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APPLICATION OF HEURISTIC TECHNIQUES AND EFFECT OF PROCESS PARAMETER ON TURNING AND FACING OPERATION-A REVIEW (2010-2015)

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ABSTRACT

In the present high competitive and rapidly changing scenario of manufacturing industries, maintaining quality is a big concern. The following factors such as machining operation, process parameters and application of optimization techniques plays a major role to increase the quality of a product. In order to achieve the quality of a product machining process parameters such as the cutting speed, depth of cut, feed rate, tool angle, type of lubrication used etc plays a major role. This paper gives an overview and the comparison of the evolutionary optimization techniques to optimize machining process parameter of both turning and facing operation in CNC and conventional lathe. Recent heuristic techniques are considered for optimization purpose, Response Surface Methodology (RSM) Genetic algorithm (GA), Simulated annealing (SA), Particle swarm optimization (PSO), Ant colony optimization (ACO) and Artificial bee colony (ABC) algorithm. Literature found that RSM and GA were widely applied by researchers to optimize the machining process parameters. The proposed research was beneficial for industries to determine the optimal cutting parameters in order to minimize the costs incurred and improving productivity of manufacturing firms and improve the quality of the process and product.

Key words: metal cutting, surface roughness, tool wear, machining time, response surface methodology (RSM), genetic algorithm (GA).

INTRODUCTION

Machining is the broad term used for the removal of material from a work piece in the form of chips. The manufacturing machining process is divided into the following categories:

- Cutting, generally involving single-point or multipoint cutting tools, each with a clearly defined geometry.
- Abrasive processes, such as grinding.
- Non traditional machining processes, utilizing electrical, chemical, and optimal sources of energy.

The quality of product can be improved by improving the manufacturing and production process. Optimum selection of the cutting parameters increases the productivity and reduces the production cost. Due to the high competitiveness and increase in demand of quality of a product in the market, the optimization of metal cutting parameters and process plays a major role in increasing the production, and to respond effectively for their needs. Many research have been done in the areas of machining, process with various process parameters that reduce the machine efficiency such as depth of cut, feed rate, spindle speed, axial / radial depth of cut, tool geometry (cutter diameter, number of teeth, side cutting edge angle, rack angle, shank diameter, helix angle, overall length of tool, nose radius., etc) torque, spindle motor current, cutting time, clearance angle, feed drive current, type of lubricants used etc [1] Optimized combination of certain parameters will increase the surface finish, reduces the tool wear, increase the tool life by decreasing the vibration produced in the machine. In this paper, a review on the optimization techniques on conventional and non-conventional metal cutting process is carried out. Figure-1 represents the flow chart of (evolutionary) optimization techniques.

CONVENTIONAL TECHNIQUES: DESIGN OF EXPERIMENTS (DOE)

Design of Experiments (DOE) is a statistical tool introduced by Fisher in 1920's to study the effect of multiple variables simultaneously.

ANALYSIS OF VARIANCE (ANOVA)

Analysis of Variance (ANOVA) is a statistical procedure and is a hypothesis-testing technique used to test the equality of two or more population means by examining the variances of samples that are taken. In most experiments, a great deal of variance (or difference) usually indicates that there was a significant finding from the research.

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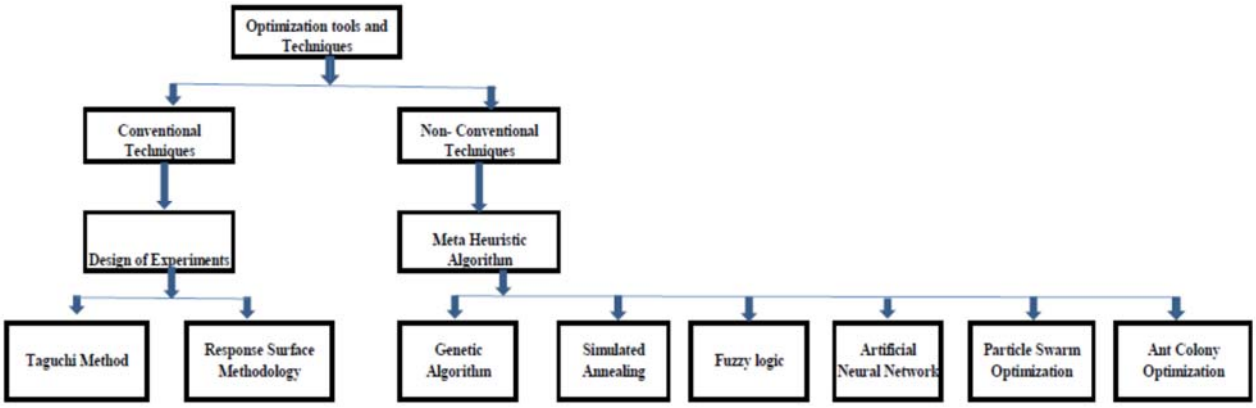

Figure-1. Optimal tools and techniques.

TAGUCHI METHOD

Taguchi has visualized a new method of conducting the design of experiments based on well defined guidelines. To study the parameter space based on the fractional factorial arrays from DoE, called orthogonal arrays. Taguchi method contains system design, parameter design, and tolerance design procedures to achieve a robust process and result for the best product quality.

RESPONSE SURFACE METHODOLOGY (RSM)

Response surface methodology (RSM) is a collection of mathematical and statistical techniques. The objective is to optimize the response (output variable) which is influenced by several independent variables (input variables). An experiment is a series of tests, called runs, in which changes are made in the input variables in order to identify the reasons for changes in the output response.

NON CONVENTIONAL TECHNIQUES

Non-conventional techniques were used for the optimization of cutting conditions in machining processes. The cutting conditions can be optimized within the constraints set by using the non-conventional approaches.

GENETIC ALGORITHM (GA)

Genetic algorithm (GA) is an optimization algorithm based on the mechanics of natural selection and genetics. In GA, candidate solutions to the given problem are analogous to individuals in a population. Each individual is encoded as a string, called chromosome. New candidate solutions are produced from parent chromosomes by the crossover operator. The mutation operator is then applied to the population. The quality of each individual is evaluated and rated by the so-called fitness function.

SIMULATED ANNEALING (SA)

Simulated annealing algorithm is a heuristic method with the basic idea of generating random displacement from any feasible solution. This process accepts not only the generated solutions, which improve the objective function but also those which do not improve it with the probability function; a parameter depending on the objective function. This algorithm has two important features: perturbation scheme for generating a new solution and an annealing schedule that includes an initial and solution.

FUZZY LOGIC

Fuzzy Logic incorporates a simple, rule-based IF X AND Y THEN Z approach to a solving control problem rather than attempting to model a system mathematically. The FL model is empirically-based, relying on an operator's experience rather than their technical understanding of the system.

ARTIFICIAL NEURAL NETWORK (ANN)

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurones) working in unison to solve specific problems.

PARTICLE SWARM OPTIMIZATION (PSO)

PSO is one of the optimization techniques belonging to EAs. The method has been developed through a simulation of simplified social models.PSO combines social psychology principles in socio-cognition human agents and evolutionary computations and has been motivated by the behaviour of organisms such as fish schooling and bird flocking.

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ANT COLONY OPTIMIZATION (ACO)

Ant Colony Optimization (ACO) is a paradigm for designing metaheuristic algorithms for combinatorial optimization problems. The main underlying idea, loosely inspired by the behaviour of real ants, is that of a parallel search over several constructive computational threads based on local problem data and on a dynamic memory structure containing information on the quality of previously obtained result.

SURFACE ROUGHNESS

Surface quality of the product is a great concern in manufacturing industry; many attentions have been made to study the effects of cutting vibration on surface finish. Table 1 shows the summary and recent techniques involved in optimizing the machining parameters on Surface roughness.

Researchers [2] developed a mathematical model to study the machining parameter by using RSM: considering the process parameters such as cutting speed, feed rate and depth of cut in finish hard turning of AISI 52100 bearing steel with CBN tool and the performance characteristics of tool life, surface roughness and cutting forces are analyzed. The feed rate and cutting speed strongly influence the surface roughness. The authors conducted [3] an experimental study on hard turning with CBN tool of AISI 52100 bearing steel, considering the input cutting parameters as cutting speed, feed rate and depth of cut and output variables as surface roughness, cutting forces. The optimization was carried out using response surface methodology (RSM); results the feed rate and cutting speed is the most influencing parameter that affects the surface roughness. An experiment was conducted by [4] considering the input parameters as feed rate, tool geometry, nose radius, and machining time to predict the surface roughness. The author concluded that the feed rate has the most significant effect on surface roughness. An attempt [5] was made to predict cutting temperature and surface finish in turning process by using RSM; considering the depth of cut, feed Rate and cutting speed as input parameter, results the depth of cut and cutting speed to be the most influencing parameter. The authors [6] carried out an optimization to predict AISI P-20 tool steel using TiN coated tungsten carbide coatings by using ANOVA, Taguchi method with logical fuzzy. The cutting speed, feed rate, depth of cut, nose radius and cutting environment are taken as parameter selection. The authors concluded that cutting speed of 160 m/min, nose radius of 0.8 mm, feed of 0.1 mm/rev, depth of cut of 0.2 mm. Process factors such as feed rate, cutting speed and tool coatings were investigated. Optimization was carried to predict surface roughness using Taguchi and ANOVA method for the turning of magnesium work pieces [7]. The researchers [8] conducted an experiment using LM 25 aluminum alloy as a work piece and carbide tool insert (K10) as tool considering the four machining parameters cutting speed, feed rate, depth of cut, and machining time. The flank wear and surface roughness was investigated. The effect of parameters on magnesium UNS M11311 by turning process and concluded that the feed rate is the influencing factors [9]. The authors [10] predicted the surface roughness; input parameter as Cutting speed, Feed rate, Depth of cut of AISI1045 material using Ceramic tools in turning operation. The researchers [11] designed an experiment by considering the spindle speed, feed rate and depth of cut as parameters using C26000 metal in a CNC turning centre with a CNMG 120408 insert. The optimization was carried out using artificial neural network (ANN) to predict the surface roughness. The authors concluded that the feed rate is the most influencing parameter. A mathematical model to predict the surface roughness in machining of EN24 steel alloy is developed [12]. The optimization was carried out using Response Surface Method. The cutting parameters such as cutting speed, feed rate and depth of cut were considered for the experiment. It was found that feed rate has the highest significance than cutting speed and depth of cut. 3D plots were drawn to find out the optimum setting for minimum surface roughness. An experiment was conducted using AISI 1040 steel to predict surface roughness. The optimization was done using Response Surface Method and Genetic algorithm using Depth of cut, feed rate and spindle speed as machining parameters and suggested that the roughness value increases with feed rate increases [13]. The authors [14] studied the characteristics of surface roughness in turning of EN31 alloy using speed, feed and depth of cut. The optimization of machining parameters was done using Genetic Algorithm. The result shows the feed rate increases the surface roughness value also increases. The optimization was carried [15] out using spindle speed, feed and depth of cut in dry turning of mild steel HSS cutting tool. ANOVA, Signal to Noise ratio and Taguchi method is used find the low surface roughness value. The authors conclude that the feed was found to be significant factor. The author [16] analyzed the optimum cutting conditions using spindle speed, feed and depth of cut on EN8 alloy. The performance of surface roughness was determined using multiple regression analysis and ANOVA, results feed was the significant factors affecting surface roughness. An experiment was conducted using mild steel with HSS cutting tool, the effect of feed, speed and depth of cut on the surface roughness as well as cutting force were analyzed. Full factorial design with two repetitions was used to find the optimal solution. Feed and spindle speed were the main influencing factors to increase surface roughness [17]. The authors [18] used ANOVA and signal to noise ratio to predict the surface roughness by using cutting parameter as insert radius, depth of cut, feed and cutting speed to turn AISI 410 steel using TiN coated P20 and P30 cutting tool. It was found that the insert radius and feed rate has significant effect on surface roughness. An experimental investigation was conducted [19] using Al6351-T6 alloy to find the optimal surface roughness. The model was predicted using regression technique and Taguchi Technique; cutting speed, feed and depth of cut were consider for turning process, results cutting speed was found to be highest

significant parameter. The authors [20] established a surface roughness ANOVA model for turning of AISI 1045 steel alloy. The effect of process parameters i.e., speed, feed and depth of cut on surface roughness. The optimization was carried out using Taguchi Method. The researchers [21] carried an ANOVA analysis to predict surface roughness by considering the machining parameters as speed, feed and depth of cut and tool geometrical parameters like back rake angle, side rack angle for turning of mild steel with HSS cutting tool. It was found that feed rate is the most significant factor. An experiment was [22] conducted on mild steel using carbide inserts under dry conditions considering the cutting speed, feed rate and depth of cut as parameter and the predication was carried out using artificial neural network on surface roughness in turning. It was concluded that increase in feed rate increases the roughness whereas increases in cutting speed decreases the roughness. The authors [23] carried out an experimental work to optimize the surface roughness and MRR in machining AISI 1018 alloy with Titanium coated Carbide inserts considering the spindle speed, feed rate and depth of cut. The optimization was done using Taguchi's method and ANOVA and suggests that the spindle speed is the most significant factor for surface roughness. An experiment was conducted by using Taguchi method and ANOVA to predict surface roughness of 52100 steel alloys with Carbide inserted cutting tool. The cutting speed, feed rate and depth of cut are considered and suggest that feed rate is the most influencing factors [24]. The authors [25] developed a mathematical model to predict the surface roughness of machining 11sMn30 alloy using carbide tip insert. The cutting parameters were cutting speed; feed rate and depth of cut are considered. It was found that the feed rate is the most significant factor to affect surface roughness. Taguchi orthogonal design is applied to optimize the cutting parameters; cutting speed, feed and depth of cut using coated carbide single point cutting tool. This experiment results the feed rate is the most significant parameter [26]. The researchers [27] considered the cutting speed and feed rate to optimize surface roughness in turning of EN8, EM31 and mild steels using TN60, TP0500 and TT8020 as tool material. Taguchi method to optimize is used for optimization purpose. It was observed that feed rate has highest effect on surface roughness. The researchers [28] utilized an optimization process to predict the cutting parameters (spindle speed, feed and depth of cut) of mild steel in turning to study the influence of parameters by using ANOVA, Taguchi method and Signal to Noise ratio.. For that feed rate was the most significant factor for surface roughness. The authors [29] used Response Surface Methodology and ANOVA to optimize the cutting speed, feed and depth of cut to predict surface roughness of Al 6061 alloy. Among the three cutting parameters depth of cut was found to be the significant factor for both surface roughness. A mathematical model was developed using speeds, feed rates and depths of cut to minimize the include tool life, surface roughness, cutting force and cutting power consumption. The optimization was carried out using Genetic Algorithm (GA) [30]. An optimization was carried to machine process parameters such as feed, speed and depth of cut on surface roughness. The prediction was carried out using an improved GA [31]. The purpose of this experimental investigation was to analyze the effect of cutting parameters; cutting speed, feed rate, depth of cut, cutting fluid in order to predict surface roughness (Ra) of AISI 1040 steel during turning operation, results feed rate has the most significant effect on surface roughness [32]. An experimental studies was conducted to optimize the cutting parameters (depth of cut, feed rate, spindle speed) in wet turning of EN24 steel. The Analysis of Variance (ANOVA), Taguchi method and Signal-to-Noise ratio were used to study the performance characteristics in turning operation [33]. The authors [34] conducted the experiment to optimize the turning process under various machining parameters by using Taguchi method of AISI 1045 steel with coated cemented carbide. An experimental investigation was conducted on turning Aluminium Silicon Carbide using polycrystalline diamond (PCD) 1600 grade insert; Cutting speed, feed rate, depth of cut is taken as constraints to optimize surface roughness, specific power and tool wear are considered as output parameter based on the techniques of Taguchi and Analysis of variance (ANOVA). [35]. A experimental study was conducted to optimize the cutting parameters; Cutting speed, feed rate and depth of cut on medium carbon steel AISI 1020 material, finally the authors concluded that cutting speed and feed rate is the dominant parameter to increase surface roughness and temperature [36]. The authors conducted an experiment to optimize the machining parameters; cutting speed, depth of cut, feed rate and tool flute to minimize surface roughness [37]. In this study [38], the Taguchi method and ANOVA was used to minimize the surface roughness by considering rake angle, cutting speed, depth of cut, and feed rate. An attempt has been made to evaluate coated carbide inserts during dry turning of hardened EN24 steel. The effect of machining parameters (depth of cut, feed and cutting speed) on surface roughness parameters (Ra and Rz) were investigated by applying ANOVA [39]. The authors [40] conducted an experiment to correlate the cutting parameters such as cutting speed, feed rate and depth of cut to predict machining force, power, specific cutting

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Table-1. Summary of recent techniques in optimizing machining parameters for surface roughness.

S. No.	Author (Surface roughness)	Material used	Input parameter	Optimization methodology	Result: influencing parameter
1	Samir Khamel, *et al*. (2012)	AISI 52100 bearing steel	Cutting speed, Feed rate, Depth of cut	RSM and ANOVA	Feed rate and Cutting speed
2	Bouacha, *et al*. (2010)	AISI 52100 bearing Steel	Cutting speed, Feed rate, Depth of cut	RSM	Feed rate and Cutting speed
3	Nexhat Qehaja, et al. (2015)		Feed rate, Nose radius, Cutting time	Regression analysis	Feed rate
4	Logesh. K *et al*. (2014)	Aluminium Al6063	Cutting Speed, feed rate, depth of Cut	Response surface methodology (RSM)	Depth of cut and cutting speed
5	Anil Gupta *et al* (2011)	AISI P-20 tool steel	Cutting speed, feed rate, depth of cut, Nose radius	ANOVA, Taguchi and Fuzzy logic	Cutting speed, Nose radius
6	Villeta *et al*. (2011)	Magnesium Work pieces	Feed rate, cutting speed	Taguchi and ANOVA method	Feed rate
7	Seeman *et al.* (2010)	LM 25 aluminum Alloy	Cutting speed, feed rate, depth of cut, machining time	Regression analysis and RSM	Cutting speed and feed rate
8	Rubio *et al*. (2011)	Magnesium UNS M11311	Cutting speed, feed rate	ANOVA method	Feed rate
9	Tao *et al.* (2013)	AISI1045	Cutting speed, feed rate, Depth of cut.	Quadratic prediction model	Feed rate
10	Natarajan *et al*. (2011)	C26000 metal	Spindle speed, Feed rate, Depth of cut	Artificial Neural Network (ANN)	Feed rate
11	Suresh Babu et al. (2011)	EN24 steel alloy	Cutting speed, Feed rate, Depth of cut.	RSM	Feed rate
12	Sahoo *et al*. (2011)	AISI 1040 steel	Depth of cut, Feed rate, Spindle speed.	RSM, ANOVA and Genetic Algorithm	Feed rate
13	Barik and N.K. Mandal	EN31 alloy	Spindle speed, depth of cut, Feed rate.	Genetic Algorithm	Feed rate
14	Davis and Alazhari Mohamed (2012)	Mild Steel	Spindle speed, depth of cut, feed rate.	Taguchi and ANOVA method	Feed rate
15	Adarsh Kumar *et al*. (2012)	EN-8 alloy	Spindle speed, Depth of cut, Feed rate.	multiple regression analysis and ANOVA	Feed rate
16	Rodrigues *et al.* (2012)	Mild steel	Spindle speed, Depth of cut, Feed rate.	ANOVA	Feed rate and Spindle Speed
17	Nitin Sharma *et al* (2012)	AISI 410 steel	Insert radius, Depth of cut, Feed rate, Cutting speed.	ANOVA and signal to noise ratio	Insert radius and feed rate
18	Somashekara and Swamy (2012)	Al6351-T6 alloy	Cutting speed, Feed rate, Depth of cut.	Taguchi Technique and ANOVA	Cutting speed
19	Upinder Kumar Yadav *et al* (2012)	AISI 1045 steel alloy	Cutting speed, Feed rate, Depth of cut.	Taguchi Method	Feed rate
20	Krishan Prasad (2013)	Mild steel	Back rake angle and Side rack angle	ANOVA	Feed rate
21	Koura *et al*. (2015)	Mild steel	Cutting speed, Feed rate and Depth of cut	Artificial neural network	Feed rate
22	Brajesh and Rahul Shukla (2014)	AISI 1018 alloy	Spindle speed, Feed rate and Depth of cut	Taguchi's method and ANOVA	Spindle speed
23	Rony *et al*. (2014),	52100 steel alloys	Cutting speed, Feed rate and Depth of cut	Taguchi method and ANOVA	Feed rate
24	Shunmugesh *et al.* (2014)	11sMn30 alloy	Cutting speed, Feed rate and Depth of cut.	Taguchi method	Feed rate
25	Sushil and Sandeep Kumar (2014)	Mild steel 1018	Cutting speed, Feed rate and Depth of cut.	Taguchi's method and ANOVA	Feed rate
26	Taquiuddin and Pratik (2014)	EN8, EM31 and mild steels	Speed Rate, Feed Rate, Depth of Cut	Taguchi method	Feed rate
27	Vishal Francis (2013)	Mild steel	Depth of cut, Feed rate, Spindle speed	Taguchi Method and ANOVA	Feed rate

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28	Bheem Singh (2015)	Al 6061 alloy.	Cutting speed, Feed rate and Depth of cut.	RSM, ANOVA	Depth of cut
29	Ansalam (2010)	SS 420 materials	Tool geometry (nose radius), Feed rate , Speed and Depth of cut	Genetic Algorithm (GA) and Taguchi's method	Feed rate
30	Yacov and Singh (2013)	AISI 1040 Medium Carbon Steel	Cutting speed, feed rate, depth of cut, cutting fluid	Regression analysis	Feed rate
31	Rahul Davis (2012)	EN24 steel	Depth of cut, Feed rate, Spindle speed	ANOVA Taguchi method	Feed rate
32	Narendra and Ajeet Singh (2015)	AISI 1045 steel	Depth of cut, Feed rate, Spindle speed	Taguchi method	Feed rate
33	Radhakrishnan *et al*. (2011)	Aluminium Silicon Carbide	Cutting speed, Feed rate, Depth of cut.	Taguchi's method and ANOVA	Feed rate
34	Adeel *et al*. (2010)	medium carbon steel AISI 1020	Cutting speed, Feed rate and Depth of cut	Taguchi techniques	Cutting speed and feed rate
35	Elssawi *et al*. (2015)	AA6061 aluminum alloy	cutting speed, Depth of cut and Feed rate. Tool flute.	Response Surface Method, Taguchi technique	Feed rate
36	Muhammad *et al*. (2011)	AISI 1018 steel	Tool rake angle, Cutting speed, Depth of cut, and Feed rate.	Taguchi and ANOVA	Feed rate, Cutting speed
37	Sudhansu Ranjan Das *et al*. (2013)	EN24 steel	Cutting speed, Depth of cut and Feed rate.	Taguchi and ANOVA	Feed rate
38	Hessainia *et al.* (2013)	42CrMo4 hardened steel	Cutting speed, Depth of cut and Feed rate.	Taguchi and RSM	Feed rate
39	Gunay and Yucel (2013)	high-alloy white cast iron	Cutting speed, Depth of cut and Feed rate.	Taguchi and ANOVA	Feed rate
40	Aouici *et al*. [2012]	AISI H11	Cutting speed, Depth of cut and Feed rate.	RSM	Feed rate and work piece hardness
41	Azizi *et al*. [2012]	AISI 52100 steel	Cutting speed, Depth of cut and Feed rate.	Taguchi and ANOVA	Feed rate
42	Edwin paul *et al*. (2013)	EN8 material	Cutting speed, depth of cut and feed rate	Taguchi method	Feed rate

force, tool wear and surface roughness on AISI 4340 steel. An investigation was carried out to find the effect of machining factors; cutting speed, depth of cut, feed rate using Taguchi method and RSM of 42CrMo4 hardened steel. The result indicates that the feed rate is the dominant factor affecting the surface roughness [41]. An experiment was carried out using Taguchi technique and ANOVA for determining minimum surface roughness in turning of high-alloy white cast iron [42]. The authors [43] have applied an response surface methodology (RSM) to optimize the effect of cutting parameters of AISI H11 with CBN tool. Results both feed rate and work piece hardness had significant significance on surface roughness. An experiment [44] was conducted to analyze the effect of cutting parameters (cutting speed, feed rate and depth of cut) of AISI 52100 steel with coated Al2O3+TiC mixed ceramic cutting tools by employing Taguchi's and ANOVA and regression analysis was carried out to predict surface roughness. The authors [45] conducted an experimental work on EN8 material to predict surface roughness and suggests that feed rate has greater Influence on the surface roughness.

TOOL WEAR

The quality of a product is strongly associated with the condition of the cutting tool. Mainly cutting tool plays a major role in surface finish due to wear, tear and breakage. Tool wear is found to have a direct impact on the quality of the product such as surface finish, dimensional accuracy. The cost of the finished product also depends on the reliability of the tool. Table 2 shows the summary of recent techniques and material used to optimize the machining parameters on Tool wear.

An orthogonal hard turning tests were conducted by the author [46] to study the effects of flank tool wear and cutting parameters (cutting speed and feed rate), on white and dark layer formation in hardened AISI 52100 bearing steel, using PCBN inserts. The prediction was carried out using Finite elements (FE) model; results cutting speed is

Table-2. Summary of recent techniques in optimizing machining parameters for tool wear.

S. No.	Authors	Material used	Input parameter	Optimization methodology	Result: influencing parameter
1	Attanasio *et al*. (2012)	AISI 52100 bearing steel	Cutting speed, Feed rate	Finite elements (FE) model	Cutting speed
2	Rahul Davis (2012)	EN24 steel	Spindle speed, Feed rate Depth of cut	ANOVA, Taguchi orthogonal design	Spindle speed
2	Anil Gupta *et al* (2011)	AISI P-20 tool steel	Cutting speed, Feed rate, Depth of cut, Nose radius.	ANOVA, Taguchi method and logical fuzzy	Cutting speed and Nose radius
3	Seeman *et al*. (2010)	LM 25 aluminum Alloy	Cutting speed, Feed rate, Depth of cut, Machining time	Regression analysis and RSM	Cutting speed and feed rate
5	Radhakrishnan *et al*. (2011)	Aluminium Silicon Carbide	Cutting speed, Feed rate, Depth of cut.	Taguchi's method and ANOVA	Feed rate
6	Rajesh (2013)	7075 Al alloy with	Cutting speed, feed rate, depth of cut and nose radius	Response surface methodology (RSM)	Cutting speed
7	Senthil kumaar *et al*. (2012)	Inconel 718	Cutting speed, feed, and depth of cut	ANOVA and artificial neural network (ANN)	Feed rate
8	Marimuthu and chandrasekaran (2011)	Stainless steel (AISI 316)	Cutting speed, feed, and depth of cut	ANOVA, Taguchi techniques and artificial neural network (ANN)	Feed rate and cutting speed
9	R. Suresh *et al*. (2012)	AISI 4340 steel	Cutting speed, feed, and depth of cut	Taguchi technique and RSM	cutting speed and feed rate
10	Das *et al*. (2015)	AISI 4140 steel	cutting speed, feed and depth of cut	ANOVA analysis	Feed rate
11	Vikas *et al*. (2013)	EN8 steel	Cutting speed, depth of cut and feed rate	ANOVA	Feed rate

Table-3. Summary of recent techniques in optimizing machining parameters for machining time.

S. No.	Authors	Material used	Input parameter	Optimization methodology	Result: influencing parameter
1	Bharathi and Baskar (2011)	Brass, aluminum, copper, and mild steel	Cutting speed, feed rate and depth of cut.	Particle swarm optimization (PSO)	Feed rate
2	Suresh and Krishnaiah (2013)	EN 41-B alloy steel	Spindle speed, feed rate and depth of cut	ANOVA, Taguchi design	Feed rate
3	Ganesan *et al*. (2011)	EN8	Cutting speed, feed rate and depth of cut.	Genetic Algorithm (GA) and PSO	Feed rate

the most influencing parameter. The authors concluded that spindle speed is the most influencing parameter to optimize tool life in dry turning of EN24 steel using taguchi method by considering the Spindle speed, Feed rate, Depth of cut as parameter [47]. An experimental investigations and effects of cutting speed, feed rate, depth of cut and nose radius in turning of 7075 Al alloy are employed. Response surface methodology (RSM) has been used to accomplish the objective of the experimental study to optimize power consumption and tool life; results cutting speed was the most significant factor followed by depth of cut, feed and nose radius [48]. An optimization was carried out using genetic algorithm coupled with artificial neural network (ANN) of facing operation on Inconel 718, considering the cutting speed, feed, and depth of cut as machining parameters to minimize flank wear and surface roughness [49]. The Surface roughness and Tool wear are studied on CNC turning of austenitic stainless steel (AISI 316). The ANOVA and Taguchi techniques are employed to study the performance characteristics of turning operation. Further the multi layered feed forward artificial neural network (ANN) is developed to predict the Surface Roughness and Tool Wear during turning process [50]. An experiment was carried out to find the machinability of surface roughness, flank wear and chip morphology of hardened AISI 4140 steel (51HRC) using PVD-TiN coated Al2O3 + TiCN mixed ceramic inserts. The optimization was carried out using ANOVA technique [51]. The authors [52] conducted an experiment using EN8 steel by focusing on the three

parameter; cutting speed, feed rate and depth of cut. The optimization was carried to optimize the flank wear and surface roughness using ANOVA technique.

MACHINING TIME

Selection of machining time is very important for predicting delivery time, manufacturing cost and also helps in planning the production process. A significant improvement in machining time may lead to increase the process efficiency and reduction in manufacturing cost. Table-3 shows the summary of recent techniques in optimizing machining parameters for Machining Time.

An investigation of two-tool parallel turning (single pass and multi pass) process parameters optimization problem was done using PSO to determine optimal machining time. The results showed that the proposed technique performed better than exhaustive search algorithm in terms of machining time and required computational time [53]. The researchers [54] used a Particle Swarm Optimization (PSO) technique to find the optimal machining parameters for minimizing machining time subjected to desired surface roughness. The Cutting speed, feed rate and depth of cut as input parameter and concluded that the feed rate is the most influencing factors. An investigation was carried out to obtain an optimal setting of process parameters in turning. Each time machining time is calculated and from which material removal rate (MRR) [55]. An investigation was carried out to optimize the machining parameters to machine an EN8 alloy to determine minimum production time. The optimization was carried out using genetic algorithm (GA) and Particle Swarm Optimization (PSO) [56]. The researchers [57] optimized the cutting parameters; to minimize the cutting time. The prediction was carried using CATIA software along with the response surface methodology.

CONCLUSION

The literature clearly gives an idea to predict and optimize the process parameters (surface roughness, tool wear and machining time) in order to improve the quality of a product and reduction of cost. By reviewing the literatures of various researchers the following condition are arrived at

a. Surface roughness, tool wear, machining time increases when the feed rate is high.
b. Surface roughness, tool wear, machining time decreases when spindle speed is high.

Since there is a limited resources available in facing operation on A22E **(BIMETAL BEARING MATERIAL),** an immense scope is available for future improvement to bring down the cost of the bearing as well as to improve the quality of the product.

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