Multi-criteria Optimization Using Taguchi and Grey Relational Analysis in CNC Turning of PEEK CF30

Francisco Mata Cabrera* and Demetrio Fuentes

Polytechnic School of Almaden, University of Castilla-La Mancha, 1 Plaza Manuel Meca, 13400 Almaden, Ciudad Real, Spain

Issam Hanafi and Abdellatif Khamlichi

Modelling and Simulation of Mechanical Systems Laboratory, Faculty of Sciences at Tetouan, University Abdelmalek Essaadi, BP. 2121 M'hannech, 93002 Tetouan, Morocco

Abdallah Jabbouri

Materials and Mechanics of Structures Laboratory, Faculty of Sciences and Technology at Tangier, University Abdelmalek Essaadi, BP 416, Tangier, Morocco

ABSTRACT: The robust design of turning parameters is dealing with the optimization of surface roughness and cutting force in turning of reinforced polyetheretherketone (PEEK) with 30% of carbon fibers (PEEK CF30) using TiN-coated cutting tools. The selected turning parameters include the cutting speed, feed rate and depth of cut. Grey–Taguchi method is combining orthogonal array design of experiments with relational analysis, which enables the determination of the optimal combination of turning parameters with the multiple criteria. The basic aim of grey relational analysis is to find the grey relational grade, which can be used for the optimization conversion from a multi-criteria problem to a single objective problem. This study not only proposes a novel optimization technique, but also contributes the satisfactory solution for multiple CNC turning objectives with profound insight.

*Author to whom correspondence should be addressed.
E-mail: francisco.mcabrera@uclm.es
Figure 1–4 appear in color online http://jtc.sagepub.com

0892-7057/11/00 1–14 $10.00/0 DOI: 10.1177/0892705711405248

KEY WORDS: PEEK CF30, turning, TiN-coated cutting tool, grey relational analysis, surface roughness, cutting force, multi-criteria optimization.

INTRODUCTION

ADVANCED COMPOSITE MATERIALS have been used to fabricate many structural parts in engineering applications. This is due to their many attractive characteristics such as light weight, high strength, high stiffness, good fatigue resistance and good corrosion resistance. Also, the ability to manufacture parts with complicated geometry using fewer components enables manufacturers to save cost compared with the same parts made of conventional metallic materials.

Machinability of thermoplastic polymers in turning is studied usually in terms of cutting forces, cutting temperature, surface quality and tool wear. The addition of short fibers to thermoplastic composites enhances their mechanical properties such as stiffness strength and hardness, and also increases the service temperature in comparison with non-reinforced thermoplastics [1–5]. It has been reported that the addition of short fibers not only reduces the coefficient of friction and wear but also decreases the thermal expansion coefficient [6]. The carbon and glass fibers are the common reinforcements in thermoplastics because of their low-expansion rate and their high-flexural modulus. The carbon fiber reinforcement provides maximum rigidity and load bearing capacity [7,8], whereas the glass fiber reinforcement provides high temperature service [9].

Surface roughness plays an important role in many areas and is a factor of great importance in the evaluation of machining accuracy [10]. Although many factors affect the surface condition of a machined part, machining parameters, such as cutting speed, feed rate, depth of cut, and work piece properties have a significant influence on the surface roughness for a given machine tool and work piece setup. Cutting forces are oscillating and periodic in nature when machining fiber-reinforced plastics (FRPs). The oscillation originates from repeated running of cutting tool into fibers and matrix phases, which produces strong variations of cutting forces magnitudes.

Most of the studies on machining show that minimizing the surface roughness is very difficult and is to be controlled. However, for the practical machining of FRP materials, it is necessary to determine the optimal machining parameters to achieve less cutting force, good surface finish, etc. Optimization of process parameters is the important criterion in the machining process to achieve high quality. To optimize the data based on the experimental results, the traditional statistical regression requires large amount of data, which causes the difficulty in treating the typical normal distribution of data and the lack of variant factors. Optimization of multiple response characteristics is more complicated than the single performance characteristics. For optimization, Taguchi method with grey relational analysis has been used. Taguchi's parameter design is widely used in conducting and analyzing experiments [11]. It offers a simple and systematic approach to optimizing design for performance, quality and cost [12]. Taguchi's approach extensively uses statistical design of experiments (DOE) [13]. By applying this technique, one can significantly reduce the number of experiments and time required for experimentation [14].

The Grey theory can provide a solution of a system in which the model is unsure or the information is incomplete [15]. It also provides an efficient solution to the uncertainty, multiple inputs and discrete data problem like machining [16]. The grey relational analysis is successfully applied already for machining process. Tosun [17] used grey relational analysis in optimizing the drilling parameters. Huang and Lin [18] applied the grey relational analysis to design the die-sinking electric discharge machining parameters. Fung [19] studied the grey relational analysis to obtain the optimal parameters. Yang et al. [20] conducted end milling operation of high purity graphite. They have optimized the end milling parameters such as cutting speed, feed rate and depth of cut for groove width and surface roughness. Chiang and Chang [21] used the grey relational analysis to optimize of the wire electric discharge machining process of particle-reinforced material with multiple performance characteristics. Recently, Chorng-Jyh et al. [22] used Taguchi method with grey relational analysis for the optimization of turning operations with multiple performance characteristics. From the above studies, it has been found that the grey relational analysis is one of the important optimization techniques and can be successfully applied for machining process such as turning.

In this study, Taguchi's L_{27} orthogonal array, S/N ratio and grey relational analysis are applied to examine how the turning parameters influence the quality targets of surface roughness and cutting force during dry turning of reinforced polyetheretherketone (PEEK) with 30% of carbon fibers (PEEK CF30) using TiN-coated cutting tools. The control factors considered are cutting speed, feed rate and depth of cut.

Experimental Work

The work material used for this investigation is the PEEK CF30 (supplied by ERTA®). It consists of cylindrical work pieces with 50 mm diameter and

Table 1. Mechanical and thermal properties of PEEK CF30 composite.

Mechanical and thermal properties	**PEEK CF30**	**Unit**
Tensile modulus	7700	MPa
Rockwell hardness	M102	–
Charpy impact resistance	35	kJ/m^2
Tensile strength	130	MPa
Melting temperature	340	°C
Density	1.41	g/cm^3
Coefficient of thermal expansion at (<150°C)	25×10^{-6}	m/m/K
Coefficient of thermal expansion at (>150°C)	55×10^{-6}	m/m/K

Figure 1. *CNC machining turn GORATU G CRONO 4S.*

100 mm length. The main mechanical and thermal properties of this study material are summarized in Table 1.

Dry turning experiments were carried out on a GORATU G CRONO 4S CNC (Figure 1) using TiN-coated cutting tools. A SDJCL 2020 K11 tool holder was used. The surface roughness was evaluated (according to ISO 4287-1:1997) with a Hommeltester T500 profilometer (Figure 2). For each palpation, five measurements were made over turned surfaces. Considering the high number of palpations to be carried out, a programmable technique was used by previously selecting a roughness profile, the cut-off (0.8 mm) and the roughness evaluator parameters, according to ISO 4287-2:1997. Three component turning forces (radial force – F_p, cutting force – F_c, and feed force – F_a) were recorded with a Kistler piezoelectric dynamometer

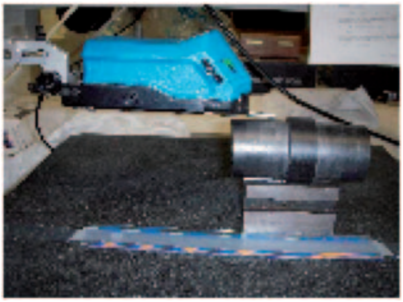

Figure 2. *Hommeltester T500 profilometer.*

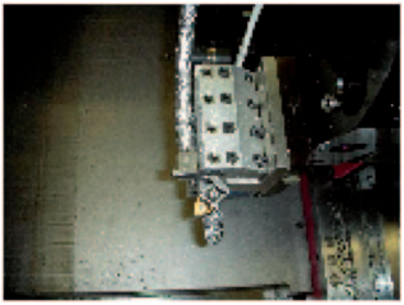

Figure 3. *Dynamometer.*

model 9121 (Figure 3) connected to a load amplifier and data acquisition board.

The experiments were conducted according to a full-factorial DOE table. The three cutting parameters selected for this investigation are cutting speed (v), feed rate (f), and depth of cut (d). Since the considered variables are multi-level variables and their outcome effects are not necessarily linearly related, it has been decided to use three level tests for each factor. The machining parameters used and their levels are shown in Table 2.

The three level L_{27} orthogonal arrays are shown in Table 3, where the numbers 1, 2, and 3 stand for the levels of the factors.

Optimization Steps Using Grey Relational Analysis

The grey relational theory provides an efficient management upon the uncertainty, multi-input and discrete data. Grey relational analysis is

Table 2. Machining parameters and their levels.

	Symbol	Level	Code
Cutting speed (m/min)	A_1	300	1
	A_2	200	2
	A_3	100	3
Feed rate (mm/rev)	B_1	0.20	1
	B_2	0.15	2
	B_3	0.05	3
Depth of cut (mm)	C_1	1.5	1
	C_2	0.75	2
	C_3	0.25	3

Table 3. Experimental results for surface roughness, cutting force and their corresponding S/N ratio.

	Factors			Measured parameters		Calculated S/N ratio	
Trial n°	*A*	*B*	*C*	Surface roughness (μm)	Cutting force (N)	S/N ratio for surface roughness	S/N ratio for cutting force
1	1	1	1	1.855	107.79	−5.37	−40.65
2	1	2	1	1.72	96.00	−4.71	−39.65
3	1	3	1	1.03	76.17	−0.26	−37.64
4	1	1	2	1.315	53.46	−2.38	−34.56
5	1	2	2	1.305	58.39	−2.31	−35.33
6	1	3	2	1.13	47.41	−1.06	−33.52
7	1	1	3	1.47	23.17	−3.35	−27.30
8	1	2	3	1.14	23.89	−1.14	−27.56
9	1	3	3	0.985	18.49	0.13	−25.34
10	2	1	1	1.255	133.03	−1.97	−42.48
11	2	2	1	1.07	125.55	−0.59	−41.98
12	2	3	1	0.945	98.65	0.49	−39.88
13	2	1	2	1.275	76.28	−2.11	−37.65
14	2	2	2	1.055	70.93	−0.47	−37.02
15	2	3	2	1.095	53.99	−0.79	−34.65
16	2	1	3	1.43	28.75	−3.11	−29.17
17	2	2	3	1.265	26.65	−2.04	−28.51
18	2	3	3	1.2	20.48	−1.58	−26.23
19	3	1	1	1.26	145.49	−2.01	−43.26
20	3	2	1	0.995	136.84	0.04	−42.72
21	3	3	1	0.89	104.19	1.01	−40.36
22	3	1	2	1.485	66.91	−3.43	−36.51
23	3	2	2	1.23	67.71	−1.80	−36.61
24	3	3	2	1.065	67.42	−0.55	−36.58
25	3	1	3	1.285	28.43	−2.18	−29.08
26	3	2	3	1.225	27.19	−1.76	−28.69
27	3	3	3	1.14	21.94	−1.14	−26.82

actually a measurement of the absolute value of the data difference between sequences, and it could be used to measure the approximate correlation between sequences. For optimization of process parameters, the following steps are followed.

CALCULATION OF S/N RATIO FOR THE RESPONSES

The signal-to-noise (S/N) ratio) is an effective representation to find significant parameters by evaluating minimum variance. A higher S/N means the better performance. Usually, there are three categories of quality characteristic in the analysis of the S/N ratio, i.e. the-lower-the-better, the-higher-the-better, and the-nominal-the-better. The S/N ratio characteristics given by:

Nominal is the best characteristic:

$$\frac{\mathrm{S}}{\mathrm{N}} = 10\log\frac{\bar{y}}{Sy^2} \tag{1}$$

Smaller the better characteristic:

$$\frac{\mathrm{S}}{\mathrm{N}} = 10\log\frac{1}{n}\left(\sum y^2\right) \tag{2}$$

and larger the better characteristic:

$$\frac{\mathrm{S}}{\mathrm{N}} = -\log\frac{1}{n}\left(\sum\frac{1}{y^2}\right) \tag{3}$$

where $\bar{y}$ is the average of observed data, Sy^2 the variation, n the number of observations, and y the observed data. The responses considered in the experiment are surface roughness and cutting force, which are having smaller-the-better characteristics. The S/N ratio of the responses considered are calculated and presented in Table 3.

NORMALIZATION OF THE EXPERIMENTAL RESULTS (DATA PREPROCESSING)

Depending on the characteristics of a data sequence, there are various methodologies of data preprocessing available for the grey relational analysis. If the target value of the original sequence is infinite, then it has a characteristic of the 'higher is better'. The original sequence can be normalized as follows:

$$x_i^*(k) = \frac{x_i^0(k) - \min x_i^0(k)}{\max x_i^0(k) - \min x_i^0(k)} \tag{4}$$

when the 'lower is better' is characteristic of the original sequence, then the original sequence should be normalized as follows:

$$x_i^*(k) = \frac{\max x_i^0(k) - x_i^0(k)}{\max x_i^0(k) - \min x_i^0(k)} \tag{5}$$

where $i = 1, \ldots, n$, m is the number of experiments data items and n the number of parameters $x_i^0(k)$ denotes the original sequence, $x_i^*(k)$ the sequence after the data preprocessing, $\max x_i^0(k)$ the largest value of $x_i^0(k)$, $\min x_i^0(k)$ the smallest value of $x_i^0(k)$. The normalized values obtained for surface roughness and cutting force are presented in Table 4.

CALCULATATION OF THE DEVIATION SEQUENCE

In grey relational analysis, the measure of the relevancy between two systems or the sequences is defined as the grey relational grade (GRG). The $x_0(k)$ is the ideal sequence for surface roughness and cutting force. The definition of the GRG in the grey relational analysis is to show the relational degree between the sequences of $x_0(k)$ and $x_i(k)$, $(i = 1, 2, \ldots, m;$ $k = 1, 2, \ldots, n)$, where m is the total number of experiment to be considered, and n the total number of observation data. The grey relational coefficient $\xi(k)$ can be calculated as follows:

$$\xi(k) = \frac{\Delta_{\min} + \zeta\Delta_{\max}}{\Delta Oi(k) + \zeta\Delta_{\max}} \tag{6}$$

where ΔOi denotes the absolute value of the difference between $x_0(k)$ and $x_i(k)$ and is also known as the deviation sequence, and ζ the distinguishing coefficient. A value of the ζ is the smaller and the distinguished ability is the larger $\zeta = 0.5$ is generally used.

$$\Delta Oi(k) = \left\| x_0^*(k) - x_i^0(k) \right\| \tag{7}$$

Table 4. The result of normalization of the response variables the deviation sequence.

Normalization			Deviation sequence	
Trial N°	Surface roughness	Cutting force	Surface roughness	Cutting force
1	1.000	0.854	0.000	0.146
2	0.897	0.799	0.103	0.201
3	0.199	0.686	0.801	0.314
4	0.531	0.515	0.469	0.485
5	0.520	0.557	0.480	0.443
6	0.324	0.456	0.676	0.544
7	0.683	0.109	0.317	0.891
8	0.337	0.124	0.663	0.876
9	0.138	0.000	0.862	1.000
10	0.467	0.956	0.862	0.044
11	0.251	0.929	0.749	0.071
12	0.082	0.811	0.918	0.189
13	0.489	0.687	0.511	0.313
14	0.232	0.652	0.768	0.348
15	0.282	0.520	0.718	0.480
16	0.646	0.214	0.354	0.786
17	0.478	0.177	0.522	0.823
18	0.406	0.050	0.594	0.950
19	0.473	1.000	0.527	0.000
20	0.152	0.970	0.848	0.030
21	0.000	0.838	1.000	0.162
22	0.696	0.623	0.304	0.377
23	0.440	0.629	0.560	0.371
24	0.245	0.627	0.755	0.373
25	0.500	0.209	0.500	0.791
26	0.434	0.187	0.566	0.813
27	0.337	0.083	0.663	0.917

$$\Delta_{\min} = \min_{\forall je} \min_{\forall k} \left\| x_0^*(k) - x_j^*(k) \right\| \tag{8}$$

$$\Delta_{\max} = \max_{\forall je} \max_{\forall k} \left\| x_0^*(k) - x_j^*(k) \right\| \tag{9}$$

The deviation sequence ΔOi, $\Delta_{\min}(k)$, and $\Delta_{\max}(k)$ for $i = 1 - 27$, $k = 1 - 2$. Using Table 3, $\Delta_{\min}$ and $\Delta_{\max}$ can be found. The values for $\Delta_{\max} = 1$ and $\Delta_{\min} = 0$. The calculated grey relational coefficient using Equation (6) for different turning conditions is presented in Table 5.

Table 5. The calculated grey relational coefficient and GRG.

	Factors			Grey relational coefficient			
Trial n°	A	B	C	Surface roughness (μm)	Cutting force (N)	GRG	Rank
1	1	1	1	1.000	0.774	0.887	1
2	1	2	1	0.829	0.713	0.771	2
3	1	3	1	0.384	0.615	0.499	14
4	1	1	2	0.516	0.507	0.512	13
5	1	2	2	0.510	0.530	0.520	12
6	1	3	2	0.425	0.479	0.452	20
7	1	1	3	0.612	0.360	0.486	17
8	1	2	3	0.430	0.363	0.397	25
9	1	3	3	0.367	0.333	0.350	27
10	2	1	1	0.367	0.920	0.644	5
11	2	2	1	0.400	0.875	0.638	6
12	2	3	1	0.352	0.726	0.539	10
13	2	1	2	0.495	0.615	0.555	8
14	2	2	2	0.394	0.589	0.492	15
15	2	3	2	0.411	0.510	0.460	19
16	2	1	3	0.585	0.389	0.487	16
17	2	2	3	0.489	0.378	0.434	22
18	2	3	3	0.457	0.345	0.401	24
19	3	1	1	0.487	1.000	0.744	3
20	3	2	1	0.371	0.943	0.657	4
21	3	3	1	0.333	0.755	0.544	9
22	3	1	2	0.622	0.570	0.596	7
23	3	2	2	0.472	0.574	0.523	11
24	3	3	2	0.398	0.573	0.486	18
25	3	1	3	0.500	0.387	0.444	21
26	3	2	3	0.469	0.381	0.425	23
27	3	3	3	0.430	0.353	0.391	26

CALCULATION OF THE GREY RELATIONAL COEFFICIENT

After the grey relational coefficient is derived, it is usual to take the average value of the grey relational coefficient as the GRG. The GRG is defined as follows:

$$\gamma i = \frac{1}{n}\sum_{k=1}^{n} \xi_j(k)$$

The calculated grey relational coefficient and GRG are presented in Table 5. The GRG graph with respect to experiment number is presented in Figure 4.

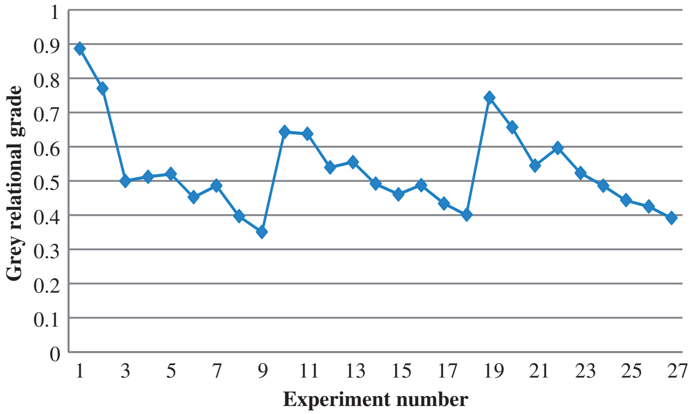

Figure 4. *GRG graph in function of experimental number.*

Table 6. Mean table for GRG.

	Level 1	Level 2	Level 3	Max−Min	Rank
A	0.54	0.52	0.53	0.01	5
B	0.66	0.51	0.42	0.23	1
C	0.60	0.54	0.46	0.14	2
AB	0.56	0.51	0.52	0.04	3
AC	0.54	0.53	0.52	0.03	4

ANALYSIS OF THE EXPERIMENTAL RESULTS USING GRG

The grey relational coefficient and GRG are calculated and presented in the previous section. From Table 5, It is found that experiment no. 1 (GRG = 0.887) machining parameter setting has the highest GRG. Therefore experiment no. 1 machining parameter setting is optimal parameter setting for attaining multiple performances simultaneously among 27 experiments. However, the relative importance among the achieving parameters for the multiple performance characteristics still needs to be analyzed so that the optimal combinations of the machining parameter levels can be determined more clearly.

SELECTION OF THE OPTIMAL LEVELS OF PROCESS PARAMETERS

For analyzing the results, mean (average) analysis has been used and is presented as response table (Table 6). The procedure for the response table is to group the GRGs by factor levels and then average them.

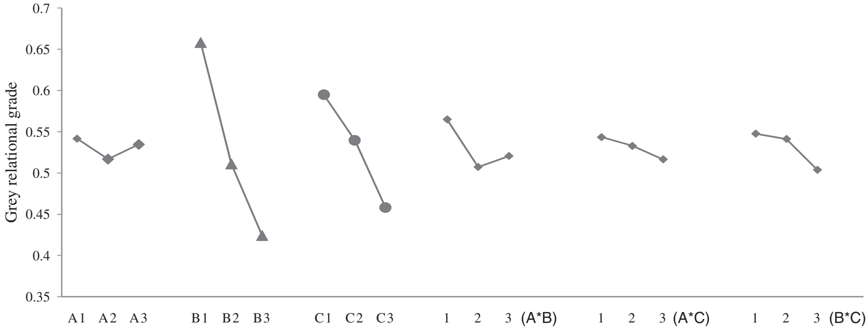

Figure 5. *GRG graph by factor level.*

The optimal level of the machining parameters is the level with the greatest GRG value. Based on the results obtained from Figure 5, the optimal parameters achieved are cutting speed at level 1, feed rate at level 1, and depth of cut at level 1 for achieving better surface roughness and cutting force. The optimal solution $A_1B_1C_1$ found in this study is only the near optimal solution.

CONCLUSION

Experiments were conducted in a CNC turning with tool material TiN-coated and reinforced PEEK with 30% of carbon fibers as work material. According to the integration of grey relational analysis and S/N ratio, the following can be concluded from this study.

1. The grey relational analysis technique converts the multiple performance characteristics into single performance characteristics, and it simplifies the optimization procedure.
2. From the response table of the average GRG, it is found that the largest value of the GRG for the cutting speed of 300 m/min, feed rate of 1.5 mm/rev and depth of cut of 0.2 mm. It is the recommended levels of the controllable parameters of the turning operations as the minimization of the surface roughness and cutting force are simultaneously considered.
3. The order of the importance for the controllable factors based on the GRG is feed rate followed by depth of cut. The interaction between the parameters also has effect on the GRG.
4. This technique is more convenient for optimizing the turning parameters in machining of PEEK CF30 within the levels studied.

5. This approach can be applied extensively to other cases in which performance is determined by many parameters at multiple quality requests.

REFERENCES

1. Mata, F., Gaitonde, V.N., Karnik, S.R. and Davim, J.P. (2009). Influence of Cutting Conditions on Machinability Aspects of PEEK, PEEK CF 30 and PEEK GF 30 Composites Using PCD Tools, *Journal of Materials Processing Technology*, **209**: 1980–1987.
2. Davim, J.P. and Mata, F. (2008). Chemical Vapor Deposition (CVD) Diamond Coated Tools Performance in Machining of PEEK Composites, *Materials and Design*, **29**: 1568–1574.
3. Davim, J.P. and Mata, F. (2007). New Machinability Study of Glass Fibre Reinforced Plastics using Polycrystalline Diamond and Cemented Carbide (K15) Tools, *Materials and Design*, **28**: 1050–1054.
4. Davim, J.P., Reis, P., Lapa, V. and Antonio, C.C. (2003). Machinability Study on Polyetheretherketone (PEEK) Unreinforced and Reinforced (GF30) for Applications in Structural Components, *Composite Structures*, **62**: 67–73.
5. Davim, J.P. and Reis, P. (2004). Machinability Study on Composite (Polyetheretherketone Reinforced with 30% Glass Fiber-PEEK GF 30) using Polycrystalline Diamond (PCD) and Cemented Carbide (K20) Tools, *International Journal of Advanced Manufacturing Technology*, **23**: 412–418.
6. Bhuhan, B. (1999). *Principles and Applications of Tribology*. Wiley, New York.
7. Park, D.C., Lee, S.M., Kim, B.C., Kim, S.H. and Lee, D.G. (2006). Development of Heavy Duty Hybrid Carbon-Phenolic Hemispherical Bearings, *Composite Structures*, **73**: 88–98.
8. Lee, S.M., Park, D.C., Kim, B.C., and Lee, D.G. (2006). Strength of Functionally Gradient Composite Hemispherical Bearings, *Composite Structures*, **73**: 145–152.
9. Harsha, A.P. and Tewari, U.S. (2003). Two-Body and Three-Body Abrasive Wear Behaviour of Polyaryletherketone Composites, *Polymer Testing*, **22**: 403–408.
10. Mata, F., Hanafi, I., Khamlichi, A., Jabbouri, A. and Bezzazi, M. (2010). On Machinability of Fiber Reinforced Polymeric Composites, *Mecanique & Industries*, **11**: 93–103.
11. Phadke, M.S. (1989). *Introduction, Quality Engineering using Robust Design*, Prentice-Hall, Englewood Cliffs, NJ.
12. Ghani, J.A., Choudhury, I.A. and Hassan, H.H. (2004). Application of Taguchi Method in the Optimization of End Milling Parameters, *Journal of Materials Processing Technology*, **145**: 84–92.
13. Park, S.H. (1996). *Parameter Design, Robust Design and Analysis for Quality Engineering,* Chapman & Hall, London.
14. Ross, P.J. (1996). *Taguchi Techniques for Quality Engineering*, McGraw-Hill, New York.
15. Deng, J.L. (1989). Introduction to Grey system. *Journal of Grey System*, **1**: 1–24.
16. Narender Singh, P., Raghukandan, K. and Pai, P.C. (2004). Optimization by Grey Relational Analysis of EDM Parameters on Machining Al-10% SICP Composites, *Journal of Materials Processing Technology*, 155–156, 1658–1661.
17. Tosun, N. (2006). Determination of Optimum Parameters for Multiperformance Characteristics in Drilling by using Grey Relational Analysis, *International Journal of Advanced Manufacturing Technology*, **28**: 450–455.

18. Huang, J.T. and Lin, J.L. (2002). Optimization of Machining Parameters Setting of Diesinking EDM Process Based on the Grey Relational Analysis with L18 Orthogonal Array, *Journal of Technology*, **17**: 659–664.

19. Fung, C.P. (2003). Manufacturing Process Optimization for Wear Property of Fiber-Reinforced Polybutylene Terephthalate Composites with Grey Relation Analysis, *Wear*, **254**: 298–306.

20. Yang, Y.Y., Shie, J.R. and Huang, C.H. (2006). Optimization of Dry Machining Parameters for High Purity Graphite in End-Milling Process, *Materials and Manufacturing Processes*, **21**: 832–837.

21. Chiang, K.T. and Chang, F.P. (2006). Optimization of WEDM Process of Particle Reinforced Material with Multiply Performance Characteristics using Grey Relational Analysis, *Journal of Materials Processing Technology*, **180**: 96–101.

22. Chorng-Jyh, T., Yu-Hsin, L., Yung-Kuang, Y. and Ming-Chang, J. (2009). Optimization of Turning Operations with Multiple Performance Characteristics using the Taguchi Method and Grey Relational Analysis, *Journal of Materials Processing Technology*, **209**: 2753–2759.