refers to the inadequate training in basic statistical concepts and methods by the engineers. Therefore, there is the necessity to integrate statistical and technological knowledge. In fact statistical approach catalyses the process innovation and, moreover, it allows putting into action a virtuous cycle of sequential learning.

1.1 Pre-design and Guidelines for Designing Experiments

In order to help the experimenters to plan all activities needed for a good testing, Coleman and Montgomery [10] suggest a path which consists of the following seven basic steps:

1. Recognition and statement of the problem;
2. Choice of factors and levels;
3. Selection of the response variable(s);
4. Choice of experimental design;
5. Conduction of the experiment;
6. Data analysis;
7. Conclusions and recommendations (followed by monitoring and/or confirmatory test).

Certainly an accurate pre-design (i.e. pre-experimental planning phase) is the solid basis on which a statistical approach has to be built.

The pre-design is the pre-experimental planning phase, in other words it is everything preceding the definition and execution of experiments, and corresponds to the suggested steps 1–3.

The first step entails elaborating and writing clearly the statement of the problem; it is an obvious step but it is harder than it may appear. It is especially needed in a working team so that everyone has a clear idea of the aim.

The selection of the response variable(s) and the choice of the factors, with their levels, is really not a simple issue. It is a crucial task and requires adequate knowledge.

The potential design factors are the parameters that considered to influence the process in study; the range over which these factors will be varied must be chosen too. Regarding the response variable(s), quoting Montgomery [4], *the experimenter should be certain that this variable really provides useful information about the process under study*.

Therefore, steps 2 and 3 represent the phases which especially require synthesis of statistical and technological skills. In fact in order to choose a good selection of factors and response variable(s) it is necessary not only to understand the statistical thinking, but also to have good process knowledge.

Who has both statistical and process knowledge has a competitive tool to perform an innovative research.

1.2 Pre-experimental Planning

According to Coleman and Montgomery [10] and Ilzarbe et al. [6], pre-design guide sheets, (split up into pre-design master guide sheets and supplementary sheets) to direct the experimentation, are suggested to be conceived, customized and implemented (as done in the presented application). Previous edition of pre-design guide sheets proposed in this chapter have been already successfully applied in several technological context [11–13].

The use of the pre-design guide sheets provides a way to systematize the process by which an experimentation team does the experimental plan. In fact these sheets drive the experimenter to clearly define the objectives and scope of an experiment and to gather information needed to design an experiment.

This document forces the experimenter to face up to fundamental questions from the early phases of the experimental activity and, moreover, it facilitates and catalyses the interaction between statistical and technological competences.

The master guide sheets contain information about the objective of the experimentation, the relevant background, the response variables and the factors (i.e. control, held-constant and noise factors). The factors are all the process input; they can be controllable or not. Control factors are controllable factors being varied during the experiment. Held-constant factors are controllable factors whose effects are not considered during the test. The noise factors are not controllable factors. Response variables are the variables of interest in an experiment (those that are measured). The supplementary sheets detail the technological relationship between the control factors and the response variables, in terms of the expected main effects and interactions. Moreover, the normal level and range as well as the measurement precision are specified for each quantitative control factor. Figure 1 shows the list of contents in the proposed pre-design guide sheets.

Obviously, it is necessary to customize the guide sheets in order to make them more appropriate and comprehensive in the specific technological and organizational context in which they are used.

According to Hahn [14] "The major contribution of the statistical plan was to add discipline to the experiment and to help ensure that it would result in as valid conclusion as possible, subject to the constraints imposed by the testing situation".

If the pre-design is done correctly, it is not too hard to choose a good DoE. To choose design involves the consideration of sample size (number of replicates), the selection of a suitable run order for the experimental trials, and the determination of whether or not blocking or other randomization restrictions are involved.

Fig. 1 List of contents in the pre-design guide sheets (master guide and supplementary sheets)

	Pre-design Guide Sheets	
1	Name, Organization, Title	
2	Objectives	
3	Relevant Background and Equipment	
4	Response Variables/Factors	Focus on supplem. sheets
5	Control Variables/Factors	
6	Factors to be "held constant"	
7	Noise factors	
8	Interactions	
9	Restrictions	
10	Responsibility for coordination	
11	Design preferences	
12	Analysis and presentation techniques	
13	Trial run?	

CONTROL FACTORS, HELD-COSTANT FACTORS, NOISE FACTORS				
Factor	Control	Held-Constant	Noise	Why this choice? What is the alleged influence of the factor on the response variables?

Fig. 2 List of control factors, held-constant factors, noise factors

Generally, factorial designs (with all several special cases of the general factorial design) are very efficient tools when an experiment involves several factors and it is necessary to study the joint effect of the factors on a response.

It is good to remember that the experiments performed with the DoE are iterative. It would be a mistake to schedule a single, large, exhaustive experiment, because this methodology is based on progressive acquisition of knowledge. Two main phases can be identified: screening and optimization.

Typically, screening or characterization experiments are used to determine which process parameters affect the response. The next phase is the optimization, which has the scope to determine the region in the important factors leading to the best possible response.

After the definition of the experimentation objective and the study of the literature about the state of the art of technological contest, it is possible to draw up the first draft list of factors. When the list is ready the research team could select the control factors from it, as a first trial. The process is iterative until the final definition of the experimental plan.

Figure 2 shows an example of table where the list of factors has to be collected.

Following, a screening testing section about waterjet machining is presented in detail.

2 Technological Context: Waterjet Machining

The development of novel high performance materials comes along with new requirements for machining strategies. If the workpiece consist of harder material than the tool, it is possible to use more wear-resistant but also cost-intensive cutting materials and tool coatings or to use hybrid processes, e.g. the application of a short time softening of the workpiece material by using heat treatment [15].

An alternative promising procedural principle is the use of an abrasive waterjet as tool. Based on the machining character the abrasive waterjet machining can be assigned to cutting processes with geometrically undefined cutting edge. According to the beam character, the waterjet may cause several machining results, including: cleaning, roughening, decoating, engraving, removal and cutting [16]. In comparison to other machining strategies, the abrasive waterjet can be applied for different machining procedures, e.g. two-and three-dimensional cutting, milling, turning, drilling, structuring or polishing.

The main advantage of this principle is that machining takes place almost without process forces. So it is suited especially for brittle materials [17]. In particular, water abrasive finejet machining enables the fabrication of most filigree contours which could not or only at a limited extent be manufactured during the main forming process of ceramics at adequate quality.

The material removal of difficult to machine materials, especially Aluminium Oxide, by using an abrasive waterjet, will be described in detail below. The following practical example shows the necessity of DoE for understanding the newly developed process of surface machining. The goal of the investigation is to receive as much information as possible about the effects of parameter adaption with the smallest possible amount of work to reduce cost and time.

As a consequence of the great variety of purity and the possibilities to manufacture high performance ceramics, it is not possible to make general statements about the machining parameters and the consequential machining results. Equal to this, the high quality machining of technical ceramics by using a water abrasive finejet does require batchwise preliminary inspection of the material removal behaviour. Based on such surveys appropriate machining parameters can be determined.

2.1 Injection Principle

The formation of the abrasive waterjet can be separated in the injection principle and the suspension principle. For the industrial use the injection principle became accepted in a wide range of applications [16]. In this system, the cutting head is built up of three main parts (cf. Figs. 3 and 4).

The water nozzle, mainly consisting of a metallic body material, contains a nozzle brick made out of sapphire or diamond and is responsible for the formation of a pure waterjet. The pure waterjet causes an underpressure in the mixing chamber due to its high kinetic energy in consequence of the high water pressure. Thus, the abrasive particles aspirate inside the mixing chamber and become entrained with the waterjet through the focusing tube. This tube is responsible for the acceleration and the moving direction of the particles. The abrasive material is the most important element of the abrasion during the machining process, the water itself, with velocities up to 840 m/s when using the experimental equipment, does only serve in order to speed up the abrasive particles [16, 18].

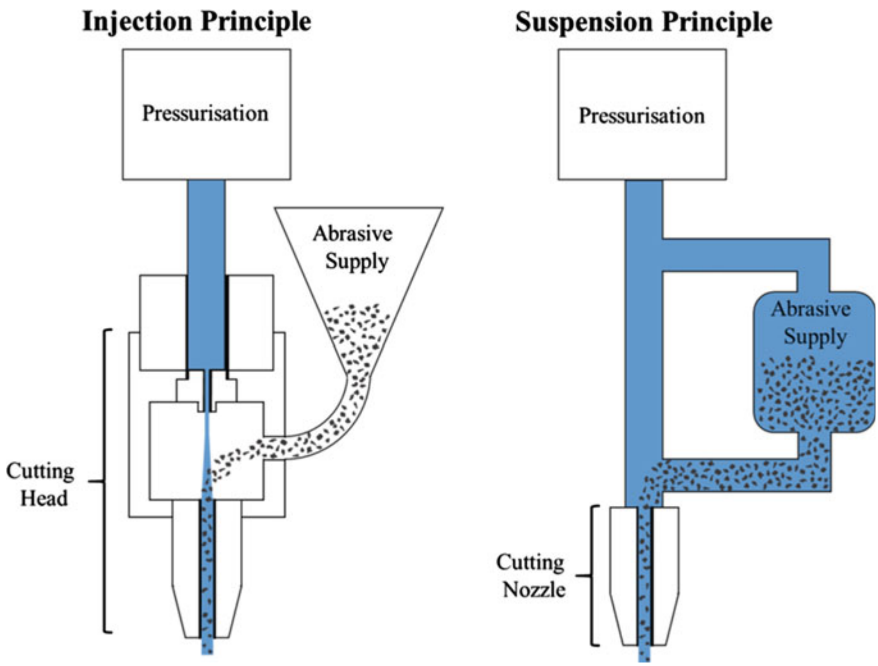
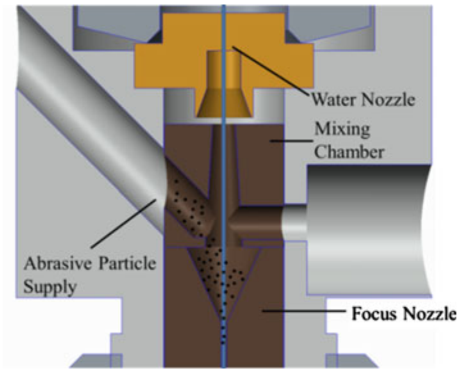


Fig. 3 Principles of the waterjet formation

Fig. 4 Cross section of a waterjet cutting head based on the injection principle



2.2 *Water Abrasive Finejet Machining*

In contrast to conventional waterjet machines, machining with the water abrasive finejet is characterized by its higher machining accuracy due to better axis positioning as a consequence of its modified machine kinematics as well as the reduced beam diameter. While in conventional applications a waterjet diameter of 0.8–1.0 mm is being used [18], a beam diameter of 0.3 mm is utilized for the described application

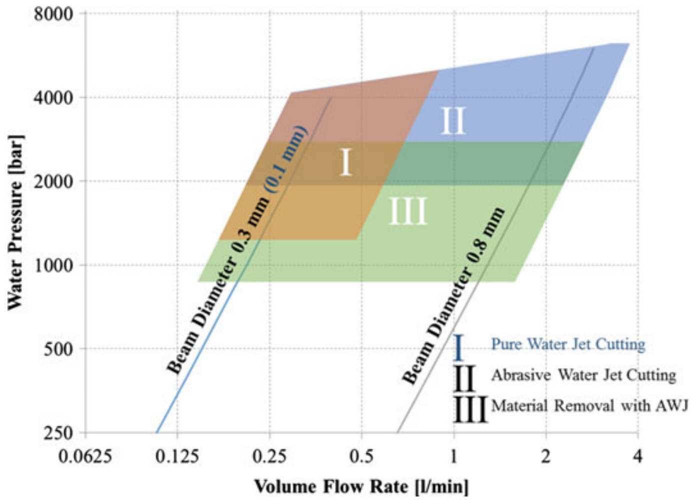


Fig. 5 Volume flow rates at different water pressures—Water Abrasive Finejet versus conventional Abrasive Waterjet

by the selection of the right nozzle circumstances and an appropriate abrasive grain size. However, the energy inside the waterjet is also being reduced as a consequence of the reduction of the beam diameter. This results in the fact that several component thicknesses and materials cannot be cut in adequate quality anymore [19]. Yet, for surface structuring with a waterjet (cf. III of Fig. 5), the reduced beam energy at an abrasive waterjet diameter of 0.3 mm is beneficial because the control of the material removal is better during the process.

2.3 *Field of Application*

2.3.1 Cutting

Conventional waterjet cutting machines have been especially developed for cutting mainly plane materials. Since about the middle of the 2000's the machining trend has first changed to the processing of three-dimensional workpieces by upgrading machines with more motion axes as well as to precise machining with reduced beam diameter.

Basically, every sort of material, except diamond, can be machined by the abrasive waterjet. Smooth and thin materials can be machined by using a pure waterjet. In contrast, for hard and difficult to cut materials, abrasive particles inside the waterjet can become essential for an efficient cutting process [16, 20]. For conventional applications, garnet sand is being widely used as abrasive material.

The high kinetic energy of the cutting jet, which also must not be underrated after the exit below the cutting zone, requires a beam catcher mostly in terms of a water basin. By the deviation of the water beam into the basin it can be guaranteed that the kinetic energy of the waterjet decreases to a non-hazardous stage.

2.3.2 Surface Structuring

For surface structuring and material removal via abrasive waterjet, garnet sand has proved to be the best kind of abrasive material. Indeed the material removal rate for machining hard materials is low, but there is better controllability of the process regarding the depth of penetration and the generation of certain surface roughnesses.

Conventional waterjet machines are only of limited suitability for structuring workpiece surfaces with a reflecting water beam. Because of the fact, that the water beam does not pierce the semi-finished products, a water basin is not essential.

Yet, the developed water fog and the reflecting beam itself stress the guides and axes of the machine as well as the cutting head very intensely. Besides the pollution with water there is the influence of the highly abrasive particles, which does especially cause abrasive wear at the machine axes. The cutting head receives long-term damages by the high kinetic energy of the reflecting water beam. Therefore, particular precautions such as splash guards and encapsulations have to be arranged to avoid damages.

Once the systems engineering requirements are accomplished, a great variety of surfaces can be fabricated by the use of the waterjet (Fig. 6). Besides constant material removal for example for machining pockets, it is possible to manufacture surface reliefs, functional surfaces or even engravings on the base material. The controllability of this machining strategy on high performance materials opens the market for new fields of application for different kinds of industrial sectors.

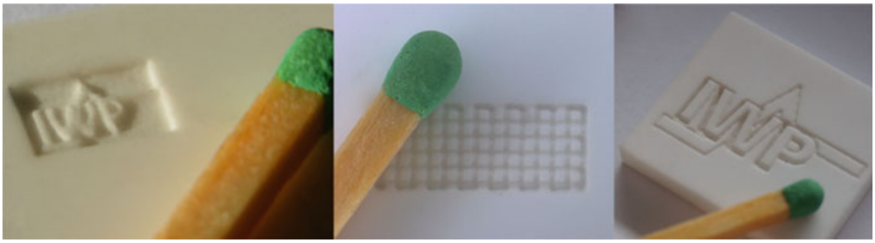


Fig. 6 Variety of application for machining Alumina with the Water Abrasive Finejet

3 Experimental Equipment

3.1 Equipment

The abrasive waterjet machine used for the study has especially been developed at Technische Universität Chemnitz for machining with a reduced beam diameter of 0.3 mm (Fig. 7). The motion in x- and y-direction takes place with the movement of the clamping table. The motion in z-direction is being operated by the cutting head. In addition to this, two rotational axes at the cutting head guarantee simultaneous five-axes machining at setting angles of the waterjet in every variance.

The water nozzle, consisting of a sapphire stone, has an inner diameter of 0.1 mm while the focus nozzle, which corresponds to the effective beam diameter, has a size of 0.3 mm in diameter.

3.2 Challenges of Data Recording

As a result of the high kinetic energy of the water during machining inside the cutting head, the abrasive effects of the abrasive particles and the adverse conditions inside the workspace (as a consequence of water fog development, splash water, the reflecting water beam during surface machining itself and the pollution by abrasive particles), reliable online-measurement of the material removal is not possible by using sensor systems. Additionally, every kind of material and the variety of mechanical properties of each material load does cause different material removal behaviour. Even the change of the surface quality of the semi-finished product has an influence on the machining result. In addition, size and form of the workpieces

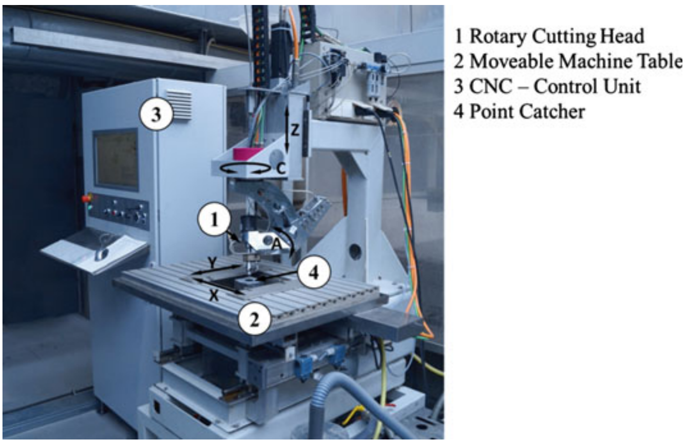


Fig. 7 Experimental equipment

play a role in data acquisition, for example during structure-borne sound measurement. Further, unchangeable effects on the machining result are: the nozzle diameter proportion, the length of the focus nozzle, geometric characteristics inside the cutting head, the accuracy of nozzle orientation, wear of the nozzles, characteristics of the high water pressure and abrasive particle supply, quality of abrasive particles and more. For these reasons, a stable and widely applicable online-monitoring cannot give information about the material removal, neither with optical nor via noise or structure-borne sound.

The huge variety of determining factors requires practical tests for each machine setting in every case of application.

To reduce costs and time and nevertheless to obtain meaningful information, the method of DoE is being applied.

4 Set-up, Design and Testing Phase

4.1 Machine Set-up

During the first step of the examinations, both the control and the held constant factors have been determined. It is important to have good knowledge about the observed machine, its characteristics and the possible influences on the machining process itself as the disregard of particular parameters can have major implications for the machining result. For this reason, it is advisable to always involve technical personal and experts for each application. The adjustable parameters, as shown in Table 1, can be categorized into cutting factors, abrasive factors and hydraulic factors.

Cutting factors are the parameters adjustable by the CNC control unit. They define the exact motion-sequences the cutting head performs during machining. Arising from the use of preliminary examinations on different types of material it became apparent, that the ideal distance between the focus nozzle tip and the workpiece surface is 0.6 mm when a beam diameter of 0.3 mm is being used.

If the cutting head is being placed closer to the workpiece surface, the machining quality does not increase. Quite the contrary, the risk of a collision between the focus nozzle and the workpiece arises when the workpiece material is uneven.

Table 1 Changeable machining parameters

Cutting factors	Abrasive factors	Hydraulic factors
Stand-off distance, d	Abrasive flow rate, $\dot{m}$	Water pressure, p
Traverse path strategy	Abrasive material	Orifice diameters, d_w/d_f
Offset distance, l	Particle size	Focus nozzle length, l_f
Traverse speed, v_f		
Impact angle along feed, α		
Impact angle vertical to feed, β		

As a quintessence of surface structuring, it is possible that the process gets interrupted due to the reflection of the water beam back inside the cutting head. In this case, the cutting head could even be damaged. In addition to that, due the focus nozzle geometry it is necessary to increase the distance between the focus nozzle and the surface of the ceramic workpiece for realizing a defined angle adjustment. For this reason the stand-off distance (d) has been increased to the minimum possible distance of 1.0 mm. The distance has been set as a held constant factor as further increasing of the gap would only cause a reduction of the kinetic energy inside the water beam as a consequence of fanning-out.

The traverse path strategy has an essential influence on the manufactured surface character. There are versatile possibilities to vary this parameter and according to this the machining result, so, for example crosswise, line by line or helical movements of the cutting head do cause varying surfaces of the pockets ground. During the first step of a crosswise movement, which is equal to line by line machining, material is being removed with a defined standoff-distance. During the second crossing step the machining takes place on the already machined surface. This means that the standoff-distance is not defined anymore if there had not been some pre-experimental studies before. So, during crosswise machining, no constant conditions are available. For machining a homogenous surface via spiral movement, it is necessary to adjust the nozzle traverse speed continuously to reach a constant effective velocity. That is why this type of movement is also not appropriate for fundamental studies. Finally the machining strategy has been set constant as line by line, because impairments are not expected as a result of the machining position.

The impact angle on the surface along the feed direction (α) has been set to be perpendicular to the workpiece surface as a held constant factor. The reason for this is the initially unknown material removal behaviour. Similar to cutting with the abrasive waterjet, there is a lag of the water beam due to the reduction of the kinetic energy with an increasing depth of penetration. This means that the waterjet is being pushed away in the opposite direction of the feed direction as a function of the feed velocity, the hydraulic factors, properties of the abrasive material supply and the workpiece material. Because of the fact that the lag is unknown during the use of different parameter settings, the angle has been set constant perpendicular to the feed direction.

It is known that an angle adaption vertical to the feed direction does change the contour of the machined gap. This means that the surface quality of the pocket ground does also change crucially. For evaluating this influence, the angle (β) has been set as a control factor. The cutting head is being positioned between 0° and 15°.

Another factor, that must have an influence on the surface quality in theory, is the distance between every single movement direction line, the so-called offset distance (l) (Fig. 8). Due to the knowledge that the stock removal is being reduced at the outwards region of the water beam, it can be assumed that different offset distances do cause different surface roughnesses. Since it is the objective to manufacture pockets inside the workpiece material, it is inevitably required to overlap

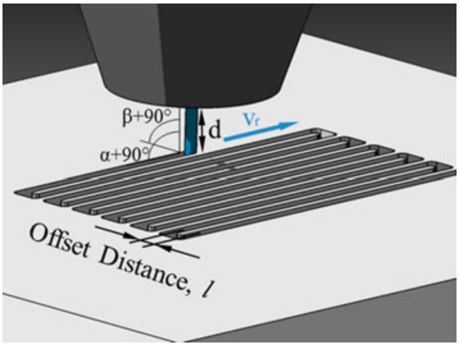


Fig. 8 Schematic diagram of the machining zone

the single gaps. Preliminary tests have shown that offset distances between 0.15 and 0.20 mm are suitable. This means that the offset distance has been set to be a control factor.

The nozzle traverse speed (v_f) also belongs to the group of the cutting factors. It is expected that a higher traverse speed does cause a reduced depth of penetration of the waterjet inside the workpiece material. Randomized tests have shown that velocities between 2 and 3 mm/s are the best configuration for surface machining of this kind of material.

Abrasive factors are all variables that are linked with the particles being added to the water beam, including the kind of abrasive particles, the grain size and the amount of abrasive material per time unit.

For industrial use, garnet sand is generally being used as abrasive material. The advantage of this material is that it is relatively low priced but nevertheless well suited for machining conventional workpiece materials. Especially for hard, difficult to cut material, it is possible to use harder abrasive particles, such as ceramic materials like Silicon Carbide, Boron Carbide or Aluminium Oxide. Though the cutting performance is much higher, hard abrasive particles are not appropriate for selective surface structuring. This fact comes along with strong increasing of wear mechanisms inside the cutting head and the focus nozzle. Wear as a disturbance variable affects the machining result.

So, as a noise factor, wear has to be avoided as far as possible. For this reasons, only garnet sand (Bengal Bay Garnet®) has been used as abrasive material.

According to experience, grain sizes between 90 and 125 microns are suitable for reliable machining with a waterjet having a diameter of 0.3 mm. So the abrasive particles have been sieved to this range size and set as held constant factor. As the abrasive particles are responsible for the material removal, the abrasive flow rate does play a major role during surface structuring. The abrasive flow rate ($\dot{m}$) has been set as a control factor. It has been varied in a range between 6.38 and 13.62 g/min to observe the effect of the change of particle quantity on the surface quality and the depth of penetration. This range has in preliminary tests been identified as useful for material removal with adequate surface quality.

Hydraulic factors describe the parameters which are responsible for the characteristic of the waterjet. A change of those parameters will have an influence on the jet velocity, in other words the kinetic energy of the water beam after leaving the water nozzle, as well as on the effective waterjet diameter. The nozzle proportions have been held constant. The diameter ratio between water nozzle and focusing tube (d_w/d_f) has to be approx. 1:3 for optimized fluidic conditions inside the water beam [21–23]. Thus, 0.3 mm as beam diameter is the minimum possible diameter to work reliably with a waterjet based on the injection principle. By using the water abrasive finejet it is possible to manufacture pockets and even surface structures at smallest dimensions.

The focus nozzle length (l_f) has also been set as a held constant factor. It was set to be 23.8 mm in length.

The only hydraulic parameter that has been varied during the examination was the water pressure (p). For conventional waterjet cutting pressures between 3000 and 4000 bar are being used in industrial applications. When the waterjet is used for surface structuring, the beam is totally reflected. The reflecting water beam still contains residual kinetic energy, so there is the risk of impairing the cutting head itself or other components of the machine. Moreover, water fog that is loaded with abrasive particles develops inside the workspace. This mixture can damage tracks and drives. A reduction of the water pressure does contain the stressing of the machine. Besides that, pre-experimental investigations have shown that a reduction of the water pressure causes a better controllability of material removal from the workpiece. For this reason, the pressure has been examined in a range between 1300 and 1800 bar during the experimental study.

In addition to the constant and varied parameters also noise factors have an influence on the result, although they are not capable of being actively influenced.

One part of this is the nozzle wear. To prevent nuisances under this effect, it is necessary either to replace the nozzles frequently or to check them in definite time steps with regard to damage or wear. Moreover, the clamping of the workpiece as well as the constitution of the workpiece material itself can have undesired effects on the result of the machining process. In addition, there are deviations during water pressurization and in the quality of the abrasive material. To exclude such influences, repetitions under the same parameter adjustments will be absolutely necessary.

In order to evaluate the machining results response variables are being used to achieve definite information about the quality as well as the economy of the machining. A quality criterion is the surface quality of the bottom of the manufactured pocket. Here, the arithmetic roughness *Ra* is being used as characteristic value. To receive information about the economy, the depth of penetration is being evaluated, linked with the material removal rate per time unit.

4.2 Design of Experiments

Basic statistical methods applied, as factorial design and ANalysis Of VAriance (ANOVA), are extensively described in literature [4]. Therefore, they have been applied in this paper without any explicit introduction or analytical formulation.

As extensively discussed before, the use and the implementation of pre-design guide sheets allowed the team to carry out the best design of experiment.

In this screening experimental stage a fractional factorial design 2^{5-1} was adopted, after the evaluation of every choice taken into account from the research team and listed in the pre-design guide sheets (Fig. 9). No main effect or two-factor interaction is aliased with other main effects or two-factor interactions, because the fractional factorial design 2^{5-1} is a resolution V design (with a defining relation of I = ABCDE and design generator E = ABCD). However, each main effect is aliased with a four-factor interaction, and each two-factor interaction is aliased with a three-factor interaction [4].

The adopted control factors are: water pressure p(A), nozzle traverse speed v_f (B) abrasive flow rate $\dot{m}$(C), offset distance l(D) and impact angle β(E).

The offset is the distance between every single motion line of the waterjet and has an important effect on the surface conditions. A proper range for the offset distance could be determined by preliminary tests.

The angle β vertical to the feed direction was chosen as control factor because of the knowledge that this factor changes the geometry of the gap and thus has an influence on the overlapping zones of parallel manufactured lines.

With the exception of the control factors, each test was performed under the same experimental conditions.

CONTROL FACTORS, HELD-COSTANT FACTORS, NOISE FACTORS

Factor	Control	Held-Constant	Noise	Why this choice? What is the alleged influence of the factor on the response variables?
Pump pressure p [bar]	X			Literature has shown that the waterjet pressure has a high influence on the response variable on ceramic material; MRR increases with increasing water pressure
Abrasive flow rate $\dot{m}$ [g/min]	X			Literature has shown that abrasive mass flow rate has a high influence on the process, it has been tested on other materials such as Aluminium 7075 and EN8 Material
Traverse speed v_f[mm/s]	X			Literature has shown that the surface quality will be significantly improved when the traverse speed increases on ceramic material
Abrasive material Am *(garnet sand)*		X		It is quite good to achieve better precision in machining, especially for ceramic material, in this way it is able to remove a significant amount of material during the process
Orifice diameter d_O [mm]		X		Literature proposes to keep it as a constant factor
Focus nozzle diameter d_N [mm]		X		Literature proposes to keep it as a constant factor
Nozzle distance d [mm]		X		Changing this parameter does not have any great influence on the response variable, and literature proposes to keep it as a constant factor
Impact angle along the feed direction α [°]		X		It is unknown how many factors do have an effect on the material removal and the jet lag when changing the angle along the feed direction, so for this design the factor is held constant
Impact angle crosswise the feed direction β [°]	X			It is known from literature that on other material the angle can have an effect on depth of cut
Abrasive particle size $Asiz$ [μm]		X		Literature proposes to keep it as constant factor
Offset distance l [mm]	X			Different offsets could change roughness
Remained water			X	Water remaining at the end of process may increase the weight of the sample
Remained abrasive			X	Abrasive material remaining on work area after every test may create a height difference that could invalidate the next test
Clamping system			X	The screwdriver force used for the clamping system can change on every test

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Fig. 9 Definition of factors in the pre-design guide sheet

Table 2 Values of control factors and held-constant factors as a result of the testing phase

Control factors	Label	MIN (−)	MAX (+)	Unit
Water pressure, p	A	1300	1800	bar
Traverse speed, v_f	B	2	3	mm/s
Abrasive flow rate, $\dot{m}$	C	6.38	13.63	g/min
Offset distance, l	D	0.15	0.20	mm
Impact angle vertical to feed, β	E	0	15	°

Held-constant factors	Value	Unit
Stand-off distance, d	1	mm
Traverse path strategy	line by line	–
Abrasive material	garnet sand	–
Particle size	90–125	µm
Orifice diameters, d_w/d_f	0.1/0.3	mm
Focus nozzle length, l_f	23.8	mm
Impact angle along feed, α	0	°

The testing phase should result in the parameter field to be investigated during the main experiments, as shown in Table 2. Tables 3 and 4 show the adopted design matrix and the test matrix listed in run order, respectively. The coded levels of the control factors in Table 3 are adopted from Table 2.

Table 3 Matrix for the 2^{5-1} design

Treatment	A	B	C	D	E = ABCD
I	+	−	+	−	+
II	−	+	−	−	−
III	+	−	−	−	−
IV	+	+	−	−	+
V	+	−	+	+	−
VI	−	+	+	−	+
VII	−	−	+	−	−
VIII	+	+	−	+	−
IX	−	−	−	+	−
X	+	+	+	−	−
XI	+	−	−	+	+
XII	−	−	+	+	+
XIII	−	+	+	+	−
XIV	−	−	−	−	+
XV	−	+	−	+	+
XVI	+	+	+	+	+

Table 4 Test matrix listed in run order

Treatment	Std order	Run order	Pressure (bar)	Tr. speed (mm/s)	Abr. flow rate (g/min)	Offset (mm)	Angle (°)
I	6	1	1800	2	16.95	0.15	15
II	3	2	1300	3	8.13	0.15	0
III	2	3	1800	2	8.13	0.15	0
IV	4	4	1800	3	8.13	0.15	15
V	14	5	1800	2	16.95	0.2	0
I	38	6	1800	2	16.95	0.15	15
II	19	7	1300	3	8.13	0.15	0
VI	23	8	1300	3	16.95	0.15	15
VII	21	9	1300	2	16.95	0.15	0
VIII	12	10	1800	3	8.13	0.2	0
VIIII	41	11	1300	2	8.13	0.2	0
VIIII	9	12	1300	2	8.13	0.2	0
VII	5	13	1300	2	16.95	0.15	0
X	8	14	1800	3	16.95	0.15	0
III	18	15	1800	2	8.13	0.15	0
VI	7	16	1300	3	16.95	0.15	15
XI	26	17	1800	2	8.13	0.2	15
XII	13	18	1300	2	16.95	0.2	15
XIII	15	19	1300	3	16.95	0.2	0
IV	20	20	1800	3	8.13	0.15	15
XI	10	21	1800	2	8.13	0.2	15
XIII	47	22	1300	3	16.95	0.2	0
XIV	33	23	1300	2	8.13	0.15	15
XIII	31	24	1300	3	16.95	0.2	0
XV	11	25	1300	3	8.13	0.2	15
VIII	44	26	1800	3	8.13	0.2	0
I	22	27	1800	2	16.95	0.15	15
V	30	28	1800	2	16.95	0.2	0
VIII	28	29	1800	3	8.13	0.2	0
XII	45	30	1300	2	16.95	0.2	15
X	40	31	1800	3	16.95	0.15	0
IV	36	32	1800	3	8.13	0.15	15
XII	29	33	1300	2	16.95	0.2	15
VIIII	25	34	1300	2	8.13	0.2	0
XIV	17	35	1300	2	8.13	0.15	15
XVI	48	36	1800	3	16.95	0.2	15
XVI	16	37	1800	3	16.95	0.2	15
XI	42	38	1800	2	8.13	0.2	15
VII	37	39	1300	2	16.95	0.15	0

(continued)

Table 4 (continued)

Treatment	Std order	Run order	Pressure (bar)	Tr. speed (mm/s)	Abr. flow rate (g/min)	Offset (mm)	Angle (°)
XVI	32	40	1800	3	16.95	0.2	15
V	46	41	1800	2	16.95	0.2	0
XV	27	42	1300	3	8.13	0.2	15
II	35	43	1300	3	8.13	0.15	0
III	34	44	1800	2	8.13	0.15	0
XIV	1	45	1300	2	8.13	0.15	15
VI	39	46	1300	3	16.95	0.15	15
XV	43	47	1300	3	8.13	0.2	15
X	24	48	1800	3	16.95	0.15	0

5 Analysis of Results and Technological Interpretation

5.1 Analysis of Variance

As three-factor (and higher) interactions can be attributed to be insignificant for the process, a fractional factorial design of 2^{5-1} has been used to provide reliable data of the main effects as well as two-factor interactions. In order to receive information about the background of the experimental results, the ANOVA was applied. By using this method it was possible to investigate the statistical significance of the main effects and two-factor interactions on the following response variables: arithmetical mean deviation of the roughness profile and the depth of cut. The analysis has been executed at a 95 % confidence level, which means that at least 95 of 100 confidence intervals, calculated based on the practical measurements, include the true value of the result. Diagnostic checking was successfully performed via graphical analysis of residuals.

Figures 10 and 11, respectively, show the influences of the determined control factors on the response variables roughness *Ra* and the average machining depth, using Pareto charts of standardized effects ($\alpha = 0.05$).

5.2 Statistical Results

The main effect of one single factor is calculated by the mean of every parameter combination at the individually adjusted level of the examined factor. Consequently, the main effects plot shows the change in response occurring by means of a change in the level of the observed factor. If the difference of the response between the levels of one factor is not the same at all levels of the other factors of the investigation, then factors do interact, that means the level of one

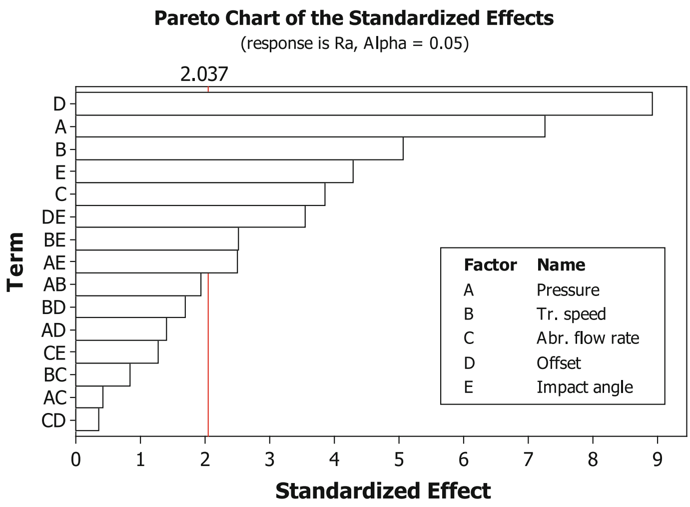


Fig. 10 Pareto chart of standardized effects (α = 0.05) for roughness *Ra*

factor has an influence on the result being achieved during a change of another factor's level.

Figures 12 and 13 show the main effects and interaction effects of the control factors of the response variable roughness. For this response variable, all control factors are significant terms in a confidence level of 95 %.

In the interaction plots of the significant two-factor interactions between impact angle and offset (DE), impact angle and traverse speed (BE) and impact angle and

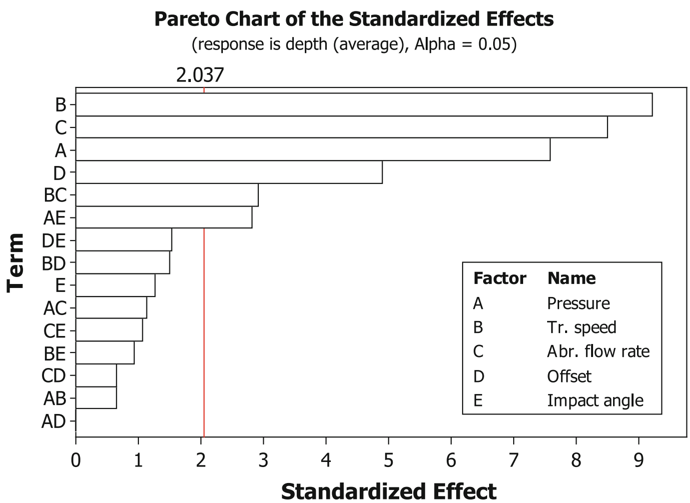


Fig. 11 Pareto chart of standardized effects (α = 0.05) for depth of cut

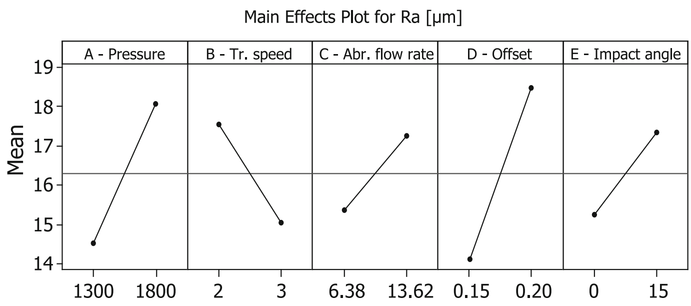


Fig. 12 Main effect plots for roughness *Ra*

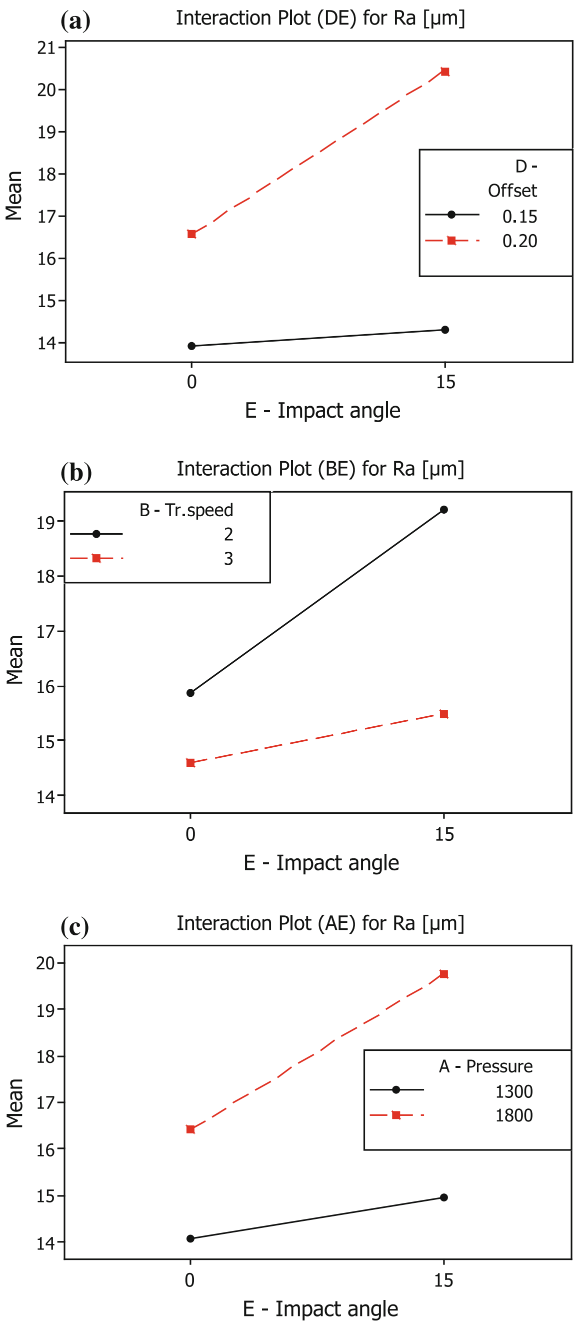
pressure (AE), it is evident that the influence of particular levels of the offset (D), the traverse speed (B) and the water pressure (A) is generally smaller at the investigated lower level of the impact angle (E).

The influences on the depth of cut are shown in the main effects plot in Fig. 14 and in the two factor interactions in Fig. 15. The significant terms, also illustrated in the Pareto-chart of the standardized effects (α = 0.05) for the response variable average depth of penetration (Fig. 11), are the main effects of pressure (A), traverse speed (B), abrasive flow rate (C), offset (D) and the interaction between traverse speed and abrasive flow rate (BC) as well as the water pressure and the impact angle across the feed direction (AE).

5.3 Technological Interpretation

As already known from versatile publications and experiences, the main effects plot shows that high water pressure causes a large machining depth. This fact is directly linked with a higher roughness of the surface (cf. Figs. 14 and 12, respectively). As it is known from abrasive waterjet cutting, the kinetic energy of the waterbeam is being reduced with increasing machining depth. During cutting, the thesis can be verified by the feed marks in the lower areas of the cutting line. When structuring surfaces, the reduction of the abrasive water beam energy as a consequence of increasing depth of penetration can be observed via the roughness value of the machined ground level. Regarding the interconnection between the water pressure and the impact angle diagonally to the feed lines [β (cf. Fig. 8), Label E] in the interaction plot for the roughness, it becomes evident that the angle (E) has only a negligible effect on the surface roughness when using a water pressure (A) of 1300 bar (Fig. 13c). When setting the water pressure (A) to the maximum value of the observed pressure range (1800 bar), the surface roughness decreases in quality at an impact angle (E) of 15°. This behaviour can be attributed to the different flow conditions at a change of the impact angle. When setting the angle (E) to 0°, the waterbeam strikes the workpiece surface perpendicularly. As a result, there is a total

Fig. 13 Interaction plots for roughness *Ra*: **a** DE, **b** BE and **c** AE



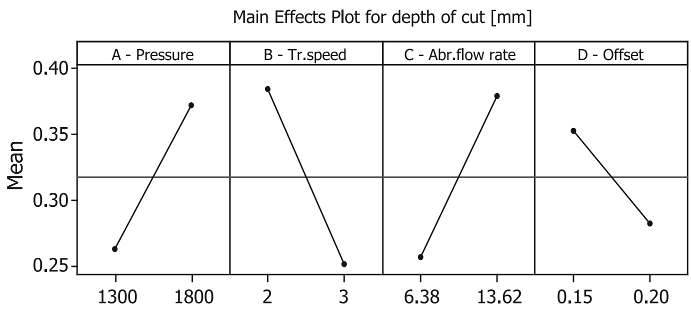
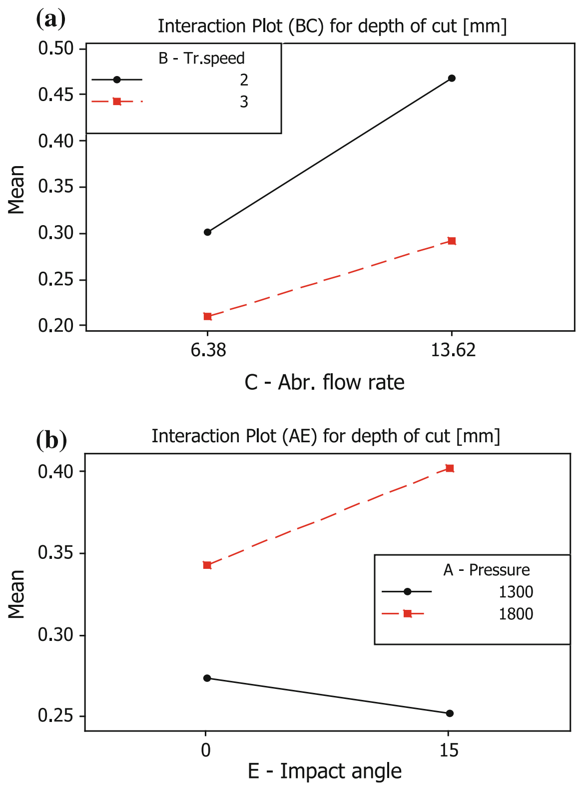


Fig. 14 Main effect plots for depth of cut

Fig. 15 Interaction plots for depth of cut: **a** BC and **b** AE



reflection of the water impeding the arriving waterjet. Consequently, the effective kinetic energy of the abrasive waterjet being responsible for the material removal is reduced at an impact angle of 0°. When using an impact angle of 15°, the value of the reflected water having an influence on the energy of the arriving waterjet is significantly lower. This means that the machining depth is higher and the surface quality becomes worse in contrast to the angle set-up of 0°, due to the reason named before.

Considering the plots, the kinetic energy of the reflecting waterbeam at the low modulation of pressure (1300 bar) must be unimportant for the effect of the waterjet impact, as the results of the different machining angles on the surface quality are almost equal.

Another explanation for the machining result is the secondary effect of the reflecting water on the surface quality. Using the maximum value of water pressure (A) causes a reflecting waterjet with high kinetic energy, which has an influence on the already manufactured surface, especially when setting the impact angle (E) to 0°. An angle adjustment of 15° results in the fact that the reflecting water takes course towards the unmanufactured offset-direction. This means that there is probably no surface softening on the already manufactured surface.

As expected, the cutting depth is strongly dependent from the motion velocity of the abrasive waterjet (B). A small feed velocity provokes a higher cutting depth as a consequence of a higher application of the waterbeam energy on one point of the workpiece. However, this is accompanied by a simultaneously higher surface roughness (cf. Figs. 14 and 12, respectively). As shown in the interaction plot Fig. 13b, the highest material removal takes place at a low feed rate (B) and an impact angle (E) of 15° due to the factors mentioned above.

The Pareto chart in Fig. 10 figures out that the offset distance (D) is the most influencing parameter on the arithmetical mean deviation of the roughness profile. In general, a low offset distance (D) has a positive effect on the roughness. The reason for this is the fact that the material removal during line by line machining is not constant across the machining width due to the circular cross section of the abrasive waterjet. Using the wrong offset distance will consequently cause a comb-shaped surface. So for this application, an offset distance (D) of 0.15 mm has proved to be the beneficial value concerning the roughness *Ra*.

Depending on the field of application, it has to be deliberated whether the combination between material removal and surface condition is acceptable. In the case of the conducted investigations the goal was to manufacture pockets in a short time at acceptable quality. The ANOVA has shown that treatment VII, whose levels of factors are water pressure (A) 1300 bar, traverse speed (B) 2 mm/s, abrasive flow rate (C) 13.62 g/min, offset distance (D) 0.15 mm and impact angle vertical to the feed direction (E) 0°, is the best parameter combination in order to achieve a high material removal rate (MRR = 7.6 mm^3/min; depth = 0.44 mm) at an adequate surface quality (Ra = 14.2 µm). For further improving of the machining result, more experimental studies could be possible with a variation of the machining strategy or other control factors on the basis of this experimental stage. Further machining steps are conceivable as well after a raw stock removal with investigated machining parameters for finishing the surface by structuring the workpiece over again.

6 Conclusion and Remarks

The results obtained in the presented applications have shown the strategic role that a systematic approach to plan a DoE plays in technological process innovation.

To improve the use of this technique, it is necessary to find the means of bringing together statistical concepts and practical knowledge in technical areas such as material science or mechanical engineering. The pre-design guide sheets proposed in this chapter and successfully adopted by the authors in other technological context are useful for this purpose.

The investigations have shown that a statistical approach on structuring surfaces of Aluminium Oxide by using abrasive waterjet is a good way to examine the influences of the different adjustable working parameters on the response variables. It was also shown that abrasive fine waterjet machining is a good way to reproduce several surface conditions of filigree and brittle workpieces with notable process stability. Based on the analysis of the results it is possible to predict the machining results of 96 % Aluminium Oxide, such as depth of cut and surface quality with appropriate systems engineering in a reasonable tolerance zone. Thus, the applied method of trial and error will not be necessary, which causes better cost efficiency. This method of finishing high performance ceramics may open a new range of applications such as medical appliances, bearing technologies and more.

Overall, the research activities are the introduction for a new manufacturing process. For further investigations it will be useful to focus on the parameter range round treatment VII. To enhance the process, it will also be necessary to establish more control factors in future investigations, e.g. the variation of abrasive particle size and material, or to switch the parallel offset motion to different machining patterns.

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Response Surface Modeling of Fractal Dimension in WEDM

Prasanta Sahoo and Tapan Kr. Barman

Abstract This chapter presents the application of fractal dimension in describing surface roughness in wire electrical discharge machining (WEDM). Conventional surface roughness parameters (center line average roughness, root mean square roughness, etc.) strongly depend on the resolution of the measuring instrument. But fractal dimension is scale invariant. As a case study, experiments are conducted on EN31 steel specimens in WEDM varying four process parameters, viz., current, voltage, pulse on time, and pulse off time. The effects of process parameters on fractal dimension are evaluated and a second order relationship between process parameters and fractal dimension is developed using response surface methodology (RSM). Also, the parameters having significant influences on fractal dimension are identified.

1 Introduction

Surface roughness is an important parameter to describe the quality of any surface. Generally, to describe surface roughness, some statistical parameters, grouped into amplitude parameters (center line average, R_a, root mean square roughness, $R_{q,}$ etc.) spacing parameters (mean line peak spacing, R_{sm}), and hybrid parameters (root mean square slope of the profile, root mean square wavelength, peak area, valley area, etc.) are used. But the main problem associated with these parameters is that theses parameters are scale dependent. When the resolution of the measuring instrument is increased or decreased, surface roughness values also change. If the sampling length for the measurement is varied, the same values for the surface roughness parameters may not be expected. To overcome this problem, it is

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required to describe surface roughness with a parameter which is scale independent and would not depend on the measuring instrument. This essentially leads to the use of fractal dimension as roughness parameter.

In this chapter, fractal dimension is used to describe surface roughness. Experiments are conducted in wire electrical discharge machining (WEDM) of EN31 steel workpieces. The experimental results for fractal dimension are analyzed to develop a second order response model using response surface methodology (RSM). The variations of fractal dimension with the selected process parameters are also studied here.

2 Fractal Dimension as Surface Roughness Parameter

Fractal dimension is derived from fractal geometry. Fractal geometry was coined by Mandelbrot [36]. As we know from Euclidean geometry that point has 0 dimension, line has 1, surface has 2 and cube has 3 dimensions and these dimensions are integers. But Mandelbrot presented an example of a coastline where he showed that the length of the natural coastline does not converge for decreasing unit of measurement. He plotted the length (L) with the unit of measurement ($\in$) using logarithmic scale and developed a relationship between L and $\in$. The relation is in the form of $L \sim \in^{1-D}$. Here, D is a real number representing the dimension of the coastline. Moreover, dimension of an object may be of noninteger values.

There are two terms, self-similarity and self-affinity, connected to a dimension. An object will be called self-similar when a part of the object requires equal magnification in all directions for the developed part to represent the replica of the original object. For many objects, exact self-similarity is not possible and then statistical self-similarity is defined. For statistical self-similarity, if a small part of the object is magnified the probability distribution of the part will be same as the original object. For self-similarity objects, the fractal dimension may be calculated as

$$D = \log N / \log m, \tag{1}$$

where N is the number of equal segments and m is the size of each segment.

But the fact is that all fractals do not have self-similarity property. That brings in the concept of self-affinity for the fractal. For self-affinity, magnification is done with unequal scaling in different directions. For self-affine fractals, dimension cannot be derived from the above equation but can be obtained from power spectra of the object. Rough surface profiles fall into this category of fractals. For a profile, fractal dimension varies between 1 and 2 and for a surface, fractal dimension varies between 2 and 3.

The concept of fractal geometry has been popularly applied in many applications like engineering fields, medical sciences, and astronomy. To describe rough machined surfaces, the concept of fractal has successfully been used in electric discharge machining [19, 45], milling [3, 11, 46, 54], cutting or grinding [2, 5, 6, 18, 20, 24, 26, 27, 44, 55], and worn surfaces [14].

It has already been established that machining surfaces have self-affinity properties. If a rough surface is magnified properly, similar appearance may be seen as shown in Fig. 1. As the resolution of the measuring instrument varies, the variances of slope and curvature change. This makes the conventional roughness parameters (R_a, R_q, R_{sm}, skewness, kurtosis, etc.) scale dependent. On the other hand, if the surface profiles are magnified appropriately, more details are revealed. Thus, it may be assumed that the profile is continuous at any length scale but cannot be differentiated at all points. The Weierstrass–Mandelbrot (W–M) fractal function [4] is used to characterize rough profiles since this function satisfies both the conditions; continuity and non-differentiability at all locations. The W−M function has a fractal dimension D, between 1 and 2, and is given by

$$z(x) = G^{(D-1)} \sum_{n=n_1}^{\alpha} \frac{\cos 2\pi\gamma^n x}{\gamma^{(2-D)n}} \quad 1 < D < 2, \gamma > 1, \tag{2}$$

where G is a scaling constant. The parameter n_1 corresponds to the low cut-off frequency of the profile. Since surfaces are nonstationary random process, the lowest cut-off frequency depends on the length L of the sample and is given by $\gamma^{n1} = 1/L$.

The power spectrum of W–M function can be expressed by a continuous function as

$$S(\omega) = \frac{G^{2(D-1)}}{2\ln\gamma} \frac{1}{\omega^{5-2D}} \tag{3}$$

Dimension D relates to the slope of the power spectrum of a surface against frequency ω in a logarithmic scale. G, the roughness parameter of a surface, does not vary with respect to frequencies of roughness and locates the spectrum on the power axis. Here, both G and D are independent of the roughness scales of the surface and thus considered as intrinsic properties. G, D, and n_1 form a complete set of scale-independent parameters to describe a rough profile. D signifies the extent of space occupied by the rough surface. In other words, surface with larger D values will have denser profile leading to a smoother topography [47, 53].

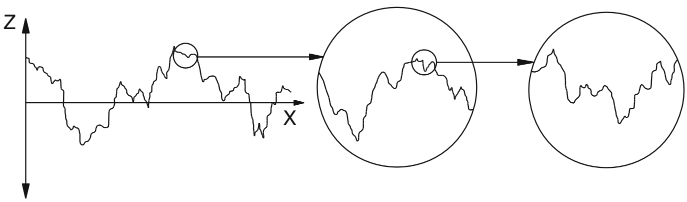

Fig. 1 Qualitative description of statistical self-affinity for a surface profile

In practice, there are many ways to calculate fractal dimension (D), viz., yardstick method, box counting method, variation method, power spectrum method, structure function method, etc. The detailed procedure to calculate fractal dimension may be found in the book “Fractal analysis in machining” [43].

3 Roughness Study in WEDM

WEDM is a popular nonconventional machining process particularly used in die making industry. The quality of the machined surface plays an important role for its appropriate function. So, researchers have always paid attention to study the effects of process parameters or controllable factors on the surface quality. Many researchers have attempted to study surface roughness in WEDM considering different machining parameters. In addition to surface roughness, some researchers have also included other machining responses like material removal rate (MRR), kerf, cutting rate, dimensional deviations, etc. An extensive literature survey shows that for surface roughness modeling, mainly conventional roughness parameters are considered. To set a scene for the present study, a brief review of literatures is presented here. For modeling and optimization of surface roughness and other response parameters, different statistical and optimization tools have been used. These include RSM [16, 21, 51], Taguchi analysis [23, 31, 35], gray Taguchi analysis for multi-response optimization [7, 9, 22, 25], artificial neural network (ANN) [12, 41, 42, 48, 51, 52], genetic algorithm (GA) [34, 35, 40], weighted principal component analysis (WPCA) [13], artificial bee colony (ABC) technique [8, 40]. Researchers also have considered different types of materials for conducting the experiments, e.g., different types of steels [8, 12, 17, 23, 28, 50–52], ceramics [32], titanium alloy [1, 16, 29, 30], magnesium alloy [31], Al/SiC composite [37], tungsten [49], Inconel material [21, 40, 41], etc. There are a few available literatures which deal with fractal dimension characterization in WEDM [10, 15, 33]. It is clear that limited attention have been paid toward fractal dimension characterization in WEDM.

4 Design of Experiments

Design of experiments (DOE) provides a systematic approach to carry out the experiments and to obtain a relationship between input process parameters with output responses. Using DOE, number of experiments for a particular problem may be minimized but the influences or the dependencies of the input parameters on the output can be established satisfactorily. DOE considers statistical approach to carry out the experiments and provides a design matrix showing at which combinations of process or input parameters experiments should be carried out. To avoid any bias, generally, experiments are conducted on a random basis. For validation and to check the repeatability of the data, experiments are repeated. Sometimes, blocking is done to arrange the experimental data into groups or blocks to make homogeneous data. There are several methodologies for DOE, viz., factorial design (full factorial design, Plackett-Burman design, etc.), central composite design (CCD), Box-Behnken design, orthogonal array (OA), etc. In the current study, CCD is selected to carry out the experiments.

A full factorial design considers all combinations of input parameters to make the design matrix, but a Box-Wilson Central Composite Design or CCD considers only factorial points, central points, and axial points. Generally, number of experiments required for CCD is lower than the same using full factorial design. Factorial points are vertices of the n-dimensional cube which are coming from the full or fractional factorial design. Central point is the point at the center of the design space. Axial points are located on the axes of the coordinate system symmetrically with respect to the central point at a distance α from the design center. CCD is used to establish relationship between input process parameter and output response parameter using RSM.

There exist two main varieties of CCD: Rotatable central composite and face centered CCD. In rotatable CCD, the variance of the predicted response at any point depends only on the distance of the point from the center point of the design. For rotatable CCD, there are factorial points, axial points, and center points. Center points may vary from three to seven. Choosing suitable numbers of center points, a design may be made orthogonal design or design of uniform precision. Considering uniform precision, for four process parameters, the rotatable CCD requires 2^4 (16) factorial points, $2 \times 4 = 8$ axial points, and seven center points. The positions of axial points will depend on the value of α. For four factor design, α is $(16)^{1/4}$, i.e., 2. Thus for four factor design, it requires 31 numbers of experiments. In a face centered cubic design (FCC), for four factors experiment, 16 (24) factorial or cube points, eight axial points (2×4) and seven central points, a total of 31 experimental runs need to be considered. During the analysis, the process parameters are always coded between +1 and −1. In the present study, Eq. (4) is used to code the factors.

$$x_i = \frac{[2x - (x_{\max} + x_{\min})]}{(x_{\max} - x_{\min})}, \tag{4}$$

where x_i is the coded value of a variable x while $x_{\max}$ and $x_{\min}$ refer to maximum and minimum values of the factor, respectively.

5 Response Surface Methodology

RSM is used to establish a relationship between design/input/process parameters with output responses. For this, it uses both mathematical and statistical techniques [39]. The influences of the process parameters on the response parameter can be also studied using this method. Also, the developed model may be used to optimize the process parameter for optimum response value. Since the relationship between the process parameter and output parameter is unknown, it is required to predict or estimate the relationship whether it is linear, quadratic or any other higher order polynomial. Generally, for these types of problems, a second order model is tried [39] in the form

$$y = b_0 + \sum_{i=1}^{n} b_i x_i + \sum_{i=1}^{n} b_{ii} x_i^2 + \sum \sum_{i<j} b_{ij} x_i x_j + \varepsilon, \tag{5}$$

where ε represents the noise or error observed in the response y such that the expected response is $(y - \varepsilon)$ and b's are the regression coefficients to be estimated.

The least square technique is used to fit a model equation that contains the input variables and minimizes the residual error measured by the sum of square deviations between the actual and estimated responses. There are statistical tools to check the adequacy of the model and its coefficients to predict the output response.

By performing analysis of variance (ANOVA), the adequacy of the model and significant factors that affect the response may be evaluated. There are two ways to check the significance of the model: F-ratio calculation and P-value. F-ratio is the ratio of variance due to the effect of a factor (the model) and variance due to the error term. F-ratio is also called the variance ratio. For a particular study, if the calculated F-ratio is greater than the tabulated value, then the selected parameter is significant at that confidence level. For a model, if the calculated F-ratio is greater than the tabulated one, then the model will be considered as an adequate model. P-value defines the probability of significance for each independent variable in the model. For a particular study, if the confidence level is set at 95 %, then the selected α-level is 0.05 (i.e., 1.0 – 0.95). A parameter is judged significantly if the calculated P-value is less or equal to the selected α-level. The present study is carried out at 95 % confidence level with the help of the commercial software Minitab (Minitab user manual) [38].

6 Experimental Details

6.1 Machine Used

For experiments, a five axis CNC WEDM (ELEKTRA, MAXICUT 434) of Electronica Machine Tools Ltd is used. Specifications of the WEDM machine are presented in Table 1. The workpiece and zinc coated brass wire electrode (diameter: 0.25 mm) are separated by dielectric medium (deionized water). The traveling of the wire in a closely controlled manner, through the workpiece, generates spark discharges and then erodes the workpiece to produce the desired shape.

6.2 Selection of Process Parameters

Four controllable factors, viz., discharge current (X_1), voltage (X_2), pulse on time (x_3), and pulse off time (X_4) are used as process parameters in this study. Process parameters with their levels are given in Table 2. Few other factors, which can be expected to have an effect on the measures of performance, are also given in Table 3. In order to minimize their effects, these factors are held constant as far as practicable.

6.3 Workpiece Material

EN 31 tool steel is selected as workpiece material in the form of a rectangular block (20 mm × 20 mm × 15 mm). It is a high carbon−steel with high degree of hardness with high compressive strength and abrasion resistance.

Table 1 Specifications of die sinking EDM machine

Maximum working dimension	400 mm × 500 mm × 150 mm
Maximum workpiece weight	235 kg
Main table traverse (X, Y)	300, 400 mm
Auxiliary table traverse (U, V)	15, 15 mm
Max. taper cutting angle	±5°/100 mm
Max. wire spool capacity	6 kg
Wire electrode diameter	0.25 mm (std.), 0.15, 0.2, 0.3 mm (option)
Wire feed rate	10 m/min (max)
Table displacement per step	0.001 mm
Outside dimension of machine	1250 mm × 945 mm × 1730 mm
Net weight of machine	1300 kg. (approx)
Dielectric fluid	Deionized water
Filtration	Mineral bed
Cooling system	1700 K Cal
Input power supply	3 phase, AC 415 V, 50 Hz
Connected load	10 KVA
Average power consumption	6–7 KVA

Table 2 Machining parameters with their levels for process

Design factors	Unit	Notation	Levels				
			−2	−1	0	1	2
Discharge current	Amp	X_1	2	4	6	8	10
Voltage	Volt	X_2	40	45	50	55	60
Pulse on time	μs	X_3	1	2	3	4	5
Pulse off time	μs	X_4	1	2	3	4	5

Table 3 Fixed parameters of the setting

Wire	Zinc coated copper wire, stratified, copper, diameter 0.25 mm
Shape	Rectangular
Location of workpiece on working table	At the center of the table
Angle of cut	Vertical
Dimension of workpiece	Thickness 6 mm Width 7 mm
Stability	Servo control
Wire speed	8 m/min
Wire tension	1000 g
Dielectric flow pressure	1.30 bar

6.4 Selection of Design of Experiments

In this study, a rotatable CCD is selected. For four process parameters with three levels, total 31 experiments are conducted based on the matrix shown in Table 4. Out of 31 experiments, there are sixteen (2^4) factorial or cube points, eight axial points (2×4), and seven center points.

6.5 Fractal Dimension Measurement

A stylus-type profilometer, *Talysurf* (Taylor Hobson, UK) is used for measuring the roughness profile. A cut-off length of 0.8 mm with Gaussian filter and traverse speed 1 mm/s along with 4 mm traverse length is used. Measurements are taken in the transverse direction on the workpieces for four times and average of four measurements is considered. The measured profile is then processed using the software *Talyprofile*. Finally, fractal dimension is evaluated following the structure function method.

7 Results and Discussion

In this section, the experimental results for fractal dimension (D) are analyzed using RSM. Using rotatable CCD, total 31 numbers of experiments are carried out varying four process parameters and the results are presented in Table 4.

With the help of Minitab statistical software, a second order response surface model for D is developed in terms of four independent process parameters in their coded forms. The developed model is presented in Eq. (6).

Table 4 Experimental design matrix and results

Sl. No.	Current (A)	Voltage (V)	Pulse on time (μs)	Pulse off time (μs)	*D*
1	6	50	3	3	1.428
2	6	50	3	3	1.428
3	6	50	3	3	1.428
4	6	40	3	3	1.415
5	4	45	2	4	1.408
6	8	55	2	4	1.360
7	8	55	4	4	1.403
8	4	45	4	2	1.363
9	6	50	3	3	1.428
10	6	50	3	3	1.428
11	6	50	3	3	1.428
12	8	55	2	2	1.390
13	6	50	5	3	1.270
14	8	45	4	2	1.383
15	4	55	4	4	1.373
16	6	60	3	3	1.440
17	6	50	3	1	1.403
18	4	55	4	2	1.263
19	4	55	2	4	1.398
20	6	50	3	5	1.383
21	6	50	3	3	1.428
22	8	55	4	2	1.325
23	8	45	2	2	1.428
24	4	45	2	2	1.353
25	8	45	2	4	1.043
26	6	50	1	3	1.423
27	10	50	3	3	1.393
28	8	45	4	4	1.320
29	4	55	2	2	1.383
30	4	45	4	4	1.388
31	2	50	3	3	1.425

$$
\begin{aligned}
D = {} & 1.42800 - 0.02842 \times X_1 + 0.02158 \times X_2 - 0.02092 \times X_3 - 0.01958 \\
& \times X_4 - 0.04912 \times X_1^2 - 0.03062 \times X_2^2 - 0.11162 \times X_3^2 - 0.06512 \\
& \times X_4^2 + 0.09975 \times X_1 \times X_2 + 0.09125 \times X_1 \times X_3 - 0.15125 \times X_1 \\
& \times X_4 - 0.09725 \times X_2 \times X_3 + 0.13525 \times X_2 \times X_4 + 0.12375 \times X_3 \times X_4
\end{aligned} \tag{6}
$$

To check the adequacy of the developed model, ANOVA is carried out for the model and results for ANOVA test are presented in Table 5. It is seen from the table

Table 5 Full ANOVA results of model coefficients for *D*

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	14	0.126277	0.126277	0.009020	2.84	0.024
Linear	4	0.012566	0.012566	0.003142	0.99	0.441
Current (A)	1	0.004845	0.004845	0.004845	1.53	0.234
Voltage (V)	1	0.002795	0.002795	0.002795	0.88	0.362
Pulse on time (μs)	1	0.002625	0.002625	0.002625	0.83	0.376
Pulse off time (μs)	1	0.002301	0.002301	0.002301	0.73	0.407
Square	4	0.029493	0.029493	0.007373	2.32	0.101
Current × Current	1	0.001760	0.004313	0.004313	1.36	0.261
Voltage × Voltage	1	0.000339	0.001676	0.001676	0.53	0.478
Pulse on × Pulse on	1	0.019815	0.022269	0.022269	7.02	0.017
Pulse off × Pulse off	1	0.007580	0.007580	0.007580	2.39	0.142
Interaction	6	0.084217	0.084217	0.014036	4.43	0.008
Current × Voltage	1	0.009950	0.009950	0.009950	3.14	0.096
Current × Pulse on	1	0.008327	0.008327	0.008327	2.63	0.125
Current × Pulse off	1	0.022877	0.022877	0.022877	7.21	0.016
Voltage × Pulse on	1	0.009458	0.009458	0.009458	2.98	0.103
Voltage × Pulse off	1	0.018293	0.018293	0.018293	5.77	0.029
Pulse on × Pulse off	1	0.015314	0.015314	0.015314	4.83	0.043
Residual error	16	0.050746	0.050746	0.003172		
Lack-of-fit	10	0.050746	0.050746	0.005075		
Pure error	6	0.000000	0.000000	0.000000		
Total	30	0.177023				

that the regression model has a *P*-value of 0.024, which means the model is significant at 95 % confidence level. It is also seen from the table that the calculated value of the *F*-ratio ($F_{\text{calculated}} = 2.84$) is more than the tabulated value of *F*-ratio

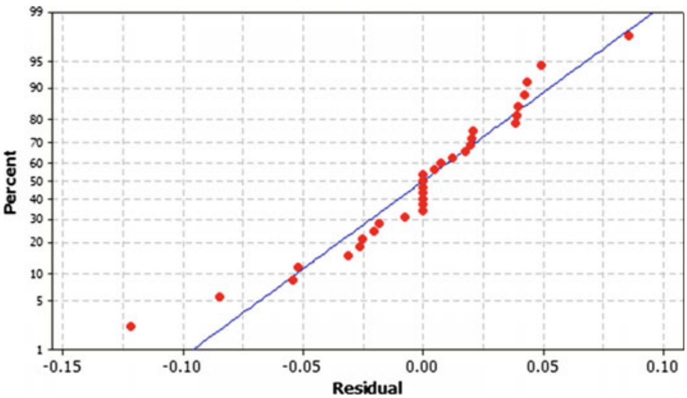

Fig. 2 Normal probability plot of the residuals for *D*

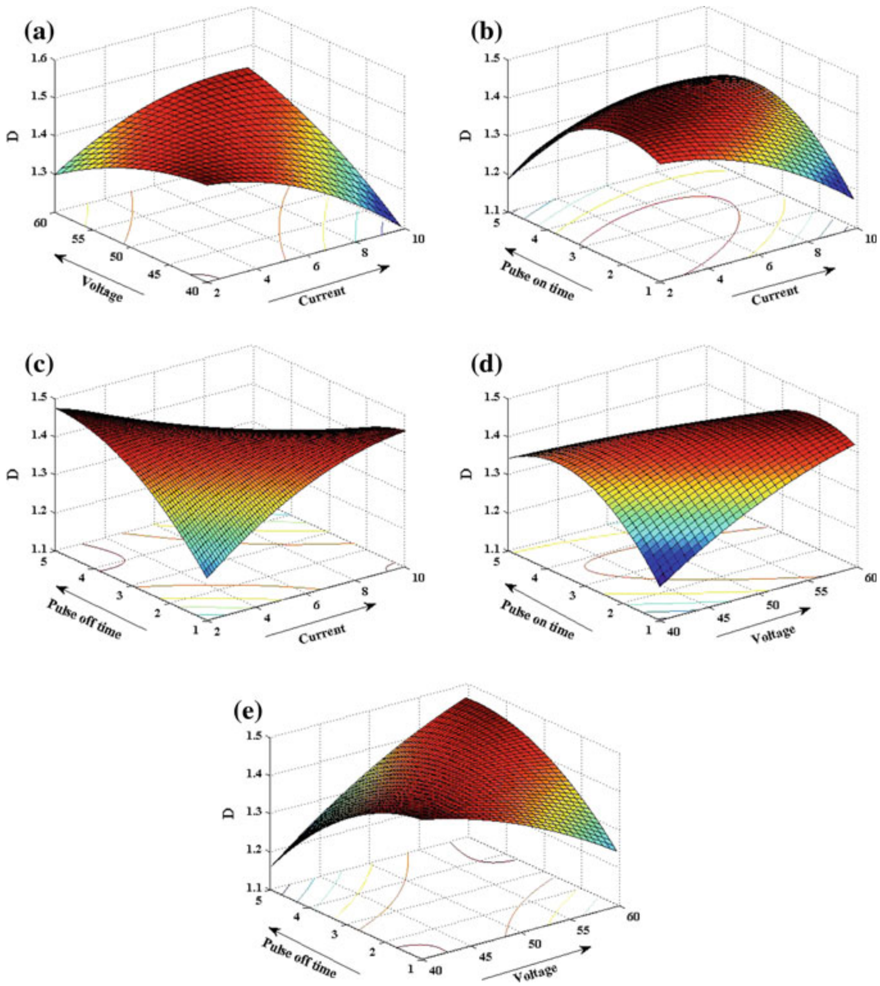

Fig. 3 Surface and contour plots for D **a** current with voltage, **b** current with pulse on time, **c** current with pulse off time, **d** voltage with pulse on time and **e** voltage with pulse off time

($F_{0.05,14,30}$ = 2.04). That implies that the model is adequate at 95 % confidence level. Normal distribution of residuals is plotted and presented in Fig. 2. It is seen that residuals follow a straight line and it follows a normal distribution. So, it can be said that the regression analysis is valid.

ANOVA results for individual parameters are also presented in Table 5. It is seen that no linear parameter is significant at 95 % confidence level in controlling fractal dimension, but some of the square and interaction terms are significant.

Three dimensional surface and contour plots are generated using the regression equation developed in the study to see the variations of fractal dimension with the process parameters. To generate the plots, two process parameters are varied while other two parameters are held constant at their mid-levels. Figure 3a shows the variation of fractal dimension with voltage and current. In this plot, pulse on time and pulse off time are held constant at 3 μs. It is seen from the graph that surface will be smoother (i.e., higher value of *D*) with a combination of higher current and higher voltage. Figure 3b depicts the variation of *D* with pulse on time and current and it is seen that higher current and pulse on time combination will provide smoother surface. Figure 3c plots the variation of *D* with pulse off time and current. From Fig. 3d it is seen that at higher values of pulse off time and voltage *D* value decreases that means the surface is getting rough. If the discharging energy is very high then there is a chance of getting violent sparks which may cause a rougher surface. Figure 3e shows that at higher pulse off time the surface is getting smoother.

8 Conclusion

In this chapter, to describe surface roughness, fractal dimension is used. To generate machined surfaces, experiments are conducted in WEDM on EN31 steel workpieces using rotatable CCD. Machined surfaces are measured for fractal dimension. A second order equation is developed for predicting fractal dimension in terms of four process parameters using RSM. It is seen that the developed model is adequate enough to predict fractal dimension with 95 % confidence level. From ANOVA results, it is seen that no individual parameter is significant in predicting fractal dimension but some of their interaction terms are significant at 95 % confidence level. Finally, the variations of fractal dimension with process parameters are demonstrated.

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Thrust Force and Torque Mathematical Models in Drilling of Al7075 Using the Response Surface Methodology

Panagiotis Kyratsis, Cesar Garcia-Hernandez, Dimitrios Vakondios and Aristomenis Antoniadis

Abstract Drilling is the most commonly used manufacturing processes for hole-making. Researchers are dealing with the development of mathematical models for a series of phenomena related to drilling i.e. burr size, surface roughness, cutting forces. The present research investigates the relationships and parametric interaction of the three input variables (tool diameter, cutting velocity, feed rate) on the thrust force and torque developed during drilling of an Al7075 workpiece with solid carbide tools. A complete set of experiments was performed and the response surface methodology (RSM) was used in order to acquire the mathematical models for both the thrust force and the torque required. The analysis of variance (ANOVA) was used to verify the adequacy of the mathematical models. The most significant factors were recognized. The main and interaction effects plots were studied and the 3D response surfaces are presented.

1 Introduction

Drilling operation can be described as a process where a multipoint tool is used for unwanted materials removal to produce a desired hole. It is an important metal cutting operation with which holes are produced in components made of metallic or non-metallic materials. The manufacturing process of drilling is considered the

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most efficient and economical method for opening holes. It has a considerable cost importance because it is widely used in the component manufacturing industry. Nearly 40 % of the metal removal operations in the automotive and aerospace industry are based on drilling [1]. It is used in aeronautical and automotive industries for assembling a variety of components. Drilling usually is one of the last production stages before the assembly step. Especially nowadays, that composites are selected and drilling becomes even more important due to manufacturability issues, studies that support the selection of the best cutting parameters for delivering the best quality is extremely crucial.

Researchers have followed a number of different approaches, when creating mathematical models in order to describe the size of the thrust force developed during drilling and the torque required. Response surface methodology (RSM) is a very popular tool and provides an excellent basis for extracting high level of engineering results when examining manufacturing processes.

The RSM is a collection of statistical and mathematical techniques used for developing, improving, and optimizing processes. It is also applied in the design, development, and formulation of new products, as well as in the improvement of existing product designs. The most extensive applications of RSM are in the industrial world, particularly in situations where several input variables potentially influence some performance measure or quality characteristic of the product/process. This performance measure or quality characteristic is called *response*. The input variables are sometimes called *independent variables*, and they are controlled during the experiments [2].

Researchers have been applying RSM with great success in a variety of phenomena dealing with drilling i.e. burr formation, surface roughness, thrust force, torque. The outcome of these studies has a significant value for industry and provides a solid basis for improving the quality of drilling as a manufacturing process.

2 Review of Literature

Kilickap investigated the influence of cutting parameters (cutting speed, feed rate and point angle) on burr height and surface roughness produced when drilling Al7075. A combination of RSM and a plan based on L_{27} Taguchi design method was used. The optimization results showed that the combination of low cutting speed, low feed rate and high point angle is necessary to minimize burr height [3].

Asilturk presented mathematical models for predicting the surface roughness of AISI 1040 steel material using both artificial neural network (ANN) and multiple regression methodology. The cutting parameters included were cutting speed, feed rate, depth of cut and nose radius. Ra and Rt were measured in 81 experiments with different cutting parameters. The calculations were based on a full factorial experimentation design and although both the aforementioned methods were used for modeling, ANN performed better than multiple regressions [4].

Gaitonde et al. described the development of mathematical models in order to investigate the effects of cutting speed, feed, drill diameter, point angle and lip clearance angle on burr height and burr thickness when drilling AISI 316L stainless steel. The analysis reveals that feed rate, drill diameter, point angle and lip clearance angles have significant effect on burr size [5].

Davim et al. investigated the relationships and parametric interactions between two controllable variables (feed rate and cutting speed) on the delamination factor at entry and exit of the holes in drilling medium density fibreboard (MDF). The experiments were based on the Taguchi's L_{18} mixed orthogonal array and the responses (delamination factor at entry and exit of the holes) have been modeled using the RSM. The analysis of variance (ANOVA) was performed in order to verify the adequacy of the mathematical models and the RSM was used to examine the main and the interaction effects of the machining parameters [6].

Yoon et al. analyzed micro drill-bits for halogen-free printed circuit boards (PCB) using Taguchi method and RSM. The first was used as an optimizing method (micro drills have many shape factors), while the later was used as a tool for building a regression surface. Optimal shapes of the micro drills were determined and it was suggested that RSM combined with other methodologies should be used in order to further analyze the performance of micro drill-bits with an increase number of shape factors [7].

Badan et al. proposed a mathematical model which calculates the drilling cutting forces based on experimental results. The research aimed in determining the influence of the cutting parameters (cutting speed, cutting depth, and feed rate) on the drilling thrust force. The material used was 40CrMnMoS8-6 steel and the tools were HAM 280 Super drill solid carbide drills. Regression analysis was successfully implemented for the acquisition of the mathematical model [8].

Cicek et al. studied the effects of cutting parameters i.e. cutting speed, feed rate and deep cryogenic treatment, on thrust force when drilling AISI 316 stainless steel. M35 HSS twist drills were cryogenically treated at −196 °C for 24 h and tempered at 200 °C for 2 h after conventional heat treatment. The experimental results proved that the lowest thrust forces were measured with cryogenically treated and tempered drills. Both ANNs and multiple regression analysis were implemented to model the thrust force [9].

Jayabal and Natarajan discussed the influence of parameters on drilling characteristics of natural fibre reinforced composites by Box-Behnken design, analysis of variance and RSM techniques. The experiments were performed in order to study the effect of drill bit diameter, spindle speed and feed rate on thrust force, torque and tool wearing HSS twist drills. The mathematical models developed are generally used to predict the responses with a reasonable accuracy over a wide range of conditions [10].

Jayabal et al. investigated the mechanical and machinability characteristics of hybrid composites, e-glass and natural coir fiber. A regression model was developed for correlating the interactions of some drilling parameters (drill bit diameter, spindle speed and feed rate) and their effects on responses such as thrust force, torque and tool wear during drilling of glass-coir fiber reinforced hybrid composites. The outcome of the research proved that feed rate is playing a major role on the responses, compared to the other two variables [11].

Kumar and Baskar performed an integration of fuzzy logic (FL) with RSM in order to reduce the cost and the time consumption needed for research. Different levels of values for the spindle speed and the feed rate were examined on cutting force and surface finishing in a systematic way. Both the proposed FL-RSM and FL models were validated experimentally, but the first one performs more effectively and accurately, compare to the later [12].

Valarmathi et al. measured and analyzed the cutting conditions that influence the thrust force in drilling of particle board panels used in wood working. Spindle speed, feed rate and point angle were considered and experiments were performed based on Taguchi's methodology. The mathematical model provided by the RSM predicted with accuracy the influence of the cutting parameters on thrust force. The results showed that high spindle speed with low feed rate minimizes the thrust force in drilling of pre-laminated particle board panels [13].

The objectives of the present study were to determine the effects of the cutting parameters on the thrust force and the torque when drilling an Al7075 workpiece with solid carbide drill tools (KC7325 made by Kennametal) and to calculate mathematical models for both outputs using the RSM. Al7075 was selected due to its high performance for the industry manufacturers. The ANOVA was used to verify the adequacy of the mathematical models. The most significant input variables were recognized; and the main and interaction effects were studied. Finally, the 3D response surfaces for both the thrust force and the torque were plotted.

3 Experimental Work

A series of experiments were performed on a HAAS VF1 CNC machining center with continuous speed and feed control within their boundaries. The specimen used was an Al7075 plate, because it is one of the most widely used materials in a variety of industrial applications and it potentially enables the widespread adoption of the proposed models.

The plate was 150 mm × 150 mm × 10 mm in size. A Kistler type 9123 four components dynamometer was used and the signal was processed by a type 5223 multichannel signal conditioner and type 5697 data acquisition unit (Fig. 1).

The five drill tools used were made by Kennametal and commercially available. They were solid carbide drills (KC7325) with diameters of 6, 8, 10, 12 and 14 mm.

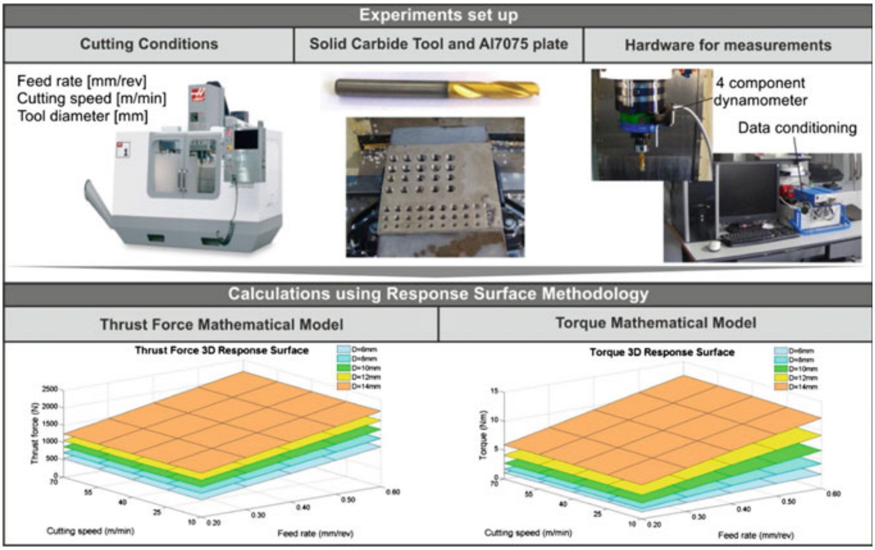

Fig. 1 Activities flow chart

Table 1 Process parameters and their levels

Factor	Notation	Unit	Levels				
			I	II	III	IV	V
Tool diameter	*D*	mm	6	8	10	12	14
Feed rate	*f*	mm/rev	0.2	0.4	0.6		
Cutting speed	*V*	m/min	10	40	70		

The feed rates of 0.20, 0.40 and 0.60 mm/rev were used together with cutting velocity values of 10, 40 and 70 m/min. In each experiment, both the thrust force and the torque required were measured. The process parameters with their symbols, levels and units are presented in Table 1. A total of 45 experiments were performed at all combinations of cutting speed, feed rates and tool diameters.

Figure 2 presents the thrust force and the torque measured when all the five tools were used with the different feed rates and a cutting speed of 10 m/min. When the tool diameter increases the same result is true for both the thrust force and torque required. The increase of the feed rate used, results in increasing the values of both the measured parameters.

Similar results were acquired when the cutting speed was increased to 40 m/min and to 70 m/min (Figs. 3 and 4). When comparing the values of each tool, while increasing the cutting speed, there is a tendency for limited value change in almost all cases. This means that the tools are able to keep relative constant thrust force and torque within the boundary of the cutting speeds used.

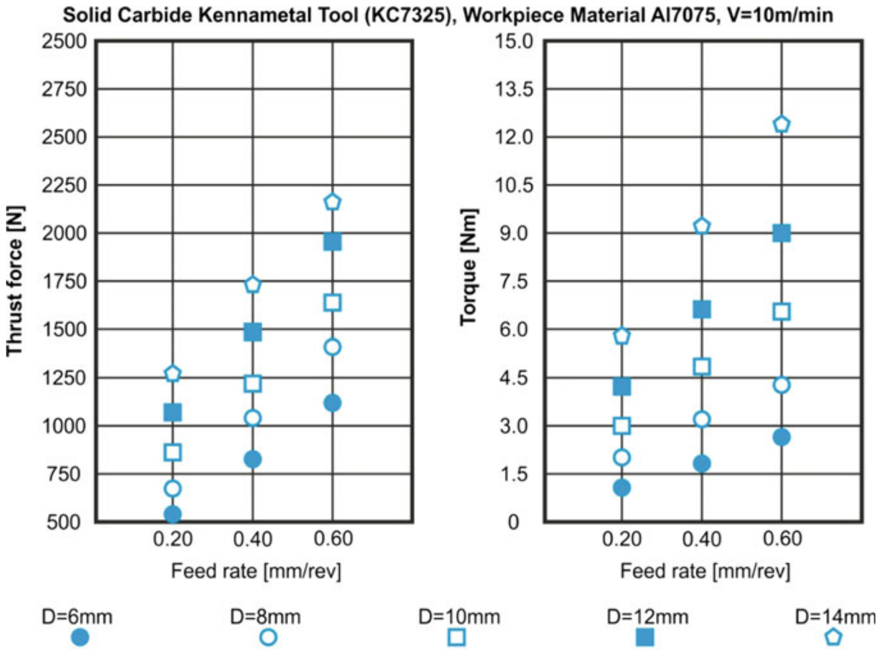

Fig. 2 Thrust force and torque required when drilling with V = 10 m/min

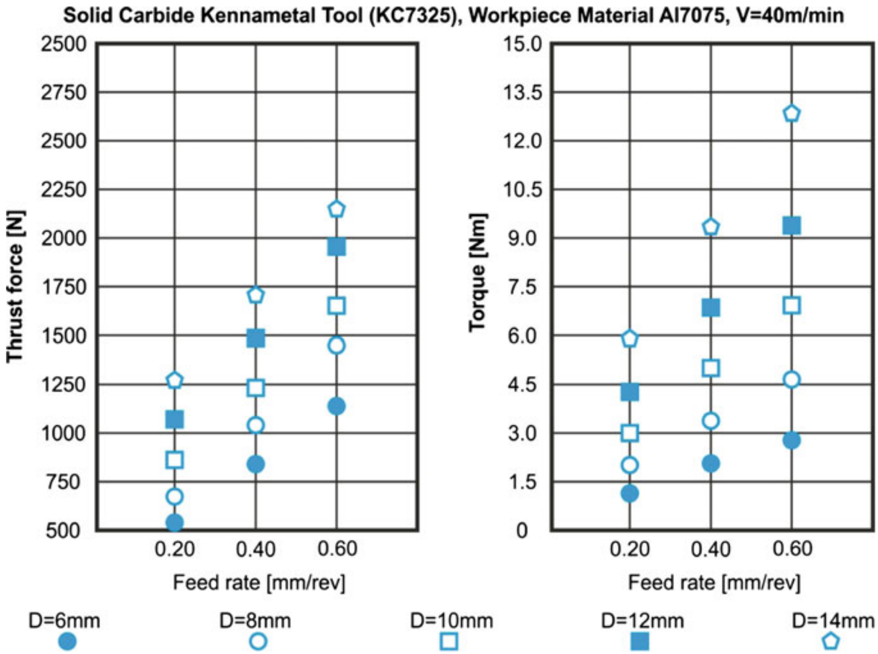

Fig. 3 Thrust force and torque required when drilling with V = 40 m/min

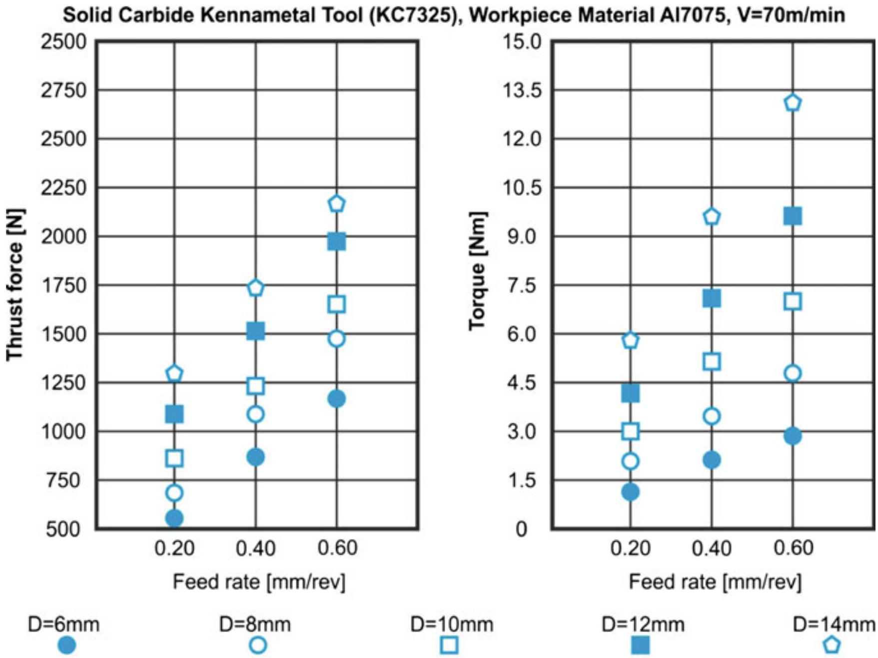

Fig. 4 Thrust force and torque required when drilling with V = 70 m/min

4 Proposed Mathematical Models for Thrust Force and Torque

The RSM is an extremely versatile tool when used for modeling problems in which response (output) is influenced by several input variables. The aim is to find the correlation between the response and the input variables. The mathematical models use the least square fitting in order to finalize the model [14]. In the present study, a full factorial approach was followed and 45 experiments were conducted as described earlier. This provides a comparatively accurate prediction of both the thrust force and torque. A polynomial mathematical model was used in order the thrust force and the torque to be calculated. These models follow the form given in the equation below.

$$Y = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_{11}X_1^2 + b_{22}X_2^2 + b_{33}X_3^2 + b_{44}X_4^2 + b_{12}X_1X_2 + b_{13}X_1X_3 + b_{14}X_1X_4 + b_{23}X_2X_3 + b_{24}X_2X_4 + b_{34}X_3X_4$$

where

- Y is the response i.e. thrust force and torque,
- Xi stands for the coded values for $i = D, V, f$, and
- $b_0,\ldots,b_{34}$ represent the regression coefficients

Using the data illustrated in Figs. 2, 3 and 4 as well as the aforementioned mathematical model, the following equations form the final mathematical model proposed for the calculation of the thrust forces (in N) and the torque (in Nm) required respectively:

$$F_z = -183 + 59.3D + 0.160V + 962f + 1.02D^2 + 0.0133V^2 + 161f^2 \\ -0.117D \times V + 83.4D \times f + 0.692V \times f$$

and

$$M_z = 2.98 - 0.697D - 0.00381V - 5.91f + 0.0478D^2 - 0.000047V^2 - 0.98f^2 \\ + 0.000353D \times V + 1.59D \times f + 0.0183V \times f$$

where

- D is the tool diameter in mm,
- f is the feed rate in mm/rev,
- V is the cutting speed used in m/min and
- the tool/workpiece materials are solid carbide/Al7075.

The adequacy of the models is provided at a 95 % confidence level (level of significance of 5 %). The ANOVA has been performed to justify the validity of the models developed. The ANOVA table consists of a sum of squares (SS) and degrees of freedom (DF). The sum of squares is usually contributed from the regression model and residual error, in other words, it is decomposed into the sum of squared deviations due to each factor and the sum of squares due to error. Mean square (MS) is the ratio of sum square to the degree of freedom and the F-ratio is the ratio of mean square of regression model to the mean square of residual error.

According to the methodology, the calculated values of the F-ratio of the developed models (Tables 2 and 3), are significantly increased compared to the tabulated value of the F-table for 95 % confidence level (2407.84 for the thrust force and 3084.78 for the torque). The P values are 0.000, which proves the highest correlation, hence both the developed response function (mathematical models) are adequate at a 95 % confidence level.

The validity of the fit of the models can also be proved, by the adjusted correlation coefficient [R-sq (adj)], which provides a measure of variability in observed output and can be explained by the factors along with the two factor interactions. This coefficient in both cases is 99.8 % and as a result the models appear to have adequate predictive ability.

In addition, the significant terms of the models, when a level of significance of 5 % is used, are those with a P-value less than 0.05. In the case of the thrust force, these factors are: D ($P = 0.000$), f ($P = 0.000$), D^2 ($P = 0.030$), $D \times V$ (P = 0.011) and $D \times f$ ($P = 0.000$), while for the torque, the significant terms are: D ($P = 0.000$), f ($P = 0.000$), D^2 ($P = 0.000$), $D \times f$ ($P = 0.000$), $V \times f$ ($P = 0.000$).

Table 2 ANOVA table for the thrust force mathematical model (F_z)

Source of variation for F_z	DF	SS	MS	F	P
Regression	9	8,877,831	986,426	2407.84	0.000
Residual error	35	14,339	410		
Total	44	8,892,170			
R-sq (adj)	99.8 %				
Predictor	Coef.	SE Coef.	T	P	
Constant	−183.35	59.660	−3.07	0.004	
D	59.31	9.606	6.17	0.000	
V	0.16	0.787	0.20	0.840	
f	961.80	148.000	6.50	0.000	
D^2	1.02	0.451	2.26	0.030	
V^2	0.01	0.007	1.86	0.071	
f^2	160.80	160.000	1.01	0.322	
$D \times V$	−0.12	0.044	−2.68	0.011	
$D \times f$	83.38	6.533	12.76	0.000	
$V \times f$	0.69	0.754	0.92	0.365	

Table 3 ANOVA table for the torque mathematical model (M_z)

Source of variation for M_z	DF	SS	MS	F	P
Regression	9	447.468	49.719	3084.78	0.000
Residual error	35	0.564	0.016		
Total	44	448.032			
R-sq (adj)	99.8 %				
Predictor	Coef.	SE Coef.	T	P	
Constant	2.98230	0.37420	7.97	0.000	
D	−0.69669	0.06026	−11.56	0.000	
V	−0.00381	0.00494	−0.77	0.446	
f	−5.91170	0.92830	−6.37	0.000	
D^2	0.04784	0.00283	16.92	0.000	
V^2	−0.00005	0.00004	−1.05	0.303	
f^2	−0.97900	1.00400	−0.98	0.336	
$D \times V$	0.00035	0.00027	1.29	0.204	
$D \times f$	1.59229	0.04097	38.86	0.000	
$V \times f$	0.01831	0.00473	3.87	0.000	

Similar results can be depicted when examining the main effects and interaction plots. Figure 5 depicts the significance of the tool diameter (D) and the feed rate used (f) from the main effect plot for the thrust force, while the interaction between tool diameter/cutting speed and tool diameter/feed rate is presented from the interaction plot.

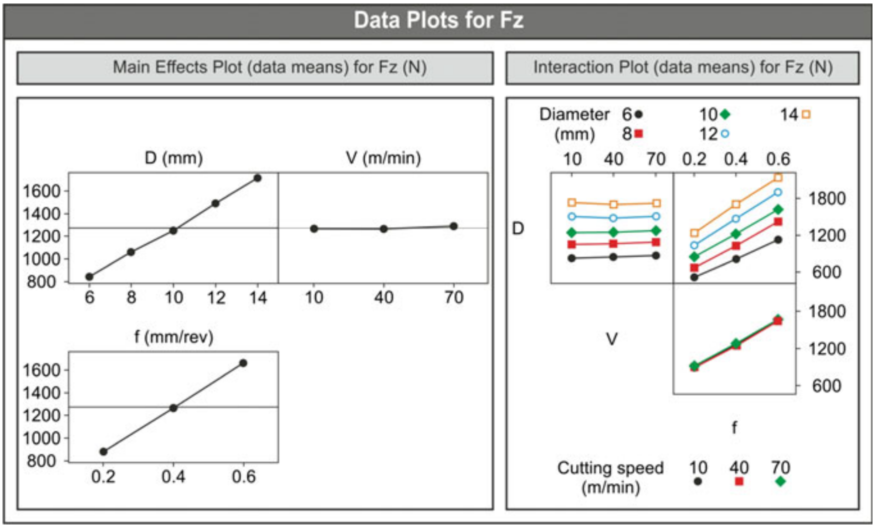

Fig. 5 Main effects and interaction plots for the thrust force

Figure 6 depicts the significance of the tool diameter (D) and the feed rate used (f) from the main effect plot for the torque, while the interaction between tool diameter/feed rate and cutting speed/feed rate is presented from the interaction plot. The accuracy of the models has been checked by the residual analysis, and it is essential that the residuals are normally distributed in order for the regression

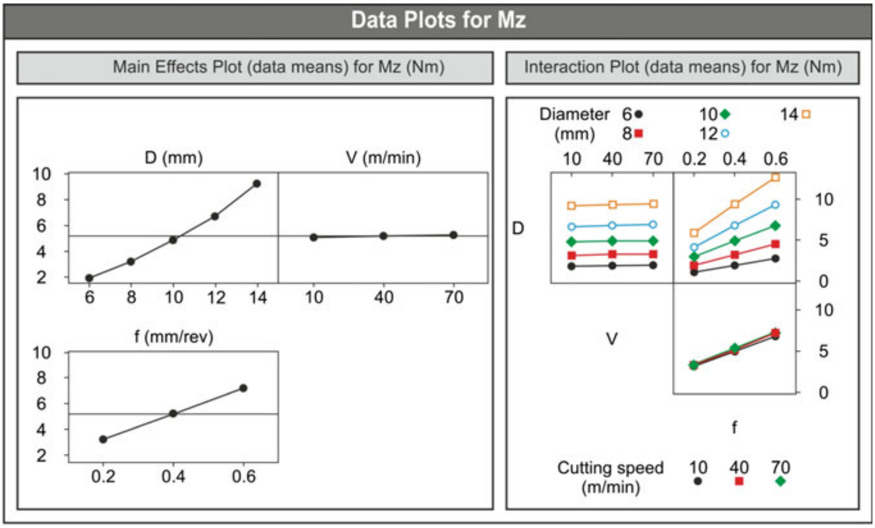

Fig. 6 Main effects and interaction plots for the torque

analysis to be valid. The normal probability plots of the residuals for both the thrust force and the torque calculated are depicted in Fig. 7. The graphs show that:

- The residuals closely follow straight lines (approximately linear patterns), denoting that the errors are normally distributed.
- Both the scatter diagrams of the thrust force and torque residuals versus the fitted values depict that the residuals are evenly distributed on both sides of the reference line.
- The residuals versus the order of the data, depict that the residuals are evenly distributed on both sides of the reference line.

The analyses proved that the prediction models sufficiently explain the relationship between the thrust force and torque with the independent variables respectively. These mathematical models could be used with high level of

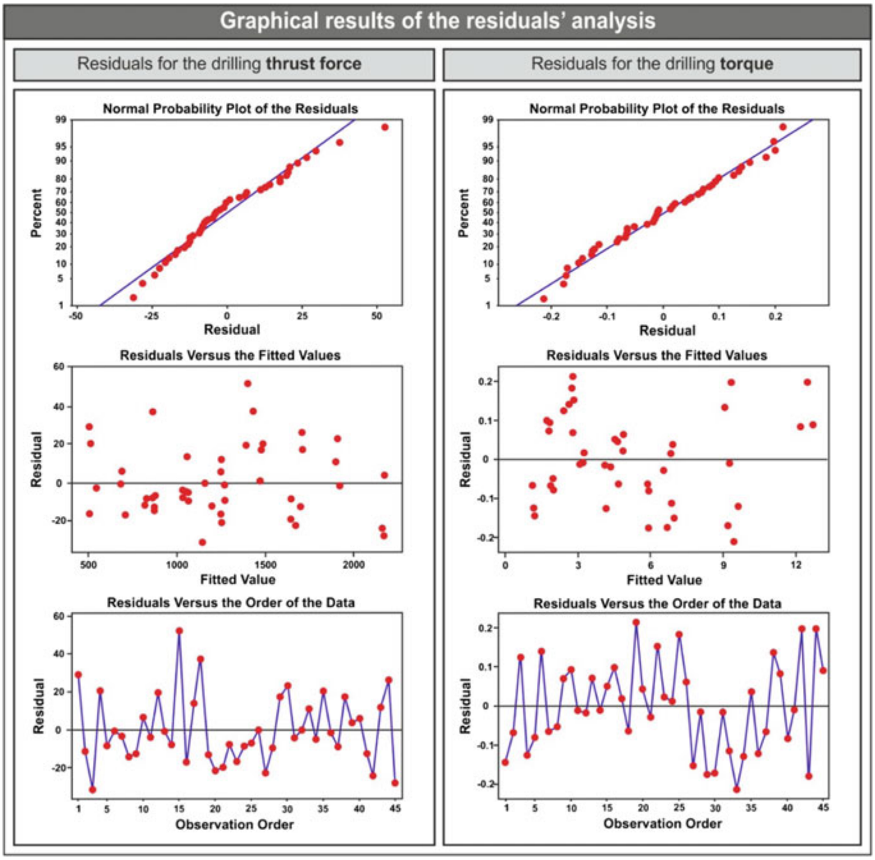

Fig. 7 Residuals analyses for the thrust force and torque

confidence from researchers and industry engineers in order to predict the thrust force and torque expected within the limitations presented in the current research.

The mathematical models developed are used to predict the thrust force and torque by substituting the values of the tool diameter, feed rate and cutting speed within the ranges selected in the experimental investigation. The response surface plots of F_z and M_z are depicted in Fig. 8. They are analyzed through the RSM prediction models by generating 3D response surface plots and it is observed that:

- At higher values of tool diameter both the thrust force and torque increase significantly.
- At increased values of feed rate they similarly increase.
- When the cutting speed increases they have a limited amount of change.

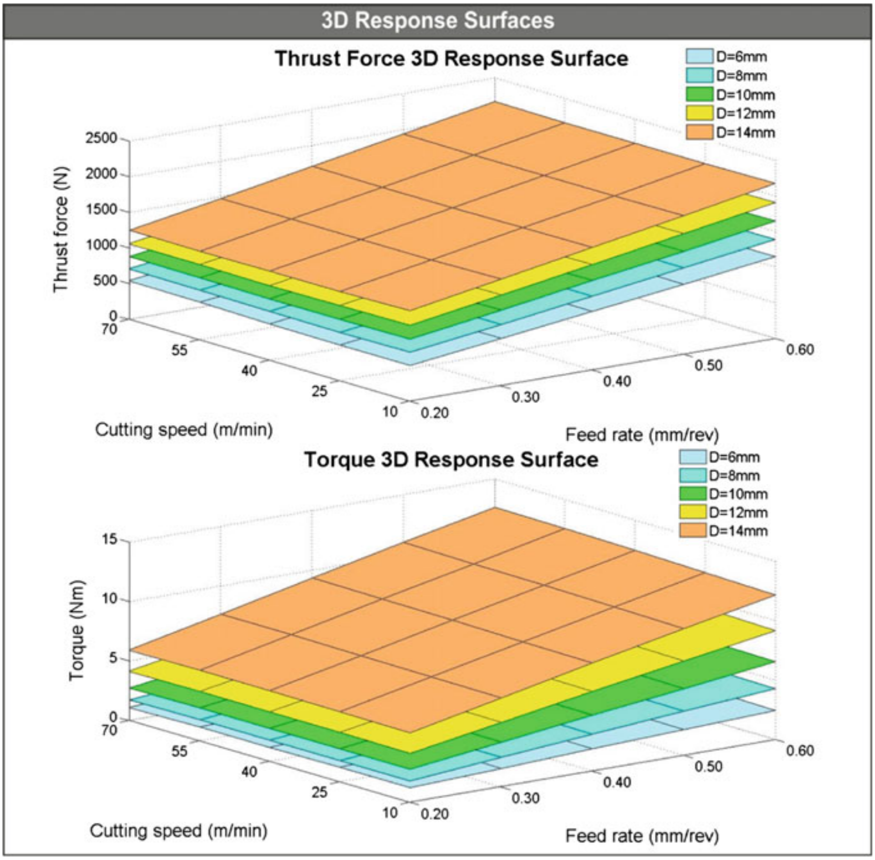

Fig. 8 3D plots of the thrust force and the torque required

5 Conclusions

The application of RSM for investigating the effects of cutting conditions (diameter, feed rate and cutting speed) on the development of thrust forces and torques are presented in the current research. A complete set of experiments (full factorial) was performed under different conditions of tool diameter, feed rate and cutting speed using a workpiece made of Al7075 and a set of KC7325 solid carbide tools made by Kennametal. The RSM was used to develop the mathematical models for the thrust force and torque.

Through ANOVA, the adequacy of the developed models was verified. Based on the analysis performed, the following conclusions are drawn:

- Increase in tool diameter and feed rate results in increased thrust force and torque.
- Different cutting speeds do not result in high differences in thrust force and torque.
- The statistically significant terms, in the case of the thrust force, are: D, f, D^2, $D \times V$, and $D \times f$.
- In the case of the torque, the statistically significant terms are: D, f, D^2, $D \times f$, $V \times f$.

The developed mathematical models were thoroughly statistically validated and can be used as a valuable tool for academics, researchers and industry engineers.

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Design of Experiments in Titanium Metal Cutting Research

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Abstract This industry supported study outlines the usage of DoE in titanium metal cutting research. Taguchi optimization methodology is applied to optimize heat treatment condition and cutting parameters in orthogonal metal cutting when machining newly developed titanium alloy Ti-54M with carbide insert tool. The control parameters evaluated are heat treatment (Annealed, Beta Annealed and STA, i.e. Solution treated and aged) cutting speed and feed rate. An orthogonal array (OA), signal-to-noise (S/N) ratio and analysis of variance (ANOVA) are employed to investigate the effect of these three control parameters on cutting tool temperature and two force components. Using Taguchi method for design of experiment (DoE), experimenters significantly reduced the time and hence cost for the experimental investigation. The results of ANOVA showed that majority of the input parameters had significant effect on the cutting tool temperature and force components. Thereafter, optimal cutting parameters and heat treatment conditions were obtained using Taguchi's analysis. The results have been transferred to the respective industry. The industry is expected to gain from this research in terms of producing titanium alloys with better machinability.

1 Introduction

Among the structural materials developed in the twentieth century, titanium and its alloys played a leading role. The high consumption of titanium alloys has increased its demand in the past few years in the aerospace sector. The excellent strength-to-weight ratio of titanium alloys decreases aircraft weight, leading to reduction in fuel consumption and emissions. The other typical aerospace material, aluminium, is electrochemically incompatible with the increasingly applied composite materials, forming a galvanic couple. Titanium does not pose this problem

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and thus is replacing aluminium in many applications [1–3]. Titanium alloys are having outstanding mechanical and physical properties but they are difficult-to-cut alloys, leading to increased tool wear and lower production rates. It is well-known fact that cost is always an important consideration in the competitive business environment. The titanium raw material may cost anywhere from three to ten times as much as steel or aluminium and the machining costs for titanium alloys are usually considerably greater than for the other materials (no less than ten times that to machine aluminium). Thus the profits of using titanium must compensate the added cost for its successful application [2, 3]. The cost of titanium use may be minimized by decreasing its machining cost. Despite the ample research on the poor machinability of titanium alloys, very few studies in the literature discussed the relationship between the microstructure and machinability parameters. The microstructure holds important keys to identify the root causes of tool wear, cutting forces and segmented chips in titanium machining and to predict the performance of a component [4–12]. By developing understanding of this interrelationship, it will be possible to reduce the production cost of machining titanium alloys.

One of the key objectives of modern industry giants is to minimize energy consumption and maximize efficiency in its machining process due to stricter environmental legislation, global competition and demands for satisfying sustainability initiatives [13]. A strategy of energy saving and increasing productivity is to adapt new material variants or advanced processes. One of those latest variants is TIMETAL® 54M (Ti54M), developed by TIMET (Largest sponge producer in the United States), an $\alpha + \beta$ alloy that offers cost benefits with higher machinability. The strength is comparable to similarly processed Ti6Al4V alloy. References [7–10] reported succinct studies on Ti-54M titanium alloy and showed that heat treatment affects machinability. Therefore, more studies need to be carried out to notice the influence of heat treatment on performance characteristics. It is essential to model a relationship between the cutting parameters and the process performance mainly due to the high cost involved in the experimentation of titanium machining. This study is an attempt to fill this gap in the research by using design of experiments (DOE) technique in place of one-factor-at-a-time experimental approach.

It is widely considered that DoE forms an essential part of the pursuit for effective improvement in process performance or product quality for metal cutting industry. Experiments are often conducted in a series of tests which produce countable outcomes in machining processes. For constant improvement in process performance or product quality, it is essential to understand the process behaviour; the amount of changeability and its influence on processes. The DoE is a technique used to define what data, in what quantity and settings must be collected during an experimentation, to satisfy two foremost goals: the statistical accuracy of the response parameters accompanied by lesser cost [14–18]. Natarajan et al. [19] successfully employed DoE technique to access the machinability of metal matrix composites. Quiza et al. [20] planned a full factorial design for carrying out finite element simulations in order to obtain the corresponding forging forces as per the industry requirement.

This chapter presents a real industry supported study. The study illustrated in this chapter is well-thought-out experiments and not simply a few experimental tests to discover the effects of changing one or more parameters at a time. The study will deliver a good base for young scholars and practitioners on how to go about executing an experiment in real industrial settings. The study will cover the experimental details, experimental design using Taguchi techniques, analysis using Minitab software, analysis of results and significance of the study. This study will increase the awareness of the application of DOE techniques in industries and its potential in tackling process optimization difficulties related to improvement in titanium machinability.

It is worthwhile to mention that the commercial availability of titanium alloys (Ti-54M) used in this research is limited and titanium producer provided limited material to carry out this study. By applying DOE technique experimenters significantly reduced the time and cost for the experimental investigation, as it is effective in investigating the effects of multiple factors on performance as well as to study the influence of separate factors to determine which factor has more impact, which has less [17].

2 Experimental Details

2.1 Material Details

Chemical composition and mechanical properties of Ti-54M titanium alloy are summarized in Table 1. The details of as-received heat treatment conditions are shown in Fig. 1.

2.2 Experimental Setup Details

Orthogonal dry machining of 5 s duration was conducted on a Lagun vertical CNC milling machine. The infrared camera system is adapted into the Vertical CNC Milling Center, as seen in Fig. 2. The workpiece was carefully integrated into the tool holder on the spindle. Workpiece is rotated and fed into the stationary tool attached to the dynamometer. During the temperature measurements in the CNC machine, in order to isolate the thermal imaging camera and the objective from the chips and any flying particles that are present in the environment of CNC machine, protection is provided. The tubular workpiece, the dynamometer, and the cutting insert are placed in order to perform orthogonal cutting tests. The experiments are carried out with thin tubes of 2 mm wall thickness with three variants of Ti54M titanium alloy. The cutting inserts were Sandvik tungsten carbide inserts (Model: TNMG 160408-23 H13A) at three feed rates (0.1, 0.15 and 0.25 mm rev^{-1}) and two

Table 1 Chemical composition and mechanical properties of Ti-54M

Chemical composition (by weight %)				
Al	V	Mo	Fe	O
5	4	0.8	0.5	0.18
Yield strength (MPa)		860		
Ultimate tensile strength (MPa)		935		
Elongation (%)		23		
Reduction in area (%)		49		
Density (g/cm^3)		4.44		

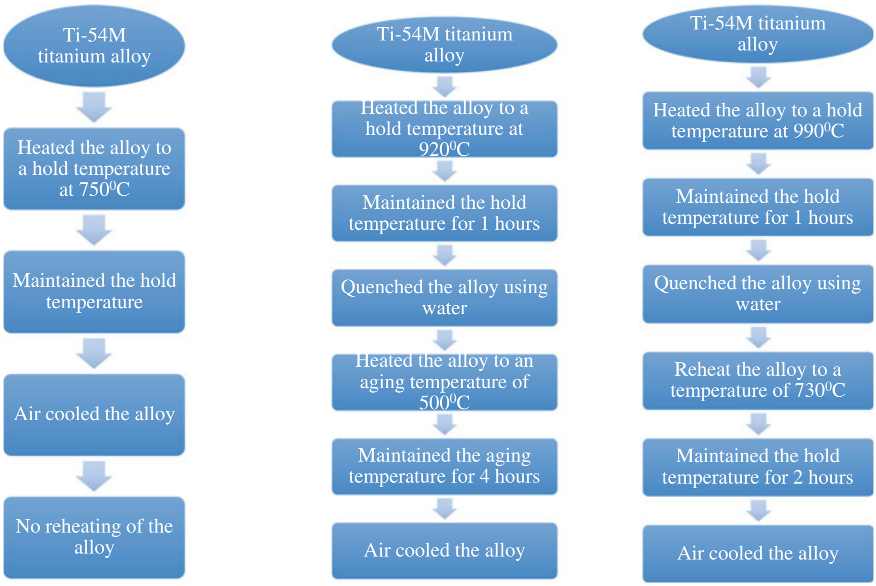

Fig. 1 Details of heat treatment conditions. **a** Annealed, **b** STA, and **c** β Annealed for Ti-54M titanium alloy

cutting speeds (40 and 80 m min^{-1}), without any coating or chip breakers. The dynamometer was firmly connected to the base plate of the machining centre. The cutting force produced by the turning process was resolved by the multi-component dynamometer directly into the orthogonal components: main cutting force (F_c) and feed force (F_k). The force components were measured practically without displacement. The dynamometer was connected to multichannel charge amplifier, which converts the dynamometer charge signals into output voltages proportional to

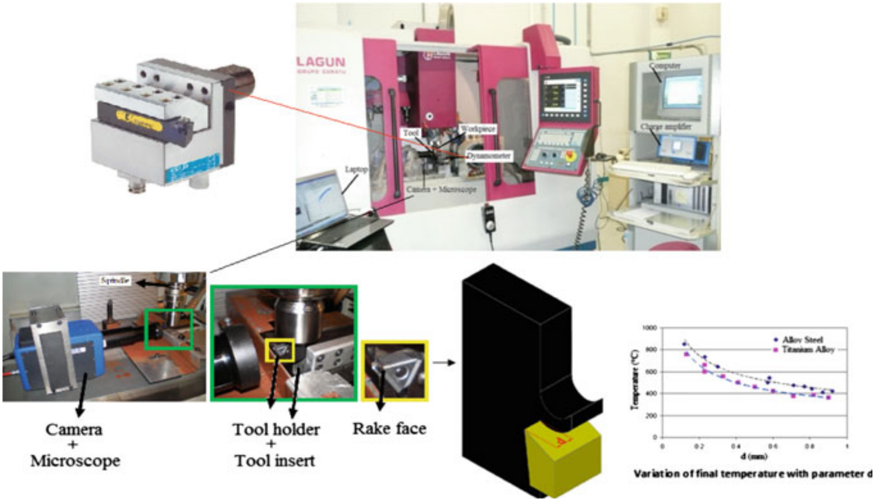

Fig. 2 Machining setup

the forces. The dynamometer was calibrated by the manufacturer in Switzerland. A simple test was conducted to see whether the output from dynamometer is still reliable or not. A metallic plate of 5 kg weight was put on the tool holder of the dynamometer. A force of 49.5 N was measured reflecting an error of −0.25 %. This small deviation may have happened because the metallic plate could not be placed at the exact place for which dynamometer was calibrated. A left hand 25 mm by 25 mm tool holder of 150 mm length with a rigid clamping system was used to hold the tool insert. To ensure edge sharpness, a new tool insert was used for each test. All the applied inserts were examined by an Sensofar optical profiler in order to verify the cutting edge radius is within 34 ± 2 μm. The Medatek and Altair softwares are used to capture force and thermal sequences respectively. The acquisition procedure is as follows:

i. Ready the Medatek and Altair softwares to capture force and thermal sequences.
ii. When the dynamometer and camera are ready, the vertical machining centre program is commenced and the dynamometer and camera are triggered simultaneously.
iii. When the data acquisition is completed, the sequences automatically loaded itself within the Medatek and Altair softwares and the files are saved. The frames are examined for pixel saturation and image quality. Integration time of 200 μs provided acceptable image quality. If the image quality is poor, the test is repeated following slight adjustments to the setup.

It is also required to synchronize the measurement of cutting forces, temperature measurement with the machining process (it will take more than one person to handle all equipment). The acquisition process was continued by repeating the above steps for all the desired feeds and speeds. Each test was carried out three times to check uncertainty in the result.

2.3 Experimental Design

This work makes use of Taguchi's method of experimental design. Taguchi's concept provides an efficient, simple and systematic approach of using orthogonal arrays (OAs) for laying out the experiments to determine optimal parameters. The optimal conditions are recognized by studying the main effects of each of the parameters. The general trend to influence by each parameter is specified by the main effects. In deciding the nature of control to be established on a production process, the knowledge of contribution of individual parameters plays a crucial role [18]. In nutshell, Taguchi method is a robust design procedure extensively used in industries for making the process/product insensitive to any uncontrollable elements such as environmental variables. The major steps required for the experimental design using Taguchi concept are (1) comprehending objective function, (2) ordering of the cutting parameters and their levels, (3) choice of a suitable OA, (4) carrying out experiments and data analysis for determination of the optimal levels.

2.3.1 Comprehending Objective Function

Taguchi strongly endorses for multiple runs, is to use signal-to-noise (S/N) ratio. This approach is to be used to measure the performance characteristics deviating from the desired values. The S/N ratio is a simultaneous quality metric linked to the loss function [13]. The loss associated can be minimized by maximizing the S/N ratio. The S/N ratio determines the most vigorous set of operating settings from variation within the results. The objective function in this work is minimization, and hence the ratio of S/N is defined according to the Taguchi method as:

$$\mathrm{S/N} = -10\ \log_{10}\left[1 \Big/ n\sum_{1}^{n} Y_i^2\right] \tag{1}$$

where S/N denotes the observed value (unit: dB), and Y_i is the value of the characteristic and n is the number of observations or number of replications in a test.

In the current research work, both analyses, i.e. the S/N data analysis and mean data analysis have been accomplished. The effects of the designated process parameters on the selected performance characteristics have been scrutinized

Table 2 Control factors and their levels

Control parameters	Level 1	Level 2	Level 3
Cutting speed (m/min)	40	80	–
Feed rate (mm/rev)	0.1	0.15	0.25
Workpiece heat treatment	Annealed (A)	β Annealed (β A)	Solution treated and aged (STA)

through the plots of the main effects based on S/N data, mean data and their respective response tables. The optimum condition for each of the performance characteristics has been established through S/N data analysis assisted by the mean data analysis.

2.3.2 Ordering of the Cutting Parameters and Their Levels

In the present investigation, three different control parameters had been selected; viz., feed rate, cutting speed, and the heat treatment of the workpiece. Two levels for cutting speed and three levels for both feed rate and heat treated workpiece conditions were selected as shown in Table 2.

2.3.3 Choice of a Suitable Orthogonal Array (OA)

The total degrees of freedom must to be computed to select a suitable OA for experimentation. OA layout stipulates the way of conducting the nominal number of experiments which may produce complete information of all the parameters that affect the performance characteristics [15, 17]. Based on the previous subsection, L_{18} array is selected for the present investigation. L_{18} array has an exceptional property that the two way interactions between the several factors are partially confounded with various columns and hence their effect on the estimation of the main effects of the various parameters is minimalized. It is impossible to evaluate the possible two factor interactions in L_{18} array but the main effects of different process parameters can be evaluated with realistic accuracy. Experiments have been repeated three times at each experimental condition instead of using outer array.

2.3.4 Carrying Out Experiments and Data Analysis for Determination of the Optimal Levels

Each trial is imitated three times, hence three experiments are made for each of the 18 experimental runs. To reduce the effect of experimental noise to the maximum possible extent, all the 54 trial runs altogether are performed in completely haphazard fashion. Every test, with a specific experimental condition, is conceded by using a fresh edge of the cutting insert. The experimental results as well as their

Table 3 Design and experimental results of the L_{18} orthogonal array experiment

Test case	Control parameters			Average experimental values of responses after 3 replications			S/N ratio (db)		
	Cutting speed	Feed rate	Heat treatment	Temperature	F_c	F_k	Temperature	F_c	F_k
1	40	0.10	STA	602	416	336	−55.5919	−52.3819	−50.5268
2	40	0.10	Annealed	547	400	291	−54.7597	−52.0412	−49.2779
3	40	0.10	β Annealed	527	407	310	−54.4362	−52.1919	−49.8272
4	40	0.15	STA	613	548	393	−55.7492	−54.7756	−51.8879
5	40	0.15	Annealed	650	550	308	−56.2583	−54.8073	−49.771
6	40	0.15	β Annealed	584	553	324	−55.3283	−54.8545	−50.2109
7	40	0.25	STA	770	765	430	−57.7298	−57.6732	−52.6694
8	40	0.25	Annealed	784	818	352	−57.8863	−58.2551	−50.9309
9	40	0.25	β Annealed	799	835	378	−58.0509	−58.4337	−51.5498
10	80	0.10	STA	857	388	327	−58.6596	−51.7766	−50.291
11	80	0.10	Annealed	894	406	302	−59.0268	−52.1705	−49.6001
12	80	0.10	β Annealed	780	407	305	−57.8419	−52.1919	−49.686
13	80	0.15	STA	883	494	322	−58.9192	−53.8745	−50.1571
14	80	0.15	Annealed	977	529	306	−59.7979	−54.4691	−49.7144
15	80	0.15	β Annealed	881	536	313	−58.8995	−54.5833	−49.9109
16	80	0.25	STA	1040	716	352	−60.3407	−57.0983	−50.9309
17	80	0.25	Annealed	1012	752	340	−60.1036	−57.5244	−50.6296
18	80	0.25	β Annealed	1021	782	352	−60.1805	−57.8641	−50.9309

calculated S/N ratios are abridged in Table 3 for cutting tool temperature and force components as the response variables. Decisions must be made regarding which parameters affect the performance of a process; analysis of variance (ANOVA) is the statistical treatment applied to the results of the experiments in predicting the contribution of each parameter against a stated level of confidence. The study of ANOVA Table for a given analysis helps to determine which of the parameters need control and which do not [15]. Minitab 16 Software has been used to determine ANOVA and mean effect plot. ANOVA was carried out after gathering all the data for all combinations, the contribution of each factor was predicted and the best parametric level along with confidence intervals (C.I.) is determined. The next section presents results and discussion on the present work.

3 Results and Discussion

3.1 ANOVA

The results obtained through experimentation are analysed using ANOVA for detecting the important factors affecting the performance measures. The cutting tool temperature results obtained through the application of ANOVA is shown in Table 4. The results of ANOVA for the cutting force (F_c) and feed force (F_k) are shown in Tables 5 and 6, respectively. A significance level of $\alpha = 0.05$ (confidence level of 95 %) is used to carry out this crucial analysis. Tables 4, 5 and 6 show the comprehended significance levels, associated with the *F*-tests for each source of variation. The *P*-values of ANOVA is shown in the second from last columns of the tables. When *P*-values are less than 0.05, the source effect on response is considered to be statistically significant at 95 % confidence level. The *F*-test is based on the principle which states that the larger the *F*-value for a particular parameter, the greater the effect on the performance characteristic due to the change in that process parameter [3]. In Table 4, the ANOVA result shows that the *F*-value for the cutting speed parameter is larger than that of the other two parameters, i.e. the cutting speed has the largest contribution to the cutting tool temperature. The percentage contribution in the last column of the tables reflects the portion of the total variation observed in the experiment attributed to each parameter. The effect of heat treatment condition on cutting tool temperature is found to be statistically insignificant (*P*-value > 0.05). Cutting speed and feed rate contributed 69.13 and 26.46 %, respectively (Fig. 3a).

In Tables 5 and 6, the ANOVA result shows that the feed rate parameter is having larger *F* value than that of the other two parameters, i.e. the largest contribution to the cutting force and feed force is due to the feed rate. The effect of all the input parameters on cutting force is found to be statistically significant (*P*-value < 0.05). Cutting speed, feed rate and heat treatment contributed 0.99, 97.20 and 0.72 %, respectively (Fig. 3b). The effect of cutting speed factor on feed force is

Table 4 Analysis of variance for cutting tool temperature (means)

Source	DF	Seq SS	Adj SS	Adj MS	*F*	*P*	Contribution (%)
Cutting speed	1	338,665	338,665	338,665	378.40	0.000	69.13
Feed rate	2	129,631	129,631	64,816	72.42	0.000	26.46
Heat treatment	2	6317	6317	3159	3.53	0.080	1.29
Feed rate × heat treatment	4	8120	8120	2030	2.27	0.151	1.66
Residual error	8	7160	7160	895			1.46
Total	17	489,893					

Table 5 Analysis of variance for cutting forces (means)

Source	DF	Seq SS	Adj SS	Adj MS	*F*	*P*	Contribution (%)
Cutting speed	1	4418	4418	4418	13.60	0.006	0.99
Feed rate	2	432,172	432,172	216,086	665.39	0.000	97.20
Heat treatment	2	3214	3214	1607	4.95	0.040	0.72
Feed rate × heat treatment	4	2198	2198	549	1.69	0.244	0.49
Residual error	8	2598	2598	325			0.58
Total	17	444,600					

Table 6 Analysis of variance for feed forces (means)

Source	DF	Seq SS	Adj SS	Adj MS	*F*	*P*	Contribution (%)
Cutting speed	1	2289.4	2289.4	2289.39	4.75	0.061	10.37
Feed rate	2	9808.8	9808.8	4904.39	10.17	0.006	44.42
Heat treatment	2	5927.4	5927.4	2963.72	6.14	0.024	26.84
Feed rate × heat treatment	4	197.6	197.6	49.39	0.10	0.979	0.89
Residual error	8	3859.1	3859.1	482.39			17.48
Total	17	22,082.3					

found to be statistically insignificant (P-value > 0.05). Feed rate and heat treatment contributed 44.42 and 26.84 %, respectively (Fig. 3c).

In Tables 4 and 5 the ANOVA result shows that the F value for the factor heat treatment is smaller than that of the other two parameters, i.e. the least contribution to the cutting tool temperature and cutting force is due to the heat treatment. However, regardless of statistically insignificant results, the heat treatment contribution is found to be noteworthy. For instance; with change of heat treatment condition, change in the chips' morphology is observed. The observable difference in the shear localized bands in the chips of the analysed alloys can be seen more clearly by using Leica Z16 APO optical magnifier at cutting speed of 80 m/min and

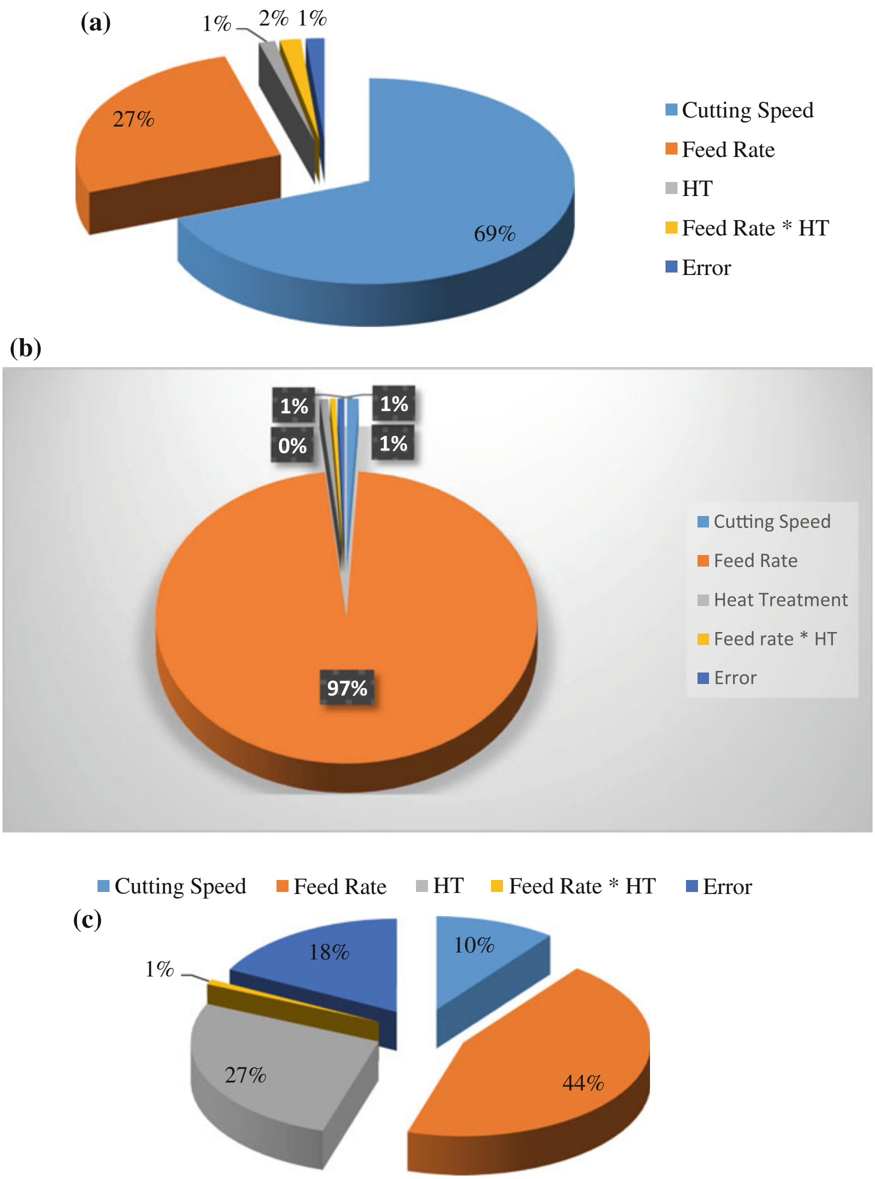

Fig. 3 Pie chart of factor % contribution for **a** cutting tool temperature, **b** cutting force, **c** feed force (ANOVA mean data)

feed rate of 0.25 mm/rev. The reason is that machining of the stronger form of the alloy resulted in generation of higher feed forces and cutting tool temperatures even at relatively higher cutting speeds and feed rates because larger amount of power is required to deform the material plastically.

3.2 S/N Ratios and Means Evaluation for Optimal Design

The average values of the performance characteristics for each parameter at different levels are represented by the mean response. The average values of Mean data and S/N data for cutting speed, feed rate and heat treatment are obtained separately, and are given in Tables 7, 8, and 9. These values are plotted in Figs. 4 and 5. In the Taguchi method, the higher the levels for S/N ratio, the better the overall performance, meaning that the parameter levels with the highest S/N ratio value should always be selected. Regardless of the lower-the-better/higher-the-better quality characteristic, the greater S/N ratio corresponds to the smaller variance of the response characteristics around the target value [21].

Based on the S/N ratio and ANOVA, the optimal input parameters for cutting tool temperature are the cutting speed at level 1 and the feed rate at level 1 (Table 7). It is clear from Table 9 that the cutting speed at level 2, the feed rate at level 1 and heat treatment condition at level 2 are best choice, in terms of the cutting force. The optimal input parameters for feed force are the feed rate at level 1 and heat treatment condition at level 1.

Table 7 Response table for means and S/N ratios (smaller is better) for temperature

Level	S/N data			Mean data		
	V_c	f	Heat treatment	V_c	f	Heat treatment
1	−56.20	−56.72	−57.97	652.9	701.2	810.7
2	−59.31	−57.49	−57.83	927.2	764.7	794.2
3		−59.05	−57.46		904.3	765.3
Rank	1	2	3	1	2	3

Table 8 Response table for means and S/N ratios (smaller is better) for cutting forces

Level	S/N data			Mean data		
	V_c	f	Heat treatment	V_c	f	Heat treatment
1	−55.05	−52.13	−54.88	588.0	404.0	576.8
2	−54.62	−54.56	−54.60	556.7	535.0	554.5
3		−57.81	−55.02		778.0	586.7
Rank	2	1	3	2	1	3

Table 9 Response table for means and S/N ratios (smaller is better) for feed forces

Level	S/N data			Mean data		
	V_c	f	Heat treatment	V_c	f	Heat treatment
1	−50.74	−49.87	−49.99	346.9	311.8	316.5
2	−50.21	−50.28	−51.08	324.3	327.7	360.0
3		−51.27	−50.35		367.3	330.3
Rank	3	1	2	3	1	2

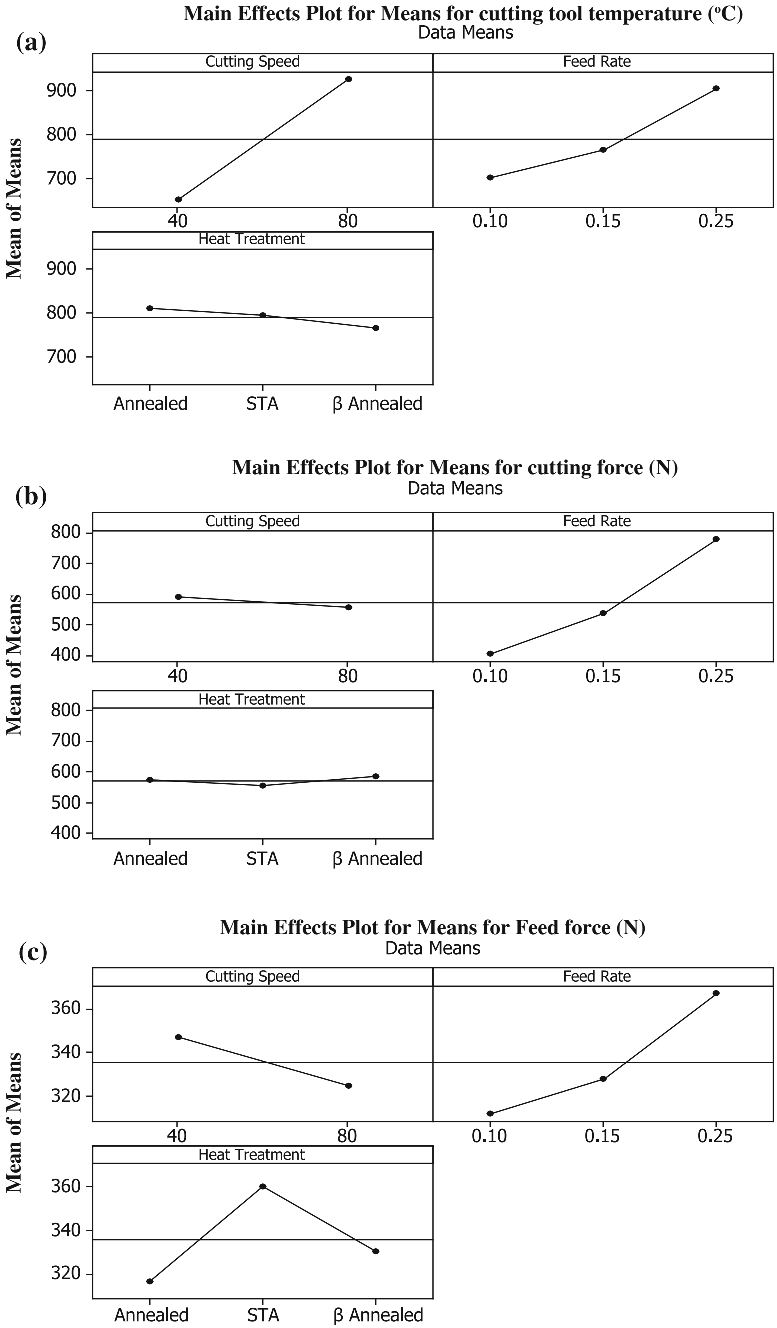

Fig. 4 Main effect plots (means) for **a** cutting force (F_c), **b** feed force (F_k), and **c** cutting tool temperature (^oC)

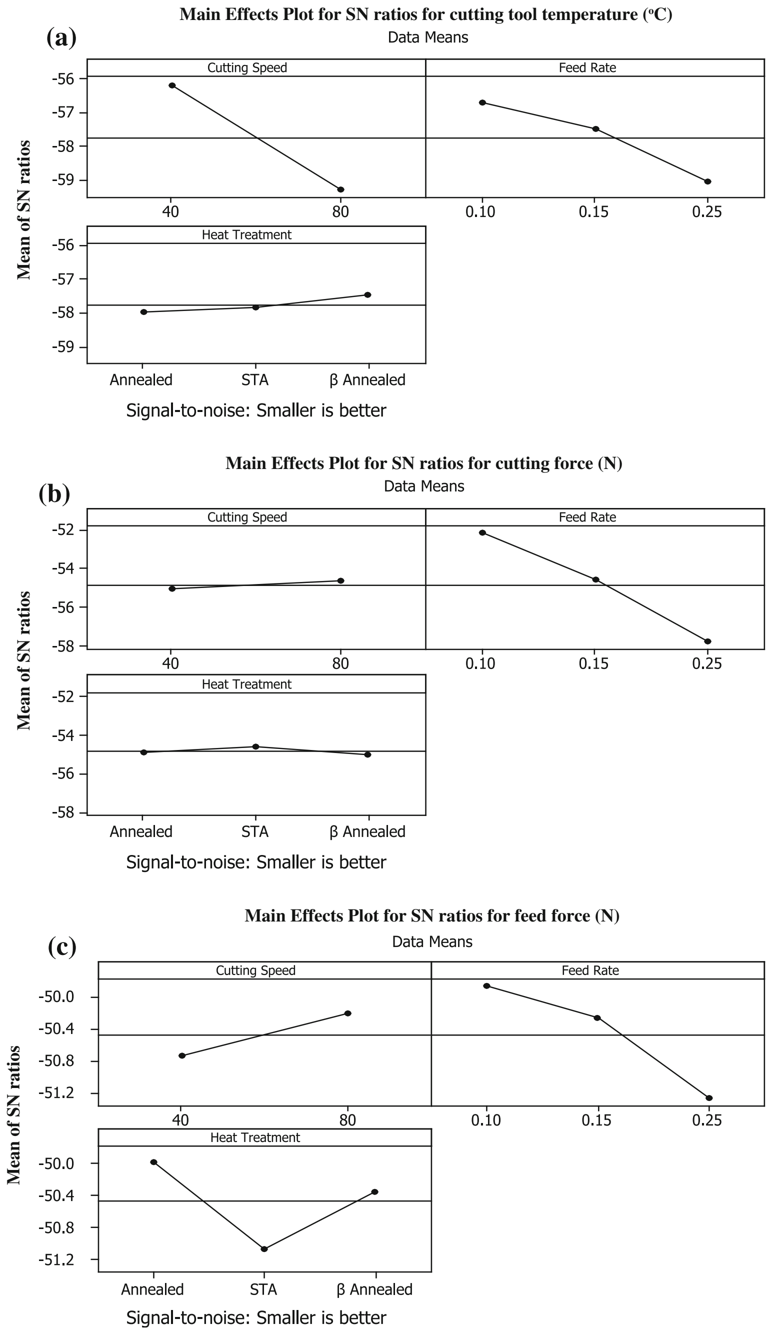

Fig. 5 Main effect plots (S/N ratio) for **a** cutting force (F_c), **b** feed force (F_k), and **c** cutting tool temperature (^{o}C)

The Tables 7, 8 and 9 include ranks based on Delta statistics, which compare the relative magnitude of effects. The Delta statistic is calculated by subtracting the lowest from the highest average for each parameter. Ranks are assigned based on Delta values; the highest Delta value is assigned rank 1, rank 2 to the second highest, and so on. The descending order of ranks is given as $V_c > f >$ heat treatment; $f > V_c >$ heat treatment and $f >$ heat treatment $> V_c$ for cutting tool temperature, cutting and feed forces, respectively.

From these results, it can be observed that (a) as cutting speed increases, the forces decrease and the cutting temperature increases; (b) as feed rate increases, the cutting force and the cutting temperature increases and the feed force decreases; and (c) as the hardness of the workpiece increases due to heat treatment, both the forces and the cutting temperature increases.

In addition to the above observations, the optimal parameters for the forces and the cutting temperature can also be deduced.

3.3 Optimum Quality Characteristics Approximation

To determine the near optimum or the range of process parameter levels where global optimum exists is an utmost advantage of conducting Taguchi's methodology [15]. The level of a parameter that gives the minimum value of cutting tool temperature, cutting and feed forces symbolizes the optimum level for that parameter. The significant parameter selected for the cutting tool temperature are $\bar{V}_{c1}$ and $\bar{f}_1$. The optimal value of the cutting force can be computed as

$$\mu_{\mathrm{CTT}} = \bar{V}_{c1} + \bar{f}_1 - \bar{T}_{\mathrm{CTT}} \tag{2}$$

where μ_{CTT} is mean value of the cutting tool temperature, $\bar{T}_{\mathrm{CTT}}(\mathit{Overall\ average\ of\ cutting\ tool\ temperature}) = 790\,^{\circ}\mathrm{C}$ (Table 3) and are $\bar{V}_{c1}$ and $\bar{f}_1$ are average values of the cutting force and feed force, respectively (Table 5), i.e. $\mu_{\mathrm{CTT}} = 564.1\,^{\circ}\mathrm{C}$.

$$\mathrm{CI} = \sqrt{F_{\alpha}(1, f_e) V_e / n_{\mathrm{eff}}} \tag{3}$$

where $F_{\alpha}(1, f_e)$ = the F-ratio at a confidence level of 95 % against DOF 1 and error DOF f_e, V_e = error variance, n_{eff} is the effective number of replications:

$$n_{\mathrm{eff}} = N / \{1 + (\text{Total DOF in the estimation of mean})\} \tag{4}$$

where N = total number of results. The C.I. at 95 % is ±18.78 °C. Thus, the predicted optimum cutting tool temperature is at $545.32 < \mu_{\mathrm{CTT}} < 582.88$ °C.

The significant parameters selected for the cutting force are $\bar{V}_{c2}$, $\bar{f}_1$ and $\overline{HT}_2$ (Table 6). The optimal value of the cutting force can be computed as

$$\mu_{F_c} = \bar{V}_{c2} + \bar{f}_1 + \overline{HT}_2 - 2\bar{T}_{F_c} \tag{5}$$

i.e. $\mu_{F_c} = 371.2\,\text{N}$.

By using Eqs. (3) and (4), the C.I. at 95 % is ±13.86 N. Thus the predicted optimum feed force is $357.34 < \mu_{F_c} < 385.06$ N.

The significant factors selected for the feed forces are $\bar{f}_1$ and $\overline{HT}_1$ (Table 7). The optimal value of the feed force can be computed as

$$\mu_{F_k} = \bar{f}_1 + \overline{HT}_1 - \bar{T}_{F_k} \tag{6}$$

i.e. $\mu_{F_k} = 292.3\,\text{N}$.

By using Eqs. (3) and (4), the C.I. at 95 % is ±15.41 N. Thus, the predicted optimum feed force is $276.89 < \mu_{HT} < 307.71$ N.

4 Significance of the Study

An exhaustive experimental study was conducted to assess the influence of control variables such as cutting speed, feed rate, and the heat treatment of the workpiece on the machinability of the Ti-54M titanium alloy in terms of response variables such as cutting force, feed force, and cutting temperature using Taguchi techniques. The following conclusions can be drawn from the research:

- It is found that the Taguchi techniques for parameter design provide a systematic methodology for the optimization of the cutting parameters and heat treatment conditions.
- The optimum levels of the cutting speed, the feed rate and the heat treatment condition have been established for getting minimum cutting tool temperature, cutting and feed forces of orthogonally machined Ti-54M titanium alloy.
- The minimum cutting tool temperature is found with cutting speed of 40 m min^{-1} and feed rate of 0.1 mm rev^{-1}. The heat treatment condition has no statistically significant effect on the cutting tool temperature and thus should be set at a level which provides superior strength.
- The minimum cutting force is found with cutting speed of 80 m min^{-1}, feed rate of 0.1 mm rev^{-1} and STA heat treatment condition. The minimum feed force is found with feed rate of 0.1 mm rev^{-1} and annealed heat treatment condition. The cutting speed was found to have statistically insignificant effect on feed force and thus must be set at a level which is most suitable and cost-effective to industry.

This gain in knowledge can be leveraged to develop varieties of these alloys by changing their chemical composition and/or heat treatment for different applications. The existing scarce database on machinability of these alloys is supplemented with the experimental studies performed in this work for the industry need. This original contribution to the existing database will help the academicians and practitioners in this area to develop numerical models in future for commercial research. Khanna and Bajpai [22] have initiated developing numerical models for this newly developed titanium alloy and showed that use of FEM can lead to reduced machining time and manufacturing cost as well. The results of this work have been transferred to the respective industry. The industry is expected to gain from this research in terms of improved productivity and reduced cost.

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Parametric Optimization of Submerged Arc Welding Using Taguchi Method

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Abstract Submerged Arc Welding (SAW) process has tremendous applications in industrial sectors. The quality of weld joint depends on optimal process parameters. This chapter presents the optimization study for materials with application in valves. Input parameters are voltage, current, and speed of welding; output parameters are penetration and bead width. Taguchi L_9 orthogonal array has been constructed. Signal-to-noise ratio and ANOVA have been used to analyze welding characteristics so as to generate optimal welding parameters. Also, confirmation analyzis has been done.

1 Introduction

Welding is one of the significant metal fabrication processes. Submerged Arc Welding (SAW) has tremendous applications in valves manufacturing [1]. The quality of welded joint typically depends on the input parameters, namely welding current, welding voltage, and welding speed [2]. In order to attain optimum results, the influence of parameters on welding process as well the varying conditions must be understood. The influence of welding input parameters on output parameters, namely penetration depth and bead width are essential and are analyzed [3]. Experimental design approach proposed by Taguchi has been used in this study.

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Orthogonal Array and ANOVA are used to analyze the welding characteristics as well as to perform the welding parameters optimization. Also, confirmation tests have been conducted to compare the experimental and predicted values.

2 Literature Review

The literature has been analyzed from the viewpoint of Taguchi methods and welding processes. Sapakal[1] and Telsang [4] applied Taguchi method to determine the optimal process parameters for penetration in MIG welding. In this investigation, they considered welding current, welding voltage, and welding speed as parameters. In order to optimize welding parameters, Taguchi orthogonal array, signal-to-noise ratio, and ANOVA were used. Kumanan et al. [5] applied Taguchi technique and regression analyzis to determine the optimal process parameters of SAW process. The experiment was conducted by varying voltage, welding current, welding speed, and electrode stick-out. Eshwar and Kumar [6] found the most significant parameters that affect mechanical properties of TIG weldments of Al 65032 alloy using S/N analyzis and mean response analyzis. The parametric design is carried out with weld condition and control parameters such as gas pressure, current, groove angle, and preheats. Three levels are considered for the control parameters based on the preliminary tests and analyzis carried out with L9 orthogonal array. Juang and Tarng [7] proposed modified Taguchi approach for selection of TIG welding process parameters of stainless steel with optimal weld pool geometry and four 'smaller-the-better' quality characteristics. Pasupathy and Ravishankar [8] performed welding using AA1050 material and studied the influence of welding parameters namely welding current and welding speed on strength of low-carbon steel. The experiments were planned based on Taguchi technique. The welding characteristics of dissimilar joints were investigated using S/N ratio and ANOVA and the welding parameters were optimized. Chauhan and Jadaun [9] optimized process parameters of MIG welding process for dissimilar metal joint for stainless steel (SS-304) and low-carbon steel using Taguchi design method. ANOVA was applied to determine the significance level of parameter. Sarkar et al. [10] reported a new procedure using analytic hierarchy process (AHP)-based Taguchi method for the selection of best welding parameters with reference to fabrication of SAW of plain carbon steel. In the investigation, three process parameters, namely wire-feed rate, stick out, and traverse speed and three response parameters, namely penetration, bead width, and bead reinforcement were considered. Also, ANOVA was applied to investigate the influence of process parameters on penetration, bead width, and reinforcement. Datta et al. [11] applied Taguchi method to obtain optimal parametric combinations to attain desired weld bead geometry and dimensions of Heat Affected Zone (HAZ) in SAW process. Taguchi L9 orthogonal array design was adopted and experiments were conducted using three different levels of traditional process parameters to obtain bead-on-plate weld on mild steel plates. Saha and Mondal [12] presented a different method to optimize SAW process parameters with multi-response characteristics by applying Taguchi's robust design approach. Experiments were performed using welding current, arc voltage, welding speed, and electrode stick-out as input process parameters to assess weld bead width and bead hardness. The optimum values were analyzed using multiobjective Taguchi method to obtain total normalized quality loss and multi-response signal-to-noise ratio. Tarng and Yang [13] applied Taguchi method to optimize welding parameters in SAW process. The factors considered for optimization include arc current, arc voltage, welding speed, electrode protrusion, and preheat temperature. Yousefieh et al. [14] presented Design of Experiment (DOE) technique, Taguchi method, to optimize pulsed current gas tungsten arc welding (PCGTAW) parameters for analyzis of corrosion resistance in the case of super duplex stainless steel (UNS S32760) welds. L9 orthogonal array of Taguchi design was used which involves nine experiments for four parameters (pulse current, background current, % on time, and pulse frequency) with three levels. ANOVA was performed on the measured data and S/N ratio was computed. Tarng and Yang [15] determined welding process parameters to obtain optimum weld bead geometry in gas tungsten arc welding (GTAW) process using Taguchi method of DOEs. They proved through ANOVA that welding speed, welding current, and polarity ratio are the significant parameters to evaluate weld bead geometry.

3 Submerged Arc Welding

SAW involves the concealment of arc using blanket of granular and fusible flux. Heat source is an arc between a bare, solid-metal (or cored) consumable wire, or strip electrode and the work piece. The arc is retained in a cavity of molten flux or slag, which refines weld metal and protects from atmospheric contamination.

Since thick steel sections can be easily joined using SAW, it is primarily used for shipbuilding, pipe fabrication, and pressure vessels [16]. In addition to joining application, it is used to build up parts and overlay with stainless or wear-resistant steel. Procedural variations in SAW include current, voltage, electrical stick-out (distance from last electrical contact to plate), travel speed, and flux depth. Variation in any of these parameters will affect the shape and penetration of weld, as well as the integrity of weld deposit.

4 Taguchi's Design Method

Taguchi approach is a designed experiment that enables the selection of a product or process that provides consistent performance. Taguchi design focus on identification of controllable factors that minimizes the effect of noise factors. During experimentation, noise factors to force variability can be manipulated and determine optimal control factor settings to develop robust process or product. A process designed with this objective will generate more consistent output regardless of the environment in which it is used. Taguchi designs use orthogonal arrays, which determine the effects of factors on the response mean and variation. An orthogonal array emphasizes balanced design with equal weightage to all factors. This enables independent assessment of factors. Time and cost associated with experimentation could be reduced during which fractionated designs are used [3].

5 Process Parameter Levels

The operating variables of SAW considered in this study include welding current, welding voltage, and welding speed. Arc voltage lengthens the arc so that the weld bead width, reinforcement, and flux consumption are increased. For the given wire diameter, on increasing weld current, the deposition rate and depth of penetration both increase. Higher speeds reduce bead width and increase the likelihood of porosity. Bead size is inversely proportional to welding speed at the same current. Though many direct and indirect parameters affect the quality of weld in SAW, the key process parameters influencing bead geometry include welding current, welding voltage, and welding speed. In this study, three levels of process parameters are considered (Table 1).

Work material:

Electrode diameter: 4 mm.
Base material: Carbon steel.
Maximum stick out: 25 mm.
Polarity: Constant current, electrode positive.
Electrode: EG.
Plate size: 300 × 110 × 16 mm.

6 L9 Orthogonal Array

Taguchi conceptualized a new approach of conducting the DOEs which are based on well-defined guidelines. This approach deploys a special set of arrays termed orthogonal arrays. These standard arrays emphasize the way of conducting reduced number of experiments which could generate complete information of all the factors that affect performance parameters. The core aspect of orthogonal arrays rests with

Table 1 Welding parameters

Welding parameters	Level 1	Level 2	Level 3
Welding current	450	550	650
Welding voltage	28	30	32
Welding speed	300	450	600

Table 2 L9 orthogonal array

Expt. No.	Process parameters		
	Welding current	Welding Voltage	Welding speed
1	1	1	1
2	1	2	2
3	1	3	3
4	2	1	2
5	2	2	3
6	2	3	1
7	3	1	3
8	3	2	1
9	3	3	2

selecting the level combinations of the input design variables for each experiment. In this chapter, an experiment has been conducted to understand the influence of three different independent variables (each variable has three level values). In this case, L_9 orthogonal array forms appropriate choice. This array assumes that there is no interaction between any two factors (Table 2).

7 Signal-to-Noise Ratio

The product of ideal quality should reciprocate appropriately in the same way to the signals provided by the control factors. According to Taguchi, variability in product performance with reference to noise factors should be minimized while variability with reference to signal factors must be maximized. Signal factors include those factors that are controlled by operator of the product to obtain final response. Noise factors are those which the operator does not have control over. The goal of Taguchi's DOEs is to determine the best settings of control factors that are involved in the production process, in order to maximize S/N ratio.

There are three Signal-to-Noise ratios of common interest for optimization

(1) Smaller-the-Better:
In cases where the occurrence of some undesirable product characteristics should be minimized

$$n = -10\,\mathrm{Log}_{10}[\text{mean of sum of squares pertaining to measured data}] \tag{1}$$

(2) Larger-the-Better:
In cases where the occurrence of certain product characteristics should be maximized.

$$n = -10\,\mathrm{Log}_{10}[\text{mean of sum squares of reciprocal pertaining to measured data}] \tag{2}$$

(3) Nominal-the-Best:
There is a fixed signal value and the variance around this value can be recognized as the result of noise factors

$$n = 10\,\mathrm{Log}_{10}\frac{\text{square of mean}}{\text{variance}} \tag{3}$$

In any welding process, the amount of penetration of the weld bead is directly related to the quality of weld bead. Hence, to calculate S/N ratio, it is considered to be ‘larger-the-better’. The S/N ratios corresponding to penetration is presented in Table 3.

Similarly, to obtain optimum welding characteristics, smaller-the-better characteristics for bead width should be considered. The calculated S/N ratio for bead width is presented in Table 4.

The main objective of Taguchi’s process is to maximize S/N ratio irrespective of the category of quality whether it is higher-the-better or lower-the-better. The mean

Table 3 Results of experimentation for penetration and S/N ratio

Expt. No.	Welding current	Welding voltage	Welding speed	Penetration mm	S/N ratio
1	450	28	300	3.416	10.6704
2	450	30	450	2.923	9.3166
3	450	32	600	3.485	10.8441
4	550	28	450	4.614	13.2816
5	550	30	600	4.304	12.6774
6	550	32	300	7.800	17.8419
7	650	28	600	5.945	15.4830
8	650	30	300	7.694	17.7230
9	650	32	450	4.747	13.5284

Table 4 Results of experimentation for bead width and S/N ratio

Expt. No.	Welding current	Welding voltage	Welding speed	Bead width	S/N ratio
1	450	28	300	22.560	−27.0668
2	450	30	450	17.122	−24.6711
3	450	32	600	14.992	−23.5172
4	550	28	450	17.439	−24.8304
5	550	30	600	16.297	−24.2422
6	550	32	300	29.500	−29.3964
7	650	28	600	15.128	−23.5956
8	650	30	300	20.735	−26.3341
9	650	32	450	26.162	−28.3534

Table 5 Table depicting response for signal-to-noise ratios for penetration

Level	Welding current	Welding voltage	Welding speed
1	10.28	13.14	15.41
2	14.60	13.24	12.04
3	15.58	14.07	13.00
Delta	5.30	0.93	3.37
Rank	1	3	2

Table 6 Table depicting response for signal-to-noise ratios for bead width

Level	Welding current	Welding voltage	Welding speed
1	−25.09	−25.16	−27.60
2	−26.16	−25.08	−25.95
3	−26.09	−27.09	−23.78
Delta	1.07	2.01	3.81
Rank	3	2	1

of multi-response signal-to-noise ratio for each level of welding parameters for penetration is consolidated and shown in Table 5.

Similarly, the multi-response S/N ratio for bead width is shown in Table 6.

Figures 1 and 2 show the multi-response signal-to-noise graph for penetration and bead width, respectively, and dashed line represented in Figs. 1 and 2 indicate

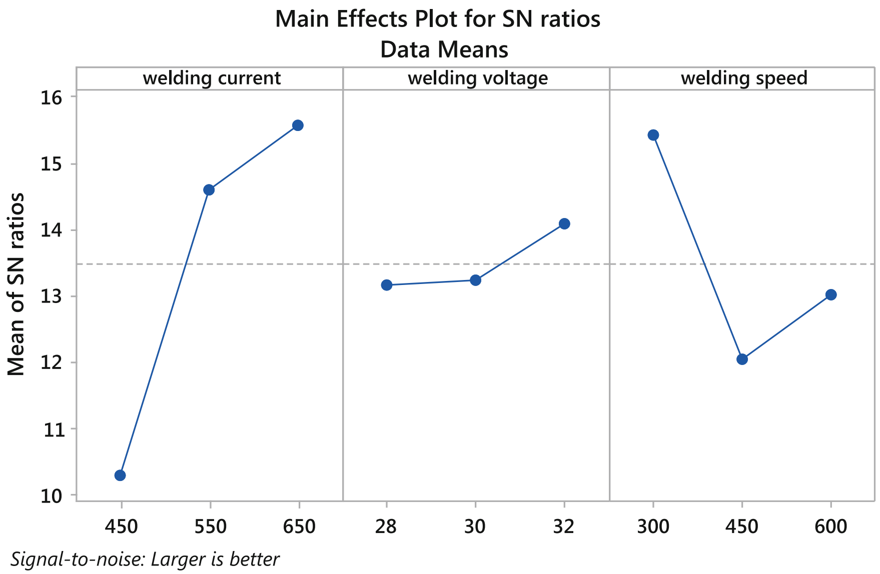

Fig. 1 Main effect plot for S/N ratio of penetration

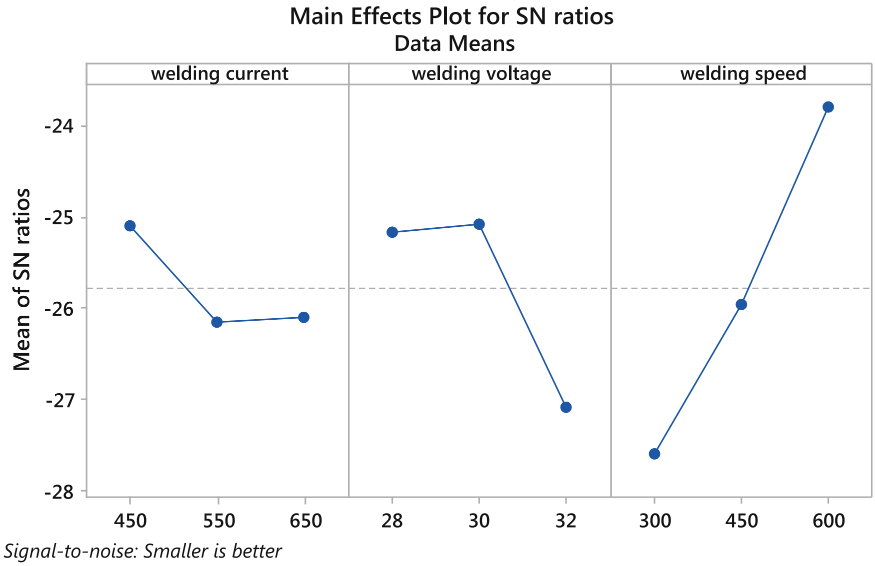

Fig. 2 Main effect plot for S/N ratio of bead width

the value of total mean of the multi-response signal-to-noise ratio. Multi-response signal-to-noise ratio is inversely proportional to the variance of quality characteristics around desired value.

8 ANOVA

ANOVA is used to depict the importance of all process parameters on weld penetration and bead width. ANOVA is a statistics-oriented objective decision making tool used to detect any differences in mean performance of the group of items analyzed taking variation into account rather than using pure judgment. In ANOVA table, sum of squares represents total variability in S/N ratios, which is computed by the sum of squared deviations from total mean S/N ratio. It is given as

$$\mathrm{SSD} = \sum (x_i - x_n)^2 \tag{4}$$

The Degrees of Freedom (DF) refer to terms in sum of squares (SS), which can be assigned arbitrarily. For instance, the sum of deviations from mean in a sample of n observations

$$(x_1 - x)^2 + (x_2 - x)^2 + (x_3 - x)^2 + \cdots + (x_n - x)^2$$

has $(n - 1)$ degree of freedom because when $(n - 1)$ deviations are known, the nth deviation can be computed from the identity

$$(x_1 - x) + (x_2 - x) + (x_3 - x) + \cdots + (x_n - x) = 0$$

The mean sum of squares can be calculated as

$$\text{Mean sum of squares (MS)} = \frac{\text{Sum of square}}{\text{Degrees of freedom (DF)}} \quad (5)$$

F is called variance ratio.

$$F = \frac{\text{MS}}{\text{MS (error)}} \quad (6)$$

F, thus obtained, is to be compared with F0.05 and F0.01 (from standard F tables) to analyze whether the term (main effect or interactive effect) enforces a significant effect on selected response with 95 % confidence level. A factor is said to have significant effect on a response if F value obtained from table is found to be less than the computed or calculated F value. ANOVA is done using statistical package MINITAB.

The results of ANOVA pertaining to penetration and bead width are presented in Tables 7 and 8, respectively.

From Table 7, it can be seen that welding current possess the highest influence over penetration as it has the highest F value at 95 % confidence level.

From Table 8, it can be seen that welding speed possess the highest influence over bead width as it has the highest F value at 95 % confidence level.

Table 7 Analyzs of variance for S/N ratios for penetration

Source	Degrees of freedom	Sum of squares	Mean sum of squares	*F*	*P*
Welding current	2	47.749	23.8747	7.33	0.120
Welding voltage	2	1.560	0.7801	0.24	0.807
Welding speed	2	18.084	9.0419	2.78	0.265
Residual error	2	6.510	3.2552		
Total	8	73.904			

Table 8 Analyzis of variance for S/N ratios for bead width

Source	Degrees of freedom	Sum of squares	Mean sum of squares	*F*	*P*
Welding current	2	2.170	1.085	0.52	0.659
Welding voltage	2	7.738	3.869	1.85	0.351
Welding speed	2	21.956	10.978	5.24	0.160
Residual error	2	4.188	2.094		
Total	8	36.052			

Table 9 Results of the confirmation experiment

	Initial welding parameters	Optimal welding parameters	
		Prediction	Experiment
Level	A1B1C1	A3B3C1	A3B3C1
Penetration	3.416	8.027	7.852
S/N ratio	10.6704	18.0911	17.899
Level	A1B1C1	A2B3C1	A2B3C1
Bead width	22.560	13.175	14.54
S/N ratio	−27.0668	−22.3953	−23.251

9 Confirmation Test

This is the last step in Taguchi's design method. From the main effects plot of S/N ratio shown in Figs. 1 and 2, optimum values of welding parameters corresponding to maximum S/N ratio are predicted. In this study for maximum penetration, the optimum level of welding parameters for penetration is predicted to be

Welding current	650
Welding voltage	32
Welding speed	300

Similarly, the optimum values for the least bead width is predicted to be

Welding current	550
Welding voltage	32
Welding speed	300

Now, experiments are conducted having the above values for welding parameters and value of penetration and bead width are noted. The predicted values of penetration and bead width are compared with reference to actual values and a good agreement is attained between predicted and experimented values as shown in Table 9.

10 Conclusion

This chapter reports the study on optimization of process parameters of SAW using Taguchi method. Material used in valves has been considered. Appropriate input and output parameters have been considered. L_9 orthogonal array has been devised. Signal-to-noise (S/N) ratio and ANOVA are used for welding process parameters optimization. From the study, the optimal penetration is found to be 8.027 mm and S/N ratio is 18.0911.

Generally, the results are similar to those obtained by Karaoglu and Secgin [17]. Bead width is more sensitive to voltage and speed variations when compared to bead height and penetration. Current is the most significant parameter with reference to penetration. Penetration is almost nonsensitive to voltage and speed [17]. Karaoglu concluded that at maximum heat input level (maximum current and voltage levels and minimum level of welding speed), current sensitivity of penetration, and speed sensitivity of bead width attain maximum values. Sarkar et al. [10] concluded that the effect of wire-feed rate on weld geometry is more significant than other welding parameters in SAW process. However, in the present study, it has been inferred that welding current has significant effect on weld bead characteristics than other parameters.

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