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Application of response surface methodology in the optimization of cutting conditions for surface roughness

H. Öktem [a,*], T. Erzurumlu [b], H. Kurtaran [b]

[a] *Department of Mechanical Engineering, University of Kocaeli, 41420 Kocaeli, Turkey*
[b] *Department of Design and Manufacturing Engineering, GIT, 41400 Gebze, Kocaeli, Turkey*

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Abstract

This paper focuses on the development of an effective methodology to determine the optimum cutting conditions leading to minimum surface roughness in milling of mold surfaces by coupling response surface methodology (RSM) with a developed genetic algorithm (GA). RSM is utilized to create an efficient analytical model for surface roughness in terms of cutting parameters: feed, cutting speed, axial depth of cut, radial depth of cut and machining tolerance. For this purpose, a number of machining experiments based on statistical three-level full factorial design of experiments method are carried out in order to collect surface roughness values. An effective fourth order response surface (RS) model is developed utilizing experimental measurements in the mold cavity. RS model is further interfaced with the GA to optimize the cutting conditions for desired surface roughness. The GA reduces the surface roughness value in the mold cavity from 0.412 μm to 0.375 μm corresponding to about 10% improvement. Optimum cutting condition produced from GA is verified with the experimental measurement.

Keywords: Milling; Cutting conditions; Surface roughness; Injection molding; Response surface methodology; Genetic algorithm

1. Introduction

Recent developments in manufacturing industry have contributed to the importance of CNC milling operations [1,2]. Milling process is required to make mold parts used for producing plastic products. It is also preferred in machining mold parts made of Aluminum 7075-T6 material. Aluminum 7075-T6 material as chosen in this study is commonly utilized in aircraft and die/mold industries due to some advantages such as high resistance, good transmission, heat treatable and high tensile strength [3,4].

The quality of plastic products manufactured by plastic injection molding process is highly influenced by that of mold surfaces obtained from the milling process. Surface quality of these products is generally associated with surface roughness and can be determined by measuring surface roughness [5]. Surface roughness is expressed as the irregularities of material resulted from various machining operations. In quantifying surface roughness, average surface roughness definition, which is often represented with R_a symbol, is commonly used. Theoretically, R_a is the arithmetic average value of departure of the profile from the mean line throughout the sampling length [6]. R_a is also an important factor in controlling machining performance. Surface roughness is influenced by tool geometry, feed, cutting conditions and the irregularities of machining operations such as tool wear, chatter, tool deflections, cutting fluid, and workpiece properties [7,11,16]. The effect of cutting conditions (feed, cutting speed, axial–radial depth of cut and machining tolerance) on surface roughness is discussed in this study.

Several researchers have studied the effect of cutting conditions in milling and plastic injection molding processes such as in vacuum-sealed molding process [5]. Analytical models have been created to predict surface roughness and tool life in terms of cutting speed, feed and axial depth of cut in milling steel material [8,9]. An effective approach has also been presented to optimize surface finish in milling Inconel 718 [10].

* Corresponding author. Tel.: +90 262 742 32 90; fax: +90 262 742 40 91.
E-mail address: hoktem@kou.edu.tr (H. Öktem).

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In this study, a fourth order response surface (RS) model for predicting surface roughness values in milling the mold surfaces made of Aluminum (7075-T6) material is developed. In generating the RS model statistical response surface methodology (RSM) is utilized. The accuracy of the RS model is verified with the experimental measurement. The developed RS model is further coupled with a developed genetic algorithm (GA) to find the optimum cutting condition leading to the least surface roughness value. Cutting condition is represented with cutting parameters of feed, cutting speed, axial–radial depth of cut and machining tolerance. The predicted optimum cutting condition by GA is validated with an experimental measurement.

The RS model and GA developed and utilized in this study present several advantages over other methods in the literature. The RS model is a higher order and more sophisticated polynomial model with sufficient accuracy. The GA eliminates the difficulty of user-defined parameters of the existing GAs. Details of the RS model generation by RSM and the optimization process by GA are given in the following sections.

2. Experimental procedures

2.1. Plan of experiments

An important stage of RS model generation by RSM is the planning of experiments. In this study, cutting experiments are planned using statistical three-level full factorial experimental design. Cutting experiments are conducted considering five cutting parameters: feed (f_t), cutting speed (V_c), axial depth of cut (a_a), radial depth of cut (a_r) and machining tolerance (m_t). Overall $3^5 = 243$ cutting experiments are carried out. Low–middle–high level of cutting parameters in cutting space for three-level full factorial experimental design is shown in Table 1. Ranges of cutting parameters are selected based on recommendation of Sandvik Tool Catalogue [12]. Milling operations are performed at the determined cutting conditions on a DECKEL MAHO DMU 60 P five axis CNC milling machine. Surface roughness (R_a) values are measured from the mold surfaces.

2.2. Tool and material

Cutting tool used in experiments has the diameter of 10 mm flat end mill with four teeth. The material of the tool is PVD AlTiN coated with solid carbide. It has the helix angle of 45° and rake angle of 10°. Machining experiments are performed in the mold cavity on aluminum (7075-T6) block with dimensions of 120 mm × 120 mm × 50 mm. The chemical composition of workpiece material is given in the following specification (wt.%): 1.6 Cu, 2.5 Mg, 0.23 Cr, 5.40 Zn. The hardness of workpiece is measured as 150 BHN. The mechanical properties of aluminum material are: tensile strength of 570 MPa, yield strength of 505 MPa, shear strength of 330 MPa and elongation of 11%.

Table 1
Low–middle–high levels of cutting parameters in three-level full factorial design of experiment

Cutting parameters	Three- level values
Feed, f_t (mm/tooth)	0.08–0.105–0.13
Cutting speed, V_c (m/min)	100–200–300
Axial depth of cut, a_r (mm)	0.3–0.5–0.7
Radial depth of cut, a_r (mm)	1–1.5–2
Machining tolerance, m_t (mm)	0.001–0.0055–0.01

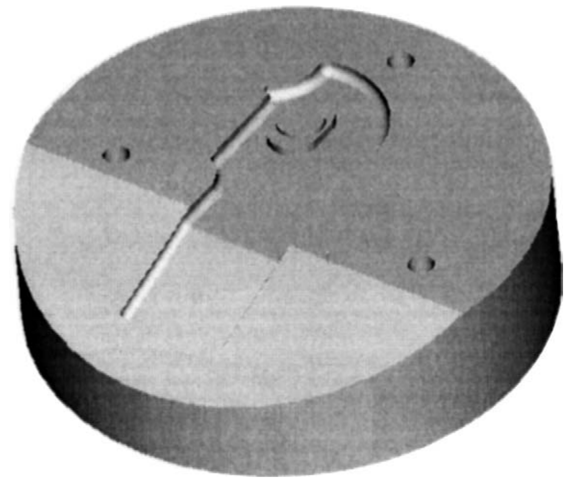


Fig. 1. Mold part.

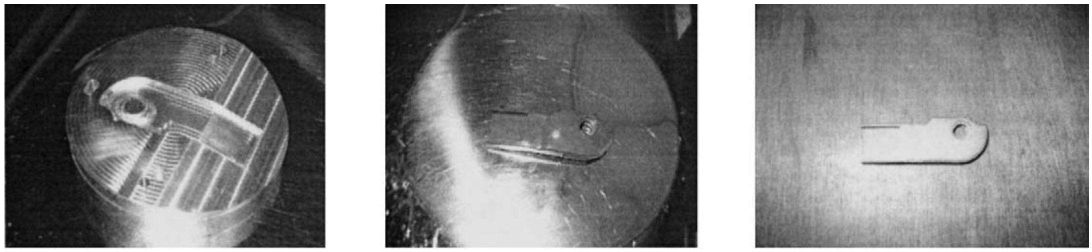
Surface roughness is measured with Surftest 301 profilometer at traverse length of 2.5 mm along centerline of sampling. Converting the measurement into a numerical value, mathematical definition of R_a is used. Since this way of conversion is common in the literature it is adopted in this study as well [7–9]. Each R_a measurement is repeated at least three times. Average of three R_a values is saved to establish RS model.

2.3. Mold parts

The mold part used in this study is utilized to produce the components of an orthose part in biomechanical applications. It is shown in Fig. 1. Orthose parts are generally utilized in walking apparatus that holds human legs in stable position during walking. It binds the kneecap region of leg and is equipped with cylindrical bars that are made of aluminum material in diameter of 12 mm and length of 300 mm. Orthose part consists of three main components; one of them is employed as the working model in this study.

2.4. Manufacturing the components of orthose part

Three machining processes are implemented in order to manufacture each component of the orthose part in an integrated manner. Firstly, the selected component is machined in CNC milling machine. R_a values are then taken from the surfaces in the mold cavity. Secondly, plastic product is injected



(a) The Mold part milled (b) Plastic product (c) Die casting part

Fig. 2. The parts obtained from three machining process.

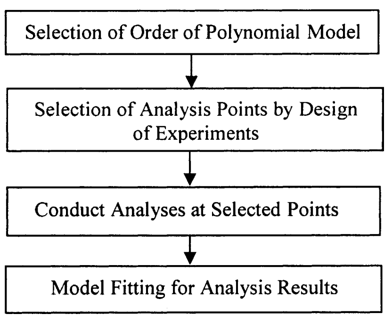


Fig. 3. The stages taken in creating a response surface model by RSM.

in plastic injection machine produced by ARBURG. Polyacetal (POM) C 9021 material is used to inject the polymer material. The properties of polymer material has the density of solution 1.2 g/cm^3, the ejected temperature of 165 °C, viscosity of 50 Pa s and melt flow-fill rate of 0.8 cm^3/min. Finally, net casting process is applied for producing die casting part. Mold part, plastic product and die casting part are illustrated in Fig. 2.

3. Response surface model for surface roughness

RS model, which is an analytical function, in predicting surface roughness values is developed using RSM. RSM uses statistical design of experiment (experimental design) technique and least-square fitting method in model generation phase. It is summarized in Fig. 3. RSM was originally developed for the model fitting of physical experiments by Box and Draper [13] and later adopted in other fields. RS model is formulated as following polynomial function:

$$f = a_0 + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n}\sum_{j=1}^{n} a_{ij} x_i x_j + \cdots \quad (1)$$

where a_0, a_i and a_{ij} are tuning parameters and n is the number of model parameters (i.e. process parameters). In this study, to create RS model, a computer program has been written in MATLAB programming language.

The RS program developed has the capability of creating RS polynomials up to 10th order if sufficient data exist. All cross terms (i.e. interactions between parameters) in the models can be taken into account. RS models can also be generated in terms of inverse of parameters. That is, $x_{\rm i}$ can be replaced as $\frac{1}{x_i}$ (i.e. inversely) in RS model if desired, in creating the RS models, 243 surface roughness values determined based on three-level full factorial experimental design for five parameters ($f_{\rm t}$, $V_{\rm c}$, $a_{\rm a}$, $a_{\rm r}$ and $m_{\rm t}$) are used The 243 data sets for surface roughness are divided into two parts; training data set and the check (i.e. test) data set. Training data set includes 236 surface roughness values and is utilized in model fitting procedure. Because of large number of values and to save space, training data is shown in Fig. 4, rather than in a table. In Fig. 4, abscissa indicates the data set number and the ordinate indicates the corresponding surface roughness value. Check data sets include seven surface roughness values and are used in checking the accuracy of the RS model. Check data sets are shown in Table 2. They

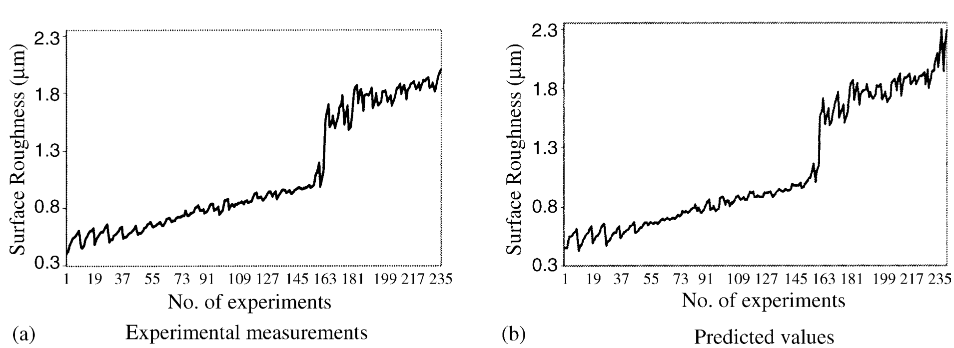


Fig. 4. Comparison of experimental measurements with RS prediction for surface roughness.

Table 2
The data set used for checking the accuracy of RS model

Set number	Cutting conditions					R_a (μm)		
	f_t	V_c	a_a	a_r	m_t	Measurement results	RSM model	Maximum test error (%)
1	0.105	200	0.7	1	0.001	0.591	0.589	
2	0.105	200	0.7	1.5	0.001	0.629	0.627	
3	0.105	200	0.3	1	0.0055	0.781	0.775	
4	0.08	200	0.7	1.5	0.0055	0.899	0.895	2.05
5	0.08	100	0.7	2	0.0055	0.978	0.996	
6	0.08	200	0.3	1.5	0.01	1.674	1.706	
7	0.105	200	0.5	2	0.01	1.856	1.893	

Table 3
The accuracy error of several RS models

Reciprocal flag	First order	Second order	Third order	Fourth order
[0 0 0 0 0]	27	7	4.8	2.7
[0 0 1 0 0]	25.9	7.28	5.8	2.95
[0 0 0 0 1]	52.4	10.9	4.0	2.99
[1 1 0 0 0]	27.2	6.63	4.8	**2.05**
[0 1 1 0 0]	25.9	7.0	5.5	2.55
[0 0 0 1 1]	54.9	10.5	3.7	2.7
[1 1 1 0 0]	25.8	7.03	5.7	2.5
[0 1 1 1 0]	27.5	7.0	5.9	2.8
[1 1 1 1 1]	53.03	10.5	4.7	2.7

are selected from 243 data sets to show a good distribution in the cutting parameters' space and thereby to have a good check on the accuracy of the RS model.

In this study, RS models of varying orders from first order to fourth order are created and tested with the developed program. Several RS model created are demonstrated along with their accuracy errors in Table 3. In reciprocal section in Table 3, 0 indicates a parameter (x_i), 1 indicates the inverse of a parameter ($\frac{1}{x_i}$). The full fourth order polynomial function of the form:

$$R_a = a_0 + a_1\frac{1}{f_t} + a_2\frac{1}{V_c} + a_3a_a + a_4a_r + a_5m_t + \cdots + a_n\left(\frac{1}{f_t}\frac{1}{V_c}a_aa_rm_t\right)^4 + \cdots + a_m(m_t)^4 \quad (2)$$

fits best (with minimum fitting error) to the training data set. The accuracy of the RS model was checked using the check data set. The maximum accuracy error is found to be about 2.05%. This indicates that RS model generated has sufficient accuracy in predicting surface roughness within the range of cutting parameters.

4. Optimization of cutting conditions for surface roughness

4.1. Optimization problem formulation

Since it is indicator of surface quality in milling of mold surfaces, surface roughness value is desired to be as low as possible. Low surface roughness values can be achieved efficiently by adjusting cutting conditions with the help of an appropriate numerical optimization method. For this, minimization of surface roughness problem must be formulated in the standard mathematical format as below:

$$\text{Find}: f_t, V_c, a_a, a_r, m_t \quad (3a)$$

$$\text{Minimize}: R_a(f_t, V_c, a_a, a_r, m_t) \quad (3b)$$

$$\text{Subjected to constraints}: R_a \leq 0.412\ \mu\text{m} \quad (3c)$$

Within ranges :

$$0.08\,\text{mm} \leq f_t \leq 0.13\,\text{mm}$$
$$100\,\text{mm} \leq V_c \leq 300\,\text{mm}$$
$$0.3\,\text{mm} \leq a_a \leq 0.7\,\text{mm}$$
$$1\,\text{mm} \leq a_r \leq 2\,\text{mm}$$
$$0.001\,\text{mm} \leq m_t \leq 0.01\,\text{mm}.$$

In Eq. (3), R_a is the RS model developed in Section 3. f_t, V_c, a_a, a_r and m_t are the cutting parameters. In the optimization problem definition above, a better solution is also forced through the constraint definition. Constraint definition searches a surface roughness value (R_a), which is less than the lowest value in 243 data set if possible. Minimum surface roughness value in 243 data set is 0.412 μm. The ranges of cutting parameters in optimization have been selected based on the recommendation of Sandvik Tool Catalogue.

4.2. Optimization problem solution

The optimization problem expressed in Eq. (3) is solved by coupling the developed RS model with the developed genetic algorithm as shown in Fig. 5.

The genetic algorithm [14] solves optimization problem iteratively based oh biological evolution process in nature (Darwin's theory of survival of the fittest). In the solution procedure, a set of parameter values is randomly selected. Set is ranked bashed on their surface roughness values (i.e. fitness

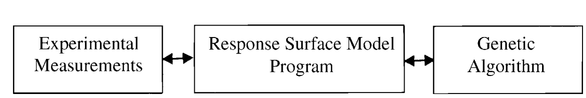


Fig. 5. Interaction of experimental measurements, RS model and GA during surface roughness optimization.

Table 4
GA parameters

Subject	Values
Population size	50
Crossover rate	1.0
Mutation rate	0.1
Number of bit	16
Number of generations	540

values in the GA literature). Best combination of parameters leading to minimum surface roughness is determined. New combination of parameters is generated from the best combination by simulating biological mechanisms of offspring, crossover and mutation. This process is repeated until surface roughness value with new combination of parameters cannot be further reduced anymore. The final combination of parameters is considered as the optimum solution. The critical parameters in GAs are the size of the population, mutation rate, number of iterations (i.e. generations), etc. and their values are given in Table 4.

The GA written in MATLAB programming language selects chromosomes based on the objective value and the level of constraint violation. Fitness values of the population are biased towards the minimum objective value and the least infeasible sets in offspring phase. Most of GAs in the literature converts the constrained optimization problem into an unconstrained optimization problem through penalty function before the solution. This brings the difficulty of appropriate selection of problem dependent penalty coefficient which requires user experience. In the program used in this study, this difficulty is avoided since no problem dependent coefficient is needed [15].

4.3. Optimization results and discussion

By solving the optimization problem, the GA reduces the surface roughness of mold surfaces from 0.412 μm to 0.375 μm by about 10% compared to the initial cutting condition. The best (optimum) cutting condition leading to the minimum surface roughness is shown in Table 5. The predicted optimum cutting condition by GA is further validated with a physical measurement. Predicted surface roughness value is compared with the measurement in Fig. 6. From Fig. 6 it is seen that GA result agrees very well with the measurement.

Table 5
The best cutting condition

Parameters	After optimization
Cutting condition	
f_t (m/tooth)	0.083
V_c (m/min)	200
a_a (mm)	0.302
a_r (mm)	1.002
m_t (mm)	0.002
R_a (μm)	
Measurement	0.370
GA	0.375

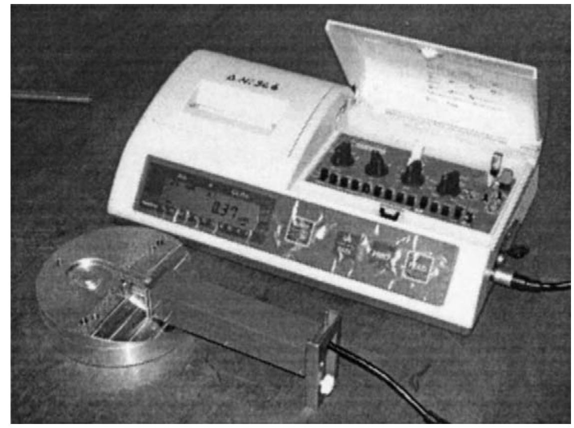


Fig. 6. Surface roughness measurement.

5. Conclusions

In this study, a fourth order RS model for predicting surface roughness values in milling mold surfaces made of Aluminum (7075-T6) material was developed. In generating the RS model statistical RSM was utilized. The accuracy of the RS model was verified with the experimental measurement. The accuracy error was found to be insignificant (2.05%). The developed RS model was further coupled with a developed GA to find the optimum cutting condition leading to the least surface roughness value. Surface roughness of the mold surfaces, which was 0.412 μm before optimization, was reduced to 0.375 μm after optimization. GA improved the surface roughness by about 10%. The predicted optimum cutting condition was validated with an experimental measurement. It was found that GA prediction correlates very well with the experiment. Difference was found to be less than 1.4%. This indicates that the optimization methodology proposed in this study by coupling the developed RS model and the developed GA is effective and can be utilized in other machining problems such as tool life, dimensional errors, etc. as well.

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