

# State of Art Optimization Techniques for Machining Parameters Optimization during Milling

Satish Kumar, Arun Kumar Gupta, Pankaj Chandna

**Abstract-** Optimization of machining parameters becomes more important; when high capital cost NC machines are employed for high precision and efficient machining. Minimization of unit cost and time along with minimum tool and workpiece deflection, improved surface finish & tool life under certain boundary conditions are key objectives of the optimization problem. Optimization methods for milling include in-process parameters relationship with machining objectives and determination of optimal cutting conditions. Development of cost-effective mathematical models is still a challenging task. However, there has been a considerable improvement in the techniques of modeling and optimization during the last two decades. In this paper, several modeling and optimization techniques reported for the milling operations have been reviewed and are for milling, classified for different criteria. Issues related to performance of several evolutionary algorithms, machining parameters, objectives and constraints have also been identified. From the survey of optimization techniques during milling operations it has been found that search techniques perform better than experimental approaches for optimization of process parameters. However, the experimental techniques play a vital role in prediction models for different machining objectives.

**Keywords—**Optimization of Machining Parameters, Milling, SA, GA, Taguchi, RSM, DOE, Review

## I. INTRODUCTION

In manufacturing of mechanical components, milling is one of the most essential metal cutting processes. The application of milling has been increased with the introduction of high speed machining (HSM) and improvement in the milling equipments. In today's competitive environment, increasing profit rate and quality of production by optimization of machining parameters are the vital issues. The economy and quality of production are highly influenced by machining parameters such as cutting speed, feed rate, width of cut (step over), depth of cut and tool diameter etc.

Besides these parameters, the milling operations are also affected by the capability of machine tools, tool materials and type of coolants used to a great extent. To select the machining parameters, the handbook references or human experiences are generally used.

The optimization of machining parameters (OMP) is one of the most logically studied manufacturing problems. In these problems, an optimum combination of machining parameters is to be found for improving machine efficiency in term of cost and accuracy. Selection of optimal machining condition for better machining process efficiency is a key factor of the problem.

**Revised Manuscript Received on August 25, 2019.**

**Satish Kumar**, Research Scholar, Mechanical Engineering Department, NIT Kurukshetra Haryana INDIA

**Arun Kumar Gupta**, Associate Professor, Mechanical Engineering Department, Maharishi Markandeshwar (Deemed to be) University, Mullana, Ambala, Haryana INDIA Email: arun78gupta@gmail.com

**Pankaj Chandna**, Professor, Mechanical Engineering Department, NIT Kurukshetra Haryana INDIA

The common objective of the researchers in OMP problems is to identify and tune the controllable variables such that there is minimum effect of uncontrollable or noise variables on the process performance. On the whole, the machining processes which maintain balance between cost and quality of production are presumed to be efficient.

Optimization methods for milling include in-process parameters relationship with machining objectives and determination of optimal or near to optimal cutting conditions. Over the years, several analytical and experimental approaches have been applied for mathematical modeling of process parameters such as speed (S), feed per tooth (fz), depth of cut (DOC) and width of cut (WOC). There are various limitations and advantages of these approaches; however, the experimental approach provides more realistic results. Several cost-effective experimental techniques such as Taguchi method (TM), response surface method (RSM) and factorial design with regression analysis and artificial neural network (ANN) have been applied for mathematical modeling by the researchers in last two decades.

Distinct objectives of maximum tool life, maximum material removal rate (MRR), high surface finish and minimum cost of production have been achieved by several optimization techniques such as Taguchi Methodology, Genetic Algorithm (GA), simulated annealing (SA), particle swarm optimization (PSO) etc. In this paper, an attempt has been made to review critically the in-process machining parameters, objectives, constraints, prediction modeling techniques and optimization techniques specific to milling operations. The research work reported in recent past, have been classified on the basis of parameters, objectives and constraints for different tool materials and work piece materials.

## II. REVIEW OF PRIORITY CONSIDERATIONS

On reviewing of literature it has been found that most of the researchers have dealt with two distinct objectives namely, production quality (tool life, surface finish, tool deflection) and the production economy (cost, MRR, profit rate) considering various parameters like speed, feed, depth of cut, width of cut, tool diameter etc. and constraints like power, force, tool wear, surface roughness etc. The primary goal of OMP problems is to obtain the best combination of parameters, under the controlled conditions.

Optimization of Unit time and material removal rate (MRR) are the most frequently considered objectives. Higher MRR can be achieved with the expense of surface quality and tool life. Therefore, to bring the tool life and surface finish in specified range, the value of feed and speed are kept at moderate level [8]. Since, the higher feed rate and cutting speed is the cause of low heat dissipation rate, which leads to



higher MRR and lower tool life [5]. The fig. 1 shows that there is 30% average improvement of unit time in past two decades for different OMP problems. However, Kao and Lu [33] reported maximum decrease in unit time.

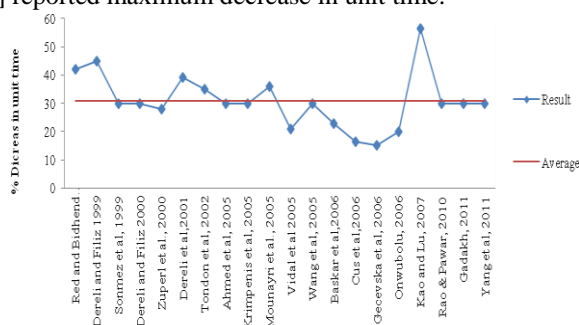
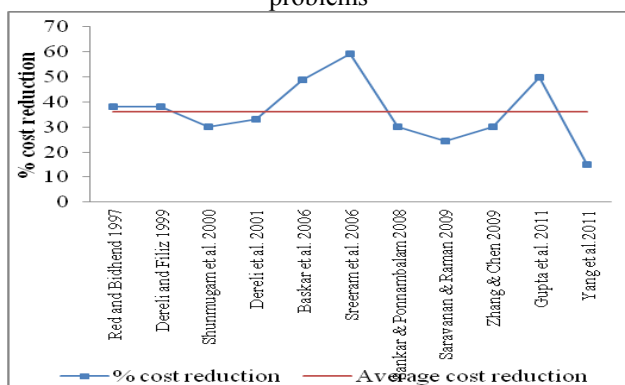


Fig. 1 Literature survey of unit time objective for OMP problems

Also unit cost has been generally considered as primary objective of OMP problems as shown in fig 2. The unit cost includes unit time, rate of production and tool life [10]. Therefore tool wear and surface finish are considered as constraints for these OMP problems [2]. On an average 36% of improvement has been reported by the researchers in past years. Only few of the researchers have considered the tool life or tool wear as the primary objectives [24], [31], [39]. Estimation of forces generated during milling operation and surface roughness with varying process parameters is also one of the important issues of OMP problems

Fig. 2 Literature survey of unit cost objective for OMP problems



From fig 3 it has been found that unit time, unit cost, MRR, Surface finish, cutting force, tool life and profit rate are the distinct objectives which are considered by 47%, 34%, 28%, 26%, 23%, 13% and 11% of the researchers respectively in last two decade. However, Unit cost includes the objective of unit time and tool life, the parameters have been studied separately by the researchers.

From table 1, it is clearly evident that most of the researchers have considered machining parameters such as speed, feed and DOC for approximation of different objective and constraint of OMP problems.

However, Very few of them have taken WOC and tool selection along with other machining parameters for OMP problems. WOC and selection of optimum tool diameter also significantly affects the objectives of OMP problems, for a particular range of parameters or machining condition.

For better understanding, the trends about the consideration of parameters for OMP problems in past practice, the fig. 4 have been plotted. It is clearly illustrated that 94% of the researchers in last two decade have considered the key parameters such as speed and feed, which influence the

TABLE I: Review of parameters, constraint and objectives considered

performance of milling. The 83% of researchers have considered depth of cut.

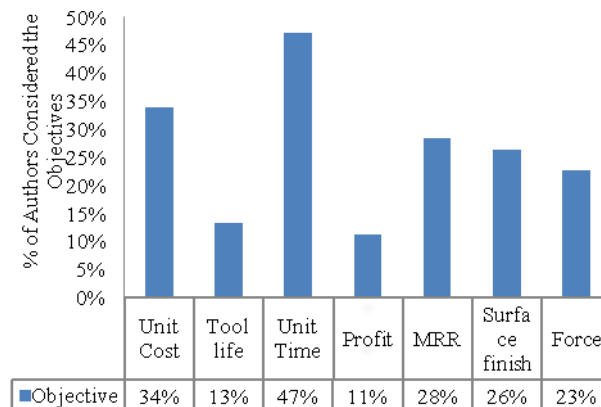


Fig. 3 Review of Objectives considered

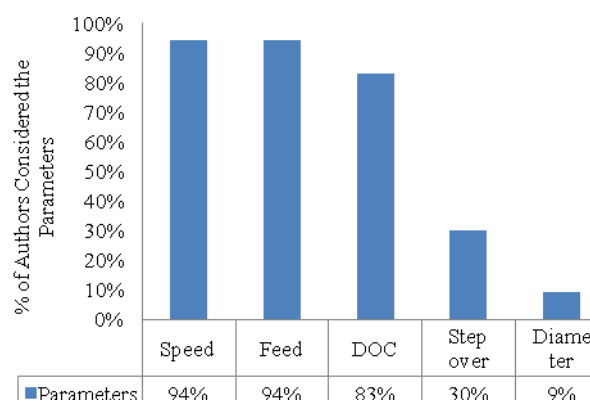


Fig. 4 Review of Parameters considered

Author	Parameters					Constraint				Objective							Tool Material	Work Piece Material
	Speed	Feed	DOC	Step over	Diameter	Power	Cutting Force	Tool Wear	Surface Roughness	Unit Cost	Tool life	Unit Time	Profit	MRR	Surface Roughness	Cutting Force		
Alauddin et al. [1]	✓	✓	✓						✓	✓			✓				Cobalt Alloy (HSS)	Steel (190 BHN)
Red and Bidhend [2]	✓	✓	✓			✓	✓		✓	✓	✓	✓	✓				HSS, Carbide	10L25
Dereli and Filiz [4]	✓	✓	✓			✓			✓	✓	✓						HSS	10L25
Sonmez et al. [5]	✓	✓	✓			✓	✓		✓		✓						HSS	Carbon steel
Dereli and Filiz [6]	✓	✓	✓								✓						HSS	10L25
Shunmugam et al. [7]	✓	✓	✓					✓	✓	✓							Cemented carbide	Grey Cast iron
Zuperl et al. [8]	✓	✓				✓			✓		✓			✓	✓		(R220-20B20-040)	16MnCrSi5XM
Baek et al. [9]		✓												✓	✓		Korea Tungsten M115 SP 04 R/L 10	Steel Ductile steel (AISI1041)
Dereli et al. [10]	✓	✓	✓							✓	✓						HSS	10L25
Souza et al. [11]	✓	✓	✓		✓					✓	✓						-----	-----
Yang and Chen [12]	✓	✓	✓		✓				✓								HSS	AL 6061
Benardos and Vosniakos [13]	✓	✓	✓												✓		WIDIA, XPNT 160412 TN-551	Aluminum Alloy
Tandon et al [14]	✓	✓				✓	✓		✓		✓					✓	HSS	MS
Ghani et al. [15]	✓	✓	✓												✓	✓	Tin Coated P10 Carbide	AISI H13
Kovacic et al. [16]	✓	✓	✓		✓											✓	-----	Aluminum alloy
Li and Li [17]	✓	✓	✓													✓	HSS	ASSAB760
Ahmed et al. [18]	✓	✓	✓			✓	✓		✓		✓						HSS	AL 7075-T6
Krimpenis et al. [19]	✓	✓	✓						✓		✓			✓			PVD-coated carbide	-----
Mounayri et al. [20]	✓	✓	✓	✓						✓	✓					✓	HSS	Aluminum 6061 T6
Ozcelik et al. [21]	✓	✓	✓	✓										✓	✓		Carbide	Inconel 718
Radhakrishnan and Nandan [22]	✓	✓	✓													✓	HSS	2205 T-351 AL
Vidal et al. [23]	✓	✓				✓	✓		✓	✓	✓						Ceramic coated	low alloy steel
Wang et al. [24]	✓	✓	✓			✓	✓			✓	✓						HSS	Carbon Steel
Brudek et al. [25]	✓	✓														✓	-----	Stainless steel
Baskar et al. [26]	✓	✓	✓			✓	✓		✓	✓	✓	✓					Carbide, HSS	10L50 leaded steel
Cus et al. [27]	✓	✓	✓	✓						✓	✓					✓	R216.44-10030-040-AL10G— GC 1010	Ck 45 and Ck 45 (XM)
Gecevaska et al. [28]	✓	✓	✓			✓	✓		✓		✓						Carbide	low alloy steel
Oktem et al. [29]	✓	✓	✓												✓		Carbide	7075-T6 AL
Onwubolu [30]	✓	✓	✓	✓		✓	✓		✓	✓	✓						HSS	MS
Sreeram et al. [31]	✓	✓	✓			✓	✓		✓	✓							Carbide	-----
Aykut et al. [32]	✓	✓	✓	✓		✓			✓							✓	Carbide	Stellite 6
Kao and Lu [33]	✓	✓	✓	✓						✓				✓			Carbide	SUS 304 Stainless



Kadirgama et al. [34]	✓	✓	✓															✓		CVD & PVD Coated Carbide	Hastelloy C22 HS	
Kopac and Karjnik [35]	✓	✓					✓	✓										✓	✓	✓	Not mentioned	Aluminum Alloy
Palanisamy et al. [36]	✓	✓	✓				✓	✓	✓										✓		-----	HSS
Abellan et al. [37]	✓	✓							✓	✓									✓	✓	Cubic Boron Nitride	AISI D3 steel
Ibraheem et al. [38]	✓	✓	✓	✓															✓		Coated carbide inserts	AISI P20
Onwubolu et al. [39]	✓	✓	✓																✓		HSS	MS
Spanoudakis et al. [40]			✓	✓	✓														✓		-----	-----
Sankar and Ponnambalam [41]	✓	✓																			-----	-----
Ginta et al. [42]	✓		✓	✓															✓		Uncoated WC-Co	Ti-6Al-4V under dry conditions
Gopalsamy et al. [43]	✓	✓	✓	✓					✓										✓		Tin coated P10 Carbide	AISI H13
Islam & Cho [44]	✓	✓		✓															✓		HSS	Aluminum 2014-
Prakasvudhisarn et al. [45]	✓	✓	✓																✓		-----	-----
Patel et al. [46]	✓	✓	✓																✓		TiTAIN coated HSS	AL alloy and Plain
Ramos et al. [47]	✓			✓					✓										✓		Sandvik Coromant	High Carbon Steel
Saravanan and Raman	✓	✓	✓				✓	✓	✓	✓	✓										-----	-----
Saffar et al. [49]			✓	✓	✓					✓	✓	✓	✓								HSS	AISI 1045
Zhang & Chen [50]	✓	✓	✓	✓																		45 steel
Moshat et al. [52]	✓	✓	✓																✓	✓	WIDIA EM-TiAlN	AL
Rao & Pawar [53]	✓	✓	✓				✓	✓		✓									✓	✓	-----	-----
Yazdi et al. [54]	✓	✓	✓																✓	✓	1C28M40	6061-T6
Gupta et al. [56]	✓	✓	✓	✓	✓	✓	✓	✓	✓												Carbide	Steel 1075
Gadakh [57]	✓	✓	✓	✓			✓	✓											✓	✓	Carbide & HSS	Hardened Steel
Mustafa [58]	✓	✓	✓																✓	✓	Coated multilayer TiAlN	Hot work tool steel
Yang et al. [60]	✓	✓	✓				✓	✓	✓	✓	✓								✓	✓	Carbide	Cast iron
Bhirud&Gawande,61]	✓	✓	✓																✓		Tungsten carbide	AISI H13 hardened
Kumar et al [62]	✓	✓	✓	✓															✓		solid carbide end mills	Al 6061 T6
Kaushik et al [63]	✓	✓	✓																✓		High speed steel	Al 7068
Palanisamy et al [64]	✓	✓	✓																✓	✓	Cemented carbide	AISI 1020 steel

### III. MACHINING PARAMETER MODELING TECHNIQUES

In order to optimize the machining parameters, it is necessary to find the correct relationship of process parameters with distinct objectives. Therefore, mathematical relations have to be developed for predicting the objectives under different constraints. The different output such as tool life, surface finish, cutting forces, MRR etc are dependent on milling processes, cutting tool geometries, cutting tool material, work piece material and machine tool conditions. Hence it is very necessary to develop the robust analytical relations for such outputs. Therefore, the explicit relations have been developed by the researchers using statistical techniques and design of experiments (DOE). Different mathematical models of process-parameters have been

developed for different milling objectives that are limited for predicting surface finish and cutting forces. Tool life and tool wear are also the significant factors that affects the production cost and quality of the manufactured products and hence need to be considered. Several cost-effective experimental techniques such as Taguchi method (TM), response surface method (RSM) and factorial design of experiments with regression analysis (RA) and artificial neural network (ANN) have been applied for mathematical modeling by the researchers. The optimization techniques like genetic programming have also been applied for minimizing the error in prediction models [16]. Li and Li [17] developed a theoretical modeling technique for cutting forces and influence of cutter runout on chip



load by simulation of sliced helical cutter. The process parameters relations developed for different OMP problems have been classified and tabulated in table II.

#### IV. REGRESSION ANALYSIS

Regression analysis is generally applied in OMP problems to predict different objectives based on process-parameters. It is very difficult to manage all variables which influence OMP problems [59]. Therefore, these variables are classified as controllable and uncontrollable variables. The real life experiments are performed on varying controllable process parameters. The effects of remaining uncontrollable parameters are also incorporated in experimental results of different objectives.

An appropriate regression method is to be selected out of different models such as mean, linear, 2F1, quadratic, cubic etc., on the basis of the experimental results trends to estimate all uncertainties. Alauddin et al. [1] predict tool life by using quadratic and linear regression models. Linear regression model was also found fit for the responses of surface roughness by Oktem et al. [29]. Multiple linear regression models have been applied for prediction of tool wear and surface finish by Gopalsamy et al. [43]. Mustafa [58] predicted surface finish and force models by using TM and regression analysis for milling of welded regions.

#### V. FUZZY SET THEORY

The fuzzy set also an important machining parameter relationship modeling technique. The theory is based on fuzzy set identifies the existence of uncertainty (uncontrollable variables) in the process. The molding technique studies the responses of designed experiments and estimates the objectives of OMP problems. Expert opinions for the process are essential for fuzzy set theory-based modeling technique. For better estimation OMP objectives and effective process control in manufacturing fuzzy set modeling technique is generally applied along with the artificial neural network.

#### ARTIFICIAL NEURAL NETWORK

Artificial neural network is based on the functioning of human brain and is applied for reasonable response of noisy input. The response is obtained on the basis of randomly

selected input used as test data. ANN works with neurons and transfer functions. There are input layer, output layer and hidden layers comprises of these neurons and transfer functions. Neuron is the smallest unit of ANN which process one or more input data. There are various teaching processes influenced by random input and weights which affect the functioning of neurons. The performance of neural network depends upon three factors i.e. selection of appropriate input/output parameters, distribution of data base and presentation of data base [32]. Beside these factors selection of neuron numbers, hidden layers, activation functions and training algorithms are also influence the performance of ANN.

Artificial neural network applications have been increasingly used in manufacturing in last two decades. More realistic models are developed by using the techniques to predict Surface finish, forces and tool wear for milling. Zuperl et al. [8] developed an online cutting force prediction model using ANN. Tandon et al. [14] developed a robust cutting force model and optimized the marching parameters using PSO for minimum unit time. Benardos and Vosniakos [13] predicted surface roughness during CNC face milling using ANN and Taguchi Design of experiments. Radhakrishnan and Nandan [22] developed cutting force prediction model using combination of multiple regression and ANN.

After development of regression model for cutting forces, the abnormal data was filtered using ANN and more accurate results have been obtained. Aykut et al. [32] developed cutting force model using DOE and ANN and provided effect of machinability on chip removal cutting parameters for face milling. Whereas the Onwubolu et al. [39] develop the model for tool wear and found more realistic results using enhanced-group method of data handling (GMDH) learning network and DOE. Prakasvudhisarn et al. [45] developed a machine learning support vector machines (SVMs) for estimation of surface roughness. Yazdi et al. [54] developed surface finish model using ANN & RSM to predict the surface finish and found it significant with feed per tooth and speed. Whereas, MRR found significant with depth of cut and feed per tooth.

TABLE II  
Review on experimental models

Response Prediction Model	Techniques	Author
Cutting Force Model	DOE & ANN	Zuperl et al. [8], Radhakrishnan and Nandan [22], Aykut et al. [32]
	Back-propagation ANN	Mounayri et al. [20]
	TM & Regression Analysis	Mustafa [58]
	Frequency response function	Ramos et al. [47]
Surface Roughness Model	DOE & ANN	Benardos and Vosniakos [13], Tandon et al. [14], Ozcelik et al. [21]
	RSM & ANN	Kadrigama et al. [34], Ginta et al. [42], Yazdi et al. [54]
	SVM similar to ANN	Prakasvudhisarn et al. [45]
	TM & Regression Analysis	Mustafa [58], Oktem et al. [29], Gopalsamy et al. [43]

	Experiments & simulation based model	Baek et al. [9]
Tool Wear Model	Enhance-GMDH learning network	Onwubolu et al. [39]
	TM & Regression Analysis	Gopalsamy et al. [43]
Tolerance Prediction Model	Using cutting force model and tool deflection model to develop tolerance prediction model.	Islam & Cho [44]
Material Removal Rate Model	ANN & RSM	Yazdi et al. [54]

## VI. PARAMETER OPTIMIZATION TECHNIQUES

Optimization of machining parameters for different cutting environment and objectives makes the problem complex. It has been very difficult to develop the robust optimization strategy which includes all the objectives and parameters. Therefore different optimization techniques and mathematical models have been developed for different milling operations. The models developed by the experimental and the empirical approaches have been optimized using exact algorithm and search techniques. As there are variety of inputs and parameters and hence the exact techniques consumes more processing time and computation efforts than search techniques. In the past, researchers have worked different optimization techniques such as statistical and search techniques for optimization the process parameters for different marching objectives under specified constraints. Therefore, the optimization techniques such as genetic algorithm (GA), Taguchi methodology (TM), response surface methodology (RSM), simulated annealing (SA), practical swarm optimization (PSO) are frequently applied to get near to optimum solution. Review related to different search and optimization techniques have been compiled III.

### a. TAGUCHI METHOD

This method was developed for process or product quality improvement in 1940's by Genichi Taguchi. The Taguchi method is based on statistically designed experiment and concepts. This method has great contribution in improvement in quality and minimization of cost by optimizing product design and manufacturing process. TM individually cannot estimate the effect of input parameters on process. But effect of parameters is estimated by applying statistical technique regression analysis and ANOVA. Due to fast response and easy to understand the TM is applied on different engineering problems. TM is applied to various manufacturing processes to optimize surface finish, tool life, cost of production, material removal rate etc. Certain level of each input parameters are decided as per requirement of the process and an orthogonal array has designed to decide combination of parameters for experiments. TM reduces the total number of experiments which makes the optimization process cost-effective.

Taguchi used signal to noise ratio as quality characteristic of choice rather than standard deviation. S/N ratio is useful statistical tool to reduce variability in process and improve quality. For different optimization conditions the S/N ratio is calculated by three different relations such as nominal is the better, smaller is the better and larger is the better.

Yang and Chen [12] used Taguchi methodology to optimize the surface finish. Ghani et al. [15] found optimal combination of machining parameters for low

resultant cutting force and good surface finish using TM, S/N ratio and ANOVA. Oktem et al. [29] optimized the effect of machining parameters on surface finish by combination of Taguchi method and regression analysis. Kopac and Karjnik [35] used gray-TM with gray-relational grade to convert the multi objective problem to a single objective problem to optimize surface roughness, cutting force and MRR simultaneously. Gopalsamy et al. [43] predicted the surface roughness & tool wear using TM and regression and optimized the machining parameters in context of tool wear using Taguchi design of experiments with S/N ratio analysis. Patel et al. [46] used Taguchi experimental design and S/N ratio to optimize surface roughness and effect of various marching parameters on surface roughness was investigated on two different work piece material. Moshat et al. [52] applied principal computational analysis (PCA) based TM to optimize surface roughness and MRR. Mustafa [58] predicted surface finish and force models by using TM and regression analysis for milling of welded regions. The S/N ratio analysis was also applied to optimize the machining parameters for the objectives.

TABLE III REVIEW OF OPTIMIZATION TECHNIQUES FOR MILLING

S.No	Optimization Technique	References	Remarks
1	Taguchi methodology	Yang and Chen [12], Oktem et al. [29], Patel et al. [46]	Optimized Surface finish
		Ghani et al. [15]	Optimize surface finish and cutting forces
		Gopalsamy et al. [43]	Minimize tool wear by optimizing the parameters.
		Moshat et al. [52]	Applied Principal Computational Analysis based TM to optimize surface roughness and MRR
		Kopac and Karjnik [35]	Grey-Relational Analysis with TM applied for OMP to minimize surface roughness, cutting forces and MRR.
2	Particle Swarm Optimization	Zuperl et al. [8], Tandon et al. [14] 2002, Mounayri et al. [20]	Have predicted force using ANN and optimize MRR
		Prakasvudhisarn et al. [45]	Developed a surface roughness model using SVMs and optimized.
		Onwubolu et al. [39]	Developed a more realistic tool wear model using enhance-GMDH learning network and optimize it.
		Rao & Pawar [53]	Have Compared PSO, SA, ABC results and concluded that PSO was better than other optimization techniques for the OMP problems.
3	Genetic Algorithm	Dereli and Filiz [4]	Developed an optimum process planning system.
		Dereli and Filiz [6]	Proposed GA for tool indexing for Automatic tool changer.
		Shunmugam et al. [7]	Provided minimum Production cost with constraint of tool life and surface finish
		Dereli et al. [10]	Gave minimum production cost and compared optimum parameters with catalogue values
		Ahmed et al. [18]	GA-SOAP gives effective production time
		Ozcelik et al. [21]	Determine minimum surface roughness under the constraints of roughness and MRR
		Baskar et al. [26]	On Comparison it was found that MA &GA performed better than other algorithms.
		Cus et al. [27]	Provided effective online monitoring system for Force & tool wear and optimize the machining parameters for efficient production.
		Gecevska et al. [28]	Developed GA & deterministic method (DM) for OMP problems.
		Onwubolu [30]	Developed tribes-based approach seemlier to GA for optimization
		Sreeram et al. [31]	Increased machining efficiency and high production rate was achieved by optimization of machining parameter using GA
		Palanisamy et al. [36]	The process is controlled under certain limit of vibration along with other constraint to increase Tool Life to a appreciable amount
		Spanoudakis et al. [40]	Weighted sum of (Remaining Volume & unit time) is considered as Fitness to optimize unit time and remaining volume.
		Saffar et al. [49]	Have calculated a tool deflection model and optimize the cutting forces using GA.
		Zhang & Chen [50]	Developed tool life model and optimized machining parameters.
		Gupta et al. [55]	Proposed hybrid GA to minimize non productive time during 2.5 D milling.
Gupta et al. [56]	Optimized machining parameters for minimizing unit cost using GA.		
Yang et al. [60]	Concluded that GA-PSO is better than other GA.		
4	Other Optimization Technique	Kumar et al [65]	Minimization of Non-Productive Time during 2.5D Milling
		Red and Bidhend [2]	Optimized machine parameter for minimum unit cost using method of feasible directions (MFD).
		Sonmez et al. [5]	OMP problem using geometric programming
		Baek et al. [9]	Optimize surface roughness during face milling using bisection

		method.
	Krimpenis et al. [19]	Nash game optimization is applied for minimization of unit time during rough machining.
	Wang et al. [24]	GSA, PGSA Compare the tech. and PGSA find suitable and efficient.
	Kao and Lu [33]	Grey-fuzzy logic applied to optimize MRR & Tool life.
	Abellan et al. [37]	Bisection Method has been applied for Max MRR with constraint of run out & surface finish.
	Gadakh [57]	Multi Objective Optimization on the basis of ratio analysis method is applied.

**VII. RESPONSE SURFACE METHOD**

RSM is a technique useful for the mathematical modeling and analyses of problems in which the response is dependent upon several variables. The technique is also applied for the optimization of machining parameters. The methodology requires developing an approximate model true response surfaces. The mathematical models of responses are developed on the basis of certain experiments. The levels of each parameter are decided as per requirement of the process and design of experiment table is formulated. On the basis of response observed by these experiments the mathematical model is predicted by multiple regression statistical tools. Screening of influential parameters is also possible using ANOVA. The interpretation of the results gives the optimum parameters. The responses are plotted on a surface graph (3-D graph) against the two most significant process parameters. The lower and upper peaks of the surface estimates the require objectives of minimization or maximization problems. Although the RSM technique is very frequently used by the researchers for prediction and optimization of manufacturing parameters, there are a few limitations in this approach. It works well for optimization of single objective OMP problems, but it is difficult to apply the technique for multi objective problems. Beside this the RSM could not estimate accurately the highly nonlinear relations. Optimization of OMP problems with certain constrains is also difficult with the RSM.

As the technique is economical and easy to understandable, it has been applied to predict the machining objectives and optimization of parameters in OMP problems frequently by the researchers, over the years. Alauddin et al. [1] developed mathematical model for tool life using Response Surface Methodology for end milling of steel. Ozcelik et al. [21] used RSM with regression analysis and ANN to predict surface roughness, whereas the optimization problem is solved by GA. Kadirgama et al. [34] developed surface roughness model using RSM with first order regression model. Ginta et al. [42] and used quarter factorial central composite design (CCD) RSM to create an efficient analytical model for surface roughness in terms of cutting speed, axial depth of cut and feed per tooth. Yazdi, et al. [54] also predicted surface roughness and MRR using experimental observation on the basis of orthogonal matrix developed by CCD RSM and optimized the machining parameter by statistical means.

**GENETIC ALGORITHM**

Genetic Algorithm (GA) works on the principles of evolutionary biology for searching the optimal solution. GA uses probabilistic selection as a basis for evolving a population of problem solutions and subsequent generations are generated according to a pre-specified breeding and mutation methods inspired by nature. Best solution is selected from the population as evaluated by fitness function. This best solution is termed as elite solution. The process remains continue till the stopping limit has not been achieved. Genetic algorithms have gained immense popularity in optimization of machining parameters problems as it generates diversify individual solution in the space under certain constraints. Some time GA gets trapped into local optima and hence set of different trial provides good results. The feature of GA for searching the optimum solution with in the specified constraint and boundaries, make it different from other experimental based optimization techniques. As compared to other statistically techniques for optimisation, the levels of parameters have to be selected for conducting certain experiments which are again depends on experiences and hand book references. Hence, the GA provides better search solution as compared to experimental based optimization techniques such as TM, RSM etc. Some of the researchers [16] have applied GA for minimization of error in prediction models to provide more accuracy. Shunmugam et al. [7] minimized the cost by optimizing the machining parameters under the constraint of tool life and surface finish using GA. Dereli et al. [10] coded the process parameters in a binary string and optimized the machining parameters using GA. Optimum parameters were also compared with the catalogue consideration in context of unit cost and time. Ozcelik et al. [21] provided good Surface finish with constraint of MRR the using GA. Wang et al. [24] compared the optimization techniques such as GSA, parallel genetic simulated annealing (PGSA), conventional parallel GA (PGA), GP & DP for optimization of machining time under different machining constraint. PGSA was reported an efficient technique for the OMP problem. Baskar et al. [26] compared the results obtained by the various methods namely genetic algorithm (GA), hill climbing (HC) and mimetic algorithm (MA) and found that GA & MA gives better optimum values of unit time, unit cost and profit rate. Cus et al. [27] provided effective online monitoring system for cutting force & tool wear and optimized the machining parameters for efficient production.

Gecevska et al. [28] developed GA & deterministic method (DM) for OMP problems. Onwubolu. [30] developed tribes-based approach seemlier to GA for





optimization production rate. Increased machining efficiency and high production rate was achieved using GA by Sreeram et al. [31]. Palanisamy et al. [36] controlled the process under certain limits of vibration along with other constraint to achieve multiple objectives of longer tool life and better surface finish using GA. Dereli and Filiz [6] developed an optimum process planning system which minimize the production time by optimum tool indexing for Automatic tool changer and by selecting the optimum combination of process parameters using GA. Ahmed et al. [18] used self organized adoptive penalty strategy for rapid convergence by focusing the boundary of feasible and infeasible solution for optimization of machining parameters.

Saffer et al, 2009 developed a tool deflection model and optimized machining parameters for minimization tool deflection using GA. Zhang & Chen [50] developed a tool life model and optimize tool life and machining time using GA. Gupta et al. [55] proposed GA to optimize machining parameters during 2.5 D milling for minimizing unit cost under the controlled machining environment. Non-productive time has also been minimized by synchronizing rapid movements of cutting tool using hybrid GA during 2.5 D milling [56]. Yang et al. [60] adopted GA-PSO technique to maximize the profit rate. GA-PSO found better than other GA developed earlier.

## VIII. PARTICLE SWARM OPTIMIZATION

Particle swarm optimization is based on swarm behavior of animals. Animal travel collectively toward a target and manage their group by decentralized management. This search technique is similar to the genetic algorithm. However, unlike GA, PSO has no evolution operators such as crossover and mutation. Each particle's movement is influenced by its local best known position and is also guided toward the best known positions in the search-space. Each particle keeps track till best solution is achieved. The movement of particles accelerates or retards depending upon the direction of motion of particle towards the global solution. The lesser parameters to control the algorithm and resilient to the problem of local minima, make this optimization technique more popular. In last one decade PSO has been successfully applied in many engineering problems. Zuperl et al. [8] improved MRR by 28% under the constraint of surface finish, cutting force and power using PSO technique. Mounayri et al. [20] developed force model using ANN and extended the PSO technique to 3D and 3(1/2) D optimization with 36% reduction in machining time. Prakasvudhisarn et al. [45] developed a machine learning support vector machines (SVMs) for estimation of surface roughness and optimized the machining parameters using PSO technique for minimum surface roughness. Tandon et al. [14] minimized unit time by 35% by optimization of machining parameter using PSO technique. Rao and Pawar [53] compared PSO with other search techniques and concluded that PSO is the best among them.

## SIMULATED ANNEALING

Simulated annealing (SA) is a generic probabilistic metaheuristic for the global optimization problem of locating a good approximation to the global optimum of a given function in a large search space. Since 1980s, Simulated Annealing (SA) search approach has been

acknowledged after motivation from physical process of cooling fluids. SA is a method for solving unconstrained and bound-constrained optimization problems. Optimum solution is calculated from the discrete search space. The heuristic is based on the method on which liquids freeze or metals re-crystallize in the process of annealing. To bring thermodynamic equilibrium the liquid at high temperature is slowly cooled and the process is termed as annealing. As cooling proceeds, the global solution reaches closer to optimum solution. There are different annealing algorithm and acceleration functions applied for variety of engineering problems. Sankar and Ponnambalam [41], optimized the machining conditions such as speed and feed, for minimum production cost of a spur gear by simulated annealing based heuristic procedure referred as aggravated simulated annealing algorithm. Kolahan and Abachizadeh [51] optimized machining parameters during turning using simulated annealing algorithm. Rao and Pawar [53] compared three optimization techniques such as SA, Artificial Bee Colony (ABC), PSO for OMP problems. Saravanan and Raman [48] minimized the total production cost subject to machine constraints such as cutting power, cutting force, tool life, surface finish of the product and the range of the operating parameters using Simulated Annealing (SA) and Genetic Algorithm (GA) during milling.

## IX. CONCLUSIONS

Significant amount of improvement was reported in different milling operations by the researchers using different optimization techniques. Cutting speed, feed and depth of cut were considered as appropriate parameters for the different OMP problems. Whereas, distinct objectives such as unit time, unit cost, MRR, cutting forces and surface roughness were frequently used for improving the efficiency of milling operations. In this paper a survey has been performed for applications of optimization techniques during milling operations. The researchers have primarily classified the OMP problems into two types i.e. prediction modeling and optimization of process parameters. Prediction models for surface roughness, tool life and cutting forces for different machine tool conditions and combinations of tool/work-piece materials are developed by statistical tool regression analysis, artificial neural network and grouping of these techniques. More realistic results were obtained by grouping of ANN and regression analysis. However, the design of experiments techniques such as Taguchi methodology and response surface methodology are being applied successfully for finding the combinations of process parameters during experiments. These DOE techniques are being widely used for optimization of machining parameters. Besides these experimental approaches, the different search techniques such as genetic algorithm and particle swarm optimization are also frequently used as these techniques provides optimum solutions under process constraints and boundary conditions with lesser computation time. It may be concluded that these optimization techniques play an important role in industrial applications for improving efficiency and



quality of production during milling.

The search optimization techniques have been applied with empirical relation rather than experimental relations for most of the OMP problems. However these empirical relations predict output under controlled machining environment only. However, the DOE techniques with statistical tools provide better prediction of objectives. Therefore, the advantages of both the search techniques and DOE techniques should be coupled together for machining operation more efficient. Moreover, limited work has been reported regarding the selection of appropriate tool diameters with width of cut, which significantly affect the efficiency of the milling operations. Therefore, the analysis of other influential parameters along with these parameters for OMP problems might be the scope of further work.

## REFERENCES

1. M. Alauddin, M. A. El Baradie and M. S. J. Hashmi, "Prediction of tool in end milling by response methodology," *Journal of Material Processing Technology*, vol. 71, pp. 456-465, 1997.
2. M. T. Rad and I. M. Bidhendi, "On the optimization of machining parameters for Milling operations on the optimization of machining parameters for Milling operations," *International Journal Mechanical Tools Manufacturing*, vol. 37, no. 1, pp. 1-16, 1997.
3. D. K. S. Park and S. H. Kim, "Artificial intelligence approaches to determination of CNC machining parameters in manufacturing: A review," *Artificial Intelligence in Engineering*, vol. 12, pp. 127-134, 1998.
4. T. Dereli and I. H. Filiz, "Optimisation of process planning functions by genetic algorithms," *Computers & Industrial Engineering*, vol. 36, pp. 281-308, 1999.
5. Sonmez, A. Baykasoglu, T. T. Dereli and T. I. H. T. Filiz, "Dynamic optimization of multi-pass milling operations via geometric programming," *International Journal of Machine Tools & Manufacture*, vol. 39, pp. 297-320, 1999.
6. T. T. Dereli and T. I. H. T. Filiz, "Allocating optimal index positions on tool magazines using genetic algorithms," *Journal of Robotics and Autonomous Systems*, vol. 33, pp. 155-167, 2000.
7. M. S. T. Shunmugam, S. V. B. T. Reddy, and A. A. T. Narendran, "Selection of optimal conditions in multi-pass face-milling using a genetic algorithm," *International Journal of Machine Tools & Manufacture*, vol. 40, pp. 401-414, 2000.
8. U. T. Zuperl, C. T. Franci and G. Valentina, "Optimization of characteristic parameters in milling by using PSO evolution technique" 2000
9. D. K. Baek, T. J. Ko and H. S. Kim, "Optimization of feed rate in a face milling operation using a surface roughness model," *International Journal of Machine Tools Manufacturing*, vol. 41, no. 3, pp. 451-462, 2001.
10. T. Dereli, I. H. Filiz and A. Baykasoglu, "Optimizing cutting parameters in process planning of prismatic parts by using genetic algorithms," *International journal of production research*, vol. 39, no. 15, pp. 3303- 3328, 2001.
11. D. Souza, Roshan Wright, Paul., Seqin, Carlo, "Automated micro planning for 2.5D pocket machining," *Journal of manufacturing Systems*, vol. 20, No. 4, 2001.
12. L. J. Yang & C. J. Chen, "A Systematic Approach for Identifying Optimum Surface Roughness Performance in End-Milling Operations," *Journal of Industrial Technology*, vol. 17, no. 2, pp. 1-8, 2001.
13. P. G. Benardos and G. C. Vosniakos, "Prediction of surface roughness in CNC face milling using neural networks and Taguchi's design of experiments," *Robotic and Computer Integrated Manufacturing*, vol. 18, no. 5/6, pp. 343-354, 2002.
14. V. Tandon, H. El-Mounayri and H. Kishawy, "NC end milling optimization using evolutionary computation," *International Journal of Machine Tools & Manufacture*, vol. 42, no. 5, pp. 595-605, 2002.
15. J. A. Ghani, I. A. Choudhury and H. H. Hassan, "Application of Taguchi method in the optimization of end milling parameters," *J Mater Process Technol*, vol. 145, no. 1, pp. 84-92, 2004.
16. M. Kovacic, J. T. Balic and M. T. Brezocnik, "Evolutionary approach for cutting forces prediction in milling," *Journal of Material Processing Technology*, vol. 155, no. 156, pp. 1647-1652, 2004.
17. X. P. T. Li and H. Z. T. Li, "Theoretical modeling of cutting forces in helical end milling with cutter run out," *International Journal of Mechanical Sciences*, vol. 46, no. 9, pp. 1399-1414, 2004.
18. N. T. Ahmad, T. T. Tanaka, and Y. T. Saito, "Optimization of cutting parameters for end milling Operation by soap based genetic algorithm," *Proceedings of the International Conference on Mechanical Engineering*, pp. 28-30, 2005.
- A. Krimpenis, P. I. K. Liakopoulos, K. C. Giannakoglou and G. C. Vosniakos, "Multi-Objective Design of optimal sculptured surface rough machining through pareto and nash techniques," *Journal of optimization and control with application to industrial and societal problems*, 2005.
19. H. El-Mounayri, H. Kishawy and J. Briceo, "Optimization of CNC ball end milling: a neural network-based model," *Journal of Materials Processing Technology*, vol. 166, no. 1, pp. 50-62, 2005.
20. B. Ozelik, H. Oktem and H. Kurtaran, "Optimum surface roughness in end milling Inconel 718 by coupling neural network model and genetic algorithm," *International Journal of Advance Manufacturing Technology*, vol. 27, no. 3/4, pp. 234-241, 2005.
21. T. Radhakrishnan and U. Nandan, "Milling force prediction using regression and neural networks," *Journal of Intelligent Manufacturing*, vol. 16, no. 1, pp. 93-102, 2005.
22. Vidal, M. Alberti, J. Ciurana, and M. Casadesu, "A decision support system for optimizing the selection of parameters when planning milling operations," *International journal of Machine Tools & Manufacture*, vol. 45, pp. 201-210, 2005.
23. Z. G. Wang, M. Rahman, Y. S. Wong and J. Sun, "Optimization of multi-pass milling using parallel genetic algorithm and parallel genetic simulated annealing," *International Journal of Machine Tools Manufacturing*, vol. 45, pp. 1726-1734, 2005.
24. G. Brudek, J. P. Wulfsberg, "Data Acquisition and Optimization of Setting and Processing Parameters in Micro Machining Operations," 6th international conference of the European Society for Precision Engineering and Nanotechnology, vol. 2, p. p. 429-432, 2006.
25. N. Baskar, P. Asokan, R. Saravanan and G. Prabhakaran, "Selection of optimal machining parameters for multi-tool milling operations using a memetic algorithm" *Journal of Material Processing Technology*, vol. 174, pp. 239-249, 2006.
26. F. Cus, M. Milfelner and J. Balic, "An intelligent system for monitoring and optimization of ball-end milling process," *Journal of Material Processing Technology*, vol. 175, no. 1/3, pp. 90-97, 2006
27. V. T. Gecevska, F. T. Cus, F. T. Lombardi, V. T. Dukowski and M. T. Kuzinowski, "Intelligent approach for optimal modeling of manufacturing systems," *Journal of Achievements in Materials and Manufacturing Engineering*, vol. 14, no. 1/2, pp. 97-103, 2006.
28. H. T. Oktom, T. T. Erzurumlu and M. T. Çöl, "A study of the Taguchi optimization method for surface roughness in finish milling of mold surfaces," *International Journal of Advance Manufacturing Technology*, vol. 28, no. 7/8, pp. 694-700, 2006.
29. G. C. Onwubolu, "Performance-based optimization of multi-pass face milling operations using Trbels," *International Journal of Machine Tool & Manufacturing*, vol. 46, pp. 717-727, 2006.
30. S. Sreeram, A. S. Kumar, M. Rahman and M. T. Zaman, "Optimization of cutting parameters in micro end milling operations in dry cutting condition using genetic algorithms," *International Journal of Advance Manufacturing Technology*, vol. 30, no. 11/12, pp. 1030-1039, 2006.
31. S. Aykut, M. Gölcü, S. Semiz, H. S. Ergür, "Modeling of cutting forces as function of cutting parameters for face milling of satellite 6 using an artificial neural network," *Journal of Materials Processing Technology*, vol. 190, no. 1-3, pp. 199-203, 2007.
32. C. Kao and H. S. Lu, "The optimal cutting-parameter selection of heavy cutting process in side milling for SUS304 stainless steel," *International Journal of Advance Manufacturing Technology*, vol. 34, no. 5/6, pp. 440-447, 2007.
33. K. Kadrigama, K. A. Abou-El-Hossein, B. Mohammad and H. Habeeb, "Statistical model to determine surface roughness when milling hastelloy C-22HS," *Journal of Mechanical Science and Technology*, vol. 21, no. 10, pp. 1651-1655, 2007.
34. J. Kopac and P. Krajnik, "Robust design of flank milling parameters based on grey-Taguchi method," *Journal of Materials Processing*

- Technology, vol. 191, no. 1-3, pp. 400-403, 2007.
35. P. Palanisamy, I. Rajendran and S. Shanmugasundaram, "Optimization of machining parameters using genetic algorithm and experimental validation for end-milling operations," International Journal of Advance Manufacturing Technology, vol. 32, pp.644-655, 2007.
  36. J.T V.T Abellan, F.T Romero, H.T R.T Siller, A.T Estruch and C.T Vila, Advances in Robotics, Automation and Control, Publisher: InTech, pp.1-20, 2008.
  37. F.T Ibraheem, S.T K.T Shather and K.A.T Khalaf "Prediction of Cutting Forces by using Machine Parameters in end Milling Process," Eng. & Tech, vol. 26, no. 11, 2008.
  38. G.C.T Onwubolu, P.T Buryan and F.T Lemke, "Modeling tool wear in end-milling using enhanced GMDHT learning networks," International Journal of Advance Manufacturing Technology, vol. 39, no. 11/12, pp. 1080-1092, 2008.
  39. P.T Spanoudakis, N.T Tsourveloudis and I. Nikolos, "Optimal Selection of Tools for Rough Machining of Sculptured Surfaces," Proceedings of the International Multi Conference of Engineers and Computer Scientists, vol. 2, 2008.
  40. S. S. Sankar and S.G. Ponnambalam, "Optimisation of gear milling process using aggravated simulated annealing algorithm", International Journal of Advanced Mechatronics Systems. Vol. 1, No.1, pp. 53 – 62, 2008.
  41. T. L. Ginta, A.K.M.N. Amin, H.C.D.M. Radzi and M.A. Lajis, "Development of surface roughness models in end milling titanium alloy Ti-6Al-4V Using Uncoated Tungsten Carbide Inserts," European journal of Scientific Research, vol.28, no.4, pp. 542-551, 2009.
  42. B. M. Gopalsamy, B. Mondal and S. Ghosh, "Taguchi method and ANOVA an approach for process parameter optimization of hard machining while machining hardened steel," Journal of scientific & Industrial research, vol. 68, pp. 686-695, 2009.
  43. M.N. Islam and D. W. Cho, "Technical and Economical optimization of Peripheral End milling process," Innovative production machines and systems conference, 2009.
  44. C. Prakasvudhisam, S. Kunnappadeelert and P. Yenradee, "Optimal cutting condition determination for desired surface roughness in end milling," Int J Adv Manuf Technol, vol. 41, no.5/6, pp.440-451, 2009.
  45. K. Patel, A. Batish and A. Bhattacharya, "Optimization of surface roughness in an end-milling operation using nested experimental design", Journal of production engineering research Development, vol. 3, pp-361-373, 2009.
  46. R.E.Z. Ramos, T.L. Schmitz, M. Traverso and A. Abbas, "Value of information and experimentation in milling profit optimization," International journal of Mechatronics and Manufacturing Systems, vol. 2, no. 5/6, pp. 580-599, 2009.
  47. R. Saravanan and J. V. Raman, "A comparative study on optimizing CNC milling operation using simulated annealing and genetic algorithm", The IUP Journal of Mechanical Engineering, Vol. 2, No. 3, pp. 7-17, 2009.
  48. R.T Jalili, Saffar, M.R.T Razfar, A.H.T Salimi and M.M.T Khani, "Optimization of Machining Parameters to Minimize Tool Deflection in the End Milling Operation Using Genetic Algorithm," World Applied Sciences Journal, vol. 6, no. 1, pp. 64-69, 2009.
  49. C.T Zhang and J.T Chen, "Methods of optimization of end milling Parameters Based on Genetic Algorithm," Proceeding of the ninth international conference on Electronic Measurement & Investments, 2009.
  50. F.T Kolahan and M.T Abachizadeh, "Optimizing Turning Parameters for Cylindrical Parts Using Simulated Annealing Method," International Journal of Engineering and Applied Sciences, Vol. 6, No. 3, pp. 149-152, 2010.
  51. S.T Moshat, S.T Datta, A.T Bandyopadhyay and P.T K.T Pal, "Optimization of CNC end milling process parameters using PCA-based Taguchi method," International Journal of Engineering, Science and Technology, vol. 2, no. 1, pp. 92-102, 2010.
  52. R.V. Rao and P.J. Pawar, "Parameter optimization of a multi-pass milling process using non-traditional optimization algorithms," Applied Soft Computing, vol.10, no. 2, pp. 445-456, 2010.
  53. M.R.S. Yazdi and A. Khorram, "Modeling and optimization of milling process by using RSM and ANN methods," International journal of Engineering and Technology, vol. 2, no.5, pp. 474-485, 2010.
  54. k. Gupta, P. Chandna and P. Tandon, " Hybrid genetic algorithm for minimizing non productive machining time during 2.5 d milling", International Journal of Engineering, Science and Technology. vol. 3, no. 1, 2011, pp. 183-190.
  55. k. Gupta, P. Chandna and P. Tandon, "Optimization of machining parameters and tool selection in 2.5d milling using Genetic Algorithm", International Journal of Innovative Technology and Creative Engineering, vol. 1, no. 8, 2011.
  56. V. S. Gadakh, "Application of MOORA method for parametric optimization of milling process," International journal of applied engineering research, dindigul, vol. 1, no.4, pp.743-758, 2011.
  57. Mustafa, "Determination and optimization of the machining parameters of the welded areas in moulds", Journal of scientific research and essays, vol. 6, no. 2, pp. 485-492, 2011.
  58. G. Quintana & J. Ciurana, "Chatter in machining processes: A review," International Journal of Machine Tools & Manufacture, vol. 51, pp. 366-376, 2011.
  59. W. Yang & Y. Guo and W. Liao, "Multi-objective optimization of multi-pass face milling using particle swarm intelligence," International Journal of Advance Manufacturing & Technology (DOI), vol. 56 no. 5-8, pp. 3187-88, 2011.
  60. Bhirud, N.L., & , Gawande, R.R. (2017). Optimization of process parameters during end Milling and prediction of work piece temperature rise. Archive of mechanical engineering, 64(3), 327-346.
  61. Kumar, S., Gupta, A.K., & Chandna, P. (2015). Optimization of neural network parameters using Grey-Taguchi methodology for manufacturing process applications. Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science. 229(14), 2651-2664.
  62. Kaushik, V.S., Subramanian, M., & Sakthivel, M. (2018). Optimization of Processes Parameters on Temperature Rise in CNC End Milling of Al 7068 using Hybrid Techniques. Materials Today: Proceedings, 5, 7037-7046.
  63. P Palanisamy, I Rajendran, S Shanmugasundaram, and R Saravanan, (2006), "Prediction of cutting force and temperature rise in the end-milling operation" Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science. Volume: 220 issue: 10, page(s): 1577-1587
  64. Kumar, S., Gupta, A.K., & Chandna, P. (2014). Minimization of Non-Productive Time during 2.5D Milling. World Academy of Science, Engineering and Technology, 8(6), 1155-1