Journal of Advanced Engineering Research
ISSN: 2393-8447
Volume 1, Issue 2, 2014, pp.105-113

A Meta-Heuristic Evolutionary Algorithm to Optimize Machining Parameters in Turning AISI 4340 Steel

K. Dhandapani*, P. Vasanthkumar, S. Nagarajan

Department of Mechanical Engineering, Adhiparasakthi Engineering College, Melmaruvathur - 603319, India

*Corresponding author email: dhandapanitvm@gmail.com, Tel: +44-27529247 Fax: +44-27529094

ABSTRACT

In this work, optimization of machining parameters cutting speed, feed rate and depth of cut is performed during turning AISI 4340 steel with uncoated carbide cutting inserts. An L9(33) Orthogonal Array is chosen based on Taguchi's Design of Experiments and the output responses flank wear, surface roughness and Material Removal Rate (MRR) were measured. Empirical models representing the output responses are developed using linear regression models. A meta-heuristic evolutionary algorithm, Non-dominated Sorting Genetic Algorithm (NSGA-II) is applied to determine the optimum set of machining parameters for minimizing flank wear and maximizing MRR considering the surface roughness values within a specific limit (constraint). Pareto optimal front comprising of a set of solutions is obtained between the objective functions. From the results obtained, it is observed that NSGA-II can be used for predicting the machining parameters and output responses with at most precision showing the supremacy of the algorithm.

Keywords - Machining parameters, Taguchi's DoE, S/N ratio, Empirical Modeling, NSGA-II

1. INTRODUCTION

Turning is the most widely used metal removal process in industries. Turning in the general sense refers to the generation of any cylindrical surface with a single point cutting tool, in which the direction of the feeding motion is predominantly axial with respect to the machine spindle. Fig. 1 shows the schematic illustration of the basic turning operation, showing depth-of-cut, d; feed rate, f; and spindle rotational speed, N in rev/min. Cutting speed is the surface speed of the workpiece at the tool tip [1].

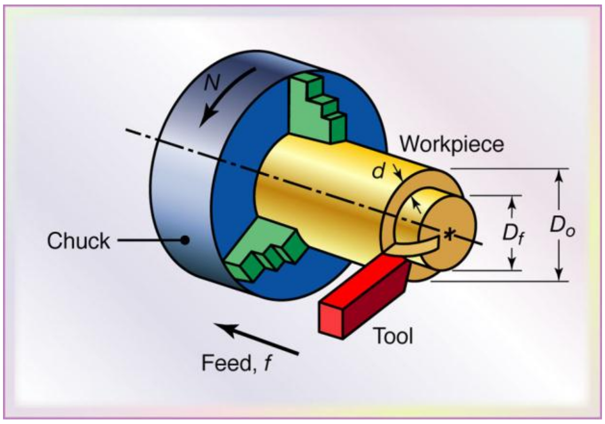

Fig.1 Schematic representation of turning process

Cutting tool life is one of the most important economic considerations in metal cutting. In roughing operations, the tool material, the various tool angles, cutting speeds and feed rates are usually chosen to give an economical tool life. On the other hand, the use of very low speeds and feeds to give long tool life will not be economical because of the low production rate. The depth of cut should be as great as is consistent with the strength and size of any cutting tool or carbide inserts when used, and the amount of stock to be removed. The feed depends on the finish desired and the strength and rigidity of the part and the machine. Cutting speed depends primarily on workpiece hardness and tool material [2].

Nalbant et al. [3] applied Taguchi's technique to determine the optimal cutting parameters in minimizing surface roughness during turning AISI 1030 bars using TiN coated tools and found that greater nose radius and lower feed rate and depth of cut produces better surface roughness. Experiments based on Taguchi's experimental design to optimize cutting conditions to obtain lowest surface roughness in turning SCM 440 alloy was conducted by Thamizhmanii et al. [4] and found that depth of cut is the most contributing factor for surface roughness, followed by feed rate. Effect of cryogenic cooling on tool wear and high frequency dynamic cutting forces during high speed machining of stainless steel, in both dry and cryogenic conditions was studied by Kumar and Choudhury [5] and found that cryogenic cooling was effective in reducing the cutting temperatures and thereby reducing flank wear by 37.39%.

Researches have studied the effects of machining parameters, PCBN tool grade and workpiece hardness to achieve better tool life, tool wear, surface roughness and MRR in hard turning of crank pin material [6]. Combined effects of cutting speed, feed rate and depth of cut on flank wear and surface roughness during turning AISI 4140 steel using Al2O3 + TiCN mixed ceramic tool is performed [7]and concluded that cutting speed is the significant parameters for flank wear and interaction effect of cutting speed and feed rate for surface roughness. Investigation on the effects of cutting parameters in turning hardened AISI H11 on flank wear (VB) and surface roughness (Ra) using CBN tool is carried out [8] and found that cutting time and cutting speed is responsible for flank wear and feed rate for higher surface roughness.

Senthilkumar et al. [9] predicted the effects of variation in machining parameters, geometrical parameters and workpiece hardness through Artificial Neural Network approach during turning with uncoated cemented carbide inserts. Taguchi's technique is applied to optimize cutting parameters in turning Ti-6%Al-4%V with coated and uncoated cemented carbide tools under dry cutting condition and high cutting speed and found that cutting speed and tool grade have a significant effect on surface roughness, contributing by 47.146% and 38.881% [10]. Multi-objective optimization problem in turning are solved by using multi-objective differential evolution (MODE) algorithm and non-dominated sorting genetic algorithm (NSGA-II) for minimum tool wear, maximum metal removal rate with constraints of temperature and surface roughness during turning EN24 steel with tungsten carbide and observed that MODE algorithm outperforms NSGA-II [11].

Srinivas and Deb [12] investigated Goldberg's notion of non-dominated sorting in GAs along with niche and speciation method to find multiple Pareto-optimal points simultaneously and suggested that the proposed method can be extended to higher dimensional and more difficult multi-objective problems. Optimization of machining and geometrical parameters during turning different hardened workpieces over flank wear and cutting zone temperature is performed by applying Taguchi's technique [13]. Apart from analyzing and optimizing the machining parameters, researchers had also analyzed the effects of variation in cutting tool geometries during turning process both experimentally and by numerical simulation [14,15] and found that better results can be achieved by altering the tool geometry [16-18]. Nowadays newly developed evolutionary algorithms such as firefly algorithm, cuckoo search algorithm, flower pollination algorithm, frog leaping algorithm, teaching-learning algorithm etc., were also applied for engineering problems to obtain the desired results [19,20] apart from analyzing the responses obtained using various data analysis techniques.

2. PROBLEM IDENTIFICATION

Selection of machining conditions to machine a particular work piece for a particular operation, which may be rough turning or finish turning is a tedious task, owing to various considerations in metal cutting. Tool life, economic machining and quality of components produced are of major considerations during turning. The machining conditions chosen should be an optimum condition, which should improve tool life by reducing flank wear, surface roughness, to improve the economic machining by increasing the MRR and to improve the quality of component. Improper selection of machining conditions will give rise to higher cutting forces and higher temperature at the tool-work piece interface favouring surface roughness and flank wear. Hence, the machining parameters such as cutting speed, feed rate and depth of cut has to be optimized to obtain better results. Hence, the final problem is to get optimized input machining parameters to have a control over the output responses by considering the problem into a Multi-objective problem [21-26].

In this analysis, machining parameters such as cutting speed, feed rate and depth of cut are optimized using a non-traditional optimization algorithm NSGA-II [27-34]. The purpose is to minimize flank wear and maximize MRR within a specific limit of surface roughness during turning AISI 4340 steel using uncoated carbide cutting tool inserts.

3. WORKPIECE & CUTTING TOOL MATERIAL

The workpiece material chosen for this analysis is AISI 4340 Nickel-chromium-molybdenum alloy steel; a high tensile strength, shock resistance, good ductility and resistance to wear steel, used in construction of aircrafts and heavy vehicle crankshaft, gear shaft, camshaft and propeller shaft etc. The chemical composition of the workpiece material is shown in Table 1, whose hardness is 217 BHN. The cutting tool insert used in this study is uncoated cemented carbide insert of WIDIA brand, whose ISO designation is CNMG 120404 and Brinell hardness value of 1433 BHN.

Table 1 Chemical composition of AISI 4340 steel

Sl. No	Elements Present	Alloying %
1	Carbon	0.372
2	Silicon	0.278
3	Manganese	0.570
4	Phosphorus	0.030
5	Sulphur	0.026
6	Chromium	1.106
7	Molybdenum	0.320
8	Nickel	1.467
9	Aluminum	0.023
10	Copper	0.140
11	Niobium	0.064
12	Vanadium	0.033
13	Ferrous	95.571

4. EXPERIMENTAL SETUP & METHODOLOGY

The experiments are conducted on a CNC Turning center of diameter 350 mm, between centers 600 mm, spindle speed 4500 rpm, main motor power of 11kW. After performing the machining process, the flank wear is measured and recorded by using a Mitutoyo digital tool makers microscope of specifications, eyepiece 15X, view field diameter 13mm, objective 2X, working distance 67mm, total magnification 30X. The surface roughness parameters values are measured using Surfcorder SE 3500 whose specification is measuring range of Z: 600 μm X: 100 mm, measuring magnification of Z: 50-500,000 X: 1-5,000, measuring speed of 0.05-2 mm/s, Z traverse range of 250 mm. Material removal rate is determined by noting the time of machining and weight of material removed.

4.1 Taguchi's Design of Experiment (DoE)

Taguchi's technique is a powerful tool in quality optimization [35]. Taguchi's technique makes use of a special design of orthogonal array (OA) to examine the quality characteristics through a minimal number of experiments [36]. Taguchi's DoE is used to design the orthogonal array for three parameters varied through three levels. The control parameters and their levels chosen [37] are shown in Table 2.

Application of the Taguchi technique is accomplished in two phases: Design of the experiment, which includes determining controllable and noise factors and the level to be investigated, which determines the number of repetitions and; Analysis of the results to determine the best possible factor combination from individual factor influences and interactions [38].

The various combinations of cutting speed, feed rate and depth of cut based on which the experiments are to be conducted is presented in Table 3.

Table 2 Control Parameters and its Levels

Parameter / Level	Symbol	Level 1	Level 2	Level 3
Cutting Speed (m/min)	A	136	122	108
Feed Rate (mm/rev)	B	0.203	0.330	0.432
Depth of Cut (mm)	C	0.1	0.2	0.3

Table 3 Inner Array of Taguchi L_9 Orthogonal Array

Sl. No	Cutting Speed (m/min)	Feed Rate (mm/rev)	Depth of Cut (mm)
1	136	0.203	0.1
2	136	0.330	0.2
3	136	0.432	0.3
4	122	0.203	0.2
5	122	0.330	0.3
6	122	0.432	0.1
7	108	0.203	0.3
8	108	0.330	0.1
9	108	0.432	0.2

4.2 Multiple Linear Regression Models

Regression is conceptually simple technique for investigating functional relationship between output and input decision variables of a process and may be useful for manufacturing process data description, parameter estimation and control [39]. The criteria for fitting the best line through the data in simple linear regression is to minimize the sum of squares of residuals (S_r) between the measured values of response and the values of response calculated with the regression model. The linear fit is expressed as:

$$y = a_0 + a_1 x \qquad (1)$$

where 'y' is the value of response and 'x' is the value of variable. Multiple linear regressions are the useful extension of the linear regression when the response is a linear function of two or more independent variables, which is the case in many practical applications. In general, the response variable *y* may be related to *k* regressor variables. The model in Equ. 2 is called a multiple linear regression model with *k* regressor variables.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \varepsilon \qquad (2)$$

The parameters β_j, $j = 0, 1, ., k$, are called the regression coefficients.

4.3 Non-Dominated Sorting Genetic Algorithm (NSGA-II)

Kalyanmoy Deb et al proposed NSGA-II [40,41]. It is the revised version of the Non-dominated Sorting Genetic Algorithm (NSGA-I). NSGA-II is computationally more efficient, which uses elitism and a crowded comparison operator. The elitist mechanism of NSGA-II consists of combining the best parents with the best offspring obtained. Firstly, NSGA-II uses an elite-preserving mechanism, thereby assuring preservation of previously found good solutions. Secondly, NSGA-II uses a fast non-dominated sorting procedure. Thirdly, NSGA-II does not require any tunable parameter, thereby making the algorithm independent of the user. Fig. 2 shows how the elites are preserved in NSGA-II.

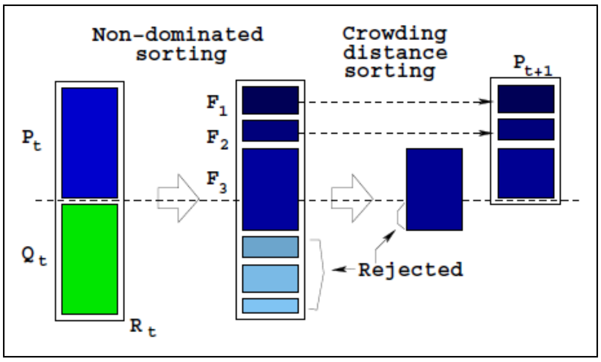

Fig. 2 Preservation of Elites in NSGA-II

During preserving the elites, NSGA-II builds a population of competing individuals, ranks and sorts each individual according to non-domination level to create new pool of offspring and produces a new combined pool of population by combining the parents and offspring. By adding a crowding distance to each member of the newly generated population, the NSGA-II then conducts niching. To keep a diverse front by making sure each member stays a crowding distance apart it uses this crowding distance in its selection operator to explore the fitness landscape. The pseudo code of the improved version of NSGA, NSGA-II is shown in Fig. 3 [42].

The values of the parameters that have been used in the NSGA-II technique are Variable type = Real variable, Population size=100, Crossover probability =0.9, Real-parameter mutation probability =1, Real-parameter SBX parameter =10, Real-parameter Mutation parameter =100, Total number of generations=100.

5. RESULTS AND DISCUSSION

Based on the L9 Orthogonal array designed using Taguchi's DoE experiments are conducted. In this study, 9 different workpieces are taken and for each level a separate workpiece is used and after performing the turning operation the output responses flank wear, surface roughness and MRR are determined and the values are given in Table 4.

Table 4 Measured Output responses

Sl. No	Flank wear (mm)	Surface roughness (µm)	MRR (gm./min)
1	0.126	2.46	0.017
2	0.067	2.34	0.043
3	0.144	3.71	0.06
4	0.079	1.43	0.013
5	0.086	2.44	0.041
6	0.058	3.37	0.026
7	0.112	2.18	0.023
8	0.023	2.57	0.009
9	0.045	3.45	0.047

It is observed from the experimental results that, when the cutting speed is increased from 108 m/min to 122 m/min, flank wear and MRR increases by 23.83% and 1.52% whereas surface roughness is reduced by 11.71%. When cutting speed is further increased from 122 to 136 m/min the responses flank wear, surface roughness and MRR increases by 51.14%, 17.56% and 49.81%.

A decrease in flank wear by 44.51% and increase in surface roughness by 21.11% and MRR by 75.44% is noticed when feed rate is changed from 0.203 to 0.33 mm/rev. With increase in feed rate from 0.33 to 0.432 mm/rev, a considerable increase in flank wear by 40.44%, surface roughness by 43.27% and MRR by 42.95 is observed.

When the depth of cut is changed from 0.1 mm to 0.2 mm, flank wear and surface roughness are reduced by 7.68% and 14.05% with increase in MRR by 98.27%. When depth of cut is further changed from 0.2 to 0.3 mm, flank wear drastically increases by 78.96% with surface roughness increasing by 15.37% and MRR increasing by 20.41%.

Using Minitab-16, statistical software, empirical models are developed using multiple linear regression equations for the measured output responses flank wear, surface roughness and MRR which are given in Equ. (6-8).

```
procedure NSGA-II(N′, g, f_k(x_k))    ▷ N′ members evolved g generations to solve f_k(x)
    Initialize Population P′
    Generate random population - size N′
    Evaluate Objective Values
    Assign Rank (level) Based on Pareto dominance - sort
    Generate Child Population
        Binary Tournament Selection
        Recombination and Mutation
    for i = 1 to g do
        for each Parent and Child in Population do
            Assign Rank (level) based on Pareto - sort
            Generate sets of nondominated vectors along PF_known
            Loop (inside) by adding solutions to next generation starting from the first front until N′ individuals found determine crowding distance between points on each front
        end for
        Select points (elitist) on the lower front (with lower rank) and are outside a crowding distance
        Create next generation
            Binary Tournament Selection
            Recombination and Mutation
    end for
end procedure
```

Fig. 3 Pseudo code for NSGA-II algorithm

$$Flank\ Wear = -0.155 + 0.00187 \times Cutting\ speed - 0.113 \times Feed\ rate + 0.225 \times Depth\ of\ cut \tag{3}$$

$$Surface\ Roughness = 0.186 + 0.0037 \times Cutting\ speed + 6.366 \times Feed\ rate - 0.117 \times Depth\ of\ cut \tag{4}$$

$$Material\ Removal\ Rate = -0.0899 + 0.000488 \times Cutting\ speed + 0.116 \times Feed\ rate + 0.12 \times Depth\ of\ cut \tag{5}$$

The objective of this work is to minimize the flank wear and maximize MRR with surface roughness as the constraint using NSGA-II. Hence the objective function is formulated as,

Objective Function: Minimze (flank wear) + Maximize (MRR).

Subject to the constraint: Surface roughness ≤ 2.5 µm.

Taking equal weightage (50%) to both flank wear and MRR and also converting the maximization of MRR to minimization of MRR (taking –ve sign), the objective function is rewritten as,

Objective function = (0.5*flank wear) – (0.5*MRR);
Subject to the constraint: Surface roughness ≤ 2.5 µm.

The lower and upper bounds of machining parameters are,

108 ≤ cutting speed ≤ 136
0.203 ≤ feed rate ≤ 0.432
0.1 ≤ depth of cut ≤ 0.3

From the simulation results obtained from NSGA-II, the optimum machining parameters are determined as, cutting speed of 109.86 m/min; feed rate of 0.3005 mm/rev and depth of cut of 0.1 mm. The predicted output responses during the optimization procedure is, flank wear of 0.039 mm, MRR of 0.0106 gm. /min and surface roughness of 2.4934 µm.

The value of combined objective function generated during optimization for each generation is shown in Fig. 4. It is observed that initially the objective function is close to 0.047 and as the number of generation increases; the combined objective function converges towards minimization of objective function and finally settles around 0.014. It is also observed that the convergence of combined objective function is faster towards the final optimum result.

The Pareto-optimal set is the non-dominated set in the entire space. The many solutions trading-off between two objectives minimization of flank wear and maximization of MRR is shown in Fig. 5. It is observed that one solution is better than the other in both objectives and for certain other pair of points, one solution is better than other in one objective and is worse in the another objective. When this happens between two solutions, it is called as non-dominated solution as shown.

The variation of flank wear for each generation during optimization procedure is shown in Fig. 6. It is observed that the flank wear values is initially 0.0418 mm and finally it settles to 0.039 mm. The aim is to lower the flank wear and the results obtained shows that the flank wear is lowered during the optimization process.

The variation of MRR during the optimization process is shown in Fig. 7. During the process, initially the MRR values are lower at after some generations it settles to a higher value of 0.0106 gm./min. The aim of obtaining higher MRR is achieved through this optimization procedure.

Based on the optimum machining parameters determined from NSGA-II algorithm as cutting speed of 109.86 m/min; feed rate of 0.3005 mm/rev and depth of cut of 0.1 mm, an confirmation experiment is conducted and the output responses obtained are given in Table 5 along with the predicted output responses obtained from the simulation result. It is observed that a reduction in flank wear by 58.65% and surface roughness by 10.56% is obtained when comparing the results with average experimental values. A reduction in MRR by 58.06% is achieved due to the value of surface roughness constraint chosen which satisfies the chosen objective.

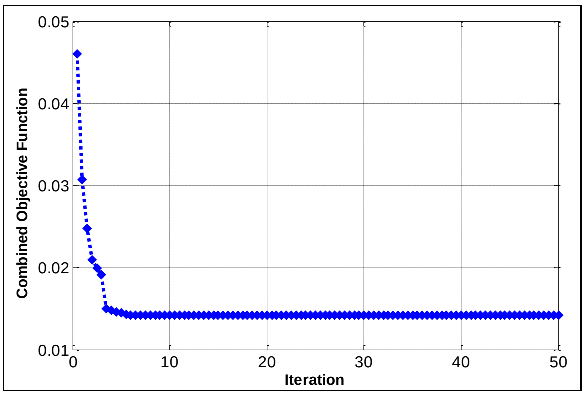

Figure 4 Variation of Combined objective function with generations

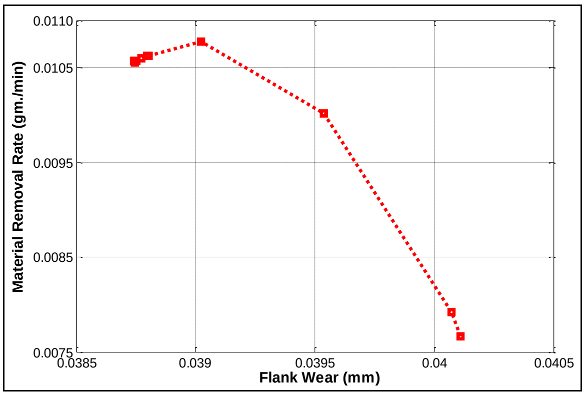

Figure 5 Pareto Optimal front between Flank wear and MRR

Table 5 Results of confirmation experiment based on NSGA-II output

Sl. No	Output Response	Predicted Responses	Experimental Output
1	Flank wear	0.039	0.034
2	Surface roughness	2.493	2.28
3	MRR	0.0106	0.013

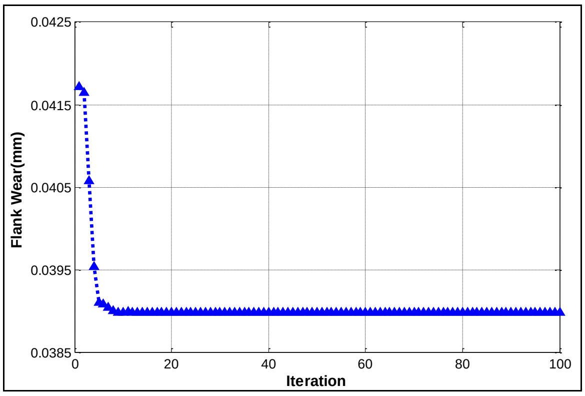

Figure 6 Variation of Flank wear during optimization

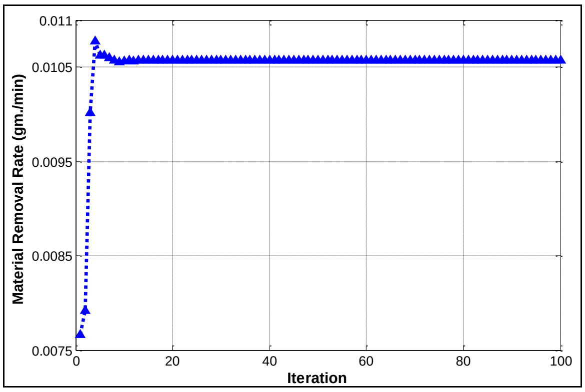

Figure 7 Variation of MRR during optimization

6. CONCLUSION

The conclusions derived by applying a meta-heuristic evolutionary NSGA-II algorithm on turning AISI 4340 steel with carbide cutting inserts are as follows.

- Multiple Linear regression models were developed for the output responses flank wear, surface roughness and MRR using Minitab software.

- The optimum machining parameters are determined as cutting speed of 109.86 m/min; feed rate of 0.3005 mm/rev and depth of cut of 0.1 mm using NSGA-II. The predicted output responses are flank wear of 0.039 mm, MRR of 0.0106 gm. /min and surface roughness of 2.4934 µm with a combined objective function values of 0.014.

- The Pareto-optimal set is the non-dominated set in the entire space which shows a solution trading-off between two objectives minimization of flank wear and maximization of MRR.

- Confirmation experiment performed with optimum conditions obtained using NSGA-II shows a reduction in flank wear by 58.65%, surface roughness by 10.56% and MRR by 58.06% is obtained when comparing the results with average experimental values.

REFERENCE

[1] Serope Kalpakjian., and Steven R. Schmid, *Manufacturing Engineering and Technology*, Prentice-Hall, 2001.

[2] George Schneider. and Jr Cmfge, *Cutting Tool Applications*, GMRS Associates, 2002.

[3] M. Nalbant, H. Gokkaya, and G. Sur, Application of Taguchi method in the optimization of cutting parameters for surface roughness in turning, *Materials & Design*, 28, 2007, 1379-1385.

[4] S. Thamizhmani, S. Saparudin, S, and S. Hassan, Analysis of surface roughness by turning process using Taguchi method, *Journal of Achievements in Materials and Manufacturing Engineering*, 20(1-2), 2007, 503-506.

[5] K.V.B.S. Kalyan Kumar, and S.K. Choudhury, Investigation of tool wear and cutting force in cryogenic machining using design of experiments, *Journal of Materials Processing Technology*, 203, 2008, 95-101.

[6] T. Tamizharasan, T. Selvaraj, and A. Noorul Haq, Analysis of tool wear and surface finish in hard turning, *International Journal of Advanced Manufacturing Technology*, 28, 2006, 671-679.

[7] Ersan Aslan, Necip Camuscu, and Burak Birgoren, Design optimization of cutting parameters when turning hardened AISI 4140 steel (63 HRC) with Al_2O_3 + TiCN mixed ceramic tool, *Materials & Design*, 28, 2007, 1618-1622.

[8] Handi Aouici, Mohamed Athmane Yallese, Brahim Fnides, Kamel Chaoui, and Tarek Mabrouki, Modeling and Optimization of hard turning of X38CrMoV5-1 steel with CBN tool: Machining parameters effects on flank wear and surface roughness, *Journal of Mechanical Science and Technology*, 25(11), 2011, 2843-2851.

[9] N. Senthilkumar, T. Tamizharasan, and V. Anandakrishnan, An ANN approach for predicting the cutting inserts performances of different geometries in hard turning, *Advances in Production Engineering & Management*, 8(4), 2013, 231-241.

[10] G. Akhyar, C.H. Che Haron, and J.A. Ghani, Application of Taguchi method in the Optimization of Turning Parameters for Surface Roughness, *International Journal of Science Engineering and Technology*, 1(3), 2008, 60-66.

[11] S.H. Yang, and U. Natarajan, Multi-objective optimization of cutting parameters in turning process using differential evolution and non-dominated sorting genetic algorithm-II approaches, *International Journal of Advanced Manufacturing Technology*, 49, 2009, 773-784.

[12] N. Srinivas, and K. Deb, Multiobjective Optimization using Nondominated Sorting in Genetic Algorithms, *Evolutionary Computation*, 2(3), 1994, 221-248.

[13] N. Senthilkumar, and T. Tamizharasan, Impact of Interface Temperature over Flank Wear in Hard Turning using Carbide Inserts, *Procedia Engineering*, 38, 2012, 613-621.

[14] T. Tamizharasan, and N. Senthilkumar, Numerical Simulation of effects of Machining parameters and Tool Geometry using DEFORM-3D: Optimization and Experimental Validation, *World Journal of Modelling and Simulation*, 10(1), 2014, 49-59.

[15] T. Tamizharasan, and N. Senthilkumar, Optimization of Cutting insert geometry using DEFORM-3D: Numerical Simulation and Experimental Validation, *International Journal of Simulation Modelling*, 11(2), 2012, 65-76.

[16] N. Senthilkumar, T. Tamizharasan, and V. Anandakrishnan, Experimental Investigation and Performance Analysis of Cemented Carbide Inserts of different geometries using Taguchi based Grey Relational Analysis, *Measurement*, 58, 2014, 520-536.

[17] N. Senthilkumar, and T. Tamizharasan, Experimental investigation of cutting zone temperature and flank wear correlation in turning AISI 1045 steel with different tool geometries, *Indian Journal of Engineering & Materials Sciences*, 21(2), 2014, 139-148.

[18] N. Senthilkumar, and T. Tamizharasan, Effect of Tool geometry in Turning AISI 1045 steel: Experimental Investigation and FEM analysis, *Arabian Journal for Science and Engineering*, 39(6), 2014, 4963-4975.

[19] N. Senthilkumar, T. Tamizharasan, and S. Gobikannan, Application of Response Surface Methodology and Firefly Algorithm for optimizing Multiple Responses in Turning AISI 1045 Steel, *Arabian Journal for Science and Engineering*, 39(11), 2014, 8015-8030.

[20] N. Senthilkumar, T. Tamizharasan, and V. Anandakrishnan, An Hybrid Taguchi-Grey Relational Technique and Cuckoo Search Algorithm for Multi-Criteria Optimization in Hard Turning of AISI D3 Steel, *Journal of Advanced Engineering Research*, 1(1), 2014, 16-31.

[21] Abolfazl Golshan, Mostafa Rezazadeh Shirdar, and Izman, S, A Comparison of Optimization Methods in Cutting Parameters Using Non-dominated Sorting Genetic Algorithm (NSGA-II) and Micro Genetic Algorithm (MGA), *International Journal of Experimental Algorithms*, 2(2), 2011, 62-73.

[22] K. Palanikumar, B. Latha, V.S. Senthilkumar, and R. Karthikeyan, Multiple Performance Optimization in Machining of GFRP Composites by a PCD Tool using Non-dominated Sorting Genetic Algorithm (NSGA-II), *Metals and Materials International*, 15(2), 2009, 249-258.

[23] Jianling Chen, Multi-Objective Optimization of Cutting Parameters with Improved NSGA-II, Proc. International Conference on Management and Service Science, Beijing, China, 2009, 1-4.

[24] R. Datta, and K. Deb, A classical-cum-Evolutionary Multi-objective optimization for optimal machining parameters, *Proc. World Congress on Nature and Biologically Inspired Computing*, Coimbatore, India, 2009, 607-612.

[25] Rituparna Datta, and Anima Majumder, Optimization of turning process parameters using Multi-objective Evolutionary algorithm, *Proc. IEEE Congress on Evolutionary Computation*, Barcelona, Spain, 2010, 1-6.

[26] Kalyanmoy Deb,. and Rituparna Datta, *Hybrid Evolutionary Multi-Objective Optimization of Machining Parameters*, KanGAL Report Number 2011005, pp. 1-23.

[27] M.H. Gholami, and M.R. Azizi, Constrained grinding optimization for time, cost, and surface roughness using NSGA-II, *The International Journal of Advanced Manufacturing Technology*, 73(5-8), 2014, 981-988.

[28] Jun Li, Xiaoyong Yang, Chengzu Ren, Guang Chen, Yan Wang, Multiobjective optimization of cutting parameters in Ti-6Al-4V milling process using nondominated sorting genetic algorithm-II, *The International Journal of Advanced Manufacturing Technology*, 2014, DOI: 10.1007/s00170-014-6311-8.

[29] Qiulian Wang, Fei Liu, Xianglian Wang, Multi-objective optimization of machining parameters considering energy consumption, *The International Journal of Advanced Manufacturing Technology*, 71(5-8), 2014, 1133-1142.

[30] K. Sivakumar, C. Balamurugan, and S. Ramabalan, Simultaneous optimal selection of design and manufacturing tolerances with alternative

manufacturing process selection, *Computer-Aided Design*, 43(2), 2011, 207–218.

[31] Yusliza Yusoff, Mohd Salihin Ngadiman, and Azlan Mohd Zain, Overview of NSGA-II for Optimizing Machining Process Parameters, *Procedia Engineering*, 15, 2011, 3978–3983.

[32] M. Durairaj, and S. Gowri, Parametric Optimization for Improved Tool Life and Surface Finish in Micro Turning Using Genetic Algorithm, *Procedia Engineering*, 64, 2013, 878–887.

[33] H. Ganesan, and G. Mohankumar, Optimization of Machining Techniques in CNC Turning Centre Using Genetic Algorithm, *Arabian Journal for Science and Engineering*, 38(6), 2013, 1529-1538.

[34] Ajay Batish, Anirban Bhattacharya, Manwinder Kaur, and Manjot Singh Cheema, Hard turning: Parametric optimization using genetic algorithm for rough/finish machining and study of surface morphology, *Journal of Mechanical Science and Technology*, 28(5), 2014, 1629-1640

[35] Ranjit K. Roy, Design of experiments using the Taguchi approach: 16 steps to product and process improvement, Wiley-Inderscience Publication, 2001.

[36] T. Tamizharasan, and N. Senthilkumar, Analysis of Surface Roughness and Material Removal Rate in Turning using Taguchi's Technique, *Proc. IEEE – International Conference on Advances in Engineering, Science and Management*, Nagapattinam, India, 2012, 231-236.

[37] Erik Oberg, Franklin D. Jones, Holbrook L. Horton, and Henry H. Ryffel, *Machinery's Handbook, 28th ed.*, Industrial Press, New York, 2008.

[38] N. Senthilkumar, T. Ganapathy and T. Tamizharasan, Optimization of Machining and Geometrical parameters in Turning process using Taguchi Method, *Australian Journal of Mechanical Engineering*, 12(2), 2014, 233-246.

[39] Douglas C. Montgomery, *Design and Analysis of Experiments, 8th ed.*, John Wiley & Sons, Inc., USA, 2013.

[40] Kalyanmoy Deb, Amrit Pratap, Sameer Agarwal. and T. Meyarivan, A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II, *IEEE Transactions on Evolutionary Computation*, 6(2), 2002, 182-197.

[41] Kalyanmoy Deb, and T. Goel, Controlled elitist non-dominated sorting Genetic Algorithms for Better Convergence, *Evolutionary Multi-Criterion Optimization*, 1993, 2001, 67-81.

[42] Carlos A. Coello Coello, Gary B. Lamont, and David A. Van Veldhuizen, *Evolutionary Algorithms for Solving Multi-Objective Problems, 2nd ed.*, Springer Science+Business Media, LLC, 2007.