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

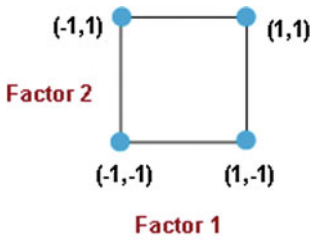


Fig. 1 Trial points of the 2^2 design

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:

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

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

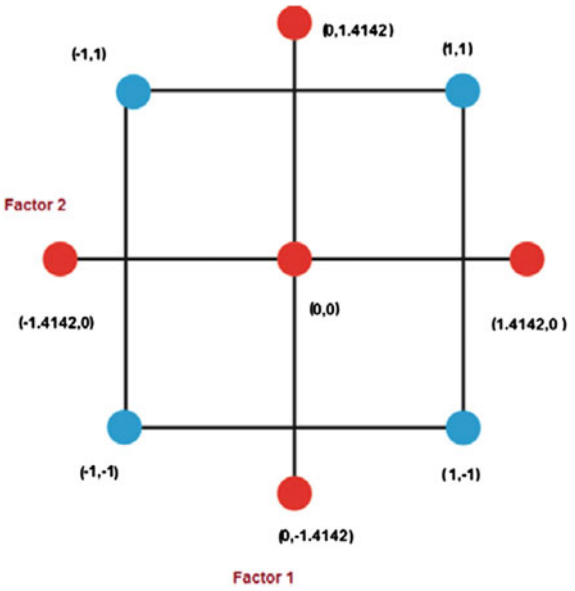


Fig. 2 A schematic of the trial points used in a two-factor central composite design

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

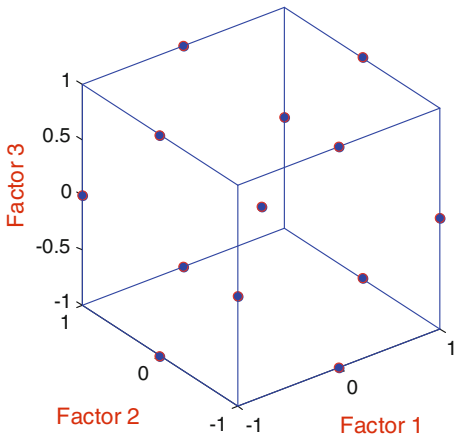


Fig. 3 A schematic of the trial points in a three-factor Box–Behnken design

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

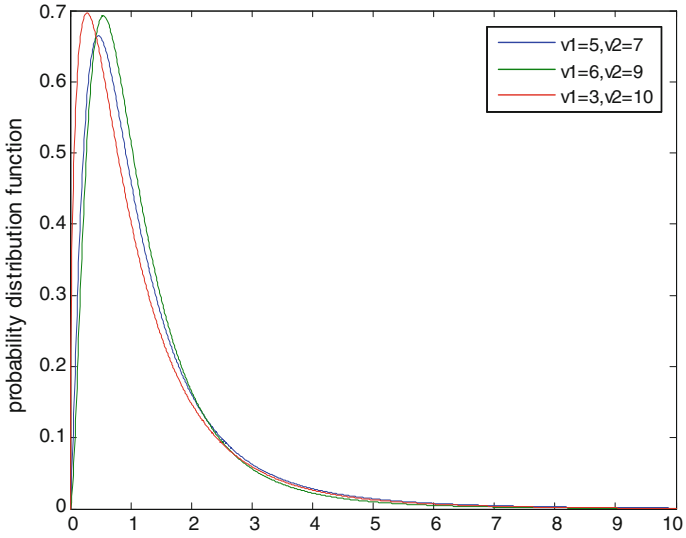


Fig. 4 The *F*-distribution in various cases (*v1* degrees of freedom of nominator, *v2* degrees of freedom of denominator)

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.

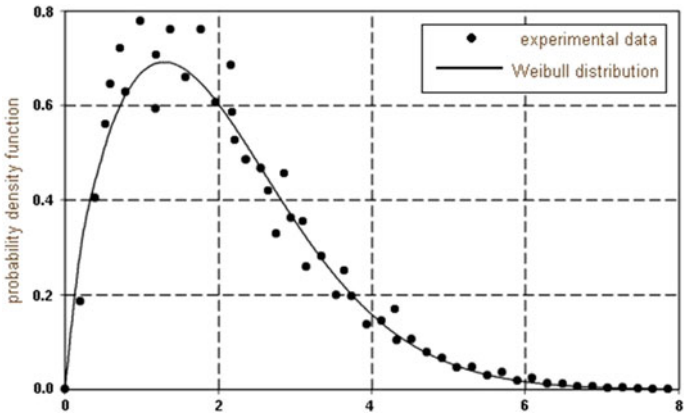


Fig. 5 Experimental data fitted into Weibull distribution

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

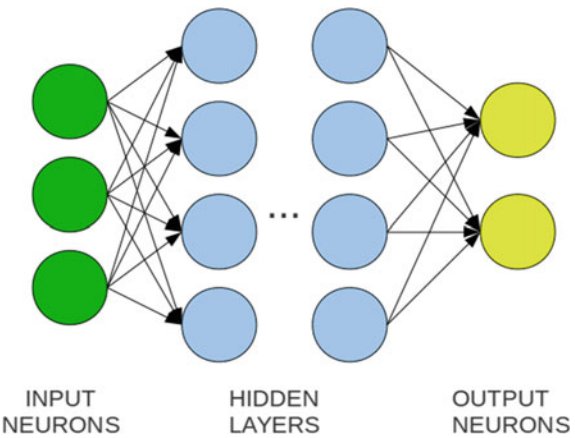


Fig. 6 The architecture of a feedforward ANN

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:

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

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

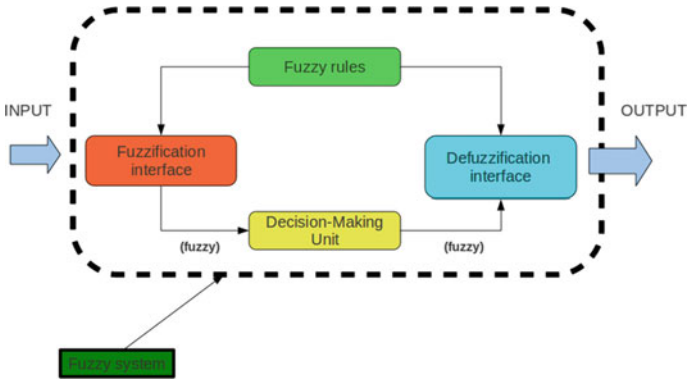


Fig. 7 Configuration of a fuzzy logic system

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

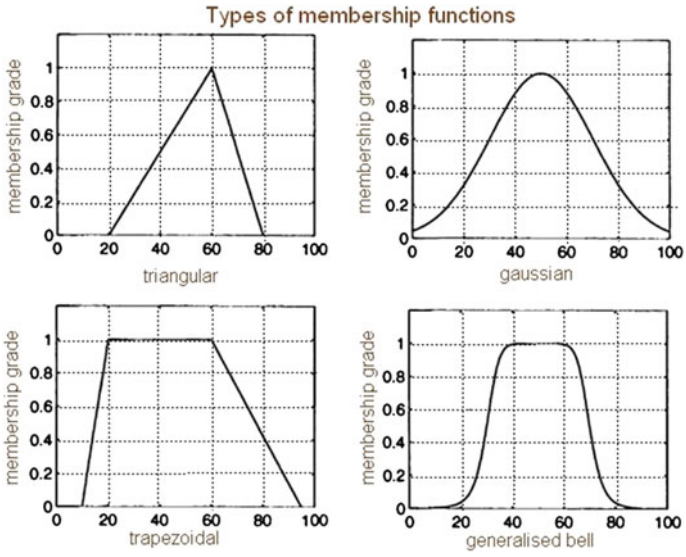


Fig. 8 Various types of membership functions

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:

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

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

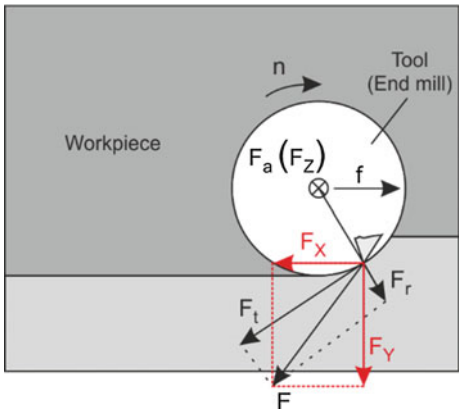
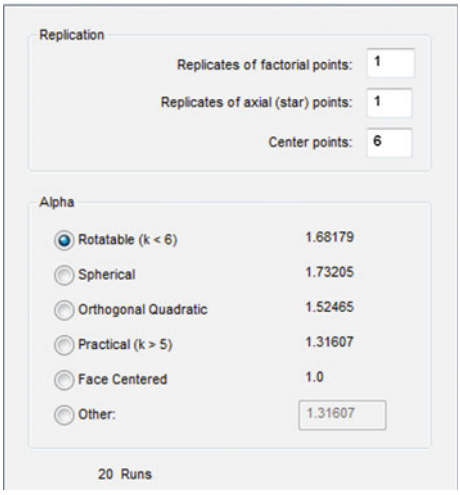


Fig. 9 The relationships between the components of cutting forces

	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

	Sequential	Lack of fit	Adjusted	Predicted	
Source	*p*-value	*p*-value	*R*-Squared	*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.

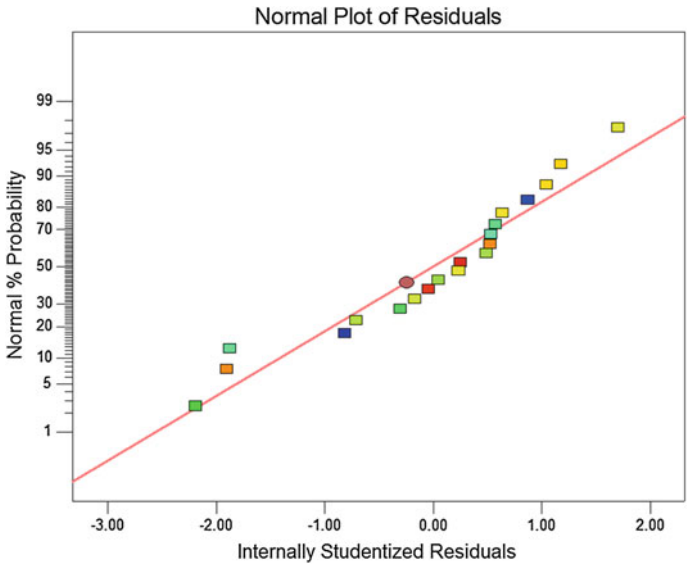


Fig. 12 Normal probability plot of residuals for temperature T

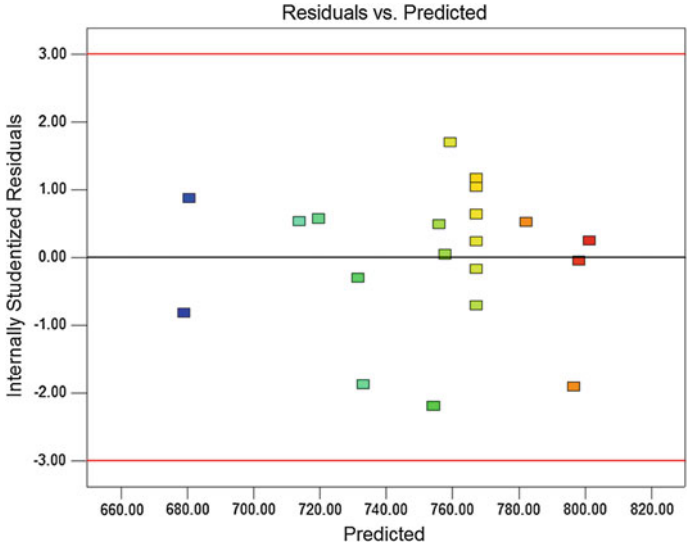


Fig. 13 Residuals versus predicted response for temperature T

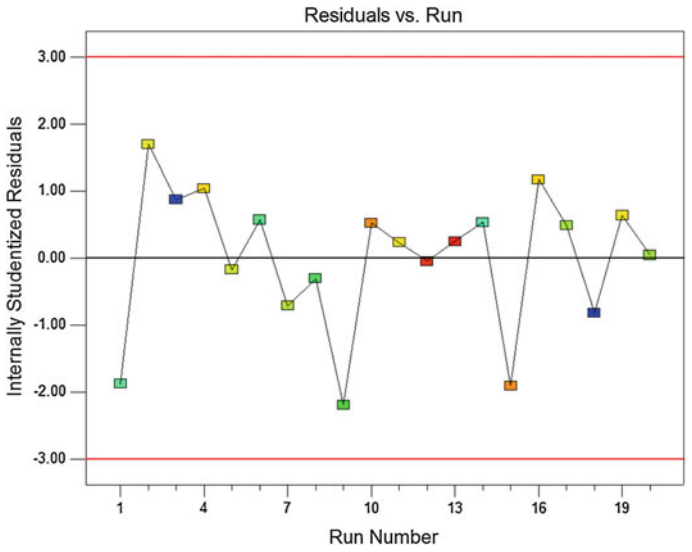


Fig. 14 Residuals versus run for temperature *T*

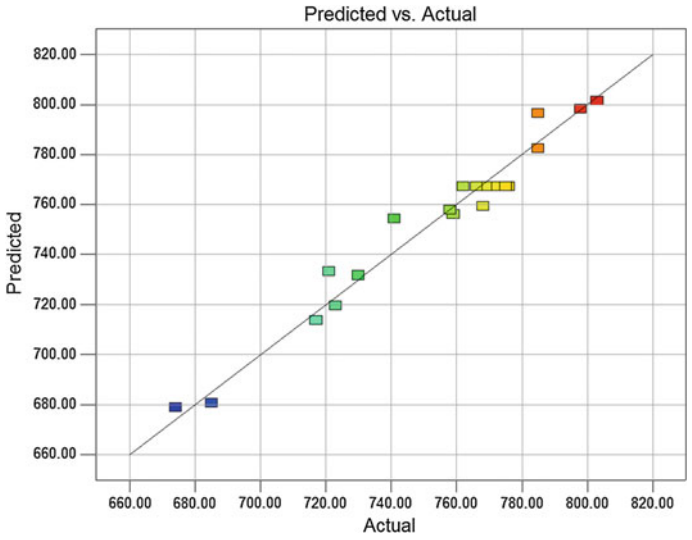


Fig. 15 Predicted response versus actual for temperature *T*

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:

$$T = 440.75 + 2.03 \cdot v_c + 58.30 \cdot a_p + 1903.04 \cdot f + 486.67 \cdot a_p \cdot f - 22.51 \cdot a_p^2 - 12341.64 \cdot f^2 \quad (23)$$

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

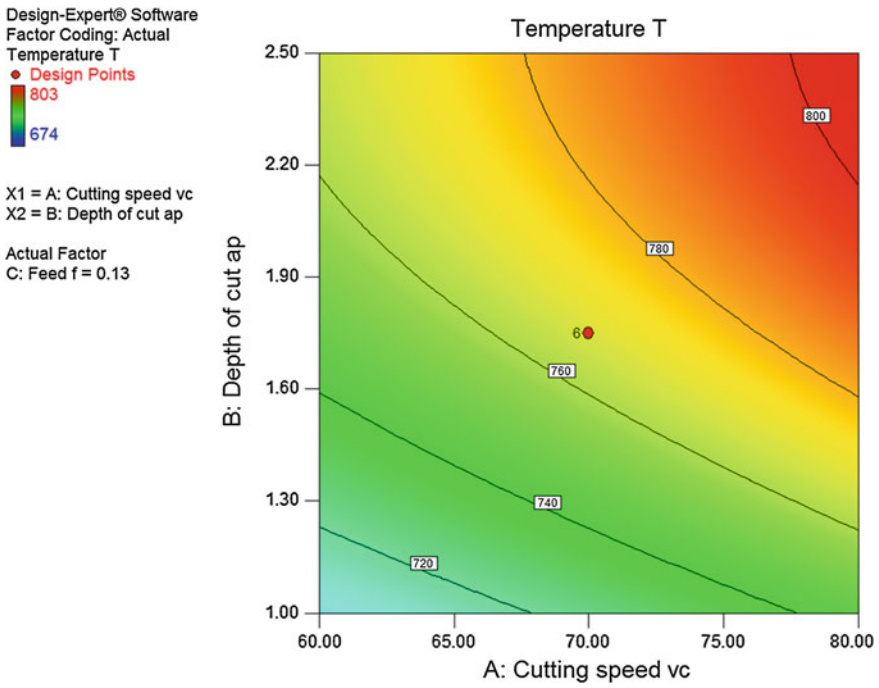


Fig. 16 Response surface contour plot representing the temperature T dependence on the depth of cut a_p and cutting speed v_c for feed $f = 0.13$ mm/tooth

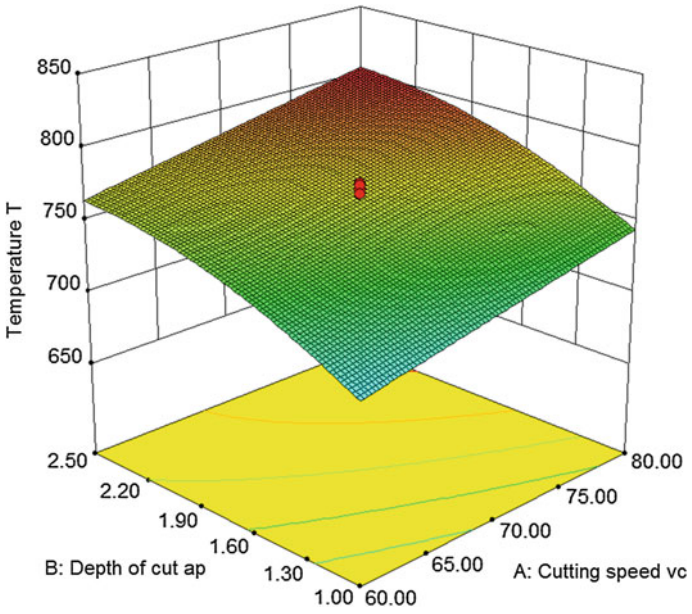


Fig. 17 Response surface 3D representing the temperature T dependence on the depth of cut a_p and cutting speed v_c for feed $f = 0.13$ mm/tooth

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

$$> F_t = 85.61 - 3.92 \cdot v_c + 289.44 \cdot a_p + 1472.84 \cdot f \tag{24}$$

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:

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

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.

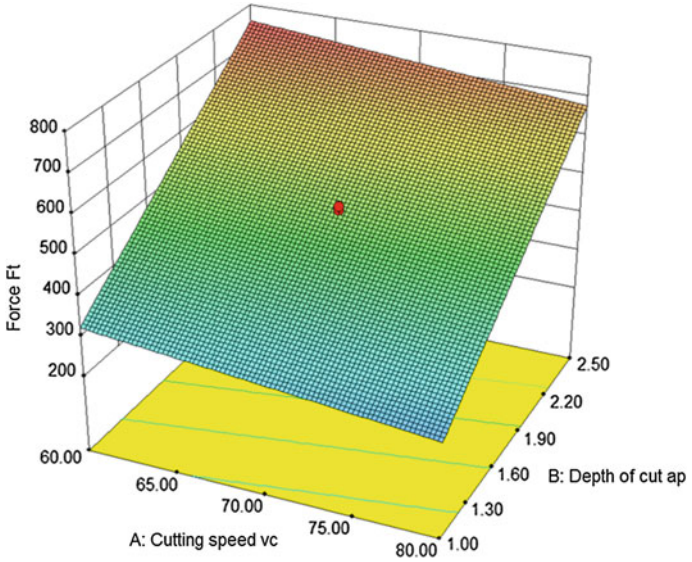


Fig. 18 Response surface 3D representing the tangential force F_t dependence on the depth of cut a_p and cutting speed v_c for feed $f = 0.13$ mm/tooth

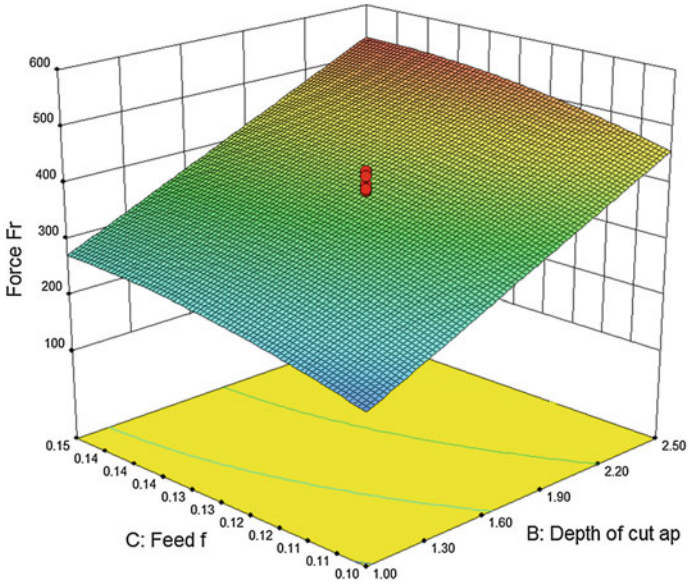


Fig. 19 Response surface 3D representing the radial force F_r dependence on the depth of cut a_p and feed f

References

1. Rao RV (2011) Advanced modeling and optimization of manufacturing processes. Springer, London
2. Fisher RA (1926) The arrangement of field experiments. J Minist Agric G B 33:503–513
3. Fisher RA (1935) The design of experiments. Oliver and Boyd, Edinburgh
4. Montgomery DC (2012) Design and analysis of experiments. Wiley, New York
5. Fang K-T, Qin H (2003) A note on construction of nearly uniform designs with large number of runs. Stat Probab Lett 61:215–224
6. Qin H, Chen Y-B (2004) Some results on generalized minimum aberration for symmetrical fractional factorial designs. Stat Probab Lett 66:51–57
7. Chatterjee K, Fang K-T, Qin H (2005) Uniformity in factorial designs with mixed level. J Stat Plann Infer 128:593–607
8. Qin H, Li D (2006) Connection between uniformity and orthogonality for symmetrical factorial designs. J Stat Plann Infer 136:2770–2782
9. Hong Q, Shangli Z, Kaitai F (2006) Construction uniform designs with two- or three-level. Acta Math Sci 26B(3):451–459
10. Tsao H-SJ, Patel MH (2013) An intuitive design pattern for sequentially estimating parameters of a 2^k factorial experiment with active confounding avoidance and least treatment combinations. Comput Ind Eng 66:601–613
11. Suen C-Y, Das A, Midha CK (2013) Optimal fractional factorial designs and their construction. J Stat Plann Infer 143:1828–1834
12. Tsao H-SJ, Patel MH (2015) A general intuitive design pattern for optimally sequencing treatment combinations in 2^k factorial experiment and a simple estimation algorithm. Comput Ind Eng 85:423–436
13. Levi R (1965) Evaluation of machining conditions by factorial experiment. Int J Mach Tool Des Res 5:217–221
14. Sahin Y, Motorcu AR (2005) Surface roughness model for machining mild steel with coated carbide tool. Mater Des 26:321–326
15. Park SJ, Kim DH, Lee CM (2012) A study determining the optimal machining conditions for a 40,000 rpm ultrahigh speed spindle system. Precis Eng 36:451–457
16. Mandal N, Doloi B, Mondal B (2013) Predictive modelling of surface roughness in high speed machining of AISI 4340 steel using yttria stabilized zirconia toughened alumina turning insert. Int J Refract Metal Hard Mater 38:40–46
17. Venkatesan K, Ramanujam R, Joel J, Jeyapandiarajan P, Vignesh M, Tolia DJ, Krishna RV (2014) Study of cutting force and surface roughness in machining of Al alloy hybrid composite and optimized using response surface methodology. Procedia Eng 97:677–686
18. Qehaja N, Jakupi K, Bunjaku A, Bruçi M, Osmani H (2015) Effect of machining parameters and machining time on surface roughness in dry turning process. Procedia Eng 100:135–140
19. Pei ZJ, Ferreira PM (1999) An experimental investigation of rotary ultrasonic face milling. Int J Mach Tools Manuf 39:1327–1344
20. Yang Y-K, Chuang M-T, Lin S-S (2009) Optimization of dry machining parameters for high-purity graphite in end milling process via design of experiments methods. J Mater Process Technol 209:4395–4400
21. Nithyanandam GK, Pezhinkattil R (2014) A Six Sigma approach for precision machining in milling. Procedia Eng 9:1474–1488
22. Rajmohan T, Palanikumar K (2013) Application of the central composite design in optimization of machining parameters in drilling hybrid metal matrix composites. Measurement 46:1470–1481
23. Tagliaferri F, Leonardi G, Semmler U, Kuhl M, Palumbo B (2013) Study of the influences of laser parameters on laser assisted machining processes. Procedia CIRP 8:170–175

24. Assarzadeh S, Ghoreishi M (2013) Statistical modeling and optimization of process parameters in electro-discharge machining of cobalt-bonded tungsten carbide composite (WC/6 %Co). Procedia CIRP 6:463–468
25. Shabgarf MA, Badamchizadeh MA, Ranjbary G, Amini K (2013) Fuzzy approach to select machining parameters in electrical discharge machining (EDM) and ultrasonic-assisted EDM processes. J Manuf Syst 32:32–39
26. Muthukumar V, Rajesh N, Venkatasamy R, Sureshbabu A, Senthilkumar N (2014) Mathematical modeling for radial overcut on electrical discharge machining of Incoloy 800 by response surface methodology. Procedia Mater Sci 6:1674–1682
27. Bhosale SB, Pawade RS, Brahmankar PK (2014) Effect of process parameters on MRR, TWR and surface topography in ultrasonic machining of alumina-zirconia ceramic composite. Ceram Int 40:12831–12836
28. Çaydaş U, Hasçalik A (2008) A study on surface roughness in abrasive waterjet machining process using artificial neural networks and regression analysis method. J Mater Process Technol 202:574–582
29. Sahin Y (2009) Comparison of tool life between ceramic and cubic boron nitride (CBN) cutting tools when machining hardened steels. J Mater Process Technol 209:3478–3489
30. Asiltürk I, Akkuş H (2011) Determining the effect of cutting parameters on surface roughness in hard turning using the Taguchi method. Measurement 44:1697–1704
31. Cetin MH, Ozcelik B, Kuram E, Demirbas E (2011) Evaluation of vegetable based cutting fluids with extreme pressure and cutting parameters in turning of AISI 304L by Taguchi method. J Clean Prod 19:2049–2056
32. Asiktürk I, Neşeli S (2012) Multi-response optimization of CNC turning parameters via Taguchi method-based response surface analysis. Measurement 45:785–794
33. Abhang LB, Hameedullah M (2012) Optimization of machining parameters in steel turning operation by Taguchi method. Procedia Eng 38:40–48
34. Camposeco-Negrete C (2013) Optimization of cutting parameters for minimizing energy consumption in turning of AISI 6061 T6 using Taguchi methodology and ANOVA. J Clean Prod 53:195–203
36. Günay M, Yücel E (2013) Application of Taguchi method for determining optimum surface roughness in turning of high-alloy white cast iron. Measurement 46:913–919
37. Singarvel B, Selvaraj T, Jeyapaul R (2014) Multi objective optimization in turning of EN25 steel using Taguchi based utility concept coupled with principal component analysis. Procedia Eng 97:158–165
38. Sarıkaya M, Güllü A (2014) Taguchi design and response surface methodology based analysis of machining parameters in CNC turning under MQL. J Clean Prod 65:604–616
39. Khanna N, Davim JP (2015) Design-of-experiments application in machining titanium alloys for aerospace structural components. Measurement 61:280–290
40. Kant G, Sangwan KS (2015) Predictive modeling for power consumption in machining using artificial intelligence techniques. Procedia CIRP 26:403–407
41. Shahrom MS, Yahya NM, Yusoff AR (2013) Taguchi method approach on effect of lubrication condition on surface roughness in milling operation. Procedia Eng 53:594–599
42. Sreenivasulu R (2013) Optimization of surface roughness and delamination damage of GFRP composite material in end milling using Taguchi design method and artificial neural network. Procedia Eng 64:785–794
43. Pang JS, Ansari MNM, Zaroog OS, Ali MH, Sapuan SM (2014) Taguchi design optimization of machining parameters on the CNC end milling process of halloysite nanotube with aluminium reinforced epoxy matrix (HNT/Al/Ep) hybrid composite. HBRC J 10:138–144
44. Davim JP (2003) Study of drilling metal-matrix composites based on the Taguchi techniques. J Mater Process Technol 132:250–254
45. Siddiquee AN, Khan ZA, Goel P, Kumar M, Agarwal G, Khan NZ (2014) Optimization of deep drilling process parameters of AISI 321 steel using Taguchi method. Procedia Mater Sci 6:1217–1225

46. Wang CC, Yan BH (2000) Blind-hole drilling of Al2O3/6061 Al composite using rotary electro-discharge machining. J Mater Process Technol 102:90–102
47. Tzeng Y-F, Chen F-C (2003) A simple approach for robust design of high-speed electrical-discharge machining technology. Int J Mach Tools Manuf 43:217–227
48. George PM, Raghunath BK, Manocha LM, Warrier AM (2004) EDM machining of carbon-carbon composite—a Taguchi approach. J Mater Process Technol 145:66–71
49. Lin Y-C, Chen Y-F, Wang D-A, Lee H-S (2009) Optimization of machining parameters in magnetic force assisted EDM based on Taguchi method. J Mater Process Technol 209:3374–3383
50. Prabhu S, Vinayagam BK (2011) AFM investigation of Inconel 825 with multi wall carbon nano tube in electrical discharge machining process using Taguchi analysis. Arch Civ Mech Eng XI 1:149–170
51. Durairaj M, Sudharsun D, Swamynathan N (2013) Analysis of process parameters in wire EDM with stainless steel using single objective Taguchi method and multi objective grey relational grade. Procedia Eng 64:868–877
52. Sudhakara D, Prasanthi G (2014) Application of Taguchi method for determining optimum surface roughness in wire electric discharge machining of P/M cold worked tool steel (Vanadis-4E). Procedia Eng 97:1565–1576
53. Lodhi BK, Agarwal S (2014) Optimization of machining parameters in WEDM of AISI D3 steel using Taguchi technique. Procedia CIRP 14:194–199
54. Goswami A, Kumar J (2014) Optimization in wire-cut EDM of Nimonic-80A using Taguchi's approach and utility concept. Eng Sci Technol Int J 17:236–246
55. Chang C-W, Kuo C-P (2007) Evaluation of surface roughness in laser-assisted machining of aluminium oxide ceramics with Taguchi method. Int J Mach Tools Manuf 47:141–147
56. Venkatesan K, Ramanujam R, Kuppan P (2014) Analysis of cutting forces and temperature in laser assisted machining of Inconel 718 using Taguchi method. Procedia Eng 97:1637–1646
57. Tsai FC, Yan BH, Kuan CY, Huang FY (2008) A Taguchi and experimental investigation into the optimal processing conditions for the abrasive jet polishing of SKD61 mold steel. Int J Mach Tools Manuf 48:932–945
58. Singh R, Khamba JS (2007) Taguchi technique for modeling material removal rate in ultrasonic machining of titanium. Mater Sci Eng A 460–461:365–369
59. Yünlü L, Çolak O, Kurbanoğlu C (2014) Taguchi DOE analysis of surface integrity for high pressure jet assisted machining of Inconel 718. Procedia CIRP 13:333–338
60. Mian AJ, Driver N, Mativenga PT (2011) Identification of factors that dominate size effect in micro-machining. Int J Mach Tools Manuf 51:383–394
61. El Baradie MA (1991) Computer aided analysis of a surface roughness model for turning. J Mater Process Technol 26:207–216
62. Noordin MY, Venkatesh VC, Sharif S, Elting S, Abdullah A (2004) Application of response surface methodology in describing the performance of coated carbide tools when turning AISI 1045 steel. J Mater Process Technol 145:46–58
63. Öktem H, Erzurumlu T, Kurtaran H (2005) Application of response surface methodology in the optimization of cutting conditions for surface roughness. J Mater Process Technol 170:11–16
64. Horng J-T, Liu N-M, Chiang K-T (2008) Investigating the machinability evaluation of hadfield steel in the hard turning with Al_2O_3/TiC mixed ceramic tool based on the response surface methodology. J Mater Process Technol 208:532–541
65. Neşeli S, Yaldız S, Türkes E (2011) Optimization of tool geometry parameters for turning operations based on the response surface methodology. Measurement 44:580–587
66. Mandal N, Doloi B, Mondal B (2011) Development of flank wear prediction model of zirconia toughened alumina (ZTA) cutting tool using response surface methodology. Int J Refract Metal Hard Mater 29:273–280
67. Suresh R, Basavarajappa S, Samuel GL (2012) Predictive modeling of cutting forces and tool wear in hard turning using response surface methodology. Procedia Eng 38:73–81

68. Makadia AJ, Nanavati JI (2013) Optimization of machining parameters for turning operations based on response surface methodology. Measurement 46:1521–1529
69. Kumar R, Chauhan S (2015) Study on surface roughness measurement for turning of Al 7075/10/SiCp and Al 7075 hybrid composites by using response surface methodology (RSM) and artificial neural networking (ANN). Measurement 65:166–180
70. Dambhare S, Deshmukh S, Borade A, Digalwar A, Phate M (2015) Sustainability issues in turning process: a study in Indian machining industry. Procedia CIRP 26:379–384
71. Camposeco-Negrete C (2015) Optimization of cutting parameters using response surface method for minimizing energy consumption and maximizing cutting quality in turning of AISI 6061 T6 aluminum. J Clean Prod 91:109–117
72. Alauddin M, El Baradie MA, Hashmi MSJ (1997) Prediction of tool life in end milling by response surface methodology. J Mater Process Technol 71:456–465
73. Wang M-Y, Chang H-Y (2004) Experimental study of surface roughness in slot end milling Al2014-T6. Int J Mach Tools Manuf 44:51–57
74. Arunpremnath A, Alwarsamy T, Abhinav T, Krishnakant CA (2012) Surface roughness prediction by response surface methodology in milling of hybrid aluminium composites. Procedia Eng 38:745–752
75. Subramanian M, Sakthivel M, Sooryaprakash K, Sudharakan R (2013) Optimization of end mill tool geometry parameters for Al7075-T6 machining operations based on vibration amplitude by response surface methodology. Measurement 46:4005–4022
76. Subramanian M, Sakthivel M, Sooryaprakash K, Sudhakaran R (2013) Optimization of cutting parameters for cutting force in shoulder milling of Al7076-T6 using response surface methodology and genetic algorithm. Procedia Eng 64:690–700
77. Dikshit MK, Puri AB, Maity A (2014) Experimental study of cutting forces in ball end milling of Al2014-T6 using response surface methodology. Procedia Mater Sci 6:612–622
78. Durakbasa MN, Akdogan A, Vanli AS, Bulutsuz AG (2015) Optimization of end milling parameters and determination of the effects of edge profile for high surface quality of AISI H13 steel by using precise and fast measurements. Measurement 68:92–99
79. Kansal HS, Singh S, Kumar P (2005) Parametric optimization of powder mixed electrical discharge machining by response surface methodology. J Mater Process Technol 169:427–436
80. Habib SS (2009) Study of the parameters in electrical discharge machining through response surface methodology approach. Appl Math Model 33:4397–4407
81. Shandilya P, Jain PK, Jain NK (2012) Parametric optimization during wire electrical discharge machining using response surface methodology. Procedia Eng 38:2371–2377
82. Rajesh R, Anand MD (2012) The optimization of the electro-discharge machining process using response surface methodology and genetic algorithms. Procedia Eng 38:3941–3950
83. Mohanty CP, Sahu J, Mahapatra SS (2013) Thermal-structural analysis of electrical discharge machining process. Procedia Eng 51:508–513
84. Sahu J, Mohanty CP, Mahapatra SS (2013) A DEA approach for optimization of multiple responses in electrical discharge machining of AISI D2 steel. Procedia Eng 51:585–591
85. Singh V, Pradhan SK (2014) Optimization of WEDM parameters using Taguchi technique and response surface methodology in machining of AISI D2 steel. Procedia Eng 97:1597–1608
86. Liu D, Huang C, Wang J, Zhu H, Yao P, Liu ZW (2014) Modeling and optimization of operating parameters for abrasive waterjet turning alumina ceramics using response surface methodology combined with Box-Behnken design. Ceram Int 40:7899–7908
87. Sankar M, Gnanavelbabu A, Rajkumar K (2014) Effect of reinforcement particles on the abrasive assisted electrochemical machining of aluminium-boron carbide-graphite composite. Procedia Eng 97:381–389
88. Xu K, Zeng Y, Li P, Zhu D (2015) Study of surface roughness in wire electrochemical micro machining. J Mater Process Technol 222:103–109
89. Pandey PM, Reddy NV, Dhande SG (2003) Improvement of surface finish by staircase machining in fused deposition modeling. J Mater Process Technol 13:323–331

90. Muthukrishnan N, Davim JP (2009) Optimization of machining parameters of Al/SiC MMC with ANOVA and ANN analysis. J Mater Process Technol 209:225–232
91. Bhushan RK (2013) Optimization of cutting parameters for minimizing power consumption and maximizing tool life during machining of Al alloy SiC particle composites. J Clean Prod 39:242–254
92. Varaprasad Bh, Srinivasa Rao Ch, Vinay PV (2014) Effect of machining parameters on tool wear in hard turning of AISI D3 steel. Procedia Eng 97:338–345
93. Ramanujam R, Venkatesan K, Saxena V, Joseph P (2014) Modeling and optimization of cutting parameters in dry turning of Inconel 718 using coated carbide inserts. Procedia Mater Sci 5:2550–2559
94. Tseng T-LB, Kwon YJ (2014) Characterization of machining quality attributes based on spindle probe, coordinate measuring machine, and surface roughness data. J Comput Des Eng 1(2):128–139
95. Slamani M, Gauthier S, Chatelain J-F (2015) A study of the combined effects of machining parameters on cutting force components during high speed robotic trimming of CFRPs. Measurement 59:268–283
96. Logins A, Torims T (2015) The influence of high-speed milling strategies on 3D surface roughness parameters. Procedia Eng 100:1253–1261
97. Krishnaraj V, Prabukarthi A, Ramanathan A, Elanghovan N, Kumar MS, Zitoune R, Davim JP (2012) Optimization of machining parameters at high speed drilling of carbon fiber reinforced plastic (CFRP) laminates. Compos B 43:1791–1799
98. Singh PN, Raghukandan K, Rathinasabapthi M, Pai BC (2004) Electric discharge machining of Al-10 %SiCp as-cast metal matrix composites. J Mater Process Technol 155–156: 1653–1657
99. Tzeng Y-F, Chen F-C (2007) Multi-objective optimization of high-speed electrical discharge machining process using a Taguchi fuzzy-based approach. Mater Des 28:1159–1168
100. Saha SK, Choudhury SK (2009) Experimental investigation and empirical modeling of the dry electric discharge machining process. Int J Mach Tools Manuf 49:297–308
101. Chattopadhyay KD, Verma S, Satsangi PS, Sharma PC (2009) Development of empirical model for different process parameters during rotary electrical discharge machining of copper-steel (EN-8) system. J Mater Process Technol 209:1454–1465
102. Courbon C, Kramar D, Krainik P, Pusavec F, Rech J, Kopac J (2009) Investigation of machining performance in high-pressure jet assisted turning of Inconel 718: an experimental study. Int J Mach Tools Manuf 49:1114–1125
103. Kibria G, Doloi B, Bhattacharyya B (2013) Experimental investigation and multi-objective optimization of Nd: YAG laser micro-turning process of alumina ceramic using orthogonal array and grey relational analysis. Opt Laser Technol 48:16–27
104. Dittrich M, Dix M, Kuhl M, Palumbo B, Tagliaferri F (2014) Process analysis of water abrasive fine jet structuring of ceramic surfaces via design of experiment. Procedia CIRP 14:442–447
105. Chan JWK, Tong TKL (2007) Multi-criteria material selections and end-of-life product strategy: grey relational analysis approach. Mater Des 28:1539–1546
106. Pan LK, Wang CC, Wei SL, Sher HF (2007) Optimizing multiple quality characteristics via Taguchi method-based grey analysis. J Mater Process Technol 182:107–116
107. Yin MS (2013) Fifteen years of grey system theory research: a historical review and bibliometric analysis. Expert Syst Appl 40:2767–2775
108. Arce ME, Saavedra A, Miguez JL, Granada E (2015) The use of grey-based methods in multi-criteria decision analysis for the evaluation of sustainable energy systems: a review. Renew Sustain Energy Rev 47:924–932
109. Horng J-T, Chiang K-T (2008) A grey and fuzzy algorithms integrated approach to the optimization of turning Hadfield steel with Al_2O_3/TiC mixed ceramic tool. J Mater Process Technol 207:89–97

110. Sahoo AK, Sahoo B (2013) Performance studies of multilayer hard surface coatings (TiN/TiCN/Al_2O_3/TiN) of indexable carbide inserts in hard machining: part II (RSM, grey relational and techno economical approach). Measurement 46:2868–2884
111. Dabade UA (2013) Multi-objective process optimization to improve surface integrity on turned surface of Al/SiCp metal matrix composites using grey relational analysis. Procedia CIRP 7:299–304
112. Mukherjee S, Kamal A, Kumar K (2014) Optimization of material removal rate during turning of SAE 1020 material in CNC lathe using Taguchi technique. Procedia Eng 97:29–35
113. Vinayagamoorthy R, Xavior MA (2014) Parametric optimization on multi-objective precision turning using grey relational analysis. Procedia Eng 97:299–307
114. Nayak SK, Patro JK, Dewangan S, Gangopadhyay S (2014) Multi-objective optimization of machining parameters during dry turning of AISI 304 austenitic stainless steel using grey relational analysis. Procedia Mater Sci 6:701–708
115. Ganta V, Chankradhar D (2014) Multi objective optimization of hot machining of 15-5PH stainless steel using grey relation analysis. Procedia Mater Sci 5:1810–1818
116. Lu HS, Chang CK, Hwang NC, Chung CT (2009) Grey relational analysis coupled with principal component analysis for optimization design of the cutting parameters in high-speed end milling. J Mater Process Technol 209:3808–3817
117. Yan J, Li L (2013) Multi-objective optimization of milling parameters—the trade-offs between energy production rate and cutting density. J Clean Prod 52:462–471
118. Maiyar LM, Ramanujam R, Venkatesan K, Jerald J (2013) Optimization of machining parameters for end milling of Inconel 718 super alloy using Taguchi-based grey relational analysis. Procedia Eng 64:1276–1282
119. Nair A, Govindan P, Ganesan H (2014) A comparison between different optimization techniques for CNC end milling process. Procedia Eng 97:36–46
120. Rajmohan T, Palanikumar K, Kathirvel M (2012) Optimization of machining parameters in drilling hybrid aluminium metal matrix composites. Trans Nonferrous Met Soc China 22:1286–1297
121. Taşkesen A, Kütükde K (2013) Experimental investigation and multi-objective analysis on drilling of boron carbide reinforced metal matrix composites using grey relational analysis. Measurement 47:321–330
122. Rajmohan T, Palanikumar K, Prakash S (2013) Grey-fuzzy algorithm to optimize machining parameters in drilling of hybrid metal matrix composites. Compos B 50:297–308
123. Pandey RK, Panda SS (2014) Optimization of bone drilling parameters using grey-based fuzzy algorithm. Measurement 47:386–392
124. Prasanna J, Karunamoorthy L, Raman MV, Prashanth S, Chordia DR (2014) Optimization of process parameters of small hole dry drilling in Ti-6Al-4V using Taguchi and grey relational analysis. Measurement 48:346–354
125. Singh PN, Raghukandan K, Pai BC (2004) Optimization by grey relational analysis of EDM parameters on machining Al-10 %SiCp composites. J Mater Process Technol 155–156: 1658–1661
126. Chiang K-T, Chang F-P (2006) Optimization of the WEDM process of particle-reinforced material with multiple performance characteristics using grey relational analysis. J Mater Process Technol 180:96–101
127. Lin MY, Tsao CC, Hsu CY, Chiou AH, Huang PC, Lin YC (2013) Optimization of micro milling electrical discharge machining of Inconel 718 by grey-Taguchi method. Trans Nonferrous Met Soc China 23:661–666
128. Khan ZA, Siddiquee AN, Khan NZ, Khan U, Quadir GA (2014) Multi response optimization of Wire electrical discharge machining process parameters using Taguchi based grey relational analysis. Procedia Mater Sci 6:1683–1695
129. Talla G, Gangopadhyay S, Biswas CK (2014) Multi response optimization of powder mixed electric discharge machining of aluminum/alumina metal matrix composite using grey relation analysis. Procedia Mater Sci 5:1633–1639

130. Mhatre MS, Sapkal SU, Pawade RS (2014) Electro discharge machining characteristics of Ti-6Al-4V alloy: a grey relational optimization. Procedia Mater Sci 5:2014–2022
131. Saedon JB, Jaafar N, Yadaya MA, Saad NH, Kasim MS (2014) Multi-objective optimization of titanium alloy through orthogonal array and grey relational analysis in WEDM. Procedia Technol 15:833–841
132. Çaydaş U, Hasçalik A (2008) Use of the grey relational analysis to determine optimum laser cutting parameters with multi-performance characteristics. Opt Laser Technol 40:987–994
133. Li C-H, Tsai M-J (2009) Multi-objective optimization of laser cutting for flash memory modules with special shapes using grey relational analysis. Opt Laser Technol 41:634–642
134. Rao R, Yadava V (2009) Multi-objective optimization of Nd: YAG laser cutting of thin superalloy sheet using grey relational analysis with entropy measurement. Opt Laser Technol 41:922–930
135. Acherjee B, Prakash S, Kuar AS, Mitra S (2014) Grey relational analysis based optimization of underwater Nd: YAG laser micro-channeling on PMMA. Procedia Eng 97:1406–1415
136. Das MK, Kumar K, Barman TK, Sahoo P (2014) Optimization of surface roughness and MRR in electrochemical machining of EN31 tool steel using grey-Taguchi approach. Procedia Mater Sci 6:729–740
137. Kao PS, Hocheng H (2003) Optimization of electrochemical polishing of stainless steel by grey relational analysis. J Mater Process Technol 140:255–259
138. Mukherjee SN, Basu SK (1967) Multiple regression analysis in evaluation of tool wear. Int J Mach Tools Des Res 7:15–21
139. Sokovic M, Bahor M (1998) On the inter-relationships of some machinability parameters in finish machining with cermet TiN (PVD) coated tools. J Mater Process Technol 78:163–170
140. Tosun N, Özler L (2002) A study of tool life in hot machining using artificial neural networks and regression analysis method. J Mater Process Technol 124:99–104
141. Lin JT, Bhattacharyya D, Kecman V (2003) Multiple regression and neural networks analyses in composites machining. Compos Sci Technol 63:539–548
142. Asiltürk I, Çunkaş M (2011) Modeling and prediction of surface roughness in turning operations using artificial neural network and multiple regression method. Expert Syst Appl 38:5826–5832
143. Korkut I, Acir A, Boy M (2011) Application of regression and artificial neural network analysis in modelling of tool-chip interface temperature in machining. Expert Syst Appl 38:11651–11656
144. Özel T, Karpat Y (2005) Predictive modeling of surface roughness and tool wear in hard turning using regression and neural networks. Int J Mach Tools Manuf 45:467–479
145. Leone C, D'Addona D, Teti R (2011) Tool wear modelling through regression analysis and intelligent methods for nickel base alloy machining. CIRP J Manuf Sci Technol 4:327–331
146. Mandal N, Doloi B, Mondal B, Das R (2011) Optimization of flank wear using zirconia toughened alumina (ZTA) cutting tool: Taguchi method and regression analysis. Measurement 44:2149–2155
147. Chen B, Chen X, Li B, He Z, Cao H, Cai G (2011) Reliability estimation for cutting tools based on logistic regression model using vibration signals. Mech Syst Signal Process 25:2526–2537
148. Sahoo AK, Baral AN, Rout AK, Routra BC (2012) Multi-objective optimization and predictive modeling of surface roughness and material removal rate in turning using grey relational and regression analysis. Procedia Eng 38:1606–1627
149. Garcia-Plaza E, Nunez PJ, Salgado DR, Cambero I, Herreza Olivenza JM, Sanz-Calcedo JG (2013) Surface finish monitoring in taper turning CNC using artificial neural network and multiple regression methods. Procedia Eng 63:599–607
150. Agrawal A, Goel S, Bin Rashid W, Price M (2015) Prediction of surface roughness during hard turning of AISI 4340 steel (69 HRC). Appl Soft Comput 30:279–286
151. Ahmad MAF, Nuawi MZ, Abdullah S, Wahid Z, Karim Z, Dirhamsyah M (2015) Development of tool wear machining monitoring using novel statistical analysis method, I-kaz^{TM}. Procedia Eng 101:355–362

152. Ciurana J, Quintana G, Garcia-Romeu ML (2008) Estimating the cost of vertical high-speed machining centres, a comparison between multiple regression analysis and the neural networks approach. Int J Prod Econ 115:171–178
153. Chakraborty P, Asfour S, Cho S, Onar A, Lynn M (2008) Modeling tool wear progression by using mixed effects modeling technique when end-milling AISI 4340 steel. J Mater Process Technol 205:190–202
154. Wibowo A, Desa MI (2012) Kernel based regression and genetic algorithms for estimating cutting conditions of surface roughness in end milling machining process. Expert Syst Appl 39:11634–11641
155. Zain AM, Haron H, Qasem SN, Sharif S (2012) Regression and ANN models for estimating minimum value of machining performance. Appl Math Model 36:1477–1492
156. Rao KV, Murthy BSN, Rao NM (2013) Cutting tool condition monitoring by analyzing surface roughness, workpiece vibration and volume of metal removed for AISI 1040 steel in boring. Measurement 46:4075–4084
157. Kanlayasiri K, Boonmung S (2007) Effects of wire-EDM machining variables on surface roughness of newly developed DC 53 die steel: design of experiments and regression model. J Mater Process Technol 192–193:459–464
158. Obikawa T, Shinozuka J (2004) Monitoring of flank wear of coated tools in high speed machining with a neural network ART2. Int J Mach Tools Manuf 44:1311–1318
159. Ezugnu EO, Fadare DA, Bonney J, Da Silva RB, Sales WF (2005) Modelling the correlation between cutting and process parameters in high-speed machining of Inconel 718 alloy using an artificial neural network. Int J Mach Tools Manuf 45:1375–1385
160. Davim JP, Gaitonde VN, Karnik SR (2008) Investigations into the effect of cutting conditions on surface roughness in turning of free machining steel by ANN models. J Mater Process Technol 205:16–23
161. Umbrello D, Ambrogio G, Filice L, Shivpuri R (2008) A hybrid finite element method—artificial neural network approach for predicting residual stresses and the optimal cutting conditions during hard turning of AISI 52100 bearing steel. Mater Des 29:873–883
162. Kurt A (2009) Modelling of the cutting tool stresses in machining of Inconel 718 using artificial neural networks. Expert Syst Appl 36:9645–9657
163. Tiryaki S, Malkoçoğlu S, Özşahin Ş (2014) Using artificial neural networks for modeling surface roughness of wood in machining process. Constr Build Mater 66:329–335
164. Azmi AI (2015) Monitoring of tool wear using measured machining forces and neuro-fuzzy modelling approaches during machining of GFRP composites. Adv Eng Softw 82:53–64
165. Zain AM, Haron H, Sharif S (2010) Prediction of surface roughness in the end milling machining using artificial neural network. Expert Syst Appl 37:1755–1768
166. Kannan TDB, Kannan GR, Kumar BS, Baskar N (2014) Application of artificial neural network modeling for machining parameters optimization in drilling operation. Procedia Mater Sci 5:2242–2249
167. Tsai K-M, Wang P-J (2001) Comparisons of neural network models on material removal rate in electrical discharge machining. J Mater Process Technol 117:111–124
168. Markopoulos A, Vaxevanidis NM, Petropoulos G, Manolakos DE (2006) Artificial neural networks modeling of surface finish in electro-discharge machining of tool steels. In: Proceedings of ESDA 2006, 8th Biennial ASME conference on engineering systems design and analysis, Torino, Italy, pp 847–854
169. Markopoulos AP, Manolakos DE, Vaxevanidis NM (2008) Artificial neural network models for the prediction of surface roughness in electrical discharge machining. J Intell Manuf 19 (3):283–292
170. Rao GKM, Rangajanardhaa G, Rao DH, Rao MS (2009) Development of hybrid model and optimization of surface roughness in electric discharge machining using artificial neural networks and genetic algorithm. J Mater Process Technol 209:1512–1520
171. Chen H-C, Lin J-C, Yang Y-K, Tsai C-H (2010) Optimization of wire electrical discharge machining for pure tungsten using a neural network integrated simulated annealing approach. Expert Syst Appl 37:7147–7153

172. Khan MAR, Rahman MM, Kadirgama K (2014) Neural network modeling and analysis for surface characteristics in electrical discharge machining. Procedia Eng 90:631–636
173. Benkirane Y, Kremer D, Moisan A (1999) Ultrasonic machining: an analytical and experimental study on contour machining based on neural network. Ann CIRP 48 (1):135–138
174. Jain RK, Jain VK, Kalra PK (1999) Modelling of abrasive flow machining process: a neural network approach. Wear 231:242–248
175. Petri KL, Billo RE, Bidanda B (1998) A neural network process model for abrasive flow machining operations. J Manuf Syst 17(1):52–64
176. Jain RK, Jain VK (2000) Optimum selection of machining conditions in abrasive flow machining using neural network. J Mater Process Technol 108:62–67
177. Vaxevanidis NM, Markopoulos A, Petropoulos G (2010) Artificial neural network modelling of surface quality characteristics in abrasive water jet machining of trip steel sheet. In: Davim JP (ed) Artificial intelligence in manufacturing research. Nova Science Publishers Inc, New York, pp 79–99
178. Zain AM, Haron H, Sharif S (2011) Estimation of the minimum machining performance in the abrasive waterjet machining using integrated ANN-SA. Expert Syst Appl 38:8316–8326
179. Zadeh LA (1965) Fuzzy sets. Inf Control 8(3):338–353
180. Azadegan A, Porobic L, Ghazinoory S, Samouei P, Kheirkhah AS (2011) Fuzzy logic in manufacturing: a review of literature and a specialized application. Int J Prod Econ 132:258–270
181. Mohd Adnan MRH, Mohd Zain A, Haron H (2011) Consideration of fuzzy components for prediction of machining performance: a review. Procedia Eng 24:754–758
182. Ralston PAS, Stoll KE, Ward TL (1992) Fuzzy logic control of chip form during turning. Comput Ind Eng 22(3):223–230
183. Balazinski M, Bellerose M, Czogala E (1994) Application of fuzzy logic techniques to the selection of cutting parameters in machining processes. Fuzzy Sets Syst 63:307–312
184. Chen Y, Hui A, Du R (1995) A fuzzy expert system for the design of machining operations. Int J Mach Tools Manuf 35(12):1605–1621
185. Hashmi K, Graham ID, Mills B (2003) Data selection for turning carbon steel using a fuzzy logic approach. J Mater Process Technol 135:44–58
186. Hashmi K, Graham ID, Mills B, Hashmi MSJ (2003) Adjustment approach for fuzzy logic model based selection of non-overlapping machining data in the turning operation. J Mater Process Technol 142:152–162
187. Hanafi I, Khamlichi A, Cabrera FM, Nunez Lopez PJ, Jabbouri A (2012) Fuzzy rule based predictive model for cutting force in turning of reinforced PEEK composite. Measurement 45:1424–1435
188. Azmi AI (2012) Design of fuzzy logic model for the prediction of tool performance during machining of composite materials. Procedia Eng 38:208–217
189. Ramanujam R, Venkatesa K, Saxena V, Pandey R, Harsha T, Kumar F (2014) Optimization of machining parameters using fuzzy based principal components analysis during dry turning operation of Inconel 625—a hybrid approach. Procedia Eng 97:668–676
190. Sharma S, Tamang S, Devarasiddappa D, Chandrasekran M (2014) Fuzzy logic modeling and multiple performance optimization in turning GFRP composites using desirability function analysis. Procedia Mater Sci 6:1805–1814
191. Venkataramaiah P, DharmaReddy K, Meramma P (2014) Analysis of influence of feed rate and tool geometry on cutting forces in turning using Taguchi method and fuzzy logic. Procedia Mater Sci 5:1692–1701
192. Thakur A, Dewangan S, Patnaik Y, Gangopadhyay S (2014) Prediction of work hardening during machining Inconel 825 using fuzzy logic method. Procedia Mater Sci 5:2046–2053
193. Marani Barzani M, Zalnezhad E, Sarhan AAD, Farahany S, Ramesh S (2015) Fuzzy logic based model for predicting surface roughness of machined Al–Si–Cu–Fe die casting alloy using different additives-turning. Measurement 61:150–161

194. Huang PT, Chen JC (1998) Fuzzy logic-base tool breakage detecting system in end milling operations. Comput Ind Eng 35(1–2):37–40
195. Peres CR, Guerra REH, Haber Haber R, Alique A, Ros S (1999) Fuzzy model and hierarchical fuzzy control integration: an approach for milling process optimization. Comput Ind 39:199–207
196. Iqbal A, He N, Li L, Dar NU (2007) A fuzzy expert system for optimizing parameters and predicting performance measures in hard-milling process. Expert Syst Appl 32:1020–1027
197. Kim D, Jeon D (2011) Fuzzy-logic control of cutting forces in CNC milling processes using motor currents as indirect force sensors. Precis Eng 35:143–152
198. Mahesh TP, Rajesh R (2014) Optimal selection of process parameters in CNC end milling of Al 7075-T6 aluminium alloy using a Taguchi-fuzzy approach. Procedia Mater Sci 5:2493–2502
199. Ali YM, Zhang LC (1997) Estimation of residual stresses induced by grinding using a fuzzy logic approach. J Mater Process Technol 63:875–880
200. Lezanski P (2001) An intelligent system for grinding wheel condition monitoring. J Mater Process Technol 109:258–263
201. Nandi AK, Pratihar DK (2004) Automatic design of fuzzy logic controller using a genetic algorithm—to predict power requirement and surface finish in grinding. J Mater Process Technol 148:288–300
202. Virivinti N, Mitra K (2014) Fuzzy expected value analysis of an industrial grinding process. Powder Technol 268:9–18
203. Lin C-T, Chung I-F, Huang S-Y (2001) Improvement of machining accuracy by fuzzy logic at corner parts for wire-EDM. Fuzzy Sets Syst 122:499–511
204. Lin JL, Lin CL (2005) The use of grey-fuzzy logic for the optimization of the manufacturing process. J Mater Process Technol 160:9–14
205. Kao CC, Shih AJ (2008) Design and turning of a fuzzy logic controller for micro-hole electrical discharge machining. J Manuf Process 10:61–73
206. Vundavilli PR, Paprappagoudar MB, Kodali SP, Benguluri S (2012) Fuzzy logic-based expert system for prediction of depth of cut in abrasive water jet machining process. Knowl-Based Syst 27:456–464
207. Kanish TC, Kuppan P, Narayanan S, Ashok SD (2014) A fuzzy logic based model to predict the improvement in surface roughness in magnetic field assisted abrasive finishing. Procedia Eng 97:1948–1956
208. Hashmi K, El Baradie MA, Ryan M (1999) Fuzzy logic based intelligent selection of machining parameters. J Mater Process Technol 94:94–111
209. El Baradie MA (1997) A fuzzy logic model for machining data selection. Int J Mach Tools Manuf 37(9):1353–1372
210. D' Errico G (2001) Fuzzy control systems with application to machining process. J Mater Process Technol 109:38–43
211. Hashmi K, El Baradie MA, Ryan M (1998) Fuzzy logic based intelligent selection of machining parameters. Comput Ind Eng 35(3–4):571–574
212. Mpofu K, Tlale NS (2012) Multi-level decision making in reconfigurable machining systems using fuzzy logic. J Manuf Syst 31:103–112
213. Sharif Ullah AMM, Habib KH (2006) A human-assisted knowledge extraction method for machining operations. Adv Eng Inf 20:335–350
214. Chandrasekaran M, Muralidhar M, Krishna CM, Dixit US (2010) Application of soft computing techniques in machining performance prediction and optimization: a literature review. Int J Adv Manuf Technol 46:445–464
215. Reddy SVB, Shunmugan MS, Narendran TT (1998) Optimal sub-division of the depth of cut to achieve minimum production cost in multi-pass turning using a genetic algorithm. J Mater Process Technol 79:101–108
216. Sardinas RQ, Santana MR, Brindis EA (2006) Genetic algorithm-based multi-objective optimization of cutting parameters in turning process. Eng Appl Artif Intell 19:127–133

217. D' Addona DM, Teti R (2013) Genetic algorithm-based optimization of cutting parameters in turning processes. Procedia CIRP 7:323–328
218. Del Prete A, Primo T, Franch R (2013) Super-Nickel orthogonal turning operations optimization. Procedia CIRP 8:164–169
219. Dhabale R, Jatti VKS, Singh TP (2014) Multi-objective optimization of turning process during machining of AlMg1SiCu using non-dominated sorted genetic algorithm. Procedia Mater Sci 6:961–966
220. Shunmugan MS, Reddy SVB, Narendran TT (2000) Selection of optimal conditions in multi-pass face-milling using a genetic algorithm. Int J Mach Tools Manuf 40:401–414
221. Wang ZB, Rahman M, Wong YS, Sun J (2005) Optimization of multi-pass milling using parallel genetic algorithm and parallel genetic simulated annealing. Int J Mach Tools Manuf 45:1726–1734
222. Oktem H, Erzurumlu T, Erzincanli F (2006) Prediction of minimum surface roughness in end milling mold parts using neural network and genetic algorithm. Mater Des 27:735–744
223. Hou T-H, Su C-H, Liu W-L (2007) Parameters optimization of a nano-particle wet milling process using the Taguchi method, response surface method and genetic algorithm. Powder Technol 173:153–162
224. Rao RV, Pawar PJ (2010) Parameter optimization of a multi-pass milling process using non-traditional optimization algorithms. Appl Soft Comput 10:445–456
225. Dikshit MK, Puri AB, Maity A, Banerjee AJ (2014) Analysis of cutting forces and optimization of cutting parameters in high speed ball-end milling using response surface methodology and genetic algorithm. Procedia Mater Sci 5:1623–1632
226. Dhavamani C, Alwarsamy T (2012) Optimization of machining parameters for aluminum and silicon carbide composite using genetic algorithm. Procedia Eng 38:1994–2004
227. Lee K-M, Hsu M-R, Chou J-H, Guo C-Y (2011) Improved differential evolution approach for optimization of surface grinding process. Expert Syst Appl 38:5680–5686
228. Pai D, Rao S, D'Souza R (2013) Application of response surface methodology and enhanced non-dominated sorting genetic algorithm for optimization of grinding process. Procedia Eng 64:1199–1208
229. Mandal D, Pal SK, Saha P (2007) Modeling of electrical discharge machining process using back propagation neural network and multi-objective optimization using non-dominating sorting genetic algorithm-II. J Mater Process Technol 186:154–162
230. Saha P, Tarafdar D, Pal SK, Saha P, Srivastava AK, Das K (2013) Multi-objective optimization in wire-electro-discharge machining of TiC reinforced composite through neuro-genetic technique. Appl Soft Comput 13:2065–2074
231. Senthilkumar C, Ganesan G, Karthikeyan R (2011) Parametric optimization of electrochemical machining of Al/15 % SiCp composites using NSGA-II. Trans Nonferrous Met Soc China 21:2294–2300
232. Zain AM, Haron H, Sharif S (2011) Optimization of process parameters in the abrasive waterjet machining using integrated SA-GA. Appl Soft Comput 11:5350–5359
233. Aultrin KSJ, Anand MD, Jose PJ (2012) Modelling the cutting process and cutting performance in abrasive water jet machining using genetic-fuzzy approach. Procedia Eng 38:4013–4020
234. Samanta S, Chakraborty S (2011) Parametric optimization of some non-traditional machining processes using artificial bee colony algorithm. Eng Appl Artif Intell 24(6):946–957
235. Yildiz AR (2013) Optimization of cutting parameters in multi-pass turning using artificial bee colony-based approach. Inf Sci 220:399–407
236. Baskar N, Asokan P, Prabhaharan G, Saravanan R (2005) Optimization of machining parameters for milling operations using non-conventional methods. Int J Adv Manuf Technol 25(11–12):1078–1088
237. Chan FTS, Swarnkar R (2006) Ant colony optimization approach to a fuzzy goal programming model for a machine tool selection and operation allocation problem in an FMS. Robot Comput-Integr Manuf 22(4):353–362

238. Liu X, Hong Y, Zhonghua N, Jianchang Q, Xiaoli Q (2013) Process planning optimization of hole-making operations using ant colony algorithm. Int J Adv Manuf Technol 69(1–4): 753–769
239. Karpat Y, Özel T (2007) Multi-objective optimization for turning processes using neural network modeling and dynamic-neighborhood particle swarm optimization. Int J Adv Manuf Technol 35(3–4):234–247
240. Raja SB, Baskar N (2012) Application of particle swarm optimization technique for achieving desired milled surface roughness in minimum machining time. Expert Syst Appl 39(5):5982–5989
241. Marko H, Simon K, Tomaz I, Matej P, Joze B, Miran B (2014) Turning parameters optimization using particle swarm optimization. Procedia Eng 69:670–677
242. Aich U, Banerjee S (2014) Modeling of EDM responses by support vector machine regression with parameters selected by particle swarm optimization. Appl Math Model 38 (11–12):2800–2818
243. Khan Z, Prasad B, Singh T (1997) Machining condition optimization by genetic algorithms and simulated annealing. Comput Ops Res 24(7):647–657
244. Yang S-H, Srinivas J, Mohan S, Lee D-M, Balaji S (2009) Optimization of electric discharge machining using simulated annealing. J Mater Process Technol 209(9):4471–4475
245. Olvera D, Zuniga AE, Martinez-Alfaro H, Lopez de Lacalle LN, Rodriguez CA, Campa FJ (2014) Determination of the stability lobes in milling operations based on homotopy and simulated annealing techniques. Mechatronics 24(3):177–185

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