© 2016 IJSRSET | Volume 2 | Issue 6 | Print ISSN: 2395-1990 | Online ISSN : 2394-4099
Themed Section: Engineering and Technology

Optimization of Material Turning Operation – A State-of-Art Research Review

Surinder Kumar[1]*, Meenu[2], P. S. Satsangi[3]

[1]Associate Professor, Department of Mechanical Engineering,, Chandigarh Engineering College, Landran, Mohali, Punjab, India
[2]Associate Professor, Department of Mechanical Engineering, National Institute of Technology, Kurukshetra, Haryana, India.
[3] Professor, Department of Mechanical Engineering, PEC University of Technology, Chandigarh, Punjab, India.

ABSTRACT

Machining process optimization not only remains an ongoing activity but is also becoming increasingly important in industry in the drive for reduced cycle time and agile manufacturing. To achieve these goals, one of the considerations is by optimizing the machining process parameters such as the cutting speed, feed rate, tool nose radius, tool rake angle, depth of cut, and cutting environment. Recently, alternative to conventional techniques employed for machining optimization the other techniques include geometric programming, geometric plus linear programming, Non-Linear Programming, goal programming, sequential unconstrained minimization technique and dynamic programming etc. Eleven techniques are considered, namely genetic algorithm (GA), response surface methodology (RSM), simulated annealing (SA), scatter search technique (SS), multiple regression analysis (MRA), particle swarm optimization (PSO), fuzzy logic, Taugchi's technique, utility concept, artificial neural network (ANN) and ant colony optimization (ACO). This paper provides an overview of these important soft computing techniques and highlights the progress made in this area of modeling of material turning processes.

Keywords: Machining optimization, genetic algorithm, simulated annealing, scatter search technique, multiple regression analysis, fuzzy logic, Taguchi technique, artificial neural network, utility concept, response surface methodology, ant colony optimization and particle swarm optimization.

I. INTRODUCTION

The study of various methods of machining has become a keen topic of research in recent times since these have been considered as primary processes in manufacturing industry. This chapter is intended to provide background information relevant to this research. The literature reported in this chapter contains investigations of the cutting process of unidirectional glass fiber reinforced plastics (UD-GFRP) composite materials and highlights specific factors which affect their machining performance. After the introductory material, recent research in turning is reviewed so that the importance of this research in the context of other work is evident. Gaps in the existing study, proposed research plan, objectives are also addressed in this chapter. In view of this, in this chapter a brief outline of the work done on important aspects such as surface quality, cutting forces and cutting environments is discussed. The chapter also outlines the work done in the field of modeling and optimization of these parameters. The fibre-reinforced plastics (FRP) industry, which is one of the fastest growing industries in the world, concentrates on single-piece component design of complex shapes. However, there are times when the best and/or economical design calls for the manufacture of a product in parts prior to assembly. The FRP machining methods now in use utilize the existing machines and tools developed for machining conventional materials. Machines and tools exclusively designed for FRP machining are yet to be developed (Santhanakrishnan et al., 1989). The machining of FRP is different from that of metal working in many respects, because the metal behaviour is not only inhomogeneous, but also depends on fiber and matrix properties, fiber orientation and the type of weave (Konig et al., 1985). The wide difference in thermal properties of the fiber and matrix material and the relatively poor thermal conductivity of composites make it more difficult to adopt any of the unconventional technique for machining the polymeric composites. Heat affected zone low rate production are the disadvantages of unconventional machining. Moreover, unconventional processes cannot obtain the shapes that are obtained by traditional turning, drilling and therefore traditional material removal processes are the most suited for machining polymeric composites. (1) Unlike the case of homogeneous metals, where the machining is associated with plastic deformation and shearing, the machining of FRP composites is associated with plowing, cutting and cracking (Wang et al., 1995 & Pwu and Chang, 1998). (2) Glass fibre reinforced plastics (GFRPs) are extremely abrasive, thus proper selection of the cutting tool and cutting parameters is very important for a perfect machining process. (3) Some of the problems encountered are fibers pull out, short tool life, matrix debonding, burning and formation of powder like chips, rapid tool wear, rough surface finish on finished components and a defective sub-surface layer with cracks and delamination reported are (Wang and Zhang, 2003 & Davim, 2009). In addition to this, a large number of variables in the form of tool geometry, operating parameters, individual mechanical properties of constituents and different fiber matrix bond properties make the machining analysis of GFRP materials a complex one.

II. METHODS AND MATERIAL

1.1 Effect of Parameters on Surface Roughness

(Sakuma and Masafumi, 1983) measured cutting resistance and surface roughness for analyzing the machinability and tool wear in face turning of glass fibre-reinforced plastics. They also studied the effect of fibre orientation on both the quality of the machined surfaces and tool wear. (Spur and Wunsch, 1988) studied turning of glass fibre reinforced (GFR) polyester and epoxy and found an increased surface roughness for increase in the feed rate but no dependence on the cutting velocity. (Ferreira et al., 2001) observed the performance of different tool materials like ceramic, cemented carbide, Cubic Boron Nitride (CBN) and diamond while turning. Experimental results showed that only diamond tools are suitable for use in finish turning. (Davim and Mata, 2005) used a polycrystalline diamond (PCD) cutting tool to machine FRP tubes and obtained optimal cutting parameters for surface roughness. (Palanikumar et al., 2006) focused on the multiple performance machining characteristics of GFRP composites using carbide (K10) tool. Five parameters such as work piece (fiber orientation), cutting speed, feed rate, depth of cut and machining time were selected. It was found that, the machining performance in the composite machining process can be improved by including more number of parameter and levels. (Palanikumar, 2007) predicted and evaluated the surface roughness of GFRP work piece using response surface method. Four parameters such as work piece (fiber orientation), depth of cut, feed rate and cutting speed were selected to minimize the surface roughness. Coated cermets tool was used for turning process. Isik, 2008) presented research results of the machining of unidirectional glass fiber reinforced composite (UD-GFRP) and recommended optimum cutting parameters to obtain better surface quality. (Palanikumar et al., 2008) presented influence of cutting parameters such as cutting speed feed rate on surface roughness parameters R_a, R_t, R_q, R_p and R_{3z} in turning of glass fibre reinforced composite materials. Polycrystalline diamond tool was used for turning process. It was found that, the surface roughness increases with the increase of feed rate and almost decreases with the increase of cutting speed and hand lay-up process produces better surface roughness than filament winding process in machining of FRP composites. (Palanikumar, 2008) evaluated the effect of cutting parameters on the surface roughness of the GFRP composites using PCD tool. Three parameters such as cutting speed, feed rate and depth of cut were selected to minimize the surface roughness. It was found that, depth of cut shows minimum effect on surface roughness compared to other parameters.

(Naveen Sait et al., 2009) presented an influence of machining parameters on surface roughness of GFRP pipes using coated carbide (K20) tool. Three parameters such as cutting speed, feed rate and depth of cut were selected to minimize the surface roughness. It was concluded that, quality of the machined surface of filament wound GFRP pipes is better than the hand layup GFRP pipes. (Kini et al., 2010) proposed an approach for turning of a glass fiber reinforced plastic composites using coated tungsten carbide inserts. Four parameters such as depth of cut, tool nose, cutting speed and feed rate were selected to minimize the surface roughness. It was concluded that the same surface roughness for different material removal rate can be obtained using the overlaid contour graphs. (Surinder Kumar et al., 2012) investigated the turning process of the unidirectional glass fiber reinforced plastic (UD-GFRP) composites. polycrystalline diamond (PCD) tool on turning machine was used and six parameters such as tool nose radius, tool rake angle, feed rate, cutting speed, depth of cut and along with cutting environment (dry, wet and cooled (5-7° temperature)) on the surface roughness produced. It was found that the feed rate is the factor, which has great influence on surface roughness, followed by cutting speed. (Surinder Kumar et al., 2013) developed a surface roughness and delamination mathematical prediction model for the machining of unidirectional glass fiber reinforced plastics composite using multiple regression analysis and genetic algorithm by using carbide (K10) cutting tool. It was observed that the single response optimization algorithms based on efficient methodology, genetic algorithm is utilized to optimize machining parameters in the machining of UD-GFRP. From the ANOVA result, it is concluded that feed rate, cutting speed, Depth of cut, have significant effect on surface roughness A, B, E has no effect at 95% confidence level. It is found that feed rate is more significant factor than other parameters; whilst depth of cut is the least significant parameter.

1.2 Effect of Cutting Parameters on Cutting Forces

(Santhanakrishnan et al., 1989) presented machinability study in turning process of GFRP, CFRP and Kevlar fiber reinforced plastics composite using P20 carbide, Tic coated carbide, K20 carbide and HSS tool. Three parameters such as cutting speed, feed rate and depth of cut were selected. Tangential force, feed force and radial force were measured by using inductive type lath tool dynamometer. It was observed that, the K20 carbide tool performed better in machining fiber reinforced plastics composites. (An et al., 1997) investigated the machinability of glass fiber reinforced plastics by means of single crystal diamond, poly crystal diamond and cubic boron nitride tools with various geometries. Three parameters such as cutting speed, feed rate and depth of cut were selected to minimize the cutting forces. It was concluded that, the single crystal diamond tool is excellent for GFRP cutting. (Chang, 2006) investigated the machinability of high-strength glass–fiber reinforced plastics (GFRP) materials in turning with chamfered main cutting edge of P and K type carbide tools. Parameters such as nose radius, cutting depth, feed rate, cutting speed, the first side rake angle, the second side rake angle, and parallel back rake angle were selected to minimize the cutting forces and cutting temperature. It was found that, the cutting forces and cutting temperature for the chamfered main cutting edge of P type carbide tools in turning is much higher than by chamfered main cutting of K type carbide tools. (Davim and Mata, 2007) investigated the machinability in turning process of glass fibers reinforced plastics (GFRP) using polycrystalline diamond and cemented carbide tool. Two parameters such as cutting speed and feed rate were selected to minimize the cutting forces. It was observed that, the polycrystalline diamond provides a better machinability index in comparison to cemented carbide tool (K15).

Recent studies on unidirectional glass fiber composites revealed the chip formation mechanism in orthogonal cutting. In case of long oriented glass fiber, degradation of the matrix adjacent to the fiber occurs first, followed by failure of the fiber at its rear side (Rao et al., 2007). (Isik and Kentli, 2009) proposed an approach for turning of a glass fiber reinforced plastic composites using cemented carbide tool. Three parameters such as depth of cut, cutting speed and feed rate were selected to minimize the tangential and feed force. Weighting techniques was used. The multicriteria optimization problem was changed to a scalar optimization problem by creating one function. (Hussain et al., 2011) developed cutting power prediction model for turning of glass fiber reinforced plastics composite using response surface methodology. Carbide (K20), Cubic Boron Nitride (CBN) and Polycrystalline Diamond (PCD) tool was used for turning and four parameters such as cutting speed, fiber orientation angle, depth of cut and feed rate were selected. The lower power consumption was observed at low cutting speed, low feed, moderate depth of cut and low fiber orientation angle. PCD tool performed better compared to the other two tools used. (Surinder Kumar et al., 2012) developed a cutting force prediction model for the machining of UD-GFRP using regression modeling by using Polycrystalline diamond cutting tool. Three parameters such as cutting speed, depth of cut and feed rate were selected to minimize the cutting force. It was found that the depth of cut is the factor, which great influence on radial force, followed by has feed rate factor than other parameters, whilst feed rate is the least significant parameter. Also, Authors concluded that, the experimental values agreed with the predicted results indicating suitability of the Multiple Regression models.

1.3 Modeling and Optimization of Machining Parameters

(Aggarwal and Singh, 2005) reported a review of literature which showed that various traditational optimization techniques like geometric programming, Lagrange's method, goal programming, dynamic programming etc. have been successfully applied in the past for optimizing the various turning process variables. Fuzzy logic, genetic algorithm, scatter search, Taguchi technique and response surface methodology are the latest optimization technique that are being applied successfully in industrial application for optimal selection of process variables in the area of machining. Literature revealed that response surface methodology and Taguchi method are robust design techniques widely used in industries for making the product/process insensitive to any uncontrollable factors such as environmental variables. (Rajasekaran et al., 2010, 2011) used fuzzy logic for modeling and for prediction of CFRP work piece. Three parameters such as cutting speed, feed rate and depth of cut were selected to minimize the surface roughness. Cemented carbide and Cubic boron nitride cutting tool was used for turning process. It was found that the fuzzy logic modeling technique can be effectively used for the prediction of surface roughness and material removal rate in machining of CFRP composites. (Jain et al., 2000) used neural network for modeling and optimizing of the machining conditions. The results were validated by comparing the optimized machining conditions obtained using Genetic Algorithm. (Bagci and Isik, 2006) investigated the turning of UD-GFRP material. In the study, an artificial neural network and response surface model based on experimental measurement data was developed to estimate surface roughness in orthogonal cutting of GFRP**.** (Palanikumar et al., 2009) investigation focused on the multiple performance optimizations of machining characteristics of glass fiber reinforced plastics composites by using Non-dominated Sorting Genetic Algorithm. Three parameters such as cutting speed, feed rate and depth of cut were selected to minimize the surface roughness, tool flank wear and maximize the material removal rate. Polycrystalline diamond tool was used for turning operation.

(An, 2011) developed the mathematical model based on the minimum production cost criterion. The machining process parameters of multi-pass turning operation selected were speeds, feed rates and depths of cut. The constraints of the models included tool life, surface roughness, cutting force and cutting power consumption. Optimal values of machining parameters were found by GA. The model generated lower unit production costs compared with the results from the literature and machining data handbook. (Singh and Bhatnagar, 2006) investigated the influence of drilling-induced damage on the residual tensile strength of the unidirectional glass fiber-reinforced plastic composite (UD-GFRP) laminates with drilled holes for a variety of solid carbide drill point geometries under varying cutting conditions. **(**Parveen Raj et al., 2012) developed a surface roughness and delamination mathematical prediction model for the machining of glass fiber reinforced plastics composite using response surface methodology and artificial neural network by using coated and uncoated K10 cutting tool. Four parameters such as cutting speed, feed rate, depth of cut and tool material were selected to minimize the surface roughness and delamination. It was found that the developed ANN model has good interpolation capability and can be used as an effective model for good surface roughness and less damage delamination. Good surface finish coated tool performed better than uncoated tool. (Singh et al., 2002) used multi-response optimization through Utility concept and Taguchi method for optimization of the quality characteristics of MAFM process. The tradeoff between conflicting quality characteristics was made objective in the developed model through utility concept. (Surinder Kumar et al., 2013) Investigated the turning process of unidirectional glass fiber reinforced plastics composite using Taguchi's technique and Distance–Based Pareto Genetic Algorithm. PCD cutting tool was used for turning and six parameters such as tool nose radius, tool rake angle, cutting speed, feed rate, cutting environment and depth of cut were selected. It was observed that increase production rates considerably by reducing machining time.

(Meenu and Surinder Kumar, 2013) used Taugchi's method grey relation analysis to determine the optimal combination of control parameters in turning. The measures of machining performance were cutting forces. It was found that the average of grey relational grade analysis using Taguchi method, depth of cut followed by tool nose radius is found to be the most influential factor for minimization tangential force, feed force and radial force in turning process. (Meenu and Surinder Kumar, 2013) development of a surface roughness prediction model for the machining of unidirectional glass fiber reinforced plastics (UD-GFRP) composite using Artificial Neural Network (ANN). PCD cutting tool was used for turning and six parameters such as tool nose radius, tool rake angle, cutting speed, feed rate, cutting environment and depth of cut were selected. The performance of model is found to be good with mean% error -2.0506 and the feasibility of using ANN to predict surface roughness. Regression coefficient is found to be more than 0.9. (Meenu Gupta and Surinder Kumar, 2013) Investigated the turning process of unidirectional glass fiber reinforced plastics composite using Taguchi method and Grey relational analysis. PCD cutting tool was used for turning and six parameters such as tool nose radius, tool rake angle, cutting speed, feed rate, cutting environment and depth of cut were selected. Performance characteristics such as surface roughness and material removal rate are optimized during rough cutting operation. It was observed that depth of cut is the factor, which has great influence on surface roughness and material removal rate, followed by feed rate. The percentage contribution of depth of cut is 54.399% and feed rate is 5.355%. Table 1 Summarizes the Review of Literature. (See Appendix)

2. Review on Latest Techniques

The latest techniques for optimization include simulated annealing, scatter search technique, multiple regression analysis, fuzzy logic, Taguchi technique, artificial neural network, utility concept, response surface methodology, ant colony optimization and particle swarm optimization.

2.1 Genetic Algorithms

Genetic algorithms are search methods that employ processes found in natural biological evolution. These algorithms search or operate on a given population of potential solutions to find the optimum solution. To do this, the algorithm applies the principle of survival of the fittest to find better and better approximations. At each generation, a new set of approximations is created by the process of selecting individual potential solutions (individuals) according to their level of fitness in the problem domain and breeding them together using operators borrowed from natural genetics. This process leads to the evolution of populations of individuals that are better suited to their environment than the individuals that they were created from, just as in natural adaptation. The GA generally includes the three fundamental genetic operations of selection, crossover and mutation. These operations are used to modify the chosen solutions and select the most appropriate offspring to pass on to succeeding generations. GAs consider many points in the search space simultaneously and have been found to provide a rapid convergence to a near optimum solution in many types of problems, in other words, they usually exhibit a reduced chance of converging to local minima. GA suffers from the problem of excessive complexity if used on problems that are too large. The GA works with a population of feasible solutions and therefore, it can be used in multi-objective optimization problems to simultaneously capture a number of solutions (Kuriakose et al., 2005).

2.2 Simulated Annealing

Simulated annealing was developed in 1983 to deal with highly nonlinear problems. SA appears rapidly to become an algorithm of choice when dealing with financial instruments (Ingber, 1993). (William et al., 1993) tested a simulated annealing, on four econometric problems and compare it to three common conventional algorithms. Not only can simulated annealing find the global optimum, it is also less likely to fail on difficult functions because it is a very robust algorithm. The promise of simulated annealing is demonstrated on the four econometric problems. It is found that SA could be used as a diagnostic tool to understand how conventional algorithms fail. It is also found that, it could "step around" regions in the parameter space for which the function does not exist. And most importantly, it could optimize functions that are extreme difficulty to solve with conventional algorithms or it simply cannot optimize at all. The SA algorithm starts with an initial solution generated randomly. At initial stages, a small random change is made in the current solution. Then the objective function value of new solution is calculated and compared with that of current solution. If the new state is better than current state, it will be accepted. Otherwise, the new state will just be accepted with a certain probability smaller than 1 (one). This probability is affected by the quality of movement, given by $e^{-\Delta E/T}$ where T is a control parameter which corresponds to temperature in the analogy with physical annealing, and decreases according to the cooling schedule $T_{t+1}=\alpha T_t$. So, worse movements have major probability to be accepted at the beginning of algorithm when the temperature is high. After that, it becomes more improbable because the value of T is small. So in SA, the algorithm is started with a relatively high value of temperature T to avoid being prematurely trapped in a local optimum.

2.3 Multiple Regression Analysis

In statistics, regression analysis includes any techniques for modeling and analyzing several variables, when the focus is on the relationship between a dependent variable and one or more independent variables. More specifically, regression analysis helps to understand how the typical value of the dependent variable changes when any one of the independent variables is varied, while the other independent variables are held fixed. Regression analysis is widely used for prediction and forecasting, where its use has substantial overlap with the field of machine learning. Regression analysis is also used to understand which among the independent variables are related to the dependent variable and to explore the forms of these relationships (Douglas Montogomery et al., 2001).

In general, multiple-regression models with q independent variables take the form of

$y_i = \beta_0 + \beta_1.x_{i1} + \beta_2.x_{i2} + \ldots\ldots\ldots\ldots + \beta_q.x_{iq} + \varepsilon_i$ (i = 1, 2,……, n)

$= \beta_0 + \sum_{j=1}^{q} \beta_j x_{ij} + \varepsilon_i$ (j = 1, 2,…, q)

Where $n > q$, the parameter $ß_j$ measures the expected change in response y per unit increase in x_i when the other independent variables are held constant. The i^{th} observation and j^{th} level of independent variable is denoted by x_{ij}. The data structure for the multiple regression model as shown in below

Data for Multiple-Regression Model

y	x_1	x_2	$\cdots$	x_q
y_1	x_{11}	x_{12}	$\cdots$	x_{1q}
y_2	x_{21}	x_{22}	$\cdots$	x_{2q}
$\vdots$	$\vdots$	$\vdots$	$\cdots$	$\vdots$
y_n	x_{n1}	x_{n2}	$\cdots$	x_{nq}

The multiple-regression model can be written in a matrix form

y = Xß + e

Where

$$y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}_{(nX1)} \quad X = \begin{bmatrix} 1 & x_{11} & x_{12} & \cdots & x_{1q} \\ 1 & x_{21} & x_{22} & \cdots & x_{2q} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ 1 & x_{n1} & x_{n2} & \cdots & x_{nq} \end{bmatrix}_{(nXk)} \quad \beta = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_q \end{bmatrix}_{(kX1)} \quad e = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix}_{(nX1)}$$

y is (n × 1) vector of observations, X is (n × k) matrix of levels of independent variables, $ß$ is a (k × 1) vector of regression coefficients, and ***e*** is (n × 1) vector of random errors (Douglas Montogomery, 2005). If X is a (k × k) matrix, then the linear system $y = Xß + e$ has a unique least square solution given by $\hat{\beta} = (X'X)^{-1}X'y$**.** The estimated regression equation is $\hat{y} = X\hat{\beta}$, it can also be represented as:

$\hat{y}_i = \hat{\beta}_0 + \sum_{j=1}^{q} \hat{\beta}_j x_{ij}$ (i = 1, 2, …., n)

2.4 Fuzzy Logic

The fuzzy logic was first proposed by (Lotfi Zadeh, 1965) to deal with uncertainty. A fuzzy logic system (Mendel, 1995) can be defined as the nonlinear mapping of an input data set to a scalar output data. In a fuzzy set, the fuzziness is characterized by its membership function. Membership are in the range [0.0, 1.0], with 0.0 representing absolute falseness and 1.0 representing absolute truth. The components of the fuzzy logic system are:

-Fuzzifier
-Knowledge base
-Inference engine
-Defuzzifier

Fuzzifier:

It identifies the input and output of the system. A crisp set of input data are converted to a fuzzy set using fuzzy linguistic variables and membership functions.

Knowledge Base : The knowledge base contains linguistic rules (IF-THEN rules) .These rules can be provided by experts or extracted from numerical data. It is also possible to extract rules from numeric data. Once the rules have been established, the FIS can be viewed as a system that maps an input vector to an output vector.

Inference Engine:

a) Evaluate all the rules and determine their truth value
b) Combine the outputs obtained for each rule into a single fuzzy set, using a fuzzy aggregation operator.

Defuzzification : The overall result is a fuzzy value. This result should be defuzzified to obtain a crisp output.

2.5 Particle Swarm Optimization

PSO is a global optimization technique that has been developed by Kennedy and Eberhart in 1995. Particle Swarm Intelligent technique combines social psychology principles in socio-cognition human agents and evolutionary computations. PSO has been motivated by the behavior of organisms, such as fish schooling and bird flocking in order to guide swarm of particles towards most promising regions of search space. Generally, PSO is characterized as a simple concept, easy to implement and computationally efficient. Unlike the other heuristic techniques, PSO has a flexible and well-balanced mechanism to enhance the global and local exploration abilities. Thus, a PSO algorithm can be employed to solve an optimization problem. Each particle in the swarm represents a candidate solution to the optimization problem. The algorithm, which is based on a metaphor of social interaction, searches a space by adjusting the trajectories of moving points in a multidimensional space. The individual particles are drawn stochastically toward the position of present velocity of each individual, their own previous best performance, and the best previous performance of their neighbors (Abido, 2001). The main advantages of the PSO algorithm are summarized as: simple concept, easy implementation, robustness to control parameters and computational efficiency when compared with mathematical algorithm and other heuristic optimization techniques.

2.6 Taguchi Technique

In early 1950's, Dr. Genichi Taguchi, "The Father of Quality Engineering" introduced the concept of off-line quality control technique known as Taguchi parameter design. Offline quality control are those activities which are performed during the Product (or Process) Design and Development phase. He developed both a philosophy and methodology for the process of product quality improvement that depends heavily on statistical concepts and tools, especially statistically designed experiments. Many Japanese firms have achieved great success by applying his methods. It has been reported that thousand of engineers have performed tens of thousands of experiments based on his teaching (Phadke, 1989).Taguchi method is a powerful tool for the design of high quality systems. It provides simple, efficient and systematic approach to optimize designs for performance, quality and cost. Taguchi method is efficient method for designing process that operates consistently and optimally over a variety of conditions. To determine the best design, it requires the use of a strategically designed experiment. Taguchi approach to design of experiments is easy to adopt and may be applied by users with limited knowledge of statistics, hence gained wide popularity in the engineering and scientific community. Taguchi parameter design is based on the concept of fractional factorial design but the Taguchi parameter design only conducts the balanced (orthogonal) experimental combinations, which makes the Taguchi design even more effective than fractional design (Liu et al., 2001).

2.7 Scatter Search Technique (SS)

This technique originates from strategies for combining decision rules and surrogate constraints. SS is completely generalized and problem-independent since it has no restrictive assumptions about objective function, parameter set and constraint set. It can be easily modified to optimize machining operation under various economic criteria and numerous practical constraints. It can obtain near-optimal solutions within reasonable execution time on PC. Potentially, it can be extended as an on-line quality control strategy for optimizing machining parameters based on signals from sensors. (Chen and Chen, 2003) have done extensive works on this technique.

2.8 Artificial Neural Networks (ANN)

(Himmel and May, 1991) & (Hussain et al., 1991) development of neural network by the recognition that more accurately, artificial neural networks, has been motivated by the recognition that the human brain process information in ac way that is fundamentally different from the typical digital computer. An artificial neural network is a structure that is designed that to solve certain types of problems by attempting to emulate the way the human brain would solve the problem. The general form of neural network is a black box model of a type that is often used to model high dimensional, nonlinear data. Typically most neural networks are used to solve prediction problem some system, as opposed to formal model building or development of underlying knowledge of how the system works. Artificial neural network are an active area of research and application, particularly for the analysis of large, complex, highly nonlinear problems. The over fitting issue is frequently overlooked by many users and advocates of neural network and because many members of the neural network community do not have sound training in empirical model building, they often do not appreciate the difficulties over fitting many cause.

2.9 Response Surface Methodology (RSM)

Experimentation and making inferences are the twin features of general scientific methodology. Statistics as a scientific discipline is mainly designed to achieve these objectives. Planning of experiments is particularly very useful in deriving clear and accurate conclusions from the experimental observations, on the basis of which inferences can be made in the best possible manner. The methodology for making inferences has three main aspects. First, it establishes methods for drawing inferences from observations when these are not exact but subject to variation, because inferences are not exact but probabilistic in nature. Second, it specifies methods for collection of data appropriately, so that assumptions for the application of appropriate statistical methods to them are satisfied. Lastly, techniques for proper interpretation of results are devised. Inference regarding the effect of parameters on the characteristics of the process can be made. (Cochran and Cox, 1962) quoted Box and Wilson as having proposed response surface methodology for the optimization of experiments.

2.10 Utility Concept

The work of Taguchi for determining the optimal settings of controllable factors (parameters) through off-line experiments focuses on products with a single quality characteristic. But most of the products have several quality characteristics of interest. A single setting of process parameters may be optimal for one quality characteristic but the same setting may yield detrimental results for other quality characteristics. In such cases, a need arises to obtain an optimal setting of the process parameters so that the product can be produced with optimum or near optimum quality characteristics. A number of techniques have been developed for obtaining the multi-characteristic optimization of product quality. Several methodologies were developed to solve the multi-response optimization problems. Utility can be defined as the usefulness of a product or a process in reference to the expectations of the users. The overall usefulness of a process/product can be represented by a unified index termed as Utility which is the sum of the individual utilities of various quality characteristics of the process/product. The methodological basis for Utility approach is to transform the estimated response of each quality characteristics into a common index. Among various quality characteristics type viz. smaller the better, higher the better, and nominal the better suggested by Taguchi, the Utility function would be higher the better type. Therefore, if the Utility function is maximized, the quality characteristics considered for its evaluation will automatically be optimized (maximized or minimized as the case may be).

2.11 Ant Colony Optimization (ACO)

ACO algorithm was inspired by the behaviour of the ants in searching of their food sources. The original concept of ant system is introduced by Marco Dorigo in 1992. In ACO, the ant search for the foods and evaluates the food sources and brings it back to the nest. The ant then leaves a substance named pheromones as their move back to the nest. The quantity of pheromone deposited, which may depend on the quantity and quality of the food, will guide other ants to the food source (Dorigo and Blum, 2005). The other ants tend to follow the paths where pheromone concentration is higher.

III. CONCLUSION

A review of literature, we found that Taugchi's technique, response surface methodology and genetic algorithm is widely used in optimizing machining process parameters followed by PSO, ANN, SA, fuzzy logic, SS and ACO. The most machining performances considered by the researchers are surface roughness followed by machining/production costs and MRR. A review of literature on optimization techniques has revealed that there are, in particular, successful industrial applications of design of experiment-based approaches for optimal settings of process variables. There is general agreement that off-line experiments during product or process design stage are of great value. Reducing quality loss by designing the products and processes to be insensitive to variation in noise variables is a novel concept to statisticians and quality engineers. The evolutionary techniques in optimizing machining process parameters positively give good results as proven from the literature. Further, it is worth to mention here that the scope of these soft computing techniques is not limited to machining processes only rather research work has been undertaken to apply these methods to other manufacturing processes such as casting, welding and forming. Based on the literature survey performed, venture into this research is amply motivated by the fact that a little research has been conducted to obtain the optimal levels of machining parameters that yield the best machining quality in machining of unidirectional glass fiber reinforced plastics composite. Most of the researchers have investigated influence of a limited number of process parameters on the performance measures of turning process. The review of literature on machining reveals that the tool geometry, cutting conditions and cutting environment significantly affects the surface quality and other performance characteristics but the combined influence of cutting conditions, tool geometry and cutting environment on surface roughness, cutting forces (Tangential force, Feed force, Radial force) has not been studied previously for turning unidirectional glass fiber reinforced plastics composite. So, there is a need to concentrate efforts in this direction.

IV. REFERENCES

[1] An, L. (2011) "Optimal selection of machining parameters for multi-pass turning operations", Advanced Materials Research, Vol. 156–157, pp. 956–960.

[2] Aggarwal, A. and Singh, H. (2005) "optimization of machining techniques-A retrospective and literature", Sadhana, Vol. 30, part 6, pp. 699-711.

[3] Bagci, E. and Isık, B. (2006) "Investigation of surface roughness in turning unidirectional GFRP composites by using RS methodology and ANN", International Journal Advance Manufacturing Technology, Vol. 31, pp. 10–17.

[4] Chang, C.S. (2006) "Turning of glass fiber reinforced plastics materials with chamfered main cutting edge carbide tools", Journal of Material Processing Technology, Vol. 180, pp. 117-129.

[5] Chen, M. and Chen, K.Y. (2003) "Determination of optimum machining conditions using scatter search", New optimization techniques in engineering, pp. 681–697.

[6] Cochran, G. and Cox, G.M. (1962) "Experimental design", New Delhi: Asia Publishing House.

[7] Davim, J.P. and Mata, F. (2005) "Optimisation of surface roughness on turning fibre reinforced plastics (FRP's) with diamond cutting tools", The International Journal of Advanced Manufacturing Technology, Vol. 26, pp. 319–323.

[8] Davim, J.P. and Mata, F. (2007) "New machinability study of glass fibre reinforced plastics using polycrystalline diamond and cemented carbide (K15) tools", Materials and Design, Vol. 28 pp. 1050-1054.

[9] Davim, J.P. (2009) "Machining Composite Materials", Wiley-ISTE, London, ISBN: 978-1-84821-103-4.

[10] Douglas, C., Montogomery, Elizabeth, A., Peck and Geoffrey Vining, G. (2001) "Introduction to Linear Regression Analysis", Arizona State University.

[11] Douglas Montogomery, C. (2005) "Design and Analysis of Experiments: Response surface method and designs. New Jersey: John Wiley and Sons, Inc.

[12] Dorigo, M., and Blum, C. (2005) "Ant colony optimization theory: A survey", Theoretical Computer Science, Vol. 344, NO. (2–3), pp. 243–278.

[13] Fereirra, J.R., Coppini, N.L. and Levy, Neto. (2001) "Characteristics of carbon–carbon composite turning", Journal of Materials Processing Technology, Vol. 109, pp. 65–71.

[14] Hussain, S.A., Pandurangadu, V. and Palanikumar, K. (2011) "Machinability of glass fiber reinforced plastic (GFRP) composite materials", International Journal of Engineering, Science and Technology, Vol. 3, No. 4, pp. 103-118

[15] Hussain, A.S. Yu, X. Q. and Johnson, R.D. (1991) " Application of neural computing in pharmace utical product development," pharmace utical research, Vol. 8, ppp. 1248-1252.

[16] Himmel, C.D. and May, G.S. (1991) "Advantages of plasma etch modeling using neural network over statistical techniques", IEEE Transactions on semiconductor manufacturing, Vol. 6, pp. 103-111.

[17] Isik, B. and Kentli, A. (2009) "Multicriteria optimization of cutting parameters in turning of UD-GFRP materials considering sensitivity, International Journal Advanced Manufacturing Technology, Vol. 44, pp. 1144–1153.

[18] Isık, B. (2008) "Experimental investigations of surface roughness in orthogonal turning of unidirectional glass-fiber reinforced plastic composites", International Journal Advance Manufacturing Technology, Vol. 37, pp. 42–48.

[19] Ingber, L. (1993) "practice versus theory", Mathematical Computer modelling, Vol. 18, No. 11, pp. 29-57.

[20] Kini, M.V., Chincholkar, A.M. (2010) "Effect of machining parameters on surface roughness and material removal rate in finish turning of ± 30˚ glass fibre reinforced polymer pipes", Material and Design, Vol. 31, pp. 3590-3598.

[21] Kuriakose, S., Shunmugam, M.S. (2005) "Multi-objective optimization of wire-electro discharge machining process by non-dominated sorting genetic algorithm", Journal of Materials Processing Technology, Vol. 170, pp. 133-141.

[22] Liu, Jia-Ming, Lu, Po-Yen, Weng, Wen-Kou, (2001) “Studies on modification of ITO surfaces in OLED devices by taguchi’s methods”.

[23] Meenu, Surinder Kumar, (2013) “Multi-objective optimization of cutting forces in turning of UD-GFRP Composite using Taguchi grey relational analysis,” Journal of Mechanical Engineering, Vol. 123, pp.166-177

[24] Meenu, Surinder Kumar, (2013) “Prediction of surface roughness in turning of UD-GFRP using Artifical Neural Network,” Mechanica Confab, Vol. 2, Issue 3, pp.46-56.

[25] Meenu Gupta, Surinder Kumar, (2013) “Multi-objective optimization of cutting parameters in turning using grey relational analysis, International Journal of Industrial Engineering Computations. Vol. 4, pp. 547–558.

[26] Naveen Sait, A., Aravindan, S. and Noorul Haq, A. “Influence of machining parameters on surface roughness of GFRP pipes”, Advance in Production Engineering & Management, Vol. 4, pp. 47-58.

[27] Palanikumar, K. (2007) “Modeling and analysis for surface roughness in machining glass fibre reinforced plastics using response surface methodology”, Material and Design, Vol. 28, pp. 2611-2618

[28] Palanikumar, K., Mata, F. and Davim, J.P. (2008) “Analysis of surface roughness parameters in turning of FRP tubes by PCD tool”, Journal of Materials Processing technology, Vol. 204, pp. 469–474.

[29] Palanikumar, K. (2008) “Application of Taguchi and response surface methodologies for surface roughness in machining glass fibre reinforced plastics by PCD tooling”, International Journal Advance Manufacturing Technology, Vol. 36, pp. 19–27.

[30] Palanikumar, K., Latha, B., Senthilkumar, V.S. and Karthikeyan, R., (2009) “Multiple performance optimization in machining of GFRP composites by a PCD tool using non-dominated sorting genetic algorithm (NSGA-II)”, Met. Mater. Int., Vol. 15, No. 2, pp. 249-258.

[31] Parveen Raj, P., Elaya Perumal, A. and Ramu, P. (2012) “Prediction of surface roughness and delamination in end milling of GFRP using mathematical model and ANN”, Indian journal of engineering & materials sciences, Vol. 19, pp. 107-120.

[32] Phadke, S.M. (1989) “Quality engineering using robust design”, Prentice Hall, Englewood Cliffs, New Jersey.

[33] Pwu, H.Y. and Ho-Cheng, H. (1998) “Chip formation model of cutting fibre reinforced plastics perpendicular to fibre axis”, Journal Manufacturing Science Engineering, Vol. 120, pp. 192±196.

[34] Rajasekaran, T., Palanikumar, K., Vinayagam, B.K. and Prakash, S. (2010) “Influence of Machining Parameters on Surface Roughness and Material Removal Rate in Machining Carbon Fiber Reinforced Polymer Material”, IEEE, pp. 75-80.

[35] Rajasekaran, T., Palanikumar, K. and Vinayagam, B.K. (2011) “Application of fuzzy logic for modeling surface roughness in turning CFRP composites using CBN tool”, Production Engineering Res. Deve., Vol. 5, pp. 191–199.

[36] Rao, G.V.G., Mahajan, P. and Bhatnagar, N. (2007) “Micro-mechanical modeling of machining of FRP composites cutting force analysis”, Composite Science Technology, Vol. 67, pp. 579–593.

[37] Santhanakrishnan, G., Krishnamurthy, R. and Malhotra S.K. (1989) “High speed steel tool wear studies in machining of glass fibre-reinforced plastics”, wear, Vol. 132, pp. 327-336.

[38] Sakuma, By Keizo and Seto Masafumi (1983) “Tool wear in cutting glass fiber reinforced plastics (the relation between fiber orientation and tool wear)”, Bulletin of the JSME, Vol. 26, No. 218, pp. 1420-1427.

[39] Singh, I. and Bhatnagar, N. (2006) “Drilling of uni-directional glass fiber reinforced plastic (UD-GFRP) composite laminates”, International Journal Advance Manufacturing Technology, Vol. 27, No. 9-10, pp. 870–876.

[40] Singh, S., Shan, H.S. and Kumar, P. (2002) “Parametric optimization of magnetic-field assisted abrasive flow machining by the Taguchi method”. Quality Reliability Engineering Int., Vol. 18, pp 273–283.

[41] Surinder Kumar, Meenu, P.S. Satsangi and H.K.. Sardana, (2012) “Multiple regression model for cutting force in turning UD-GFRP using polycrystalline diamond cutting tool”. International Journal of Advanced Engineering Technology, Vol. 3, Issue 1, pp. 108-112.

[42] Surinder Kumar, Meenu, P.S. Satsangi and H.K. Sardana, (2012) “Optimization of surface roughness in turning unidirectional glass fiber reinforced plastics (UD-GFRP) composites using polycrystalline diamond (PCD) cutting tool”. Indian Journal of Engineering & materials sciences, Vol. 19, pp. 163-174.

[43] Surinder Kumar, Meenu, P.S. Satsangi, (2013) “Multiple performance optimization in machining of UD-GFRP composites by a PCD tool using distance – based Pareto genetic algorithm (DPGA), Vol. 2, Issue 2, pp. 49-62.

[44] Surinder Kumar, Meenu, P.S. Satsangi, (2013) “Optimization of surface roughness in turning unidirectional glass fiber reinforced plastic (UD-GFRP) composite using carbide (k10) cutting tool, Asian academic research journal of multidisciplinary, Vol. 1, Issue 9, pp.105-128.

[45] Wang, D.H., Ramulu, M. and Arola, D. (1995) “Orthogonal cutting mechanisms of graphite/epoxy composites. Part I. Unidirectional laminate”, International Journal Machine Tools Manufacture, Vol. 35, No. 12, pp. 1623±1638.

[46] Wang, X. M. and Zhang, L. C. (2003) “An experimental investigation into the orthogonal cutting of unidirectional fibre reinforced plastics”, International Journal Machine Tools Manufacturing, Vol. 43, No. 10, pp. 1015–1022.

[47] William, L., Goffe Gary D. and Ferrier, John Rogers, “Global optimization of statistical functions with simulated annealing”, 1993, pp.1-39.

[48] Zadeh, L.A., (1965) “Fuzzy set”, Information and Control, Vol. 8, pp. 338-353.

Appendix

Summarizes the Review of Literature
Table 1: Summary of Recent Machining Optimization Technique

Sr. No.	Year /Author	Cutting Tool Materials	Input Parameters	Output Responses	Techniques	Researcher's Findings	Remarks
1	(An et al., 1997)	Single crystal diamond, Poly crystal diamond and CBN	Cutting speed, feed rate and depth of cut	Surface roughness, cutting force and power spectrum density	Single objective optimization using Taguchi's technique	It was found that the surface roughness is not related to depth of cut and cutting speed.	Authors did not take tool geometry and cutting environment into consideration. Further, material removal rate is not measured and multi-objective optimization is not carried out.
2	(Sakuma and Seto, 1983)	Cemented carbide tools P20, M10, K10	Cutting speed, feed rate, depth of cut, tool material and cutting fluid	Surface roughness and tool wear in facing test	Single objective optimization	Cutting fluid used was (Wl-1) of 3% concentration and flow rate 1.5 l/min, which was used to wash out chips.	Authors did not take tool geometry into consideration. Further, cutting forces, material removal rate are not measured and multi-objective optimization is not carried out.
3	(Lee, 2001)	Single crystal diamond, Poly crystal diamond and CBN	Cutting speed, feed rate, depth of cut and tool nose radius	Surface roughness, cutting force and power spectrum density	Single objective optimization	It was found that the surface roughness does not depend on depth of cut and cutting speed.	Author did not take tool rake angle and cutting environment into consideration. Further, material removal rate is not measured and multi-objective optimization is not carried out.
4	(Palanikumar et al., 2003)	Sintered carbide tool	Cutting speed, feed rate, depth of cut, tool nose radius and workpiece fiber orientation	Surface roughness, cutting force and tool wear	Single objective optimization using Taguchi's technique	It was found that the tool wear, surface roughness and forces increased with increase in feed rate and decreased with increase in tool radius. The cutting force was reduced with reduction in feed rate but the cutting force decreased with increase in cutting speed.	Authors did not take cutting environment into consideration. Further, material removal rate is not measured and multi-objective optimization is not carried out.
5	(Davim and Mata, 2004)	PCD	Cutting speed and feed rate	Surface roughness	Single objective optimization using Taguchi's technique and Statistical analysis	It was found that the feed rate is the cutting parameter that has the highest physical as well statistical influence on surface roughness in workpiece.	Authors did not take tool geometry, depth of cut and cutting environment into consideration. Further, cutting forces, material removal rate are not measured and multi-objective optimization is not carried out.
6	(Palanikumar et al., 2004)	TiC coated carbide tool	Cutting speed, feed rate, depth of cut and fiber orientation	Surface roughness	Single objective optimization using Taguchi's technique and Yates correlation model	Parameters were optimized to attain minimum surface roughness. Feed rate is the factor, which has great influence on surface roughness, followed by cutting speed.	Authors did not take tool geometry and cutting environment into consideration. Further, material removal rate, cutting forces are not measured and multi-objective optimization is not carried out.
7	(Palanikumar et al., 2006)	Coated cermet tool	Cutting speed, feed rate, depth of cut and fiber orientation	Surface roughness	Single objective optimization using Taguchi's technique	Parameters were optimized to attain minimum surface roughness. This technique is convenient to predict the main effects of different influential combination of machining parameters.	Authors did not take tool geometry and cutting environment into consideration. Further, material removal rate, cutting forces are not measured and multi-objective optimization is not carried out.
8	(Palanikumar et al., 2006)	Carbide (K10) tool	Cutting speed, feed rate, depth of cut, machining time and	Surface roughness, specific cutting pressure and MRR	Grey relation analysis and Single objective optimization using	It was concluded that the work piece (fiber orientation) is the factor which has great influence on machining of GFRP composites, followed by machining time.	Authors did not take tool geometry and cutting environment into consideration. Further, cutting forces are not measured.

			workpiece fiber orientation		Taguchi's technique		
9	(Palanikumar et al., 2006)	Carbide (K10)	Cutting speed, feed rate, depth of cut, machining time and fiber orientation	Surface roughness, tool wear and MRR	Single objective optimization using Taguchi's technique and Fuzzy logic	It was found that the Taguchi method with fuzzy logic technique using MRPI converts the multiple performance characteristics into Single performance characteristics and therefore, simplifies the optimization procedure.	Authors did not take tool geometry and cutting environment into consideration. Further, cutting forces are not measured.
10	(Eyup Bagci and Birhan Isık, 2006)	Cermets tools	Cutting speed, feed and depth of cut	Surface roughness	Artificial Neural Network (ANN) and Response Surface (RS) model	It was found that the ANN model involves more computational time than response Surface model.	Authors did not take tool geometry and cutting environment into consideration. Further, cutting forces, material removal rate are not measured and multi-objective optimization is not carried out.
11	(Chang, 2006)	P and K type carbide tool	Cutting speed, feed rate, depth of cut and rake angle	Cutting temperature and forces	Reliability measurement techniques	The cutting forces and cutting temperature for the chamfered main cutting edge of P type carbide tools in turning were much higher than that experienced by chamfered main cutting edge of K type carbide tools.	Author did not take cutting environment into consideration. Further, surface roughness, material removal rate are not measured and multi-objective optimization is not carried out.
12	(Palanikumar and Davim, 2006)	Coated carbide tool	Cutting speed, feed rate, depth of cut and workpiece fiber orientation	Tool wear	Single objective optimization using Taguchi's technique and Yates correlation model	It was concluded that the accuracy of the developed model can be improved by including more number of parameters and levels.	Authors did not take tool geometry and cutting environment into consideration. Further, surface roughness, material removal rate and cutting forces are not measured and multi-objective optimization is not carried out.
13	(Davim and Mata, 2007)	Cemented carbide (K15) tools and PCD	Cutting speed, feed rate and rake angle	Surface roughness and specific cutting pressure	Single objective optimization using Taguchi's technique and Machinability index	It was observed that the feed rate is the cutting parameter that has the highest physical as well statistical influence on surface roughness and specific cutting pressure. Polycrystalline diamond tool provides a better machinability index in comparison to cemented carbide tool (K15).	Authors did not take tool geometry and cutting environment into consideration. Further, cutting forces, material removal rate are not measured and multi-objective optimization is not carried out.
14	(Palanikumar, 2007)	Coated cermets tool	Cutting speed, feed rate, depth of cut and fibre orientation	Surface roughness	Single objective optimization using Taguchi's technique and Response Surface Method	It was found that the surface roughness decreases with the increase of cutting speed. The surface roughness increases with the increase of fibre orientation angle.	Author did not take tool geometry and cutting environment into consideration. Further, cutting forces, material removal rate are not measured and multi-objective optimization is not carried out.
15	(Rao et al., 2007)	Solid tungsten carbide tool	Cutting speed, depth of cut, fiber orientation angle, rake, relief angle and edge radius	Cutting forces	Finite element method	It was found that the experimental and numerical investigations provide a better understanding of the origin of cutting forces, matrix damage, interfacial debonding and possible locations of fiber breakage during the orthogonal machining of UD-	Authors did not take feed rate and cutting environment into consideration. Further, surface roughness, material removal rate are not measured and multi-objective optimization is not carried out.

						GFRP composites.	
16	(Birhan Isik, 2008)	Cermet tool	Cutting speed, feed rate, depth of cut, tool radius and rake angle	Surface roughness	Geometrical product specification model	It was found that the surface roughness does not depend on depth of cut.	Author did not take cutting environment into consideration. Further, material removal rate, cutting forces are not measured and multi-objective optimization is not carried out.
17	(Aravindal et al., 2008)	Carbide tool	Cutting speed, feed rate and depth of cut	Surface roughness, flank wear and crater wear	Single objective optimization using Taguchi's technique and statistical techniques	It was concluded that all of the objectives considered are significantly improved by using the optimization technique and regression modeling.	Authors did not take tool geometry and cutting environment into consideration. Further, material removal rate, cutting forces are not measured and multi-objective optimization is not carried out.
18	(Palanikumar, 2008)	PCD tool	Cutting speed, feed rate, depth of cut and wet cutting environment	Surface roughness	Response surface method	Wet cutting was performed using a water soluble cutting fluid. Sufficient care was taken to remove the highly abrasive GFRP machining chips.	Author did not take tool geometry into consideration. Further, material removal rate, cutting forces are not measured and multi-objective optimization is not carried out.
19	(Naveen Sait et al., 2009)	Coated carbide tool (K20 grade)	Cutting speed, feed rate and depth of cut	Surface roughness, flank wear, crater wear and cutting force	Single objective optimization using Taguchi's technique and desirability function analysis	It was concluded that the depth of cut is the significant machining parameter followed by cutting velocity and feed rate for machining filament wound GFRP pipes.	Authors did not take tool geometry and cutting environment into consideration. Further, material removal rate is not measured.
20	(Palanikumar and Davim, 2009)	Coated cemented and carbide tool	Cutting speed, feed rate, depth of cut and workpiece fiber orientation	Tool wear	Single objective optimization using Taguchi's technique and Yates correlation model	It was found that the cutting speed is a factor, which has great influence on tool flank wear, followed by feed rate.	Authors did not take tool geometry and cutting environment into consideration. Further, surface roughness, cutting forces and material removal rate are not measured and multi-objective optimization is not carried out
21	(Palanikumar et al., 2009)	PCD tool	Cutting speed, feed rate and depth of cut	Surface roughness, tool flank wear and material removal rate	Non-dominated Sorting Genetic Algorithm	The multi-objective evolutionary algorithm based efficient methodology, NSGA-II, was used to optimize machining parameters in the machining of GFRP composites.	Authors did not take tool geometry and cutting environment into consideration. Further, cutting forces are not measured.
22	(B. Isık & A. Kentli, 2009)	Cemented carbide tools	Cutting speed, feed, depth of cut and tool nose radius	Cutting forces and material removal are	Statistical techniques (sensitivity)	Sensitivity approach was used which can be applicable easily and also reliable.	Authors did not take cutting environment and tool rake angle into consideration. Further, surface roughness is not measured.
23	(Kini et al., 2010)	Coated tungsten carbide	Cutting speed, feed rate, depth of cut and tool nose	Surface roughness and MRR	Single objective optimization using Taguchi's technique	It was found that the feed rate is main factor that influence the surface roughness, followed by the depth of cut. For material removal rate, depth of cut is main influence factor followed by the tool nose radius.	Authors did not take tool geometry and cutting environment into consideration. Further, cutting forces are not measured and multi-objective optimization is not carried out.

24	(Hussain et al., 2010)	Carbide (K20) tool	Cutting speed, feed rate, depth of cut and workpiece fiber orientation	Surface roughness	Response Surface Methodology	It was concluded that the moderate cutting speed, low feed, low fiber orientation angle and moderate depth of cut are preferred for machining of GFRP composites.	Authors did not take tool geometry and cutting environment into consideration. Further, cutting forces, material removal rate are not measured and multi-objective optimization is not carried out.
25	(Sait, 2010)	Coated Carbide tool inserts (K20)	Cutting Speed, feed rate and depth of cut	Surface roughness, machining force and tool wear	Particle Swarm Optimization and single objective Genetic algorithm	It was observed that the evolutionary techniques are quiet good enough in determining the optimum machining parameters for GFRP pipes.	Author did not take tool geometry and cutting environment into consideration. Further, cutting forces, material removal rate are not measured and multi-objective optimization is not carried out.
26	(Hussain et al., 2011)	PCD, CBN, Carbide (K20) tool	Cutting speed, feed rate, depth of cut and workpiece fiber orientation	Surface roughness and cutting forces	Response Surface Methodology	It was found that the low cutting forces and better surface finish are observed using PCD tool. In comparison to other tools used, Adaptive Neuro Fuzzy Inference System (ANFIS) was suggested to model and analyse the problem.	Authors did not take tool geometry and cutting environment into consideration. Further, material removal rate is not measured and multi-objective optimization is not carried out.
27	(Hussain et al., 2011)	Carbide (K20) tool	Cutting speed, feed rate, depth of cut and workpiece fiber orientation	Surface roughness	Single objective optimization using Taguchi's technique and Fuzzy logic technique	It was concluded that the technique used is simple and can be used for on line monitoring, if proper equipments are used. The model can reduce the tedious model making, computational cost and time.	Authors did not take tool geometry and cutting environment into consideration. Further, cutting forces, material removal rate are not measured and multi-objective optimization is not carried out.
28	(Hussain et al., 2011)	PCD, CBN, Carbide (K20) tool	Cutting speed, feed rate, depth of cut, workpiece fiber orientation	Cutting power	Single objective optimization using Taguchi's technique and Response Surface Methodology	It was concluded that, the lower power consumption was observed at lower cutting speed, low feed rate, high depth of cut and lower fiber orientation angle while machining GFRP composites with PCD cutting tool.	Authors did not take tool geometry and cutting environment into consideration. Further, surface roughness, cutting forces and material removal rate are not measured and multi-objective optimization is not carried out.
29	(Ntziantzias et al., 2011)	P20 Carbide tool	Cutting speed and feed rate	Cutting forces	Kienzle Victor model	It was found that the number of machining parameters can be extended and hence the data base can be improved by extensive experimentation.	Authors did not take tool geometry, depth of cut and cutting environment into consideration. Further, surface roughness, material removal rate are not measured and multi-objective optimization is not carried out.
30	(Behera et al., 2013)	HSS tool	Cutting speed, feed rate and depth of cut	Cutting force and surface roughness	Single objective optimization using Taguchi's technique	It was found that the depth of cut is the most significant parameter for cutting force followed by feed rate.	Authors did not take tool geometry and cutting environment into consideration. Further, material removal rate is not measured and multi-objective optimization is not carried out.
31	(Varghese et al., 2013)	Uncoated aluminum oxide ceramic inserts	Feed rate, length of the tool from tool holder, depth of cut and constant speed	Cutting force and surface roughness	Single objective optimization using Taguchi's technique and Grey based method	It was found that the moderate feed rate, minimum tool length and moderate depth of cut gave optimal results.	Authors did not take tool geometry and cutting environment into consideration. Further, material removal rate is not measured.

32	(Hussain et al., 2014)	Carbide (K20) cutting tool.	Cutting speed, feed rate, depth of cut and fiber orientation	Surface roughness, cutting force, specific cutting pressure and cutting power	Single objective optimization using Taguchi's technique and fuzzy logic	It was observed that Taguchi method and fuzzy logic facilitates simultaneous acquisition of low surface, roughness, low cutting force, low specific cutting pressure and low cutting power in machining GFRP Composites with carbide (K20).	Authors did not take tool geometry and cutting environment into consideration. Further, material removal rate is not measured.
33	(Parida and Routara, 2014)	Carbide tool	Cutting speed, feed rate and depth of cut	Material removal rate and surface roughness	Single objective optimization using Taguchi's technique and TOPSIS method	It was observed that there is a good agreement between the estimated value and the experimented value using TOPSIS method for multi response optimization.	Authors did not take tool geometry and cutting environment into consideration. Further, cutting forces are not measured.
34	(Parida et al., 2014)	Cemented carbide tool	Cutting speed, feed rate and depth of cut	Material removal rate and surface roughness	Single objective optimization using Taguchi's technique and Grey Relational Analysis	It was observed that depth of cut is the most significant parameter for surface roughness followed by feed rate and spindle speed for multiple performance characteristics.	Authors did not take tool geometry and cutting environment into consideration. Further, cutting forces are not measured.
35	(Hussain et al., 2014)	PCD tool	Cutting speed, feed rate, depth of cut and fiber orientation	Surface roughness	Response Surface Methodology and Genetic Algorithm	To increase the quality of the surface finish, the RSM model was interfaced with an effective GA to find the optimum process parameter values.	Authors did not take tool geometry and cutting environment into consideration. Further, cutting forces, material removal rate are not measured and multi-objective optimization is not carried out.