OPTIMIZATION TECHNIQUES IN TURNING - A REVIEW

Puneet NP[1], Srinivasa Pai P[2] and Grynal D'Mello[3]

[1]M.Tech scholar, [2]Professor, [3]Asst. Professor,
Dept. of Mech. Engg., NMAM Institute of Technology, Nitte
[1]E-mail : puneetnp12@gmail.com

Abstract: *This paper reviews the literature on use of optimization techniques in machining operations, particularly turning. Optimization techniques have undergone lot of changes and developments and include conventional methods like Weighted sum method, Ellipsoid algorithm etc. and advanced techniques like Genetic Algorithm (GA), Particle Swarm Optimization (PSO) etc. The review has been carried out considering different objectives like cost, cutting forces, production time and surface roughness. The review considers application of single method and combination of methods and its use in conventional and non-conventional material machining. Finally a case study which involves application of GA and PSO for optimizing surface roughness in high speed turning of mild steel is presented.*

Keywords: *Optimization, Response Surface Methodology, Artificial Neural Network, Genetic Algorithm, Particle Swarm Optimization*

1. INTRODUCTION

Machining is a complicated process in which many variables can directly affect the desired results. As aerospace and defense sector is booming in the present days, high precision machining with low cost and good quality surface finish has become mandatory to satisfy the robust design requirements. It has been considered to be a challenging work in the industries as high strength cutting tools have been used to machine some difficult to machine materials like titanium and its alloys, Inconel and many more.

Turning is one of the types of machining where material is removed from the surface of a rotating work piece using a single point cutting tool. In present scenario, all the industries go for CNC turning than traditional turning to minimize time, material wastage and to increase accuracy and productivity. High speed turning is gaining popularity which is considered to be the advanced manufacturing technology with a great need in the future which can produce good surface finish [1]. It is commonly used to perform the turning experiments at higher cutting speed and feed rates than conventional machining.

The main parameters considered in machining are cutting speed, feed rate and depth of cut. Combination of these parameters decides the quality of the product. When the cutting tool comes in contact with the work piece, cutting tool vibrations are generated, which are caused due to a complex interaction of the above mentioned parameters and can adversely affect the surface roughness [2]. Along with these parameters, some other parameters like cutting forces, cutting zone temperature, coolant conditions etc., affect the surface roughness. The effect of these parameters on the turning operation has been the topic of interest for last two decades. Surface Roughness is an important output parameter in machining process which can influence the quality of mechanical parts. Other output parameters studied by researchers include tool wear, cutting tool vibrations, cutting forces etc.

The optimization techniques are useful to find the optimum solution or unconstrained maxima or minima of continuous and differentiable functions. An optimization algorithm is a procedure executed iteratively by comparing various solutions till an optimum or a satisfactory solution is obtained. The method chosen for any particular case will depend primarily on the character of the objective function, the nature of the constraints and the number of independent and dependent variables.

The general objective in optimization is to choose a set of values of the variables subject to various constraints that will produce desired optimum response for the chosen objective function. Several optimization techniques have been used to find optimal solutions to numerous engineering problems. Conventional and non-conventional optimization techniques have been used in minimizing or maximizing the objectives in various problems [3].

Optimization of machining parameters is an important factor in the field of manufacturing. Usually in the industries, the machining parameters are selected based on the machine tool manufacturer's recommendation. But these selection influences tool life, economy and other related factors. Application of optimization techniques is helpful in determining optimal values for various machining parameters; so that the output in terms of machining cost, surface finish, cutting time, power consumed etc. can be optimized to meet the demand of quality products and to compete in the market [4].

1.1 Optimization Techniques

Various researchers have used different optimization techniques for optimizing the parameters to minimize/maximize the desired output. Some of the commonly used optimization techniques are as follows:

1. Genetic Algorithm (GA): The GA technique is based on the natural process of evolution to solve optimization and search problems. There are three main operators in GA which are reproduction, crossover and mutation. To apply GA in optimization of machining process parameters, the process parameters are encoded as genes by primary encoding [3].
2. Particle Swarm Optimization (PSO): PSO technique was first introduced by Kennedy and Eberhart [5] to solve continuous optimization problems. The swarm is composed of volume-less particles with stochastic velocities, each of which represents a feasible solution. The algorithm finds the optimal solution through moving the particles in the solution space.
3. Ant Colony Optimization (ACO): ACO algorithm was inspired by the behavior of the ants in searching of their food sources. The ants search for the foods and evaluate the food sources and bring it back to the nest. The ant then leaves a substance named pheromones as they move back to the nest. The quantity of pheromone which may depend on the quality and quantity of the food will guide other ants to the food source. The other ants tend to follow the paths where pheromone concentration is higher [3].

This study presents the review of most commonly used optimization techniques in machining. Sections in this review are classified based on the objective functions defined in various optimization studies, which include cost, production time, tool wear, cutting forces and surface roughness. Finally, a case study on the application of GA and PSO for optimizing surface roughness in high speed turning of steel has been presented at the end.

2. LITERATURE REVIEW

This section presents the review of literature regarding the use of optimization techniques in machining particularly turning. A brief presentation of the review carried out in the field of optimization as applied to machining particularly turning is given in Table 1.

The review covers different objective functions like cost, cutting force, production time, wear etc. and also use of single or multiple objective function optimization techniques. This also covers the application of optimization techniques not only for conventional materials like steel but also non-conventional materials like titanium based alloys, composite materials etc.

2.1 Optimization with Cost as Objective Function

Abdelouahhab Jabri et al. [6] optimized cutting conditions like cutting speed feed rate and depth of cut (DOC) for two objective functions: minimizing cutting cost and used tool life time. The multi-objective technique was based on Genetic Algorithm (GA). The results obtained from GA were presented in Pareto frontier graph.

Yi Zheng Lee et al. [7] used two optimization techniques; Particle Swarm Optimization (PSO) and the hybrid of Genetic Algorithm and Artificial Immune System (GA-AIS) to optimize the cutting conditions (speed, feed rate and DOC) to minimize the unit production cost. Multipass turning operations were carried out with rough machining and finishing. They concluded that

Table 1: Objectives for Optimization and the Techniques used by Different Researchers

Authors	Year	CM	NCM	Objective						Technique		
				Cost	CF	PT	wear	SR	MO	SM	Comb.	AI
J. Wang et al.	2002	✓				✓				DA		
M.V. Ribeiro et al.	2003		✓				✓			✓		
Hari Singh et al.	2004	✓					✓			TM		
J. Paulo Davim et al.	2005		✓					✓		✓		
Wassila Bouzid	2005	✓							✓	✓		
M. Nalbant et al.	2007	✓						✓		TM		
Yiğit Karpat et al.	2007	✓							✓			✓
Anderson P. Paiva et al.	2007	✓							✓			✓
Alakesh Manna, et al.	2008		✓	✓							✓	
T. Srikanth et al.	2008	✓						✓		✓		
Ahmet Hascalik, et al.	2008		✓						✓	TM		
Jenn-Tsong Horng et al.	2008	✓							✓			✓
H.Ganesan et al.	2011	✓				✓					✓	
Dushyant P. Patel et al.			✓						✓	GA		
S. Bharathi Raja et al.	2011	✓						✓		PSO		
Yi Zheng Lee et al.	2012	✓		✓							✓	
Arun Kumar Parida et al.	2012	✓			✓					✓		
M.Sanjeev Kumar et al.			✓					✓		GA		
A.V.N.L. Sharma et al.	2012		✓					✓		PSO		
Rahul Davis et al.	2012	✓						✓		TM		
Vaibhav B. Pansare et al.	2012	✓						✓		ACO		
Mohamed WalidAzizi et al.	2012	✓							✓	TM		
Poornima et al.	2012	✓						✓		GA		
Thanongsak Thepsonthi eta l.	2012		✓						✓	PSO		

Satyanarayana Kosaraju et al.	2012		✓						✓	TM		
J. S. Senthil kumaar et al.	2012		✓						✓			✓
Abdelouahha Jabri et al.	2013	✓		✓						GA		
A. Belloufi et al.	2013	✓		✓								✓
Dusan Petkovic et al.	2013	✓		✓						GA		
Ali R. Yildiz	2013	✓		✓							✓	
Vikas B. Magdum et al.	2013	✓			✓					TM		
Kapil Kumar Chauhan et al.	2013		✓				✓			✓		
H Aouici et al.	2013		✓						✓	✓		
Mehmet Aydin et al.	2013	✓							✓			✓
K.Manilavanya et al.	2013	✓						✓		TM		
T. Sreenivasa Murthy et al.	2013	✓						✓			✓	
Mustafa Gunay et al.	2013	✓						✓		TM		
Ashvin J. Makadia et al.	2013	✓						✓		✓		
Indira G. Escamil-la-Salazar et al.	2013		✓						✓			✓
F. Jafarian et al.	2013	✓							✓		✓	
Rasool Mokhtari-Homami et al.	2014		✓						✓			✓
D. Philip Selvaraj et al.	2014	✓							✓	TM		
Khaider Bouacha et al.	2014	✓							✓		✓	
AnandS.Shivade et al.	2014	✓							✓	TM		
P. Suresh et al.	2014		✓						✓			✓
M. Adinarayana et al.	2014	✓							✓	TM		

CM = conventional material, N-CM = Non- Conventional material, CF = Cutting Force, PT = Production Time, SR = Surface Roughness, MO = Multi Objective, SM = Single Method, Comb. = Combination of methods, AI = Artificial Intelligence, GA = Genetic Algorithm, PSO = Particle Swarm Optimization, TM = Taguchi Method, DA = Deterministic Approach, ACO = Ant Colony Optimization

GA-AIS gave better results when compared to PSO and GA alone.

Dusan Petkovic et al. [4] used genetic algorithm for optimization of turning machining process. They used GA to optimize the machining parameters (cutting speed and feed) to minimize the cost of turning process. The results obtained were checked using SQP and the results from both GA and SQP were matching. According to the authors, GA was found to be better than SQP based on number of iterations and execution time.

A. Belloufi et al. [8] optimized the cutting conditions to minimize the production cost under machining constraints. The optimization technique used by them was hybrid genetic algorithm by using sequential quadratic programming (SQP). SQP was used to fine tune the results obtained from GA. The results indicated that the proposed hybrid genetic algorithm by using a SQP was effective when compared to other techniques.

Ali R. Yildiz [9] used Hybrid Taguchi-differential evolution algorithm for optimization of multi-pass turning operations. This study developed a new a hybrid optimization algorithm entitled hybrid robust differential evolution (HRDE) by adding positive properties of the Taguchi's method to the differential evolution algorithm for minimizing the production cost. The results revealed that the proposed hybrid algorithm was more effective than PSO algorithm, immune algorithm, hybrid genetic algorithm, hybrid harmony search algorithm, scatter search algorithm, GA and integration of simulated annealing and Hooke-Jeevespatter search.

Alakesh Manna et al. [10] optimized machining conditions for effective turning of E0300 alloy steel. Objective function defined in the study was unit cost of production. The optimality was determined using dynamic programming technique. The input parameters were actual machining time, set up time, tool reuse time, tool life and tool changing time. The mathematical models were developed considering the Krononberg's data used for standard turning operation. The effects of different constraints on the objective functions were analyzed through various graphical representations. Taguchi method was also used to optimize the input parameters against surface finish. Multiple regression models were developed to obtain relationships between input parameters and surface roughness. The results showed that cutting speed had higher influence on surface roughness when compared to other parameters.

2.2 Optimization with Cutting Forces as Objective Function

Vikas B. Magdum, et al. [11] performed evaluation and optimization of machining parameters for turning of EN 8 steel. They used Taguchi's parameter optimization method for the evaluation of best possible combination of machining parameters (tool shape and material, cutting speed, feed rate, depth of cut) considered in this study, for the minimization of cutting forces in different directions during machining.

Arun Kumar Parida et al. [12] optimized machining parameters in turning using Design of Experiments (DOE) and Analysis of Variance (ANOVA). In this study, machining of mild steel was done using HSS tool. Here factorial 3^k design of experiments was carried out and influence of input parameters on the objective function was analyzed using ANOVA. The experimental results showed that the cutting force and feed force were low at low feed and depth of cut and comparatively high at high feed and high depth of cut.

2.3 Optimization with Production Time as Objective Function

J. Wang, et al. [13] performed optimization of cutting conditions for single pass turning operations using a deterministic approach. The aim of this study was to determine optimal conditions to minimize the production time. The study showed the benefits in production time and cost per component, when using the optimum cutting conditions than the conditions recommended in handbooks.

H. Ganesan et al. [14] conducted optimization of machining parameters in turning process using genetic algorithm and particle swarm optimization with experimental verification. In this study, optimal machining parameters were determined against minimum production time. Constraints considered here were cutting force, power and dimensional accuracy and surface finish. The results were compared and concluded that PSO produced better results.

2.4 Optimization with Tool Wear as Objective Function

Hari Singh et al. [15] performed tool wear optimization in turning operations by Taguchi method. The experiments were conducted on EN24 steel using titanium carbide coated inserts. The objective was to optimize machining parameters (speed, feed & depth of cut) to minimize tool wear (flank wear and crater wear). Validation experiments were conducted and the results were found to be close enough to the predicted optimal values of the cutting tool characteristics (flank wear and crater wear).

Kapil Kumar Chauhan et al. [16] optimized machining parameters of titanium alloy for tool life. In this study, machining process was carried out in near dry conditions using Physical Vapor Disposition (PVD) coated cemented carbide tools. For dry or near dry machining, coolant flow rate of 50 and 100 mL/Hr were investigated. Taguchi technique was used to acquire the data. An orthogonal array and signal to noise ratio were employed to investigate the machining characteristics of titanium alloy and to optimize the machining parameters. Taguchi method was used for optimization of coolant flow rate, cutting speed, feed rate and depth of cut.

2.5 Optimization with Surface Roughness as Objective Function

T. Srikanth et al. [17] used a Real Coded Genetic Algorithm (RCGA) for optimization of cutting parameters in turning. The cutting parameters (speed, feed, depth of cut and nose radius) were optimized against the surface roughness. They explained the benefits of RCGA over existing binary genetic algorithm. The results showed that RCGA is accurate and reliable for optimization of cutting parameters.

H Aouici et al. [18] conducted experimental investigation of cutting parameters influence on surface roughness and cutting forces in hard turning of X38CrMoV5-1 with CBN tool. In this study, the effect of cutting parameters on the outputs i.e. surface roughness and cutting force components were explored by ANOVA. The relationship between parameters and variables was established using Response Surface Methodology (RSM). It was concluded that the surface roughness was mainly influenced by speed, feed rate and the cutting force components were mainly influenced by depth of cut than speed and feed rate.

A.V.N.L. Sharma et al. [19] determined optimal machining conditions for turning of Al/SiC MMC using PSO and regression analysis. In this study, ANOVA had been performed to verify the adequacy and fit of the mathematical models developed. Also multiple regression analysis was carried out to establish the relationship between input and output parameters. Results revealed that, as the feed rate increased, surface roughness had also gone up. Also, improvement of surface roughness was seen with increase in cutting speed.

Rahul Davis et al. [20] performed optimization of cutting parameters in dry turning operation of EN24 steel. The objective was to minimize the surface roughness by optimizing the cutting parameters. Carbide P-30 cutting tool was used in dry condition. Performance characteristics were studied using Signal to Noise ratio and ANOVA. Taguchi method was employed for optimization.

Vaibhav B. Pansare et al. [21] performed optimization of cutting parameters in multipass turning operation using Ant Colony algorithm. The objective was to minimize surface roughness. The process had both roughing and finishing stages. Multiple linear regressions were used to obtain relationships between cutting parameters and surface roughness, and the optimal parameters were determined using this mathematical model. The results showed that, minimum cutting speed with minimum feed and high depth of cut yielded minimum surface roughness R_a, in finish cut. The study also showed that the Ant Colony Algorithm can be easily modified to optimize turning operation, since it is problem independent.

Dushyant P. Patel et al. [22] performed optimization of process parameters for turning operation on CNC lathe for Inconel 600 using Genetic Algorithm. The main objective was to minimize surface roughness and machining time against the cutting parameters (speed, feed and depth of cut). The optimum results obtained using GA was tabulated for both roughness and machining time.

Rasool Mokhtari Homami et al. [23] performed optimization of turning process using artificial intelligence technology. System model was done using Artificial Neural Network (ANN) and optimized using GA. The aim was to minimize surface roughness and flank wear. The results showed that the nose radius, feed rate and approach angle had significant effect on flank wear and surface roughness, and the cutting velocity had showed significance on flank wear alone. The optimized parameters showed good agreement with the results obtained from validation experiments, and the flank wear and surface roughness were reduced significantly upon using the optimized results.

S. Bharathi Raja et al. [24] used particle swarm optimization technique for determining optimal machining parameters of different work piece materials in turning operation. Different work piece materials used were mild steel, copper, aluminum, brass. PSO had been used to obtain optimal machining parameters to minimize machining time subjected to surface roughness. Different input parameters were speed, feed &depth of cut and the desired output was surface roughness. It was found that optimal parameters obtained for the desired output and values from the verification experiments were matching. Hence PSO was proved to be an efficient methodology to find optimal values for any desired material.

Mehmet Aydin et al. [25] carried out the prediction of surface roughness and cutting zone temperature in dry turning processes of AISI304 stainless steel using ANFIS with PSO learning. The cutting tool used in this process was multi-layer coated (TiCN+TiC+TiCN+TiN) tungsten carbide tool insert. The approach was based on ANFIS with PSO learning. Machining was done with different speed and feeds keeping depth of cut constant. Surface roughness and cutting zone temperature data were used for training along with feed rate, cutting speed and cutting force data obtained from experiments in ANFIS for the prediction. Predicted values were compared with measured values from test data. Predicted and experimental values were in good agreement with each other.

Mohamed Walid Azizi et al. [26] conducted surface roughness and cutting forces modeling for optimization of machining conditions in finish hard turning of AISI 52100 steel. The effect of speed, feed, depth of cut and work piece hardness on surface roughness and cutting force components were studied. Cutting tool used for turning was coated Al_2O_3+TiC mixed ceramic tool. The parameters were optimized using Taguchi's L_{27} orthogonal array. The validity of linear regression model was verified using response table and ANOVA. The statistical analysis revealed that cutting speed, work piece hardness and feed rate had significant effects on surface roughness, whereas cutting force components were highly influenced by feed rate, work piece hardness and depth of cut than cutting speed. Also, the optimum conditions to produce minimum surface roughness with minimal cutting force components were searched using desirability function approach for multiple response factor optimizations.

K.Mani Lavanya et al. [27] performed optimization of process parameters in turning operation of AISI-1016 alloy steels with CBN using Taguchi Method and ANOVA. In this study, the objective was to optimize the cutting parameters (speed, feed & depth of cut) for minimizing the surface roughness. The experimental data were used to characterize the factors affecting roughness by ANOVA. Relationship between input parameters and the output was obtained using Response Surface Methodology. They concluded that depth of cut had least significance on surface roughness.

Optimizing process parameters in hard dry turning using GA and PSO non-conventional optimization techniques was done by T. Sreenivasa Murthy et al. [28]. In this study, machining of EN 41B was done using cermet tool inserts. The process parameters speed, feed & depth of cut were optimized against surface finish using GA & PSO. The results of GA were better than results from PSO, in terms of an objective function.

Mustafa Gunay et al. [29] applied Taguchi method for determining optimum surface roughness in turning of high-alloy white cast iron. The experiment was conducted by considering two hardness levels (50 HRC and 62 HRC) and by using ceramic and CBN cutting tool inserts on Ni-hard materials. Cutting parameters were speed, feed and depth of cut. Design of experiment was done using L18 orthogonal array. Optimal conditions were determined using signal to noise ratio. The effect of input parameters on surface roughness was evaluated using ANOVA. Statistical analysis showed that the parameters which influence roughness were cutting speed and feed rate.

M. Nalbant et al. [30] applied Taguchi method to optimize the cutting parameters for surface roughness in turning. Experiments were conducted on AISI 1030 steel bars using TiN coated tools. Performance characteristics were studied using signal to noise ratio, orthogonal array and ANOVA. The cutting parameters considered were insert radius, feed and depth of cut. Results showed that insert radius and feed rate were the influencing factors on surface roughness.

Ashvin J. Makadia et al. [31] performed optimization of machining parameters for turning operations based on response surface methodology. Design of Experiments was used to study the effect of speed, feed, depth of cut and tool nose radius on surface roughness of AISI 410 steel. The effect of input on output parameters were evaluated through RSM. Optimum conditions were determined using response surface contours. The results showed that surface roughness was greatly influenced by feed rate followed by tool nose radius. Validation experiments confirmed the accuracy of predicted values within 6% error.

Poornima et al. [32] optimized machining parameters in CNC turning of martensitic stainless steel using RSM and GA. The relationship between input and output parameters was derived using RSM. The influence of input parameters on the objective functions was analyzed using ANOVA. The cutting conditions (speed, feed & depth of cut) were optimized to minimize surface roughness.

2.6 Optimization Studies in Non Conventional Materials

A review on the application of optimization techniques on special alloys like titanium alloys and other non conventional materials like composites has been done in this section.

M.V. Ribeiro et al. [33] conducted optimization of titanium alloy (Ti-6Al–4V) machining. The experiments were carried out using uncoated carbide inserts. Main objective of the work was to optimize machining conditions (speed, feed and depth of cut) to maximize tool life. Results obtained when compared with experimental data, gave satisfactory accuracy.

M. Sanjeev Kumar et al. [34] conducted machining parameter optimization of Poly Tetra Fluoro Ethylene (PTFE) using Genetic Algorithm. In this study, cutting conditions (speed, feed & depth of cut) were optimized against the surface roughness. After optimization the study concluded that the GA is flexible to any kind of objective functions and hence it can be used to optimize any process.

J. Paulo Davim et al. [35] performed optimization of surface roughness on turning fibre-reinforced plastics (FRPs) with diamond cutting tools. The experiments were conducted on FRPs manufactured by filament winding and hand layup process. The objective was to establish optimal cutting conditions to get certain surface roughness R_a and R_t/R_{max}. This study showed that surface roughness decreased with cutting speed and increased with feed rate. Optimal conditions were obtained by the model developed using multiple regression analysis.

Indira G. Escamilla-Salazar et al. [36] carried out machining optimization using swarm intelligence in titanium (Ti-6Al-4V) alloy. In this study, PSO was used to optimize parameters in multiple objective high speed milling operation. A hybrid system of PSO and neural network was used to establish the relationship between performance measures and input parameters. The objective was to minimize surface roughness and temperature. Pareto optimal front were computed and plotted. The experiment showed that the swarm intelligence was effective and can be used to solve conflict problems.

Thanongsak Thepsonthi et al. [37] performed multi-objective process optimization for micro-end milling of Ti-6Al-4V alloy. In this study, multi objective PSO was implemented to optimize the process parameters to minimize surface roughness and burr formation. Results showed that surface finish was better with higher feed rate.

Satyanarayana Kosaraju et al. [38] performed Taguchi analysis on cutting forces and temperature in turning titanium Ti-6Al-4V. The effect of speed, feed rate and depth of cut on the performance characteristics cutting force and temperature was studied. Taguchi method was used to optimize the cutting parameters. Experiments were conducted using L_9 orthogonal array. Results showed that cutting speed was the most significant parameter effecting cutting force and temperature. Confirmation experiments were conducted and the results were in good agreement with the predicted values.

Ahmet Hascalik et al. [39] carried out optimization of turning parameters for surface roughness and tool life based on the Taguchi method. Input parameters were speed, feed rate and depth of cut. Ti-6Al-4V alloy was machined using CNMG 120408-883 inserts. The performance characteristics were studied using signal to noise ratio and ANOVA. Results showed that the surface roughness was mainly influenced by feed rate than cutting speed, whereas cutting speed influenced tool life. Feed rate and depth of cut had statistical influence on tool life.

D. Philip Selvaraj et al. [40] optimized surface roughness, cutting force and tool wear of nitrogen alloyed duplex stainless steel in a dry turning process using Taguchi method. They carried out turning operations using TiC and TiCN coated carbide cutting tool inserts. The cutting parameters were optimized using signal to noise ratio and the ANOVA. Results showed that the feed rate was the most influencing factor on the surface roughness and cutting force. Also, tool wear was influenced by the cutting speed.

Taguchi method was used to optimize the input parameters. The predicted results were found close to experimental results within 8% error.

2.7 Multi Objective Optimization

Some authors have considered more than one objective for optimization. A review on such studies has been described in this section.

F. Jafarian et al. [41] applied artificial neural network and optimization algorithms for optimizing surface roughness, tool life and cutting forces in turning operation. The objective was to minimize surface roughness, resultant cutting forces and to maximize tool life in turning operation. Three separate neural network models were developed to estimate outputs by varying the input parameters. These network models were used to optimize objective functions. Two optimization techniques namely, GA and PSO were used to optimize the objective functions separately. The results showed that, the trained neural network with GA as objective function produced a strong model with high accuracy to analyze the effect of each parameter on output. In this study, to optimize one specific output, other outputs were kept in a specified range.

J. S. Senthilkumaar et al. [42] used intelligent optimization and selection of machining parameters in finish turning and facing of Inconel 718. Tool used was uncoated carbide insert. Genetic algorithm was coupled with the ANN and was used as the intelligent optimization technique. The objective was to optimize machining parameters (speed, feed and depth of cut) against flank wear and surface roughness. The combined effect of feed, speed and depth of cut on surface roughness and flank wear were investigated using ANOVA. Using experimental data, the mathematical and ANN models were developed for evaluation of fitness function. Optimal parameters were obtained using Pareto optimal graph. The closeness of the optimal conditions to the experimental data was proved by verification experiments. According to the study, flank wear was highly influenced by speed, depth of cut and their interactions.

Yigit Karpat et al. [43] performed multi-objective optimization for turning processes using neural network modeling and dynamic-neighborhood particle swarm optimization (DN-PSO). In this study, the neural network models were used to define objective functions. The objective of the study was to optimize the parameters for each of three different case studies, which are: minimizing surface roughness and maximizing the productivity, maximizing tool life and material removal rate, minimizing machining induced stresses on the surface and minimizing surface roughness. The optimum conditions were selected from Pareto-optimal fronts. The study proved that DN-PSO for solving multi objective problems was efficient and effective, and it can be used for solving complex optimization problems in turning process.

A grey and fuzzy algorithm integrated approach for optimization of turning Hadfield steels with Al_2O_3/TiC mixed ceramic tools was carried out by Jenn-Tsong Horng et al. [44]. Speed, feed, depth of cut and nose radius were optimized by coupling grey relational analysis and fuzzy logic. Objective was to minimize surface roughness and flank wear. Experimental design was done using orthogonal array. Effect of input parameters on surface roughness and flank wear were found using response table, response graph and ANOVA. Validation experiments were conducted. The experimental results showed that performance characteristics were high using this algorithm.

Anderson P. Paiva et al. [45] used a multivariate hybrid approach to AISI 52100 hardened steel turning optimization. They combined response surface methodology and principal component analysis (PCA) to optimize turning parameters. Input parameters were speed, feed rate and depth of cut. The output objectives were tool life, processing cost per component, cutting time, total turning cycle time, surface roughness and material removal rate. By examining the eigenvectors of correlation matrix with the original outputs, the kind of optimization was assumed by multivariate objective function.

Khaider Bouacha et al. [46] performed analysis and optimization of hard turning operation using cubic boron nitride tool. The material used was AISI 52100 bearing steel. Output objectives were surface roughness, tool wear, metal volume removed and cutting forces considering input parameters speed, feed, depth of cut and cutting time. Performance characteristics were investigated using ANOVA and relationships between input and output parameters were established using RSM. Optimization techniques used were composite desirability function, Grey-Taguchi method and GA. Results showed that cutting speed influences tool wear. Depth of cut had major influence over cutting forces, but least significance over surface roughness. Cutting time influenced all parameters. Among all optimization methods considered, GA was the most advantageous technique.

Wassila Bouzid [47] performed cutting parameter optimization to minimize production time in high speed turning. Experiments were conducted on AISI 4340 steel using three chemical vapor deposition (CVD) coated inserts and one ceramic tool insert taking machine power and maximum spindle speed as constraints. The main objective functions were production time and surface roughness. Parameters were optimized for each inserts.

Anand S. Shivade et al. [48] optimized machining parameters for turning using Taguchi approach. The objective of the study was to optimize the machining conditions against surface roughness and tool tip temperature for turning EN8 steel using carbide insert. Experiments were designed based on Taguchi's L_9 Orthogonal array design. The influence of process parameters was analyzed using ANOVA.

P. Suresh et al. [49] optimized machining parameters in turning of Al–SiC–Gr hybrid metal matrix composites using grey-fuzzy algorithm. Grey-fuzzy logic approach offers improved grey-fuzzy reasoning grade and has less uncertainties in the output when compared with grey relational technique. The output objectives were flank wear, surface roughness and material removal rate against the input parameters speed, feed and mass fraction of SiC-Gr. In this study, the confirmatory test revealed an increase in grey-fuzzy reasoning grade from 0.619 to 0.891.

M. Adinarayana et al. [50] performed parametric analysis and multi objective optimization of cutting parameters in turning operation of AISI 4340 alloy steel with CVD cutting tools. In this study, experiments were designed and conducted using Taguchi's L_{27} Orthogonal array design. Taguchi design and regression analysis were used to predict and to optimize metal removal rate, surface roughness and power consumption. The influence of process parameters over the output function were studied using ANOVA. They also discussed the use of multi objective approach over single objective method. Results obtained showed that speed, feed and depth of cut influenced metal removal rate and power consumption whereas feed had variable effect on surface roughness. ANOVA results showed that speed had more influence on metal removal rate; depth of cut had great influence on surface roughness and power consumption.

Following observations can be drawn from above literature survey:

a) Optimization techniques have turned out to be powerful tools in the field of machining for optimizing various performance characteristics like cost, cutting force, production time, surface roughness, tool wear etc. The closeness of the experimental results and the predicted results provides the proof for this statement.

b) Optimization techniques have been used individually or in combination to improve the performance. Various parameters can be optimized to get the required output with minimum error.

c) Many researchers have attempted using more than one objective for optimization. Artificial Intelligence is widely being used to evolve the objective functions in optimization techniques, used either individually or in combination, as they provide higher modeling and prediction accuracies.

d) There has been many efforts by researchers in optimizing surface roughness during turning of both conventional and non conventional materials considering different parameters. Limited efforts have been made to optimize surface roughness considering cutting tool vibrations in machining particularly turning operations.

Considering this aspect, in the next section a case study regarding optimization of surface roughness in high speed turning of mild steel is presented. Cutting tool vibration has been considered as one of the parameters.

3. EXPERIMENTAL SET UP AND DETAILS

In this section, a case study regarding optimization of surface roughness in high speed turning of mild steel is discussed. The optimization has been carried out using GA and PSO. For both the optimization techniques, objective function has been defined in two ways; one considering the regression equation obtained using RSM and other considering the predicted output from ANN.

3.1 Machine and Instruments Used

High speed turning experiments have been carried out on a CNC turning centre HMT Stallion 1000

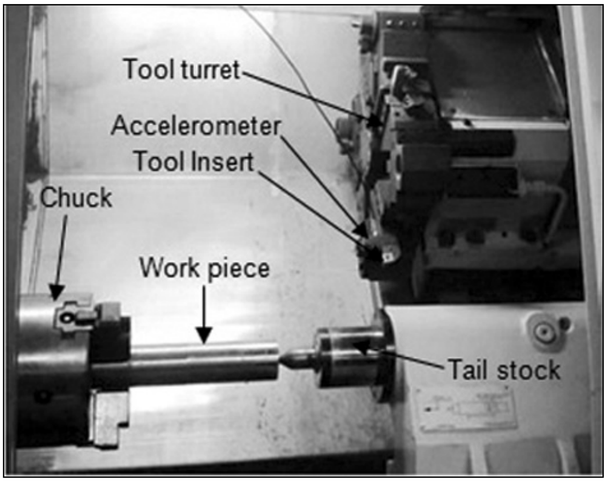

Fig 1. Experimental Set Up

make which has a maximum spindle speed of 3500 rpm. The experimental set up is shown in Fig 1. Experiments have been carried out in dry condition. The cutting tool vibrations were measured online using an accelerometer (KD37V/01) mounted on the tool holder in the feed direction. Data Acquisition system received the signals from accelerometer and these signals were processed using LABVIEW software.

Taylor Hobson Form Taly Surf 50 was used to measure surface roughness. Surface roughness readings were recorded at three different locations on the work piece surface 120^o apart and the average value was used for analysis.

3.2 Work Piece and Tool Material

A cylindrical bar of 50 mm diameter and 150 mm length was used as work piece. The work piece was turned to 5 mm cutting depth to remove the discontinuities that might have occurred during production. Hence final dimension of the work piece was 120 mm in length and 45 mm in diameter.

Tool insert was a coated carbide cutting tool CNMG 120404 and tool holder was WIDAX tool holder PCLNL 2020 K12. Nine experiments have been carried out for different spindle speeds (730, 790, 860 rpm), feeds (0.15, 0.2, 0.25 mm/rev) and constant depth of cut (0.8 mm). The turning experiments were carried out for 40 mm length, each considered as one pass.

4. PREDICTION USING RESPONSE SURFACE METHODOLOGY

Response Surface Methodology (RSM) is a combination of mathematical theory and statistical techniques and useful for modeling and analyzing problems in which a response of the output is influenced by several parameters and the objective is to optimize this response.

In this work, RSM has been used for modeling and analyzing the surface roughness in terms of cutting conditions and vibration parameters.

The mathematical relationship between independent input variables and the dependent variable has been obtained in terms of a first order model of the form

$$Y = b_0 + \sum_{i=1}^{k} b_i X_i \quad \text{.....................................(1)}$$

Where, Y is the predicted response; X is the input variable that influences the response variable, b_o the intercept and b_i is the i^{th} linear coefficient [51].

The contributions and effects of cutting speed (X_1, rpm), feed rate (X_2, mm/rev) and Root Mean Square (RMS) of vibration (X_3, g) on surface roughness (R_a, µm) has been studied. The surface roughness (R_a) has been determined as the response. The regression analysis of the data output obtained from the experimental runs has been performed by STATISTICA 8.0 software. Sample experimental and predicted values of surface roughness are given in Table 3.

The first order linear model developed using regression analysis is

$$R_a = 0.0053 - 0.00026X_1 + 7.73X_2 + 34.356X_3 \quad ..(2)$$

This equation has been considered as an objective function for Genetic Algorithm and Particle Swarm Optimization.

5. PREDICTION USING ARTIFICIAL NEURAL NETWORK (ANN)

Neural networks are nonlinear mapping systems that consist of simple processors, which are called neurons, linked by weighted connections. Each neuron has inputs and generates an output that can be seen as the reflection of local information that is stored in connections. The output signal of a neuron is fed to other neurons as input signals via interconnections. An ANN model consists of three layers such as input layer

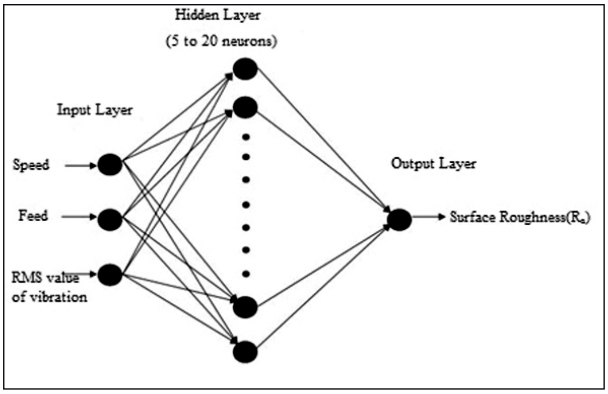

Fig 2. Structure of MLP Neural Network

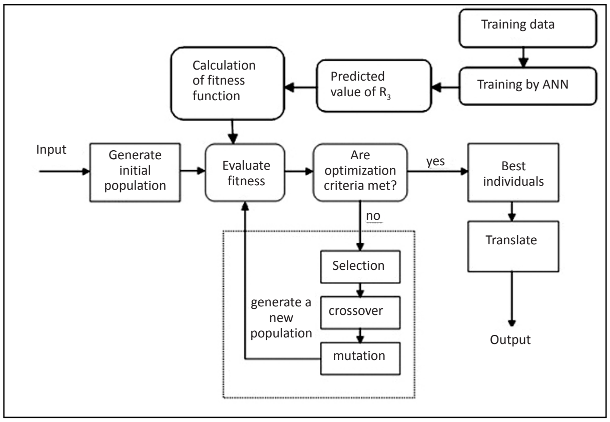

Fig 3. Flowchart of GA with ANN as Objective Function

which accepts the input variables, herein cutting speed, feed and cutting vibration, the hidden layer which has some number of neurons for the purpose of manipulation and an output layer made of one neuron to generate output (surface roughness R_a) [42]. In this work, Multi Layered Perceptron (MLP) neural network has been used to train the network. MLP is a feed forward network consisting of neurons in an input layer, one or more hidden layers and an output layer. Different layers have interconnections such that each neuron in one layer is connected to all neurons in the next layer. Processing of the information is done by the hidden neurons and output layer [52]. tansig transfer function has been selected to train the network using trainlm, trainbfg, trainscg and traincgf algorithms which are available in MATLAB Neural network toolbox [53]. The structure of MLP neural network used in this work is shown in Fig 2. Neural network model has been developed using MATLAB R2013a toolbox [53]. Number of hidden neurons has been varied between 5 to 20. The results obtained through neural network training is tabulated in an excel sheet and used for further studies.

The experimental data have been divided into two groups- 85% data for training the MLP network and remaining 15% test data. Totally 27 experimental data have been considered. 23 data has been considered for training and remaining for testing purpose. trainbfg training algorithm gave better results with an R^2 of 0.994 when compared to other training algorithms. The predicted values of R_a by ANN are given in Table 3.

From the predicted output of ANN, an objective function has been defined based on the training data.

The objective function derived from ANN is given by,

$$R_a=[X_1 \quad X_2 \quad X_3]\ [C] \qquad \text{...(3)}$$

Where, X_1 = cutting speed in rpm, X_2= feed rate in mm/rev, X_3= cutting vibration in g and [C]= matrix containing coefficients corresponding to X_1, X_2 and X_3 obtained using 23 training data.

6. OPTIMIZATION TECHNIQUES

6.1 Genetic Algorithm (GA)

Genetic algorithm has turned out to be a powerful tool in the field of optimization. It has been applied successfully to real-world problems and resulted in better search efficiency compared to traditional optimization algorithms. GA is based on the principles inspired from the genetics and evolution mechanisms observed in nature and populations of living beings. Its basic principle is the maintenance of a population of encoded solutions to the problem (genotypes) that evolve in time. It is based on the triangle of genetic solution reproduction, solution evaluation and selection of the best genotypes. Genetic reproduction is performed by means of two basic genetic operators: Crossover and Mutation. The standard flowchart for GA is shown in Fig 3. Evaluation is performed by means of the Fitness Function which depends on the specific problem and is the objective of the GA [4].

In the present study, the objective is to evaluate the optimized values of input variables (speed, feed and RMS value of vibration) to minimize surface roughness R_a.

Steps to be followed in GA can be as described as follows:

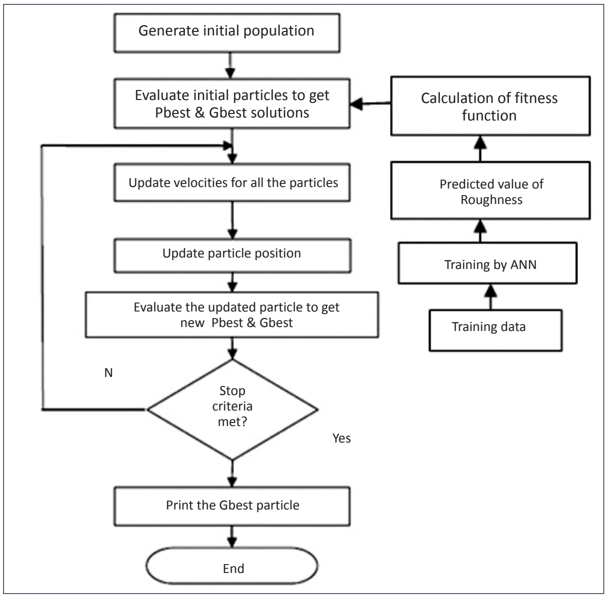

Fig 4. Flowchart of PSO With ANN as Objective Function

1. The process parameters are encoded as genes by binary encoding.
2. A set of genes is combined together to form a chromosome, which is used to perform basic mechanisms in the GA, such as crossover and mutation.
3. Crossover is the operation of exchanging some part of two chromosomes to generate new offspring, which is important when exploring the whole search space rapidly.
4. Mutation is applied after crossover to provide a small randomness to the new chromosome.
5. To evaluate each individual or chromosome, the encoded process parameters are decoded from the chromosome and are used to predict machining performance measures.
6. The fitness or objective function is a function needed in the optimization process and the selection of the next generation in the GA.
7. After a number of iterations of the GA, optimal results of process parameters are obtained by comparison of values of objective functions among all individuals [3].

In this work, objective function has been defined using two methods: using equation obtained from RSM and using output of ANN. The flowchart for GA considering ANN output as objective function is shown in Fig 3.

Here the fitness is calculated using the predicted values from ANN which is used as the objective function.

6.2 Particle Swarm Optimization (PSO)

PSO simulates the behavior of bird populations. In PSO, each single solution is a ''bird'' in the search space and it's called a ''particle''. For all of the "p" particles, a fitness value is evaluated by the fitness function to be optimized. The p particles are ''flown'' through the problem space by following the current optimum p particles. PSO is initialized with random p particles (solutions) and then optimizes by updating generations. In each iteration, each p particle is updated by following two ''best'' values. The first one that is obtained so far by any particle is called "personal best (pbest)". Another ''best'' value is the best value among all personal bests and all iterations. This best value is a global best which is called "gbest". After finding the two best values, the particle updates its velocity and positions.

To attain best position, particles are subjected to the following criteria [33].

A . The new best position is found based on any particle in the population so far and global best is called as 'gbest'.

B . Local best is called as "pbest", where the best particle position is identified by the same particle itself.

The particle velocity and particle position can be updated using the following equations.

$$V[\,] = c_1 \times rand() \times (pbest[\,] - present[\,]) + c_2 \times rand() \times (gbest[\,] - present[\,]) \quad (4)$$

$$P[\,] = V[\,] + present[\,] \quad (5)$$

Where, V[ ] is the particle velocity, P[ ] is the new particle position, present is the current particle, rand is the random number between 0 and 1, c_1 and c_2 are learning factors.

Algorithm for PSO is described as follows [33]:

Step 1 Create a uniformly distributed population of particles.

Step 2 Position of each particle is evaluated based on objective function.

Step 3 Particle's current position is updated when the present is better than the previous position.

Step 4 Best particle is determined based on particle's previous best positions.

Step 5 Particle velocity is updated.

Step 6 Particles are moved to their new positions.

Step 7 Go to step 2 until stopping criteria is satisfied.

Step 8 End

Like ANN-GA, the objective function has been defined for PSO using the output from ANN. The flowchart is shown in Fig 4.

7. RESULTS AND DISCUSSIONS

Two optimization techniques GA and PSO have been compared for surface roughness optimization using cutting speed, feed rate and RMS value of vibration. Two methods have been used to define the objective functions for both techniques: RSM and ANN.

7.1 Results Obtained Using GA (RSM Based Objective Function)

A total of 23 training data have been used to evolve the objective function using Response Surface Methodology. Optimization using GA was carried out with the optimization toolbox available in MATLAB R2013a [53]. The GA optimization toolbox is shown in Fig 5.

The steps followed to minimize the surface roughness using GA are as follows in MATLAB toolbox.

Step 1: Creating a fitness function

The equation (2) obtained from Response Surface Methodology has been used as Fitness function

$R_a = 0.0053 – 0.00026\ X_1 + 7.73\ X_2 + 34.356\ X_3$

Step 2: Select number of variables = 3

Step 3: Enter bounds of variables LB= [730 0.15 0.0047] and UB= [860 0.25 0.0239], where LB is Lower Bound and UB is Upper Bound.

Step 4: Select the population type as Double vector and enter population size = 27 (can be varied)

Step 5: Select fitness scaling 'Rank'

Step 6: Select selection procedure as 'Roulette'

Step 7: Select mutation as adaptive feasible, crossover function as single point and ratio= 0.5

Step 8: Set Migration, Algorithm settings and hybrid function as default setting.

Step 9: Stopping criteria:

Generations=100

Set Time limit, Fitness limit, Stall generation, Stall

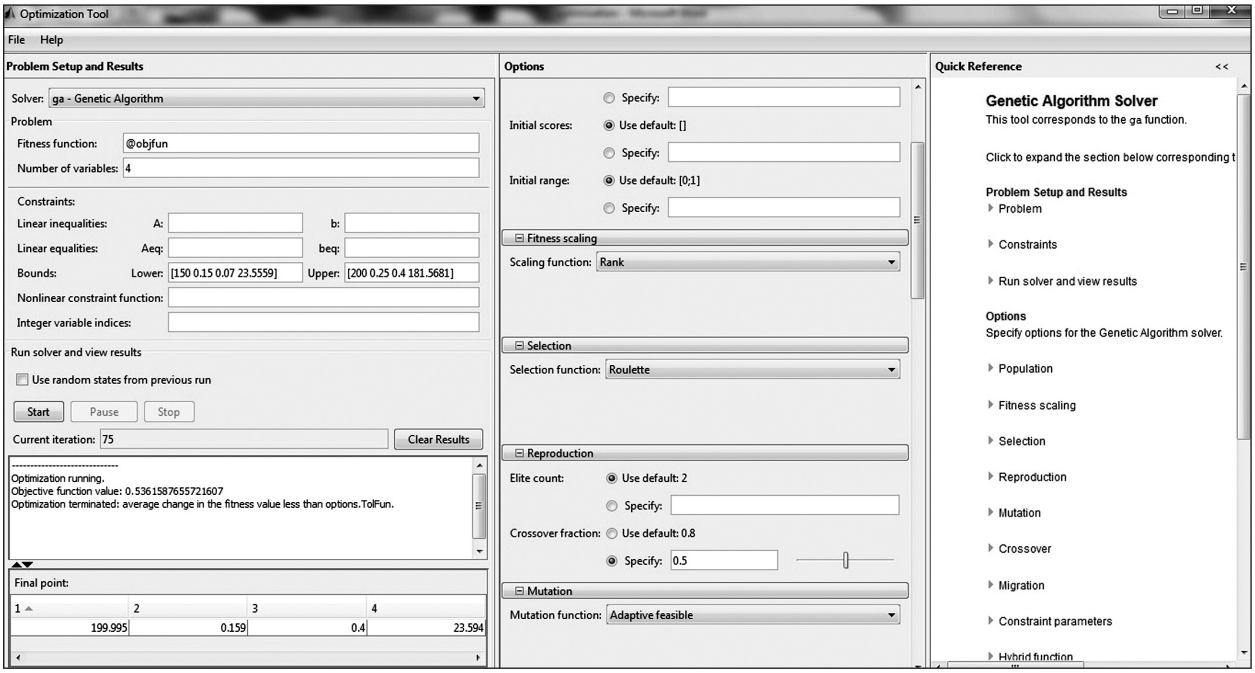

Fig 5. Snapshot of GA Optimization Toolbox

time limit, Function tolerance, Nonlinear constraint tolerance as default.

Step 10: Plot function

Plot interval: 1

Plot of Best fitness

The parameters for GA were set as mentioned above and the equation obtained from RSM was used as the objective function.

The objective was to obtain the optimum parameters to minimize surface roughness R_a. Fig 6 shows minimization of surface roughness value as it moves from 0^{th} iteration to 100^{th} iteration.

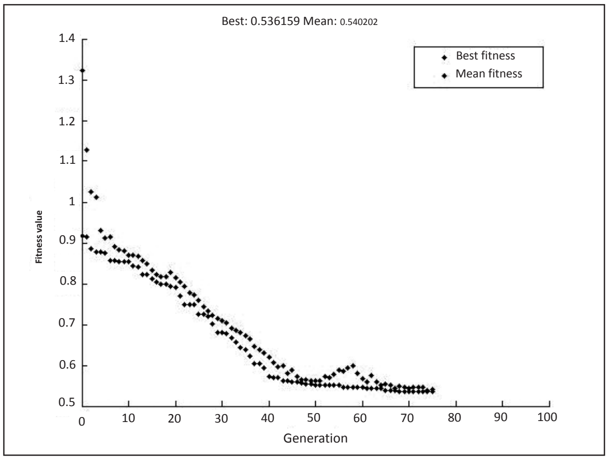

Fig 6. Fitness Value vs Generation in GA

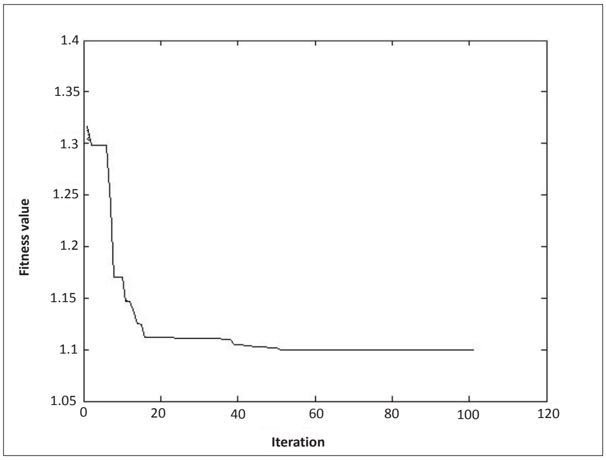

Fig 7. Fitness Value vs Iterations for PSO

The population size has been varied between 20 and 40. The minimum surface roughness value has been obtained for a population size of 36, which is R_a=1.102673 µm. The optimum values for different input parameters are -

Speed= 859.998740502 rpm

Feed rate = 0.15 mm/rev

RMS of vibration = 0.0047 g

7.2 Results Obtained Using GA (ANN Based Objective Function)

The objective function used here is Eq. (3) obtained from the output of ANN. Optimization using GA has been performed with GA optimization toolbox of MATLAB R2013a. The minimum value of surface roughness obtained is R_a=1.098727 µm for the population size of 36. Corresponding optimum values of parameters are as follows:

Cutting speed = 859.99658 rpm

Feed rate = 0.15 mm/rev

Cutting vibration = 0.0047 g

7.3 Results Obtained Using PSO (RSM Based Objective Function)

The main objective is to minimize the surface roughness of mild steel and to obtain the optimal machining conditions. PSO has been implemented using MATLAB R2013a. Optimization using PSO has been carried out for the range of values as given below:

Speed: 730 to 860 rpm

Feed rate: 0.15 to 0.25 mm/rev

RMS of vibration: 0.0047 to 0.0239 g

Equation (2) obtained using RSM has been used as fitness function in PSO. Population size has been varied from 20 to 40.

Table 2: Comparison of Results

Objective function	Optimization technique	Speed (rpm)	Feed (mm/rev)	RMS of vibration(g)	R_a (µm)
RSM	GA	859.998740502	0.15	0.0047	1.102673
	PSO	859.9712	0.15	0.0047	1.1027
ANN	GA	859.99658	0.15	0.0047	1.098727
	PSO	859.9456	0.15	0.0047	1.0987

Minimum roughness value has been obtained for a population size of 40, learning factors c_1 = 2 and c_2 = 1 and 100 iterations has been carried out.

Fig. 7 shows the plot of fitness value vs iterations. It has been observed that minimization of fitness value (in this case surface roughness) occurs well before 100th iteration and then it remains constant. Minimum surface roughness value obtained is 1.1027 µm. The optimalconditions for this minimum roughness are as follows:

Speed: 859.9712 rpm

Feed rate: 0.15 mm/rev.

RMS of vibration: 0.0047 g.

7.4 Results Obtained Using PSO (ANN Based Objective Function)

The objective function considered is the output of ANN as described in Equation (3). Minimum value of surface roughness has been obtained for the population size of 40, learning factors c_1=2 and c_2=1 and the corresponding values of surface roughness obtained is R_a= 1.0987 µm. Parameters obtained for the minimum roughness are,

Cutting speed = 859.9456 rpm

Feed rate = 0.15 mm/rev

Cutting vibration = 0.0047 g

7.5 Comparison

The results obtained using GA and PSO with objective functions based on RSM and ANN have been compared and is given in Table 2.

Two objective functions derived from RSM and ANN has been used to understand their applicability. Using regression equation as an objective function, for both GA and PSO, GA gave minimum value of surface roughness when compared with PSO. Using ANN output as an objective function, PSO produced the minimum value of surface roughness of 1.0987 µm for a speed of 859.9456 rpm, at a feed of 0.15 mm/rev and RMS of 0.0047 g.

ANN based GA and PSO gave better results when compared to RSM based GA & PSO.

8. CONCLUSION

A review has been presented on the application of optimization techniques by various researchers in the field of machining particularly turning. The different optimization techniques used

Table 3: Predicted and Experimental Values of Surface Roughness

Sl. No.	Speed (rpm)	Feed (mm/rev)	RMS of vibration (g)	Experimental Surface Roughness R_a (µm)	RSM Predicted R_a (µm)	ANN Predicted R_a (µm)
1	730	0.15	0.0088	1.35	1.283	1.29864
2	730	0.15	0.0084	1.23	1.263	1.260169
3	730	0.15	0.0079	1.19	1.245	1.207486
4	730	0.2	0.0061	1.61	1.57	1.567502
5	730	0.2	0.0106	1.65	1.72	1.648393
6	730	0.2	0.0066	1.58	1.587	1.624765
7	730	0.25	0.0113	2.39	2.135	2.394972
8	790	0.15	0.0095	1.4	1.285	1.343966
9	790	0.15	0.0089	1.21	1.264	1.271813
10	790	0.15	0.0072	1.18	1.206	1.174955
11	790	0.2	0.0147	1.79	1.85	1.785793
12	790	0.2	0.0063	1.44	1.56	1.436116
13	790	0.2	0.0047	1.29	1.506	1.302828
14	790	0.25	0.007	1.84	1.97	1.827212
15	860	0.15	0.0104	1.25	1.29	1.281464
16	860	0.15	0.0104	1.3	1.29	1.281464
17	860	0.15	0.0088	1.58	1.242	1.565877
18	860	0.2	0.0123	1.85	1.75	1.831856
19	860	0.25	0.0145	2.26	2.25	2.299587
20	860	0.25	0.0137	2.26	2.184	2.216101
21	860	0.25	0.0098	1.98	2.05	1.996319
22	790	0.25	0.0214	2.6	2.46	2.608723
23	860	0.2	0.0239	1.87	2.14	1.880378

either individually or in combination and the corresponding results are presented. The application involves single or multiple objective functions in machining application. It is seen that GA and PSO have been used widely for optimization of turning process. Also, in the recent years, it can be seen that artificial intelligence techniques are gaining popularity over the use of single optimization technique due to the higher accuracy of results obtained.

Further to establish the application of these techniques to turning, in this work, two techniques namely GA and PSO have been applied for optimization of process parameters (speed, feed rate and RMS value of vibration) using different objective functions to minimize the value of surface roughness.

a) Use of ANN based objective functions results in better optimization for both techniques when compared to RSM.

b) GA gave minimum value of surface roughness when compared to PSO. But PSO is simple to implement when compared to GA,, considering the use of mathematical operators. Computation using PSO is economical both in terms of memory required and speed when compared to GA.

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