DEA BASED TAGUCHI APPROACH FOR MULTI-OBJECTIVE OPTIMIZATION IN MACHINING POLYMERS: A CASE STUDY

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Abstract

Recently, fierce market competition has forced almost all manufacturing sectors to become more concerned on improved product quality in an economic way. Quality and productivity are two important but contradicting aspects of any manufacturing/ production process. Moreover, product quality is generally assessed by multiple indices. It is therefore, often required to optimize multiple quality features in order to determine the most favourable process environment before the product is subjected to undergo for mass production. Taguchi's philosophy provides a trade-off between quality loss and productivity by engineering judgment. However, it fails to solve multi-objective optimization problem. In this context, Data Envelopment Analysis (DEA) can be applied as the means for converting multi-objectives into an equivalent single response; which can easily be optimized using Taguchi method. Application feasibility of proposed DEA based Taguchi method has been illustrated through a case study in which nylon have been machined using various process parameters (viz. cutting speed, feed rate and depth of cut) for optimizing material removal rate (MRR) and multiple surface roughness parameters of statistical importance.

Keywords: *Data Envelopment Analysis (DEA); Taguchi method*

Introduction and State of Art

The term nylon refers to a family of plastics. The two most common grades of nylon are Nylon 6 and Nylon 6/6. The number refers to the number of methyl groups which occur on each side of the nitrogen atoms (amide groups). The term polyamide, another name for nylon, reflects the presence of these amide groups on the polymer chain. The difference in number of methyl groups influences the properties of the nylon.

Unlike polycarbonate, nylon is crystalline in nature; so the molecular chains do not have large substituent groups (such as the phenyl ring in polycarbonate). The crystalline nature of the material is responsible for its wear resistance, chemical resistance, thermal resistance, and higher mold shrinkage. The properties of nylon include:

1. very good heat resistance
2. excellent chemical resistance
3. excellent wear resistance
4. moderate to high price
5. fair to easy processing

Literature has been found rich enough highlighting various aspects of machining of conventional metals; emphasis made to a lesser extent on machining and machinability of polymeric materials. With the worldwide application of polymeric material; in depth knowledge is highly essential for better understanding of machining process behavior, parametric influence and their interaction etc. in order to produce high quality finished part in terms of dimensional accuracy, material removal rate as well as good surface finish. Part quality can be improved by proper selection and precise control of the adjustable process parameters; the combination of which is called a particular process environment. There exists tremendous need to search the most suitable process environment (optimal) in order to satisfy multi-requirements of part quality simultaneously. This invites multi-objective optimization problem which seeks to determine an optimal solution (optimal process environment) to be determined prior to initiate mass production.

Surface roughness of the finished/ machined part is an important quality characteristic in any machining operation. A number of parameters of statistical importance are defined to describe extent of surface finish. Predictive modeling, optimization of surface roughness has been addressed by pioneer researchers and highlighted in literature.

(Lou et al., 1998-99) developed a multiple regression model for predicting surface finish in end milling process. The surface roughness (R_a) predication model was constituted by considering machining parameters viz. spindle speed, feed rate and depth of cut and their interaction. (Lee and Tarng, 2001) proposed a polynomial network model to inspect surface roughness by developing the relationship between the features of the surface image and the actual surface roughness under a variation in machining parameter on turning operation. (Özel and Karpet, 2005) used neural network and regression model analysis for predicating the surface quality and tool flank wear over the machining time for variety of machining conditions in finish hard turning of AISI 52100 steel by using CBN tools. (Kirby, 2006) discussed on the application of Taguchi framework of experimental design for optimizing the surface roughness during the CNC milling. (Nalbant et al., 2007) examined the performance characteristics of the cutting parameters viz. insert radius, feed rate and depth of cut during the turning operation of AISI 1030 steel bars by using the TiN coated tools. The performance characteristic comprised the surface roughness which was optimized by using Taguchi's robust design technique.

(Routara et al., 2007) predicted optimal machining parameter condition for multi performance characteristics of the surface finish in CNC turning on AISI 1040 mild steel bar. The machining parameter viz. spindle speed, depth of cut and feed rate were used for assessing the different roughness parameters of statistical significance such as centre line average, root mean square and mean-line peak spacing. (Jurkovic et al., 2010) made a comparative study on the methods of optimization based on experimental plan in between the conventional rotatable central composite design and orthogonal array for enhancing the surface finish in finish longitudinal turning operations. (Kaladhar et al., 2011) presented a multi-characteristics response model for optimizing process parameter in turning on AISI 202 austenitic stainless steel using a CVD coated cemented carbide tool with Taguchi robust design integrated with utility concept.

(Ramesh et al., 2011) developed correlation between the process parameters viz. cutting speed, depth of cut and feed rate by using the multiple regression analysis and examined the influence of machining conditions in turning of Duplex stainless steel 2205. (Deep et al., 2011) proposed a mathematical model for analyzing the effect of the machining parameters during single and multi-pass turning by using the Real Coded Genetic Algorithm.

In this present article, Taguchi's robust technique integrated with (Data Envelopment Analysis) DEA has been used to achieve an optimal machining parameter setting for enhancing surface quality and MRR of machined nylon product. The basics and formulation of DEA technique have been well documented in literature (Liao and Chen, 2002; Liao. 2004; Gutiérrez and Lozano, 2010).

Experimentation

Samples of nylon 6 bars with dimensions of (Ø50x150) mm with cutting length of 50 mm have been used. Single point HSS Tool of Indolov SHRIRAM IK-20 has been used for the machining operation. Taguchi's L_9 orthogonal array has been used here (Table1). Table 2 indicates selected process control parameters and their limits. Three machining parameters: cutting speed, feed rate and depth of cut has been varied into three different levels are used to optimize the machining conditions. The manually operated lathe PINACHO has been used for the machining. Corresponding to each experimental run MRR and multiple surface roughness values have been computed (Table 3). The surface roughness has been measured by the Talysurf (Taylor Hobson, Surtronic 3+). One representative pictorial view of surface profile has been shown in Figure 1.

Proposed Methodology

Data Envelopment Analysis (DEA) is first formulated by *Charles, Cooper, Rhodes* in *1978* has been recognized as a valuable analytical research instrument and a practical decision-making tool. DEA is linear programming based technique which is used to empirically measure the productive efficiency of decision making units (DMUs) when the production process presents a structure of multiple inputs and outputs. The efficiency of 'multiple inputs and output factors' can be defined as the following:

E_k = weighted sum of outputs/ weighted sum of inputs

Step 1: Normalization of input response

It is necessary to normalize responses to ensure that all the attributes are equivalent and the same formal.

The given MRR response is normalized by the following equations:

$$Z_{ij} = \frac{X_{ij}}{\max X_{ij}} \quad , \quad \text{for} \quad i = 1,2,\ldots\ldots\ldots,m \quad \text{and} \quad j = 1,2,\ldots\ldots\ldots,n \tag{1}$$

For surface roughness parameters:

$$Z_{ij} = \frac{\min X_{ij}}{X_{ij}} \quad , \quad \text{for} \quad i = 1,2,\ldots\ldots\ldots,m \quad \text{and} \quad j = 1,2,\ldots\ldots\ldots,n \tag{2}$$

Here, X_{ij} is mean for the i^{th} response in the j^{th} experiment.

Step 2: Calculation for relative efficiency

For each experiment the relative efficiency has been computed by the aid of Lingo software package.

Following equation is used for the calculation of the relative efficiency:

$$\max E_{kk} = \sum_y O_{ky} V_{ky} \tag{3}$$

Such that,

$$\sum I_{kx} U_{kx} = 1$$

$$E_{ks} \leq 1 \quad \forall \text{ design such that,}$$

$$U_{kx}, V_{ky} > 0$$

Taguchi has been finally applied on relative efficiency for evaluating most favorable process environment.

Results and Discussion

Experimental data presented in Table 3 have been analyzed by aforementioned procedure. Data have been normalized first by using Eq. 1-2 respectively. Normalized data has been furnished in Table 4. Normalized data of different surface roughness parameters has been treated as input factor whereas normalized data of MRR has been considered as output factor in LINGO software for assessing the relative efficiency (Table 5). Finally, Taguchi has been adopted on relative efficiency for assessing optimal condition and $N_2 f_3 d_2$ has been predicated (Figure 2) as more favorable machining condition. Predicted result has been verified through confirmatory test. Table 6 represents factor ranking in accordance with their degree of significance.

Conclusions

The preceding research has applied DEA coupled with Taguchi's optimization technique for determining favorable machining conditions in machining of nylon. This approach can be recommended for continuous quality improvement and off-line quality of any production process.

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Table 1: L_9 orthogonal array

Sl. No.	Factorial combinations (coded)		
	N	f	d
1	1	1	1
2	1	2	2
3	1	3	3
4	2	1	2
5	2	2	3
6	2	3	1
7	3	1	3
8	3	2	1
9	3	3	2

Table 2: Domain of experiments
(Process control parameters and their limits)

Factors	Unit	Level 1	Level 2	Level 3
Cutting speed	m/min	360	530	860
Feed rate	mm/rev	0.083	0.166	0.331
Depth of cut	mm	2	3	4

Table 3: Experimental data

R_q (µm)	R_a (µm)	R_t (µm)	MRR (mm^3/min)	R_{ku}	R_z (µm)	R_{sm} (mm)	R_q (µm)
1.613	1.350	8.433	1436.839	2.407	7.177	0.044	1.613
5.013	4.190	39.800	3992.675	9.827	19.967	0.098	5.013
5.563	4.760	23.533	9909.792	2.067	21.000	0.162	5.563
2.333	1.786	18.397	4290.983	17.900	10.960	0.055	2.333
3.100	2.640	12.633	7693.065	2.167	11.200	0.082	3.100
5.337	4.653	20.067	5298.241	1.803	18.633	0.160	5.337
1.067	0.858	6.823	6048.701	3.143	5.047	0.053	1.067
3.477	2.976	13.367	4762.783	2.190	12.333	0.081	3.477
4.697	4.243	18.033	18843.154	1.617	15.900	0.161	4.697

Table 4: Normalized input and output responses

R_q (µm)	R_a (µm)	R_t (µm)	MRR (mm^3/min)	R_{ku}	R_z (µm)	R_{sm} (mm)
0.661	0.636	0.809	0.076	0.672	0.703	1.000
0.213	0.205	0.171	0.212	0.165	0.253	0.451
0.192	0.180	0.290	0.526	0.782	0.240	0.274
0.457	0.480	0.371	0.228	0.090	0.460	0.812
0.344	0.325	0.540	0.408	0.746	0.451	0.538
0.200	0.184	0.340	0.281	0.896	0.271	0.277
1.000	1.000	1.000	0.321	0.514	1.000	0.842
0.543	0.288	0.510	0.253	0.738	0.409	0.547
0.227	0.202	0.378	1.000	1.000	0.317	0.276

Table 5: Calculated relative efficiency

Sl. No.	N	f	d	Relative efficiency
1	1	1	1	0.09327
2	1	2	2	1.00000
3	1	3	3	0.69478
4	2	1	2	1.00000
5	2	2	3	0.51121
6	2	3	1	0.32869
7	3	1	3	0.50403
8	3	2	1	0.32455
9	3	3	2	1.00000

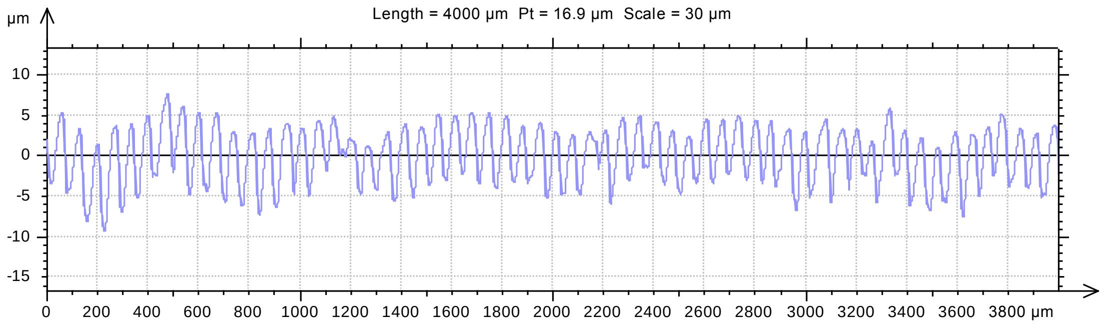

Figure 1: Representative figure of roughness profile (Sample No. 1)

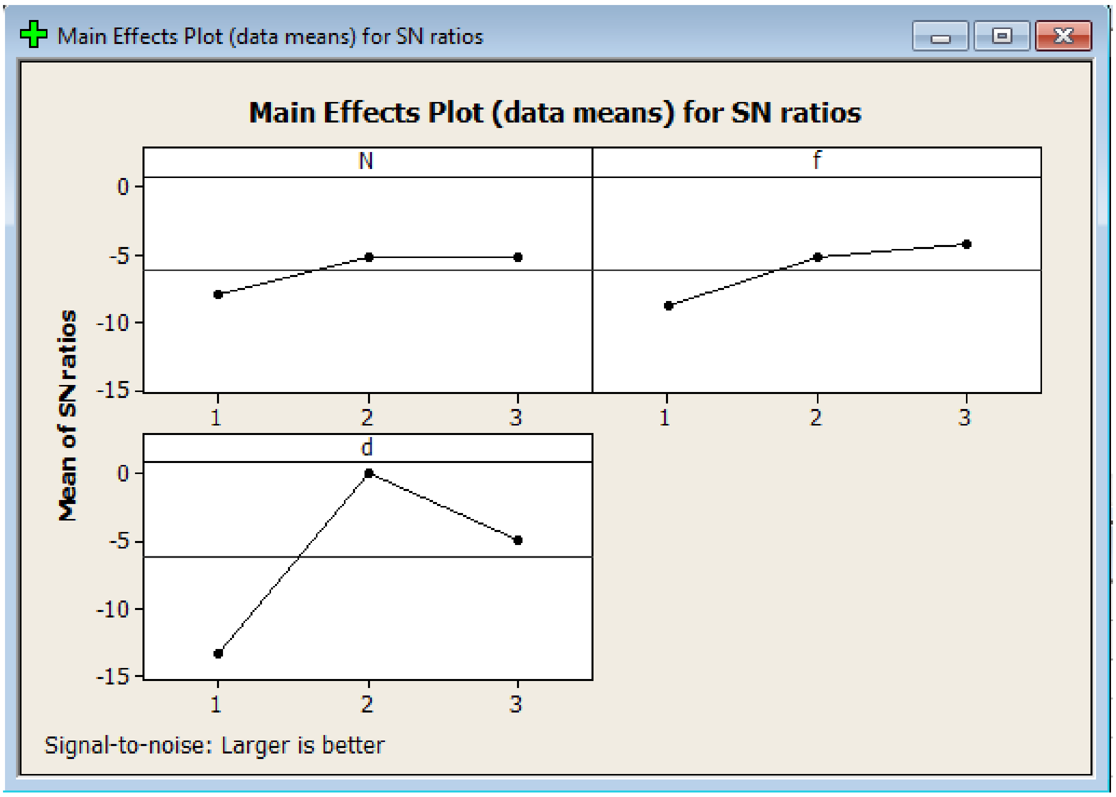

Figure 2: Evaluation of optimal setting

Table 6: Mean response table

Level	N	f	D
1	-7.9227	-8.8520	-13.3479
2	-5.1641	-5.2008	0.000
3	-5.2417	-4.2758	-4.9806
Delta	**2.7586**	**4.5762**	**13.3479**
Rank	**3**	**2**	**1**