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A genetic algorithmic approach for optimization of surface roughness prediction model

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Abstract

Due to the widespread use of highly automated machine tools in the industry, manufacturing requires reliable models and methods for the prediction of output performance of machining processes. The prediction of optimal machining conditions for good surface finish and dimensional accuracy plays a very important role in process planning. The present work deals with the study and development of a surface roughness prediction model for machining mild steel, using Response Surface Methodology (RSM). The experimentation was carried out with TiN-coated tungsten carbide (CNMG) cutting tools, for machining mild steel work-pieces covering a wide range of machining conditions. A second order mathematical model, in terms of machining parameters, was developed for surface roughness prediction using RSM. This model gives the factor effects of the individual process parameters. An attempt has also been made to optimize the surface roughness prediction model using Genetic Algorithms (GA) to optimize the objective function. The GA program gives minimum and maximum values of surface roughness and their respective optimal machining conditions.

1. Introduction

Process modelling and optimization are two important issues in manufacturing. The manufacturing processes are characterized by a multiplicity of dynamically interacting process variables [1,22]. A greater attention is given to accuracy and surface roughness of product by the industry these days. Surface finish has been one of the most important considerations in determining the machinability of materials. Surface roughness and dimensional accuracy have been important factors to predict machining performances of any machining operation [11]. The predictive modelling of machining operations require detailed prediction of the boundary conditions for stable machining [13,21]. The number of surface roughness prediction models available in literature is very limited [11,21]. Most surface roughness prediction models are empirical and are generally based on experiments in the laboratory. In addition, it is very difficult in practice, to keep all factors under control as required to obtain reproducible results [21]. Generally these models have a complex relationship between surface roughness and operational parameters, work-materials and chip-breaker types.

Optimization of machining parameters not only increases the utility for machining economics, but also the product quality to a great extent [1]. In this context, an effort has been made to estimate the surface roughness using experimental data. It has also been attempted to optimize the surface roughness prediction model using a Genetic Algorithmic approach.

2. Literature review

Since turning is the primary operation in most of the production processes in the industry, surface finish of turned components has greater influence on the quality of the product. Surface finish in turning has been found to be influenced in varying amounts by a number of factors such as feed rate, work material characteristics, work hardness, unstable built-up edge, cutting speed, depth of cut, cutting time, tool nose radius and tool cutting edge angles, stability of machine tool and workpiece-setup, chatter, and use of cutting fluids.

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Nomenclature

b_0, b_1, b_2, b_3 estimates of parameters;
C constant;
d depth of cut (mm);
f feed (mm/rev);
k_1, k_2, k_3, k_4 exponentially determined constants;
r nose radius (mm);
R_a surface roughness (μm);
v cutting speed (m/min);
x_0, x_1, x_2, x_3 logarithmic transformations of machining parameters;
Y' estimated response;
y measured surface roughness;
η surface roughness response;
ε experimental error.

Taraman [19] used Response Surface Methodology (RSM) for predicting surface roughness. A family of mathematical models for tool life, surface roughness and cutting forces were developed in terms of cutting speed, feed, and depth of cut. Hasegawa et al., [9] conducted 3^4 factorial design to conduct experiments for the surface roughness prediction model. They found that the surface roughness increased with an increase in cutting speed. Sundaram and Lambert [17,18] considered six variables i.e speed, feed, depth of cut, time of cut, nose radius and type of tool to monitor surface roughness.

Mital and Mehta [11] conducted a survey of surface roughness prediction models developed and factors influencing surface roughness. They found that most of the surface roughness prediction models were developed for steels. Boothroyd [3] investigated effect of speed, feed, depth of cut etc., on steel. Baradie [2] also emphasised the use of RSM in developing a surface roughness prediction model for turning grey cast iron of hardness 154 BHN.

Tetsutaro and Naotake [20] applied Group Method Data Handling (GMDH) algorithm for the successful prediction and detection of cutting tool failure. Das et al., [6] applied an analytic hierarchy process (AHP) for on-line tool wear monitoring. A force-based monitoring system was developed to classify the tool wear using an analytical hierarchy process.

Oslen [14] stated that R_a and R_{max} values of surface roughness tend to follow a normal distribution curve in fine turning of carbon steel with a sintered carbide tool. Petropoulous [16] found a pronounced effect of tool wear on the R_a and R_{max} values of surface roughness by statistical analysis. There had been progressive rapid deterioration of surface roughness at the first stage of tool wear, and fluctuations of surface roughness values at point of tool failure causing considerable deviations in surface roughness from time to time.

It appears that a considerable amount of work is going on optimization of machining parameters, based on different criteria [4–7] such as tool wear, vibrations, surface roughness, unit cost etc. Nowadays artificial intelligence (AI) based modeling is a new trend in modeling for machining operations [21]. A need for tool-chip interactions in the turning and corresponding material flow behavior with surface roughness prediction was underlined. It was found that usage of heuristic methods to model prediction of surface roughness was very limited, so emphasis was laid on the development of a surface roughness prediction model.

3. Methodology

In this work, experimental results were used for modelling using response surface roughness methodology (RSM) [12]. The RSM is practical, economical and relatively easy for use and it was used by lot of researchers for modelling machining processes [2,9,17–19]. It was also successfully used for application in tool life testing [23,19] surface analysis [11,19] and friction damping characteristics [15]. The experimental data was utilized to build mathematical model (first-order and second-order model) by regression method. This mathematical model was taken as objective function and was optimized using a Genetic Algorithmic approach to obtain the machining conditions for the required surface finish.

3.1. RSM mathematical formulation

The data collected from the experiments was used to build a mathematical surface model using response surface methodology. The response surface methodology [12] is a collection of mathematical and statistical techniques that are useful for modelling and analyzing problems in which response of interest is influenced by several variables, and the objective is to obtain the response.

The following linear relationship could be considered for achieving this.

$$Y = f(v,f,d,r) + \varepsilon$$

Where v, f, d, r are speed, feed, depth of cut and tool nose radius respectively of the machining processes, and ε is error which is normally distributed with mean=*0* according to observed response Y.

Let $f(v,f,d,r) = \eta$

The surface represented by 'η'is called response surface.

The relationship between surface roughness and other independent variables is modelled as follows

$$R_a = C\, v^{k1} f^{k2} d^{k3} r^{k4}$$

Where 'C' is a constant and k_1, k_2, k_3, k_4 are parameters.

The above function can be represented in linear mathematical form as follows

$$\ln R_a = \ln C + k_1 \ln v + k_2 \ln f + k_3 \ln d + k_4 \ln r$$

The first-order linear model of the above equation can be represented as follows

$$Y_1' = y - \varepsilon = b_0x_0 + b_1x_1 + b_2x_2 + b_3x_3 + b_4x_3$$

Where Y_1' is the estimated response based on first-order equation and y is the measured surface roughness on a logarithmic scale. x_1, x_2, x_3, x_4 are logarithmic transformations of speed, feed, depth of cut and nose radius respectively, 'ε' is the experimental error and b values are estimates of corresponding parameters.

The second-order model is as follows

$$Y_2' = y - \varepsilon = b_0x_0 + b_1x_1 + b_2x_2 + b_3x_3 + b_4x_4 + b_{12}x_1x_2 + b_{23}x_2x_3 + b_{14}x_1x_4 + b_{24}x_2x_4 + b_{13}x_1x_3 + b_{34}x_3x_4 + b_{11}x_1^2 + b_{22}x_2^2 + b_{33}x_3^2 + b_{44}x_4^2.$$

Where the parameters i.e. b_0, b_1, b_2, b_3, b_4 , etc are to be estimated.

Y_2' is the estimated response based on second-order equation.

3.2. Optimization by genetic algorithms

Genetic Algorithms are search algorithms for optimization, based on the mechanics of natural selection and genetics [8,10]. The power of these algorithms is derived from a very simple heuristic assumption that the best solution will be found in the regions of solution space containing high proposition of good solution, and that these regions can be identified by judicious and robust sampling of the solution space.

The mechanics of Genetic Algorithms is simple, involving copying of binary strings and the swapping of the binary strings. The simplicity of operation and computational efficiency are the two main attractions of the Genetic Algorithm approach. The computations are carried out in three stages to get a result in one generation or iteration. The three stages are (a) Reproduction (b) Cross-over (c) Mutation [8,10].

3.2.1. Reproduction

This is the first of the genetic operators. It is a process in which copies of the strings are copied into a separate string called the 'mating pool', in proportion to their fitness values. This implies that strings with higher fitness values will have a higher probability of contributing more strings as the search progresses.

3.2.2. Crossover

This operator, second among the genetic operators, is mostly responsible for the progress of the search. It swaps the parent strings partially, causing offspring to be generated. In this, a crossover site along the length of the string is selected randomly, and the portions of the strings beyond the crossover site are swapped.

3.2.3. Mutation

It is one of last GA operators, this is the occasional random alteration (with a small probability) of the value of a string position. In binary strings, this simply means changing 1 to 0, or vice versa.

4. Experimental details

A detailed survey has been carried out to find out how machining parameters affect surface roughness. Based on this, the four parameters, namely speed, feed, depth of cut and nose radius of the cutting tool were selected for experimentation [9,11]. A simple three level (3^4) factorial design of experiments was adopted for experimentation. A Talysurf6 instrument was used to measure surface roughness (R_a) of the machined components. A high precision NH–22 HMT lathe was used for experimentation. The work-piece material used for experimentation was mild steel. The cutting tools used for experimentation were CNMG 120404, CNMG 120408, CNMG 120412 and of 4025 grade. The tool holder used for experimentation was PCLNR M12.

Eighty-one (3^4) experiments were conducted by varying all the parameters identified, to study the influence of these parameters on surface roughness, and every machined component was taken to measure surface roughness. The surface roughness was measured with Talysurf6 at 0.8 mm cut-off value.

Table 1
Output values of Genetic Algorithm Program with respect to input machining parameters

S. No	Speed (m/min)	Feed (mm/rev)	Depth of cut (mm)	Nose radius (mm)	Max roughness (μm)	Min roughness (μm)
1	95.0–170.0	0.1–0.2	0.5–1.0	0.4–0.8	3.345	1.304
2	95.0–170.0	0.1–0.2	0.5–1.0	0.8–1.2	3.686	1.814
3	95.0–170.0	0.1–0.2	1.0–1.5	0.4–0.8	3.280	1.687
4	95.0–170.0	0.1–0.2	1.0–1.5	0.8–1.2	3.133	1.623
5	95.0–170.0	0.2–0.3	0.5–1.0	0.4–0.8	5.046	1.932
6	95.0–170.0	0.2–0.3	0.5–1.0	0.8–1.2	5.479	2.612
7	95.0–170.0	0.2–0.3	1.0–1.5	0.4–0.8	4.865	2.453
8	95.0–170.0	0.2–0.3	1.0–1.5	0.8–1.2	4.475	2.536
9	170.0–280.0	0.1–0.2	0.5–1.0	0.4–0.8	3.346	1.198
10	170.0–280.0	0.1–0.2	0.5–1.0	0.8–1.2	3.654	1.088
11	170.0–280.0	0.1–0.2	1.0–1.5	0.4–0.8	5.733	1.033
12	170.0–280.0	0.1–0.2	1.0–1.5	0.8–1.2	2.915	0.882
13	170.0–280.0	0.2–0.3	0.5–1.0	0.4–0.8	5.086	2.114
14	170.0–280.0	0.2–0.3	0.5–1.0	0.8–1.2	5.476	1.897
15	170.0–280.0	0.2–0.3	1.0–1.5	0.4–0.8	4.854	1.802
16	170.0–280.0	0.2–0.3	1.0–1.5	0.8–1.2	4.349	1.521

5. Results and discussion

In order to satisfy the present day needs of manufacturing industry, carbide inserts with the above specifications were identified. The effect of nose radius was also considered, apart from the effects of process parameters on the surface roughness. Most researchers have used central composite design and rotatable design in order to reduce experimentation. Obviously the models developed were based on only a few experimental results [2,11,17–19]. The general 3^n factorial design was adopted for this present work, as followed in [9]. So, $81(3^4)$ experiments were conducted, and the surface roughness (R_a) of all these components was measured. The experimental results were modelled using RSM and respective first-order and second-order models were developed. The models were analyzed based on regression coefficient and an appropriate model was selected for optimization.

The proposed first-order model developed from the above functional relationship using RSM method is as follows:

$$Y = 1.029483-0.11222x_1 + 0.564299x_2 -0.08131x_3 + 0.022143x_4 \quad (1)$$

The multiple regression coefficient of the first-order model was found to be 0.653. This shows that the first-

Table 2
Optimum values of machining conditions predicted by GA Program for corresponding maximum and minimum values of surface roughness in Table 1

S. No	Optimum machining conditions for maximum values of surface roughness (Speed, feed, depth of cut, nose radius)				Optimum machining conditions for minimum values of surface roughness (Speed, feed, depth of cut, nose radius)			
1	170.0	0.2	1.0	0.8	95.0	0.1	0.5	0.4
2	151.9	0.2	0.5	1.2	170.0	0.1	1.0	1.1
3	147.8	0.2	1.5	0.4	95.0	0.1	1.0	0.4
4	118.4	0.2	1.0	1.2	170.0	0.1	1.5	1.2
5	170.0	0.3	0.5	0.8	95.0	0.2	0.5	0.4
6	165.6	0.3	0.5	1.2	95.0	0.2	0.5	0.8
7	160.9	0.3	1.5	0.4	95.0	0.2	1.0	0.4
8	128.9	0.3	1.0	1.2	170.0	0.2	1.5	1.2
9	173.9	0.2	0.5	0.8	280.0	0.1	1.0	0.8
10	170.0	0.2	0.5	1.2	280.0	0.1	1.0	1.2
11	170.0	0.2	1.5	0.4	280.0	0.1	1.5	0.8
12	170.0	0.2	1.0	0.8	280.0	0.1	1.5	1.2
13	189.4	0.3	0.5	0.8	280.0	0.2	1.0	0.8
14	170.0	0.3	0.5	1.2	280.0	0.2	1.0	1.2
15	170.0	0.3	1.5	0.4	280.0	0.2	1.5	0.8
16	170.0	0.3	1.0	0.8	280.0	0.2	1.5	1.2

order model can explain the variation to the extent of 65.3%.

The transformed eq. of surface roughness prediction is as shown below:

$$R_a = 28.14185 v^{-0.192844} f^{0.814111} d^{-0.117306} r^{0.031946} \qquad (2)$$

The eq. (2) is derived from eq. (1) by substituting the coded values of x_1, x_2, x_3, and x_4 in terms of *ln*v, *ln*f, *ln*d, and *ln*r. The first-order eq. was not adequate to represent this process, hence a second order model was developed to represent the process. The following is the second-order eq. of the RSM model with multiple regression coefficient of 0.801.

$$\begin{aligned} Y = {} & 1.069931 - 0.17825x_1 + 0.604826x_2 \\ & - 0.11697x_3 + 0.04038x_4 - 0.2292x_1^2 \\ & + 0.135699x_2^2 + 0.020495x_3^2 + 0.020624x_4^2 \\ & + 0.114738x_1x_2 - 0.01912x_2x_3 - 0.1797x_3x_4 \\ & - 0.18259x_4x_1 - 0.19632x_3x_1 - 0.02006x_2x_4 \end{aligned} \qquad (3)$$

Where '*Y*' is the estimated response of surface roughness on a logarithmic scale, x_1, x_2, x_3, x_4 are logarithmic transformations of speed, feed, depth of cut and tool nose radius.

The above second-order mathematical eq. was optimized using Genetic Algorithms. The input machining parameter levels were fed to the GA program. The GA program uses different types of crossover and mutation operators to predict maximum and minimum values of surface roughness. This approach provides optimum machining conditions for corresponding, given maximum and minimum values of surface roughness. This gives the range of surface roughness values for a certain range of machining parameters. Table 1 shows some of the maximum and minimum values of surface roughness with respect to input machining ranges. Table 2 shows the optimum machining conditions predicted by GA program for corresponding maximum and minimum values of surface roughness in Table 1. Eq. (3) was plotted in Fig. 1(a)–(i) as surface roughness contours (sections) for each of response surfaces at three selected levels of nose radius along with three constant depth of cuts. The selected levels are chosen as r=0.4, 0.8, 1.2 (as per international standards) and depth of cut as d=0.5, 1.0, 1.5 mm for plotting the contours. It can be seen from Fig. 1 that surface roughness decreases with an increase in cutting speed, and increases as feed increases. It was also observed that an increase in depth of cut, and nose radius, increased surface roughness. The combined effect of all parameters could be diagrammatically seen by above contours, as it could lead to better visualization at the shop floor level.

Hence, in order to reduce machining time and to achieve a better surface roughness and metal removal rate, a combination of high speed and low feed, with moderate depth of cut and nose radius must be selected for machining processes. Above contour plots represent similar effects of surface roughness as reported by Baradie, Taraman and Hasegawa [2,19,9].

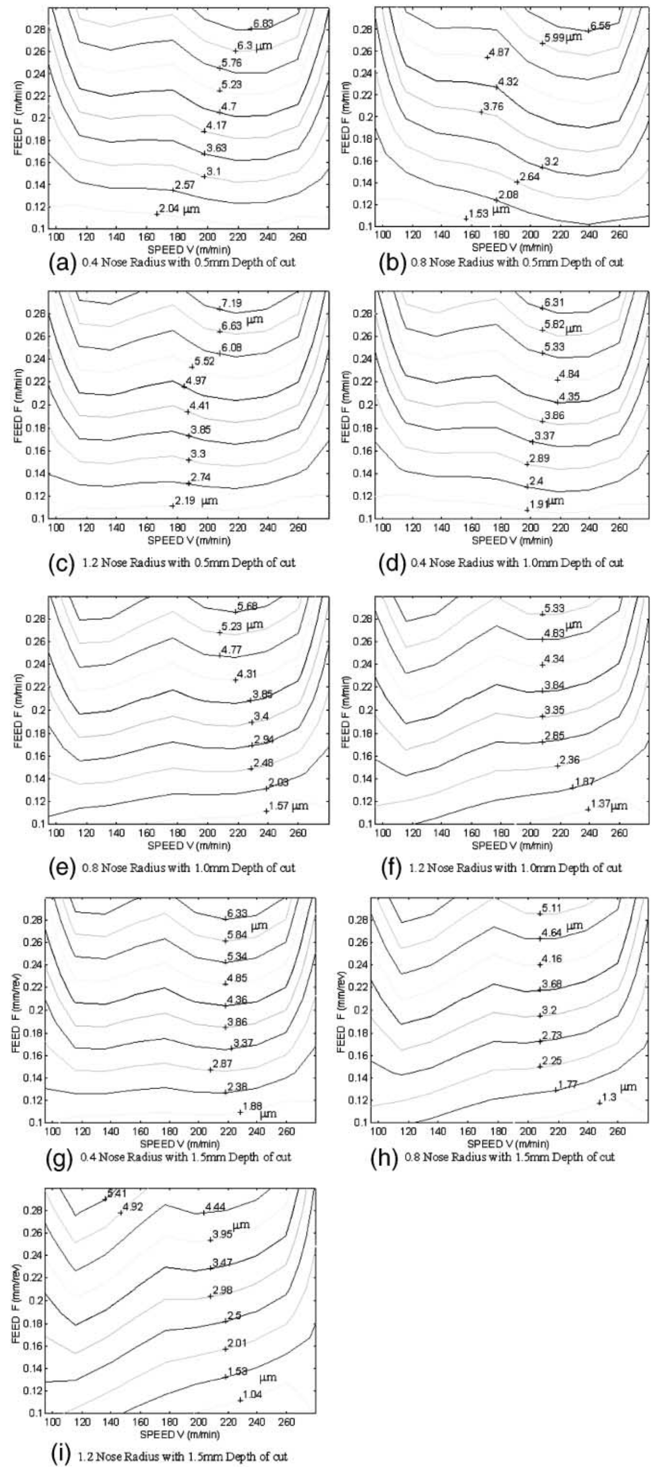

Fig. 1. Surface Roughness Contours in cutting Speed-Feed Planes at the selected levels of nose radius and depth of cut.

This GA approach provides optimum machining conditions for corresponding given maximum and minimum values of surface roughness. This approach is quite advantageous in order to have the range of surface roughness values, and their corresponding optimum machining conditions, for a certain range of input machining parameters. This would be helpful for a manufacturing engineer to choose machining conditions for desired machining performance of a product. The GA approach, used to optimize using the mathematical model, was found to be the most useful technique for research. With the known boundaries of surface roughness and machining conditions, machining could be performed with a relatively high rate of success, with selected machining conditions.

The methodology of prediction models, along with optimum machining conditions, can be used in computer-aided process planning (CAPP), and computer aided manufacturing (CAM). The predictive capability of GA could also be incorporated for automatic monitoring, in order to plan operations. The surface roughness prediction model developed, takes into account cutting speed, feed rate, depth of cut, cutting tool, nose radius and their interactions. With the known boundaries of surface roughness and machining conditions, machining could be performed with a relatively high rate of success with selected machining conditions.

6. Conclusions

The two-stage effort of obtaining a surface roughness model by surface response methodology, and optimization of this model by Genetic Algorithms, has resulted in a fairly useful method of obtaining process parameters in order to attain the required surface quality. This has validated the trends available in the literature, and extended the data range to the present operating conditions, apart from improving the accuracy and modelling by involving the most recent modelling method. The application of the GA approach to obtain optimal machining conditions will be quite useful at the Computer-aided process planning (CAPP) stages in the production of high quality goods with tight tolerances by a variety of machining operations, and in adaptive control of automated machine tools.

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