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Research Paper

OPTIMIZATION FOR SURFACE ROUGHNESS, MRR, POWER CONSUMPTION IN TURNING OF EN24 ALLOY STEEL USING GENETIC ALGORITHM

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Determination of optimal cutting parameters is one of the most important elements in any process planning of metal parts. The evolutionary algorithm Genetic Algorithm (GA) is used to improve many solutions of optimization complex problems in many applications. The present paper reviewed the ideal selection of cutting parameters in turning operation of En24 work material using PVD coated tool using GA and its variants. This study deals with GA algorithm in different machining aspects in turning operation like surface roughness, material removal rate, and power consumption.

Keywords: GA, Optimization, Turning

INTRODUCTION

The selection of optimal cutting parameters, like the number of passes, depth of cut for each pass, feed and speed, is a very important issue for every metal cutting process. In workshop practice, cutting parameters are selected from machining databases or specialized handbooks, but the range given in this sources are actually starting values, and are not the optimal values (Dereli *et al.*, 2001). Optimization of cutting parameters is usually a difficult work, where the following aspects are required: knowledge of machining; empirical equations relating the tool life, forces, power, surface finish, etc., to develop realistic constrains; specification of machine tool capabilities; development of an effective optimization criterion; and knowledge of mathematical and numerical optimization techniques (Sonmez *et al.*, 1999). In any optimization procedure, it is a crucial aspect to identify the output of chief importance, the so-called optimization objective or optimization criterion. Some multi-objective

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approaches have been reported in cutting parameters optimization (Lee and Tarng, 2000; Zuperl and Cus, 2003; and Cus and Balic, 2003), but mainly they use a prior techniques, where the decision maker combines the different objectives into a scalar cost function. This actually makes the multi-objective problem, single-objective prior to optimization (Van Veldhuizen and Lamont, 2000). Comparing citations by technique, in the last years, evidences the popularity of a posteriori techniques (Van Veldhuizen and Lamont, 2000). In dealing with multiobjective optimization problems, classical optimization methods (weighted sum methods, goal programming, min-max methods, etc.) are not efficient, because they cannot find multiple solutions in a single run, thereby requiring them to be applied as many times as the number of desired Pareto-optimal solutions. On the contrary, studies on evolutionary algorithms have shown that these methods can be efficiently used to eliminate most of the above-mentioned difficulties of classical methods (Soodamani and Liu, 2000). In this paper, a multi-objective optimization method, based on a posteriori techniques and using genetic algorithms, is proposed to obtain the optimal parameters in turning processes.

MATERIALS AND METHODS

Specification of Work Material

The work material used for the present study is En 24 alloy steel. The chemical composition of the work material is shown in Table 1.

Process Parameters

Genetic Algorithm

GA is an evolutionary algorithm technique which borrows the idea of survival of the fittest amongst an interbreeding population to create a search strategy. It uses only the fitness value and no other knowledge is required for its operation. It is a robust search technique different to the problem solving methods used by more traditional algorithms which tend to be more deterministic in nature and get stuck up at local optima. The three basic operators of GA are reproduction, crossover and mutation. Initially a finite population of feasible solutions to a specified problem is maintained. Through reproduction, it then iteratively creates new populations from the old by ranking the solutions according to their fitness values. Crossover leads to interbreeding the fittest solutions to create new offsprings which are optimistically closer to the optimum solution to the problem at hand. As each generation of solutions is produced, the weaker ones fade away without producing off springs, while the stronger mate, combining the attributes of both parents, to produce new and perhaps unique off springs to continue the cycle. Occasionally, mutation is introduced into one of the solution strings to further diversify the population in search for a better solution.

The present work optimizes the desired response and control parameters by writing the mathematical models in Equations (1), (2) and (3) combined as single multi objective

Table 1: Chemical Composition of EN 24 Alloy Steel

Element	C	Si	Mn	S	P	Cr	Ni	Mo
Composition	0.38-0.43	0.15-0.30	0.60-0.80	0.040	0.035	0.70-0.90	1.65-2.00	0.20-0.30

function as .M-file and then solved by GA TOOL BOX using the MATLAB software. The initial population size considered while running the GA is 20. A test of 10 runs with 50 generations each was conducted. During the search, the response improved linearly with the number of initial population size. The best response was measured with population size 20 after which no improvement in the response value were recorded upon further increase of population size.

EXPERIMENTATION

The experiment is conducted for dry turning operation of using EN24 Alloy steel as work material and PVD as tool material on a conventional lathe PSG A141. The tests were carried for a 500 mm length work material. The process parameters used as spindle speed (rpm), feed (mm/rev), depth of cut (mm). The response variables are surface roughness, material removal rate and power consumption. surface roughness of machined surface has been measured by a stylus (surflest SJ201-P) instrument and power consumption is measured by using Watt meter, Material removal rate is calculated.

Decision Variables

In the constructed optimization problem, three decision variables are considered: cutting speed (v), feed (f), and cutting depth (d). These really are the cutting parameters of the process.

Objective Functions

Surface roughness need to the minimum for good quality product

(Lower is the better)

The surface roughness, *Ra*

Min $R_a(s, f, d)$

Minimizing

$$Ra = 3.158S^{0.135}f^{0.110}d^{0.105} \quad \ldots(1)$$

MRR need to be maximum for increasing the production rate

(Higher is the better)

The material removal rate, *MRR*

Max $MRR(s, f, d)$

Maximizing

$$MRR = 0.003\,S^{1.23}f^{0.675}d^{0.181} \quad \ldots(2)$$

Power consumption need to be minimum for reducing the cost of finished product,

(Lower is the better)

The Power consumption, *PC*

Min $PC(s, f, d)$

Minimizing

$$PC = 0.053\,S^{1.01}f^{0.472}d^{0.156} \quad \ldots(3)$$

Constraints

$S_{min} \le S \le S_{max}$,

$$450 \le S \le 740 \quad \ldots(4)$$

$f_{min} \le f \le f_{max}$,

$$0.05 \le f \le 0.09 \quad \ldots(5)$$

$d_{min} \le d \le d_{max}$,

$$0.05 \le d \le 0.15 \quad \ldots(6)$$

RESULTS AND DISCUSSION

In order to satisfy the present day need of manufacturing industries carbide inserts with the prescribed specifications were identified. The effect of surface roughness, Material removal rate and Power Consumption with PVD tool on EN 24 is considered. The

Table 2: Process Parameters and Their Levels

Level	Speed (s) (rpm)	Feed Rate (f) (mm/rev)	Depth of Cut (d) (mm)
1.	740	0.09	0.15
2.	580	0.07	0.10
3.	450	0.05	0.05

Table 3: Experimental Data and Results for 3 Parameters, Corresponding Ra, MRR and PC for PVD Tool

S. No.	Speed (Rpm)	Feed (mm)	Depth of Cut, (mm)	Surface Roughness Ra (μm)	Material Removal Rate (mm^3/min)	Power Consumption in KW
1.	740	0.09	0.15	3.0598	0.514286	12.26053
2.	740	0.09	0.1	3.9465	0.636364	12.035
3.	740	0.09	0.05	6.1885	0.553846	8.37689
4.	740	0.07	0.15	3.0729	0.292683	10.91348
5.	740	0.07	0.1	3.4368	0.27907	9.56774
6.	740	0.07	0.05	6.5319	0.404494	6.53712
7.	740	0.05	0.15	6.1136	0.542169	9.164832
8.	740	0.05	0.1	3.4316	0.350877	7.66528
9.	740	0.05	0.05	5.1471	0.705882	4.89326
10.	580	0.09	0.15	6.3332	0.292683	6.457821
11.	580	0.09	0.1	5.1596	0.677419	5.01187
12.	580	0.09	0.05	3.8766	1.037037	7.286254
13.	580	0.07	0.15	7.8758	0.336	7.848
14.	580	0.07	0.1	3.4517	0.677419	6.72485
15.	580	0.07	0.05	3.9452	0.194805	8.766383
16.	580	0.05	0.15	5.8248	0.393443	5.80663
17.	580	0.05	0.1	2.6401	0.32345	4.361176
18.	580	0.05	0.05	4.0198	0.224439	5.445271
19.	450	0.09	0.15	4.2968	0.314136	7.659078
20.	450	0.09	0.1	5.863	0.48913	4.970542
21.	450	0.09	0.05	3.7452	0.157068	6.541089
22.	450	0.07	0.15	3.5772	0.339623	3.792101
23.	450	0.07	0.1	3.5979	0.327869	4.56132
24.	450	0.07	0.05	3.6215	0.218182	5.541289
25.	450	0.05	0.15	6.504	0.26087	6.42373
26.	450	0.05	0.1	4.1852	0.257143	5.37698
27.	450	0.05	0.05	2.5687	0.083916	3.709838

experiments were conducted by Taguchi orthogonal array L27. These experimental results are modeled as multi linear logarithmic Equations (1), (2) and (3) for surface roughness, Material removal rate and Power Consumption for PVD tool. By using these logarithmic equations, the cutting constraints formulated in Equations (4), (5) and (6) and with GA parameters, the genetic algorithm solver get the inputs like fitness function (objective function), variables constraints, population size, crossover rate, mutation probability and the plot function. W1, W2 and W3 are the weights assigned to the three objective functions and weights are assigned to the objective functions randomly such that the summation of weights should be equal to one (1). Run the Genetic solver in the MATLAB optimization toolbox software. After running several iterations the optimum cutting conditions for the minimum surface roughness (Ra), Maximum Material Removal rate (MRR) and for minimum Power Consumption (PC) were displayed in the genetic solver. The results given by the Genetic solver for different weights given to the objective functions such as Ra, MRR and PC are tabulated as follows for PVD tool. The following Table 4 is for optimum cutting condition levels that are obtained from GATOOL for minimum Ra, maximum MRR and minimum PC for PVD tool on EN 24 work piece material.

Table 4: Optimized Cutting Condition Levels for Ra, MRR and PC for PVD Tool

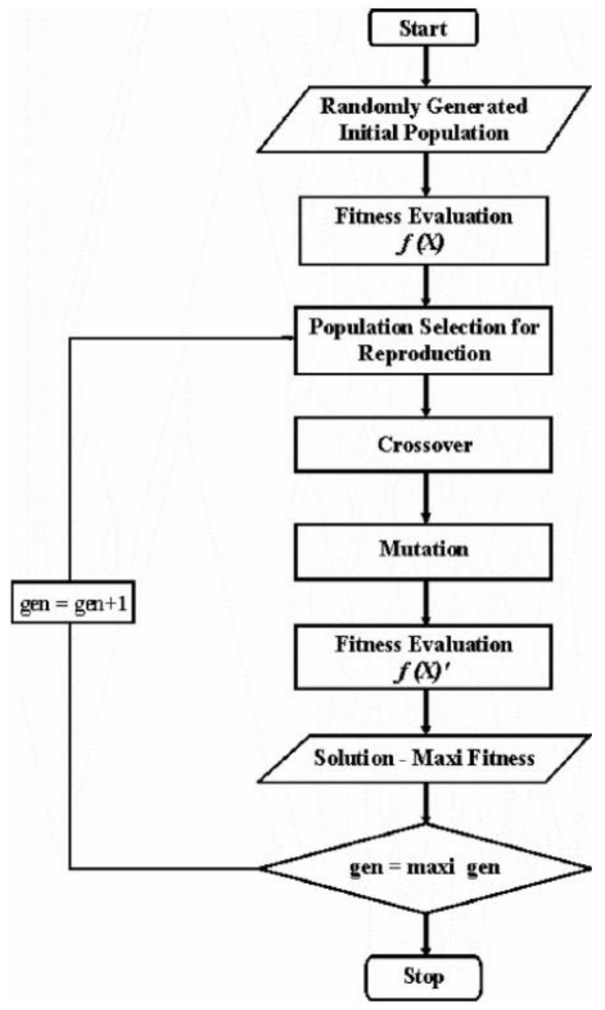
S. No.	Weights			Optimal Cutting Condition Levels		
	Speed (S)	Feed (f)	DOC (d)	W1	W2	W3
1.	0.207	0.555	0.238	732.171	0.09	0.14943
2.	0.555	0.238	0.207	730.827	0.08993	0.15
3.	0.238	0.207	0.555	709.513	0.08994	0.14612
4.	0.555	0.207	0.238	712.985	0.08997	0.14998
5.	0.207	0.238	0.555	721.393	0.08633	0.13996
6.	0.238	0.555	0.207	718.061	0.09	0.14999

Table 5: Optimal Cutting Conditions and Response Values for Different Weighting Factors (PVD)

S. No.	Weights			Optimal Cutting Condition Levels			GA		
	W1	W2	W3	Speed Rpm	Feed mm	DOC mm	Ra (μm)	MRR (mm^3)	Power Consumed (KW)
1.	0.207	0.555	0.238	740	0.09	0.25	4.8355	0.621	10.0631
2.	0.555	0.238	0.207	740	0.09	0.25	4.8358	0.6197	10.0466
3.	0.238	0.207	0.555	740	0.09	0.25	4.8034	0.5948	9.7118
4.	0.555	0.207	0.238	740	0.09	0.25	4.8198	0.6013	9.8007
5.	0.207	0.238	0.555	740	0.09	0.25	4.7709	0.5859	9.6219
6.	0.238	0.555	0.207	740	0.09	0.25	4.8247	0.6067	9.873

The optimal values that are estimated by the GA technique for different cutting conditions are in the range of actual Machining cutting conditions. These Optimal cutting condition levels are interpreted into the regression Equations (1), (2) and (3) for different weights, where we will obtain optimized surface roughness Ra, MRR and PC values. The following Table 5 is for optimized Surface roughness (Ra), Material removal Rate (MRR) and Power Consumption (PC) values from GA for PVD tool obtained from GA tool using MATLAB.

Figure 1: General Procedure for Genetic Algorithm



CONCLUSION

- As can be remarked in the result, a multi-objective optimization offers greatest amount of information in order to make a decision on selecting cutting parameters in turning.
- The Genetic Algorithm (GA) is tested to find optimal values of parameters with varying weight factors for the three objective functions with less deviation.
- In this study the GA techniques was adopted. GA technique gives effective methodology in order to find out the effective performance output and machining conditions.
- The assigned weights to the objective function shows insignificant by entrophy method.

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