

Application of Particle Swarm Optimization for Optimizing the Process Parameters in Turning of PEEK CF30 Composites

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Abstract:

This work deals with optimization of multiple characteristics in CNC turning of reinforced Poly Ether Ether Ketone (PEEK CF30) with TiN coated tools under dry condition. The considered criteria included specific cutting pressure, machining force and cutting power. Three controllable factors of the turning process consisting of cutting speed, depth of cut and feed rate were incorporated. Taguchi design of experiments method was used to arrange the experimentation task. The developed response surface models were then employed with particle swarm optimization (PSO) to optimize the cutting conditions. PSO program gives the minimum values of the considered criteria and the corresponding optimal cutting conditions.

Mots clefs: PEEK CF30; Design of experiments (DOE), Response surface methodology (RSM), particle swarm optimization (PSO).

1 Introduction

Poly ether ether ketone (PEEK) material belongs to a group of high performance thermoplastic polymers, which has excellent mechanical and thermal properties [1]. The PEEK materials have been extensively used in automobiles, aeronautical, biomechanics, oil or gas industries, robots and machines because of light weight, high specific strength and stiffness, wear resistance, dimensional stability, good corrosive resistance, low weight, physical and mechanical directional properties [2-5]. Nowadays, aluminum has been replaced by PEEK material, particularly in aerospace industry due to superior performance at higher temperatures [6].

The addition of short fibers to PEEK material results in greater improvements in stiffness; strength and hardness over unreinforced thermoplastics and provides increased service temperature [2, 3]. The carbon and glass fibers are the common reinforcements in PEEK material because of low expansion rate and high flexural modulus and hence find several applications in resistant or structural components, mainly at temperatures above 150°C. The reinforced poly ether ether ketone with 30% of carbon fiber (PEEK-CF30) constitutes cost-effective alternative to stainless steel and other metallic materials in strongly corrosive industrial applications [7]. The PEEK-CF30 is enormously abrasive when machined and brings out many undesirable results such as rough surface finish, rapid tool wear and defective subsurface layer. The cutting mechanism of this material is fairly different from that of metal [8, 9] and hence successful machining performance is significantly affected by work material

properties. As a result of improved properties and potential applications of PEEK-CF30 material, there is a need to understand the machining of this composite [10].

Hence, the objective of the present work is aimed at determining the effects as well as optimizing the cutting conditions (cutting speed and feed rate) on three different machining criteria, namely (specific cutting pressure, machining force and cutting) during turning of reinforced poly ether ether ketone with 30% of carbon fiber (PEEK-CF30) composites using TiN cutting tools. The response surface methodology (RSM) based mathematical models of proposed for the machining criteria have been developed to analyze the interaction effects of cutting speed, depth of cut and feed rate. The developed mathematical models were further utilized to determine the best combination of cutting conditions using particle swarm optimization (PSO).

2 Experimental conditions of PEEK CF30 turning

The work material used for the present investigation is reinforced PEEK CF30 manufactured by ERTA®. It consists of cylindrical work pieces with 50 mm diameter and a length of 100 mm. The main mechanical and thermal properties of work material are summarized in table 1.

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

Dry turning experiments were carried out on a GORATU G CRONO 4S CNC machine, enabling up to 26.5 kW spindle power and maximum spindle speed 3350 RPM. TiN coated ISCAR WNMG 080408-TF cutting tools were used. They were mounted on A SDJCL 2020 K11 tool holder. The three components of turning force (radial force – F_p , cutting force – F_c and feed force – F_a) were recorded with a KISTLER piezoelectric dynamometer model 9121 connected to a load amplifier and data acquisition board (Figure 1).

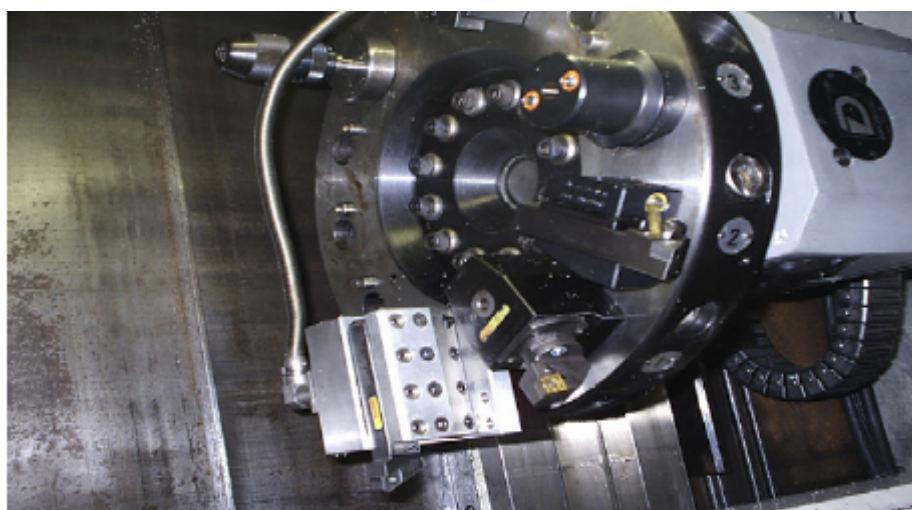


Figure 1: Kistler piezoelectric dynamometer used to measure cutting forces

The experiments were conducted according to a full factorial DOE table. The three cutting parameters selected for the present 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 linearly related, it has

been decided to use three level tests for each factor. The machining parameters used and their levels are given in table 2.

Table 2: Machining parameters, their levels and associated codes

	level	Code
Cutting speed (m/min)	300	1
	200	2
	100	3
Depth of cut (mm)	1.5	1
	0.75	2
	0.25	3
Feed rate (mm/rev)	0.20	1
	0.15	2
	0.05	3

Machinability is evaluated in terms of cutting force (F_m), cutting power (P_c) and specific cutting pressure (K_s). These quantities are calculated from the following equations

$$F_m = \sqrt{F_p^2 + F_a^2 + F_c^2} \quad (1)$$

$$P_c = F_c \cdot v \quad (2)$$

$$K_s = \frac{F_c}{f \cdot d} \quad (3)$$

where F_p is the radial cutting force, F_a the axial cutting or feed force and F_c the tangential cutting force. The experimental layout plan, performed according to a full factorial DOE table and which included 27 combinations, is given in table 3.

As there are three factors and three levels for each factor, twenty-seven experiments were performed according to the standard L27 Taguchi orthogonal array. It should be mentioned that each run was repeated 4 times and the obtained results have indicated no significant variations of the responses, in terms of cutting power and surface roughness, from one run to the other. This allows us to believe that variations of the responses should only be attributed to those of the cutting parameters. No extra noise that could prejudice the results was detected.

Table 3: Experimental layout showing machining criteria results

Cutting speed v	Depth of cut d	Feed rate f	Cutting force F _m (N)	Cutting power P _c (W)	Specific cutting pressure K _s (N/mm ²)
1	1	1	165.72	49714.92	552.39
1	1	2	143.52	43057.42	637.89
1	1	3	98.35	29504.73	1311.32
1	2	1	111.81	33544.34	745.43
1	2	2	118.97	35689.61	1057.47
1	2	3	81.34	24402.53	2169.11
1	3	1	81.47	24439.91	1629.33
1	3	2	78.77	23631.43	2100.57
1	3	3	54.92	16475.75	4393.53
2	1	1	204.15	40829.95	680.50
2	1	2	186.56	37311.21	829.14
2	1	3	129.45	25890.87	1726.06
2	2	1	151.47	30294.15	1009.80
2	2	2	136.18	27236.58	1210.51

2	2	3	92.49	18498.29	2466.44
2	3	1	96.17	19234.90	1923.49
2	3	2	87.57	17514.22	2335.23
2	3	3	62.62	12524.38	5009.75
3	1	1	223.20	22319.54	743.98
3	1	2	204.40	20440.13	908.45
3	1	3	140.24	14023.68	1869.82
3	2	1	130.78	13077.63	871.84
3	2	2	135.51	13550.96	1204.53
3	2	3	131.26	13126.19	3500.32
3	3	1	102.73	10272.96	2054.59
3	3	2	96.22	9622.20	2565.92
3	3	3	72.98	7298.07	5838.46

3 Modeling of machining criteria

3.1 Response surface methodology (RSM)

RSM is a tool which is designed to develop a direct mathematical relationship relating the controllable parameters to the experimental responses. This enables to estimate and explore more simply the effect that parameters would have on responses. In the present work, second order RSM based mathematical models of cutting force (F_m), cutting power (P_c) and specific cutting pressure (K_s) have been developed in terms of the three process parameters: cutting speed (v), depth of cut (d) and feed rate (f). Thus, the nonlinear response surface equations of F_m , P_c and K_s are interpolated according to the following equations

$$F_m = a_0 + a_1 v + a_2 d + a_3 f + a_4 vd + a_5 vf + a_6 df + a_7 v^2 + a_8 d^2 + a_9 f^2 \quad (4)$$

$$P_c = b_0 + b_1 v + b_2 d + b_3 f + b_4 vd + b_5 vf + b_6 df + b_7 v^2 + b_8 d^2 + b_9 f^2 \quad (5)$$

$$K_s = c_0 + c_1 v + c_2 d + c_3 f + c_4 vd + c_5 vf + c_6 df + c_7 v^2 + c_8 d^2 + c_9 f^2 \quad (6)$$

where a_0, \dots, c_9 are regression coefficients to be determined.

Note that even if from equations (2) and (3) we get the following relationship between (P_c) and (K_s), in equations (5) and (6) the cutting power and specific cutting pressure are assumed to be independent in order to obtain second order RSM models by quadratic polynomial regression.

The values of the regression coefficients appearing in equations (4) to (6), and which are associated to linear, quadratic and interaction terms of the mathematical models, can be determined in the least square sense by means of the following formula

$$B = (X'X)^{-1} X'Y \quad (7)$$

where B is the matrix of parameter estimates, X the regression matrix that includes linear, quadratic and interaction terms, X' denotes the transpose of X and Y is the matrix associated to given response.

3.2 Particle Swarm Optimization

Kennedy and Eberhart [11] developed the particle swarm optimization (PSO) algorithm through imitating the preying behavior of birds or fishes. In PSO, each possible solution in the searching space is seen as a 'bird', known as 'particle'. All the particles have fitness values; assessed through a fitness function to be optimized, and have velocities, which direct the flying of particles. They fly through the problem space by following the current optimum particles. If search space is D-dimensional, then the i th particle of the population, called 'swarm', which can be specified by a D-dimensional vector $s = (S_1, S_2, \dots, S_D)$. The velocity of this particle is represented by another D-dimensional vector $V = (V_1, V_2, \dots, V_D)$. The best previously visited position (pbest) of the i th particle is denoted as $P_{best} =$

(P1, P2, . . . PD). Let g be the index of the best particle in the swarm (g_{best}) and let the superscripts denote the iteration number; then, the swarm is manipulated according to the following equations:

$$V_i^{k+1} = W^k V_i^k + C_1 R_1^k (P_i^k - S_i^k) + C_2 R_2^k (P_g^k - S_i^k) \quad (8)$$

$$S_i^{k+1} = S_i^k + V_i^{k+1} \quad (9)$$

where, W is the inertia weight; C_1 and C_2 are positive constants, i.e., cognitive and social parameters respectively, also called as learning factors; R_1 and R_2 are random numbers uniformly distributed in the range $[0-1]$; $i = 1, 2, \dots, N$ and N is the size of the swarm, and $k = 1, 2, \dots$ is the current iteration.

The PSO algorithm is based on the sociometric idea called g_{best} , which connects all the members of swarm to one another. In such case, every particle is prejudiced by very best performance of any member of whole population. In PSO, the information exchange takes place only among the particle's own experience and the experience of the best particle in the swarm, instead of being carried from fitness dependent selected parents to descendants as in genetic algorithms (GA). Besides, the directional position updating used in PSO is similar to mutation of GA, with a kind of memory built in. lastly, PSO belongs to the class of evolutionary algorithms that does not use the "survival of the fittest" thought. It does not utilize a direct selection function and therefore, particles with lower fitness can survive during the optimization and potentially visit any point of the search space. The PSO has encouraging benefits over other optimization techniques:

- It is a derivative free algorithm unlike many conventional techniques.
- It has the flexibility to be integrated with other optimization techniques to form a hybrid tool.
- It has few parameters to adjust unlike many other evolutionary techniques.
- It has the ability to escape local minima.
- It is easy to implement and program with basic mathematical and logic operations.
- It can handle objective functions with probabilistic nature.
- It does not require a good initial solution to start this iteration process.

4 Results and verification

4.1 RSM models

From the experimental data, quadratic polynomial regressions were derived for the three considered machining criteria. The obtained RSM expressions write

$$F_m = 24.82 + 0.2 v + 88.60 d + 361.59 f - 0.14 vd + 0.15 vf + 254.17 df - 15.26 d^2 - 1218.29 f^2 \quad (10)$$

$$P_c = -7975 + 137 v + 5017 d + 25552 f + 37 vd + 303 vf + 47212 df - 3430 d^2 - 258964 f^2 \quad (11)$$

$$K_s = 9803.6 - 7.8 v - 6804.7 d - 48332.9 f + 1.7 vd + 30.5 vf + 12035.9 df + 1830.8 d^2 + 75247.4 f^2 \quad (12)$$

Fuzzy models were developed by using Fuzzy Inference Systems (FIS) toolbox under Matlab.

For each machining criterion model, the relevant coefficient of determination R^2 is given in table 5. From the analysis of table 5 it is evident that capabilities, R^2 factors, of the multiple regression based models as well as fuzzy based models are all higher than 0.97.

To test the adequacies of the regression based models, analysis of variance (ANOVA) was carried out and the obtained results are summarized in table 6. This table shows that P values are less than 0.05, hence the regression based models are significant to 95% level of confidence.

Table 5: R^2 values for cutting force, cutting power and specific cutting pressure models

	F_m	P_c	K_s
Multiple regression coefficients R^2 using RSM	0.97	0.98	0.98
Multiple regression coefficients R^2 using Fuzzy logic	0.98	0.98	0.99

Table 6: ANOVA of regression based models for predicting machining criteria

	SS		DF		MS		F	P
	Model	Residual	Model	Residual	Model	Residual		
Fm	50572.42	1553.33	9	17	5619.157	91.37	61.497	0.00
Pc	3.152077109	56440190	9	17	350230816	3320011	105.49	0.00
Ks	47938101	778316.4	9	17	5326456	45783.32	116.34	0.00

4.2 PSO optimization for machining criteria

The RSM based mathematical models were used to find out the optimal cutting conditions, namely, cutting speed (v) and feed rate (f), which results in minimal surface roughness parameters. In the current study, the fitness function is designed using the normalized values of RSM predicted cutting force (F_m), cutting power (P_c) and specific cutting pressure (K_s); and is given by:

The optimization problem of the present study is stated as minimizing the machining criteria, subject to machining constraints. Hence, the constrained optimization problem using PSO is given by:

$$Fit = \frac{F_m}{224} + \frac{P_c}{49715} + \frac{K_s}{5839} \quad (13)$$

- Determine the optimal values of v , d and f .
 - So as to minimize fit.
 - Subject to the constraints: $100 \leq v \leq 300$ m/min; $0.25 \leq d \leq 1.5$; $0.05 \leq f \leq 0.2$ mm/rev
- The PSO of current study consists of following steps:

Step 1: Randomly initialize m sets of particles, namely, cutting speed (v) and feed rate (f). The existing particles of each set are positioned to 'pbest' and the parameters corresponding to the best fitness among all the sets are selected as 'gbest'.

Step 2: Find out the predicted values of F_m , P_c and K_s using the RSM based models of Equations (10), (11) and (12) respectively.

Step 3: Compute the fitness of every set of parameters using Eq. (13).

Step 4: Compare the computed fitness with the fitness analogous to 'pbest', if the fitness is superior to 'pbest', then 'pbest' should be updated.

Step 5: Compare the maximum fitness value with the 'gbest' and if maximum fitness is better than 'gbest', then 'gbest' should be updated.

Step 6: Update the position and velocity of particles using Eqs. (8) and (9).

Step 7: Judge whether the program will stop (total iteration is usually set as termination rule). If true, stop the iteration; otherwise go back to step 3.

The PSO simulation was performed using MATLAB software with maximum number of 50 generations (k_{max}). In the current study, the size of the swarm used is 40. The learning factors C_1 and C_2 were set to 2.0. The inertia weight (W) is used to control the impact of preceding velocities on present velocities, which influences the trade-off between global and local exploration abilities of particles. The inertia weight was initially set to a large value (W_{max}) to allow a global search. To decrease this weight over the iterations allowing the algorithm to exploit some specific areas; the following equation is used:

$$W^k = W_{max} - \left[\frac{(W_{max} - W_{min})k}{K_{max}} \right] \quad (14)$$

where, $W_{max} = 0.80$ and $W_{min} = 0.01$. The input process parameters levels were fed to PSO program and the values of cutting conditions were predicted for minimal surface roughness. The best fitness value observed is 1.0272. The corresponding optimal parameters are presented below:

Optimal cutting conditions: $v = 100.2456$ m/min; $d = 0.2641$ mm; $f = 0.1998$ mm/rev;

Optimal solution are given: $F_m = 103.5252$ N; $P_c = 11151$ w and $K_s = 1990.2$ N/mm².

Although the above results indicate the best cutting conditions, sometimes it may not be possible to adopt this in a computer aided process planning (CAPP), computer aided manufacturing (CAM) stages

with tight tolerances and also in adaptive control machine tools. In order to overcome this situation, PSO simulations can be repeated with different range of values defined for the cutting speed, depth of cut and feed rate. Hence, the results can be employed in CAPP to set the cutting speed, depth of cut and feed rate based on their set range in order to achieve the desired goal.

Conclusion:

The investigative study on cutting force parameters during turning of PEEK- CF30 composite material using TiN cutting tool is presented in this paper. In order to analyze the effects of process parameters (cutting speed, depth of cut and feed rate) on proposed machining criteria (F_m , P_c , and K_s), the experiments were planned as per full factorial design (FFD). The second order mathematical models of machining criteria were developed using response surface methodology (RSM) and the developed models were then validated through analysis of variance (ANOVA). Based on the parametric analysis and subsequent PSO optimization, the following conclusions are drawn within the ranges of the process parameters selected:

- There exist non-linear relationships between the criteria machining and the cutting conditions and hence justifying the use of RSM based second order mathematical model with reduced number of experiments.
- The results from the current investigation are useful for the manufacturing engineers to select significant cutting conditions in turning of PEEK-CF30 work material; especially to analyze the application of TiN cutting tools to machine this reinforced composite material. The cost of TiN cutting tool is minor when compared to the cost of PCD and K10 and for certain fields of application the obtained surface roughness can be sufficient with minor cost.

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