Multi-Objective OptimizatiOn in machining Of GFRP and MMC CoMPosites: two Case ExpErimEntal rEsEarch

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Certificate of Approval

This is to certify that the thesis entitled **Multi-Objective Optimization in Machining of GFRP and MMC Composites: Two Case Experimental Research** submitted by ***Vikas Sonkar*** has been carried out under my sole supervision in fulfillment of the requirements for the award of the ***Degree of Master of Technology (M. Tech.)*** in ***Production Engineering*** at National Institute of Technology, Rourkela, and this work has not been submitted elsewhere before for any other academic degree/diploma.

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Abstract

Composite materials like GFRP and MMCs having more importance in various manufacturing industries mainly in aerospace and automotive industries and many engineering application, because of their unique mechanical properties as compare to the conventional material. Drilling is the most common machining process in manufacturing industries for assembly of components but drilling of composite may possesses many difficulties such as fiber pull out, delamination and circularity etc. which affects the quality of drilled hole. To overcome these difficulties the effect of machining parameters on different machining responses should be investigated for attaining high product quality as well as satisfactory machining process performance. Therefore, the main objective of this dissertation is to investigate the various machining performance characteristics with different machining condition in drilling of GFRP and MMCs composites by using various integrated multi objective optimization methodologies. In this presented thesis, Deng's similarity method integrated with Taguchi, TOPSIS integrated with Taguchi method (in drilling of GFRP composite) and PCA-Grey method integrated with Taguchi, Grey-TOPSIS Integrated with Taguchi method (in drilling of MMCs), have been implemented for obtaining the optimal machining conditions.

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CHAPTER 1: Introduction

1.1 Composite Materials

Composites are material made up of at least two constituent materials with significantly different physical or chemical properties, that when combined; produce a material with characteristics different from the individual components. The individual component remain separate and distinct within the finished structure or we can say that composites are form by combining two or more material together to get a desirable structure, which is better than the individual components. Composite materials have many advantages over the conventional metal/material like high specific strength, high specific stiffness, good corrosion resistance, and lower coefficient of thermal expansion. But machining of the composite materials is not an easy job; there is a remarkable difference between the machining of conventional materials and composites because of the machining behavior of composites, which differs one composite to other. Since it's physical and mechanical properties depend largely on the type of fiber, the fiber content, the fiber orientation and variability in the matrix material.

The structure of composites is made up of two phases; Matrix and Reinforcement.

Matrix: It is the constituent generally which is present in greater quantity and continuous in a composite material. Properties of the matrix can be improved by addition of other constituent.

Reinforcement: It is the second phase of composite material and main role of this phase is to enhance the mechanical properties of matrix phase. Generally reinforcement is harder, stronger and stiffer than the matrix. Reinforcement can either be particulate or fibrous.

1.2 Classification of Composite Materials

Composite materials are mainly classified into two parts according to the phase of composite, which are described as follows:

1.2.1 According to Type of Matrix Material

(a) Metal Matrix Composite (MMC)

(b) Ceramic Matrix Composite (CMC)

(c) Polymer Matrix Composite (PMC)

Metal Matrix Composite: As the name suggested that in this type of composite, metal is used for matrix phase. Metal matrix composite have higher specific modulus, higher specific strength, better properties at elevated temperatures and lower coefficient of thermal expansion as compared to the monolithic metal. Due to this properties MMCs are used in many application such as combustion chamber nozzle (in rocket, space shuttle), housings, tubing, cables, heat exchangers, structural members etc.

Ceramic Matrix Composite: In this type of composite ceramic materials are used for the matrix phase. The main motive of manufacturing ceramic composite is to improve the toughness along with strength and stiffness of composite because of this CMCs are capable to use in high temperature environment and highly stressed state.

Polymer Matrix Composite: Most commonly used matrix materials are polymeric. The reasons for this are twofold. In general the mechanical properties of polymers are inadequate for many structural purposes. In particular their strength and stiffness are low compared to metals and ceramics. These difficulties are overcome by reinforcing other materials with polymers. Secondly, the processing of polymer matrix composites need not involve high pressure and doesn’t require high temperature. Also equipment required for manufacturing polymer matrix composites are simpler. For this reason polymer matrix composites developed rapidly and soon became popular for structural applications.

Composites are used because overall properties of the composites are superior to those of the individual components for example polymer/ceramic. Composites have a greater modulus than the polymer component but aren't as brittle as ceramics. Two types of polymer composites are: fiber reinforced polymer (FRP) and particle reinforced polymer (PRP).

1.2.2 According to Nature and Arrangement of the Reinforcement Phase

(a) Particulate reinforced composite

(b) Fiber reinforced composites

(c) Hybrid composite

(d) Laminated composite

Particulate Reinforced Composite: It is the composite in which reinforcement is used in form of particulate with approximate equally distributed in all dimension of composite. Particulate reinforcement is used to high temperature performance, reduce friction, improve wear resistance and to reduce shrinkage. Particulate reinforcement is improve stiffness effectively but unable to provide strength to composite.

Fiber Reinforced Composites: Composite in which reinforcements having lengths higher than cross sectional dimension is called as fiber reinforced composite. Length of the reinforcing fiber in a single layer composite may be long or short, it depends on its overall dimensions. Composite with long fibers, oriented in one direction is known as continuous fiber reinforcement. These oriented fibers are enhancing composites strength. Composite with the short reinforced fibers is known as discontinuous fiber reinforcement. Length of fibers are neither too short to loss their fibrous nature nor too long to entangle with each other.

Hybrid Composite: composite in which two or more different types of particulates or mostly fibers used as filler in a single matrix are called hybrid composite. Due to hybridization properties of composites are improved and also it becomes economical. Composite with polymeric resin as the matrix and both glass and carbon fibers as reinforcing phase is the most commonly used hybrid composite. Because of hybridization of composites it is possible get anisotropic properties in most of the hybrid composites easily. Generally the overall properties of a hybrid composite are better than the composites having only one fiber as reinforcing phase.

Laminated Composite: It is made up by bonding a number of laminates in thickness direction. Generally three layers are arranged alternatively for better bonding between reinforcement and the polymer matrix, for example plywood and paper.

1.3 Fibre Reinforced Plastic (FRP)

Fiber reinforced polymer (FRP) composite is made up of a polymer matrix (it may be either a thermoplastic or thermoset resin, such as polyester, vinyl ester, epoxy, phenolic) incorporated with a reinforcing material like glass, carbon, aramid and boron etc. which have sufficient aspect ratio (length to thickness) to provide a discernable reinforcing function in one or more directions. Some times in FRP composite core materials and additives are also added to improve properties of the final product. During machining of FRP composites many problems arises such as fiber pull-out, burr, delamination and burning etc. it is due to the non-homogeneity of the constituent of the composite materials. GFRP (Glass Fiber Reinforced Plastic) composites are the most common used FRP composites. The main advantage of GFRP is its low cost, high tensile strength, high chemical resistance and excellent insulating properties. FRP composites also have the capability of good resistance to creep (permanent deflection under long term loading) and prevent the rapid propagation of cracks as in metals.

Advantages of FRP Composites

a) Lighter weight

b) The design can be optimized to meet stiffness, strength and manufacturing requirements

c) Part consolidation to provide pre-fabricated/pre-assembled product

d) Complex shapes are easily accomplished

e) Corrosion resistance

f) Resistant to fatigue damage with good damping characteristics

1.4 Metal Matrix Composites (MMCs)

In composites, when a metal is used as matrix phase then composite is called as metal matrix composite (MMC). Due to the metal matrix, MMCs can be distinguished from conventional metal in terms of increased strength, higher elastic modulus, high temperature sustainability, improved abrasion and wear resistance, high electrical and thermal conductivity, lighter weight and low coefficient of thermal expansion. These properties of MMCs can be controlled by the proper choice of matrix and reinforcement. Generally metal matrix serves the function of proper distribution and transfer of load to the reinforcement. Because of these properties MMCs are used in typical applications such as fabrication of satellite, missile, helicopter structures, structural support, piston, sleeves and rims, high temperature structures, drive shaft, brake rotors, connecting rods, engine block liners various types of aerospace and automotive applications etc.

Aluminum is the most common metal matrix material used as a structural design especially in the aerospace industry because of its light weight properties. Aluminum having low strength as well as low melting point therefore we can't able to use only Aluminum metal as structural material. This problem can be solved by using Aluminum as matrix material with a reinforced element such as SiC particles and whiskers. Mostly SiC particles are used as reinforcement purpose because of its having many advantages over the various reinforcement material such high modulus and strengths, excellent thermal resistance, good corrosion resistance, good compatibility with the Aluminum matrix, low cost and ready availability. In industrial applications, Aluminum alloy-based composites with silicon carbide reinforcement have created significant interest due to its high-strength, high-specific modulus and low density.

Advantages and Disadvantages of MMC

Compared to monolithic metals, PMC and CMCs, MMCs have:

a) Higher strength-to-density ratio and stiffness-to-density ratios.
b) Better fatigue resistance and lower creep rate.
c) Better elevated temperature properties.
d) Lower coefficients of thermal expansion.
e) Better wear resistance and radiation resistance.
f) Higher temperature capability with fire resistance.
g) Higher transverse stiffness and strength.
h) No moisture absorption and no outgassing.
i) Higher electrical and thermal conductivities.
j) Fabricability of whisker and particulate-reinforced MMCs with conventional metal working equipment.

Some of the disadvantages of MMCs compared to monolithic metals, PMCs and CMCs are

a) Higher cost of some material systems.
b) Relatively immature technology.
c) Complex fabrication methods for fiber-reinforced systems (except for casting).
d) Limited service experience.

1.5 Machining Aspects of Composites: State of Art

Composites offer higher stiffness and specific strength than that of conventional structural metals and are immensely being used in aerospace and automotive industries. Composites mainly comprises of light weight metal as matrix element, and the fibers, whiskers or particles as the reinforcing elements. Out of several composites, MMCs and FRP composites gained more attraction nowadays particularly in aerospace and automotive industries due to their light in weight, high specific strength and high stiffness. Hence, it became a challenge for manufacturers to study the machinability aspects of these composites. A lot of research has been carried out over the past years to study the machinability of composites using traditional machining methods such as turning, drilling etc. and reported considerable improvement in dimensional and performance characteristics like surface roughness, hole quality as well as tolerance.

Ramulu et al. (2002) studied the behavior of process parameter on machining Al_2O_3 aluminum-based metal matrix composites using different drills (high-speed steel, carbide-tipped, and polycrystalline diamond (PCD) drills). The drilling characteristics were evaluated in terms of drilling forces, tool wear, chip formation, and drilled-hole quality. It was found that PCD drills outperformed all other drills in terms of drilled-hole quality and minimum drilling forces induced. Tosun and Muratoglu (2004) experimentally examined the influence of the type of drills, point angles of drills and ageing on the drilling performance of 2124 Aluminum alloy reinforced with 17% SiC particulates. The experiments were conducted under different settings of parameters: spindle speed, feed rate and point angles of drill by using high-speed steel (HSS), TiN coated HSS and solid carbide drills. It was found that the effect of point angles on the sub-surface damage caused by the drilling operation was changed with the type of drills. Hocheng et al. (2005) investigated the delamination effect (at entrance and exit) of the drilled hole due to anisotropy and non-homogeneity of composite materials and also attempted to find the way of delamination-free drilling of composite material. Arul et al. (2006) conducted drilling experiments on GFRP with plain HSS, TiN coated HSS and tipped tungsten carbide drills. The authors found that most of the drilling defects were causing due thrust force.

Sardinas et al. (2006) proposed a multi-objective optimization methodology of the drilling process on a laminate composite material. A micro-genetic algorithm posteriori approach was used to investigate the effect of drilling parameters on material removal rate and delamination factor. Singh et al. (2006) focused to correlate drilling-induced damage with drilling parameters. Here tool point geometry was taken as the major input parameter. Along with tool geometry, cutting speed and feed rate were found also responsible for the drilling induced damage. A model was developed for evaluation of thrust, torque, and damage. In another paper, Singh et al. (2008) investigated the effects of drilling parameters on the output responses viz. thrust force and torque. Experiments were conducted and the results of ANOVA were used in developing a Finite Element model for predicting drilling induced damage. Haq et al. (2008) implemented an efficient approach for the optimization of drilling parameters on drilling Al/SiC metal matrix composite with multiple responses based on orthogonal array with grey relational analysis. Drilling parameters viz. cutting speed, feed and point angle were optimized with the considerations of multi-responses such as surface roughness, cutting force and torque. Basavarajappa et al. (2008) concentrated on the influence of cutting parameters on thrust force, surface finish, and burr formation in drilling Al2219/15SiCp and Al2219/15SiCp-3Gr composites fabricated by the liquid metallurgy method. The tools used were commercially available carbide and coated carbide drills. The results revealed that feed rate had a major influence on thrust force, surface roughness, and exit burr formation. Graphitic composites exhibited lesser thrust force, burr height, and higher surface roughness when compared to the other material and it was due to the solid lubricating property of the graphite particles. The higher surface roughness value for Al2219/15SiCp-3Gr composite was due to the pullout of graphite from the surface. Karnik et al. (2008) analyzed delamination behavior as a function of drilling process parameters at the entrance of the CFRP plates. The effect of spindle speed, feed rate and point angle had been found on the response delamination by developing an artificial neural network (ANN) model. Drilling experiments were carried out with cemented carbide (grade K20) twist drills. The results of ANN models and measured value were compared to verify the effectiveness of model to predicting delamination factor. Krishnaraj et al. (2008) carried out drilling experiments with different drill bits, namely standard twist drill, Zhirov-point drill, and multifacet drill by taking spindle speed and feed rate as input parameters to analyze the output responses such as thrust force, delamination and surface roughness. It was found that delamination was less while a multi facet drill was used. Latha et al. (2009) conducted drilling tests on GFRP composite specimens using solid carbide drill bits. A L_{27} orthogonal array was used for these tests. A fuzzy rule based model was developed to predict the delamination in drilling of GFRP composites. The proposed fuzzy rule based model could be used effectively for predicting the delamination in drilling GFRP composites. Dhavamani and Alwarsami (2012) emphasized to determine the optimum machining condition for maximizing metal removal rate and minimizing the surface roughness in drilling of Aluminum Silicon Carbide (AlSiC) by using Desirability Function (DF) approach. Taguchi method with an L_{27} design was selected for the experiment to obtain the optimal settings of factors and their effects on multiple performance characteristics. Analysis of Variance (ANOVA) was performed to verify the fit and adequacy of the developed mathematical models. A multiple regression model was used to represent relationship between input and output variables and a multi-objective optimization method based on a Genetic Algorithm (GA) was used to optimize the process. Kumar et al. (2012) examined the drilling characteristics of GF/vinyl ester composites. Drilling forces and the surface roughness were analyzed with input parameters such as drill geometry, the cutting speed and the feed rate. ANOVA analysis was performed and the results of the experimental investigation showed some important facts of the drilling behavior of GF/vinyl ester composites filled with fillers.

Mayyas et al. (2012) used multiple regression analysis (MRA) and artificial neural networks (ANN) in order to investigate the influence of some parameters on the thrust force and torque in the drilling processes of self-lubricated hybrid composite materials. In this model cutting speed, feed, and volume fraction of the reinforcement particles were used as input data and the thrust force and torque as the output data. ANNs showed better predictability results compared to MRA due to the nonlinearity nature of ANNs. The statistical analysis accompanied with artificial neural network results showed that Al_2O_3, Gr and cutting feed (f) were the most significant parameters on the drilling process, while spindle speed seemed insignificant. Abhishek et al. (2013) adopted response surface methodology to highlight the effect of machining parameters such as spindle speed, feed rate and depth of cut on machining evaluation characteristics viz. MRR, surface roughness and tool-tip temperature during the turning of CFRP composites. The research also developed a mathematical model for aforesaid characteristics to predict these performance responses on the machining of CFRP composites. Karimi et al. (2013) investigated the effect of various drilling parameters on thrust force, adjusted delamination factor and compressive residual strength of uni-directional glass/epoxy resin. Experimental results showed the feed rate was the most influencing parameter for output responses. The Acoustic Emission (AE) technique was used to observer both drilling process and compression test. The results revealed that root mean square (RMS) could be used for monitoring thrust force and AE energy for compression force. Raj et al. (2013) concentrated on evaluation of thrust force and surface roughness in drilling of Al/15%Sic/4% Graphite hybrid metal matrix composite fabricated using Stir casting method. The experiments were conducted to optimize the spindle speed and feed rate for the output performance parameters namely thrust force and surface roughness using coated carbide twist drill and carbide multifaceted drills under various cutting conditions. From the experimental results it was found that the feed rate had a major influence on thrust force and surface roughness. Shivapragash et al. (2013) focused on multiple response optimization of drilling process for composite Al-TiBr2 to minimize the damage events occurring during drilling process. Taguchi method with grey relational analysis was used to optimize the machining parameters with multiple performance characteristics in drilling of MMC Al-TiBr2. It was found that the maximum feed rate, low spindle speed were the most significant factors which affected the drilling process; the performance of the drilling process could be effectively improved by using this approach.

1.6 Objectives of the Present Work

1. To investigate on parametric appraisal and multi-response optimization in drilling of composites (GFRP and MMC).

2. To study Taguchi based integrated optimization methodologies and their application feasibility for machining performance optimization during drilling of GFRP/MMC composites.

3. To compare performance (predicted optimal setting) of Deng's Similarity Method, PCA-Grey, Grey-TOPSIS (each combined with Taguchi's philosophy) for simultaneous optimization of multi-performance-yields during drilling of GFRP/MMC composites.

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2.1 Coverage

Composite materials have been gaining immense importance in manufacturing industries, particularly in aerospace and automotive industries, due to their excellent properties as compared to other conventional metals. In manufacturing sector, drilling is a very common machining operation; whilst drilling of glass fiber reinforced polymer (GFRP) composite is substantially different from metallic materials due to fiber delamination, fiber pull-out etc. In order to produce satisfactory product quality (GFRP drilled hole), investigations on machining and machinability aspects of GFRP composites are indeed essential. Understanding of the effect of process variables viz. drill speed, feed rate, drill diameter, plate thickness etc. is very important in order to select optimal machining condition towards improving overall machining performance. Therefore, this work focuses on the analysis of drill force (thrust), torque, surface roughness (R_a) and delamination behavior (of the drilled hole) as a function of drilling process parameters. The unified aim of this work is to determine an optimal machining environment based on the concept of the 'Degree of Similarity Measure' between each alternative and the ideal solution using alternative gradient and magnitude; TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) and Deng's solution.

2.2 Background and Rationale

In recent years, GFRP composite materials are widely being used in various engineering applications such as automobile, aerospace industries, spaceship and sea vehicle industries because of their unique properties such as high specific stiffness, high specific strength, high specific modulus of elasticity, high damping capacity, good corrosion resistance, good tailoring ability, excellent fatigue resistance, good dimensional stability and a low coefficient of thermal expansion. In aforesaid fields, drilling of GRFP composite materials is a common machining operation.

During drilling of composite materials many problems arise like fiber pull-out, delamination, stress concentration, swelling, burr, splintering and micro cracking etc. which are likely to reduce machining performance. Amongst various defects, delamination (at entrance and exit of the plane of the work piece) is the most critical. Delamination can result in lowering of bearing strength and can be detrimental to the material durability by reducing the in-service life under fatigue loads. Delamination during drilling is due to compressive thrust force acting on the uncut portion and peeling force acting on the cut portion. Past investigations showed that the thrust force is the major factor which is responsible for the delamination induced during the drilling GFRP and it mainly depends on the drill materials, drill geometry and feed rate. Many of the research work focused on the behavior of drilling process parameters on machining and machinability aspects of a variety of composite materials.

Davim et al. (2004) established a correlation between cutting velocity and feed rate with the specific cutting pressure, thrust force, damage factor and surface roughness, in a GFRP material. A plan of experiments based on the Taguchi technique was established considering drilling with prefixed cutting parameters in a hand lay-up GFRP material. The analysis of variance (ANOVA) was performed to investigate the cutting characteristics of GFRP's using Cemented Carbide (K10) drills. Langella et al. (2005) presented a mechanistic model for predicting thrust and torque during composite materials drilling. The authors specified the number of coefficients to be experimentally determined and provided a detailed analysis of the problems associated with the action of the chisel edge. They concluded that the model afforded a focused approach to the definition of the most appropriate drill geometry and cutting parameters in composite materials drilling. Singh et al. (2009) conducted experiments by using 8 facet solid carbide drills based on L_{27} Orthogonal Array (OA). The process parameters investigated were spindle speed, feed rate and drill diameter. Fuzzy rule based model was developed to predict thrust force and torque in drilling of GFRP composites. The results indicated that the model could be effectively used for predicting the response variable by means of which delamination could be controlled. Kilickap et al. (2010) investigated the influence of the cutting parameters, such as cutting speed and feed rate, and point angle on delamination produced while drilling a GFRP composite. This work focused on the application of Taguchi method and analysis of variance (ANOVA) for minimization of delamination influenced by drilling parameters and drill point angle. The conclusion revealed that feed rate and cutting speed were the most influential factor on the delamination, respectively. The best results of the delamination were obtained at lower cutting speeds and feed rates. Latha et al. (2011) studied the influence of drill geometry on thrust force in drilling GFRP composites. Drilling experiments were conducted on composite materials using CNC drilling machine. The response analyzed was thrust force. The influence of drill geometry on thrust force in drilling of composite materials was carried out using three different drill bits, namely, ‘Brad and Spur’ drill, ‘multifaceted’ drill, and ‘step’ drill. The analyses of the experimental results were carried out using effect graphs and three dimensional graphs. The results indicated that the step drills were performing better than the other drills considered. Palanikumar (2011) proposed an approach for optimization of drilling parameters with multiple performance characteristics based on the Taguchi’s L_{16}, 4-level orthogonal array design with grey relational analysis. Spindle speed and feed rate were the drilling parameters and the process was optimized with consideration of multiple performance characteristics, such as thrust force, surface roughness and delamination factor. The analyzed grey results indicated that feed rate was the most influencing parameter than the spindle speed. Verma et al. (2011) proposed a fuzzy rule based model combined with Taguchi philosophy to determine the favorable machining condition for FRP composite machining thereby satisfying the conflicting criteria MRR and surface roughness simultaneously.

Tsao et al. (2012) proposed a novel method for the reduction of delamination during composite drilling by active backup force. The applied backup force contributed to suppression of the growth of the delamination at drilling exit by 60-80%. The proposed novel drilling technique revealed the potential for fabrication of composite components at low cost and minor delamination with high feed rate. Krishnamoorthy et al. (2012) used Taguchi's L_{27} orthogonal array to perform drilling of CFRP composite plates. Grey relational analysis was used to get the optimal combination of drilling parameters. Output performance parameters such as thrust force, torque, entry delamination, exit delamination and eccentricity of the holes were taken as criteria for analysis of drilled hole. ANOVA was used for analysing the input parameters and found that feed rate was the most influential factor in drilling of CFRP composites. Kumar et al. (2013) concentrated on the multi-performance optimization on machining characteristics of unidirectional glass fiber reinforced plastic (UD-GFRP) composites. The Distance-Based Pareto Genetic Algorithm (DPGA) was used to optimize the cutting condition. Tool rake angle, tool nose radius, feed rate, cutting speed, cutting environment (dry, wet and cooled) and depth of cut were used as cutting parameters for the output responses. Okutan et al. (2013) developed machine force equations in the drilling of [0°/+45°/90°/–45°] oriented GFRP with the help of Shaw and Oxford model. Experiments were conducted on the GFRP samples using 118° point angle drills under dry conditions. Input parameters: feed rate and drill diameter were analyzed on the output responses such as torque and thrust force by using mathematical models. Measured and calculated data were comparing to each other to verify the accuracy of the developed model.

The objective of the present study is to investigate the effect of the machining variables viz. drill speed, feed rate, drill diameter along with plate thickness (work piece) on the output performances like thrust force, torque, delamination factor and surface roughness (of the drilled hole) during drilling GFRP composites. Based on experimental results, an optimum design of cutting variables (optimal parameter setting) has been obtained by using Deng's similarity measure method in conjugation with Taguchi's optimization philosophy. Results obtained thereof, have been compared with that of TOPSIS.

2.3 Experimentation

Experimental Setup

Experiments have been executed on CNC drilling machine [MAXMILL 3 axis CNC machine with FANUC Oi Mate MC Controller, Model No. CNC 2000EG].

Design of Experiment (DOE)

Design of Experiment comprises of set of experiments which are to be carried out in a sequential manner for evaluating the response measurements. Taguchi's orthogonal array design of experiment is an economic as well as effective method to examine the effects of the machining parameters through limited number of experiments. The present study focused on the effects of drilling parameters such as drill speed, feed rate and thickness of the composite plates; each varied in four different levels, whereas, drill diameter has been varied in two different levels (as shown in Table 2.1) on different machining performance features namely thrust force, torque, entry-exist delamination factor and surface roughness of the drilled hole. In this experimentation, mixed level L_{16} orthogonal array has been used as shown in Table 2.2.

Work Piece and Tool material

GFRP epoxy composite samples of varying thickness (Fig. 2.3) have been used for execution of the experimentation. TiAlN coated solid Carbide drill bits [Manufacturer: WIDIA-Hanita, Product: M1308000RT] of different size such as 8 mm and 10 mm have been used for performing drilling as shown in Fig. 2.4.

Machining Performance Characteristics

Drilling operation has been carried out on GFRP composites for assessing performance characteristics such as load, torque, entry delamination factor, exit delamination factor as well as surface roughness of the drilled hole.

Thrust force and torque has been evaluated by using Digital Drilling Tool Dynamometer [Make: Medilab Enterprises, Chandigarh, INDIA], whereas, entry delamination factor and exit delamination factor has been assessed by using formula given below:

$$F_d = D_{\max}/d \qquad (2.1)$$

Where,

F_d = delamination factor,

D_{max} = maximum diameter observed in the damaged zone,

d = diameter of the drill.

Here, Surface Roughness Tester SJ-210 (Make: Mitutoyo) has been used to measure the roughness average value based on carrier modulating principle.

2.4 Proposed Methodology

2.4.1 TOPSIS

The TOPSIS (*Technique for Order Preference by Similarity to Ideal Solution*) method was firstly proposed by (Hwang and Yoon, 1981) for assessing the alternatives before the multiple-attribute decision making. TOPSIS is implemented to measure the extent of closeness to the ideal solution. The basic concept of this method is that the chosen alternative should have the shortest distance from the positive ideal solution and the farthest distance from negative ideal (anti-ideal) solution. Positive ideal solution is the composition of the best performance values demonstrated (in the decision matrix) by any alternative for each attribute. The negative-ideal solution is the composition of the worst performance values. The steps involved for calculating the TOPSIS values are as follows:

Step 1: Development of decision Matrix: The row of this matrix is allocated to one alternative and each column to one attribute. The matrix can be expressed as:

$$D = \begin{array}{c} A_1 \\ A_2 \\ . \\ A_i \\ . \\ A_m \end{array} \begin{bmatrix} x_{11} & x_{12} & . & x_{1j} & x_{1n} \\ x_{21} & x_{22} & . & x_{2j} & x_{2n} \\ . & . & . & . & . \\ x_{i1} & x_{i2} & . & x_{ij} & . \\ . & . & . & . & . \\ x_{m1} & x_{m2} & . & x_{mj} & x_{mn} \end{bmatrix} \tag{2.2}$$

Here, $A_i((i=1,2,.......,m)$ represents the possible alternatives; $x_j\ (j=1,2,........,n)$represents the attributes relating to alternative performance, $j=1,2,..........,n$ and x_{ij} is the performance of A_i with respect to attribute $X_{j.}$

Step 2: Obtain the normalized decision matrix r_{ij} .This can be represented as:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{2.3}$$

Here, r_{ij} represents the normalized performance of A_i with respect to attribute X_j.

Step 3: obtain the weighted normalized decision matrix, $Y = \lfloor y_{ij} \rfloor$ can be found as:

$$Y = w_j r_{ij}$$

$$Y = \begin{bmatrix} y_{11} & y_{12} & . & y_{1j} & y_{1n} \\ y_{21} & y_{22} & . & y_{2j} & y_{2n} \\ . & . & . & . & . \\ y_{i1} & y_{i2} & . & y_{ij} & . \\ . & . & . & . & . \\ y_{m1} & y_{m2} & . & y_{mj} & y_{mn} \end{bmatrix} \qquad (2.4)$$

Here, $\sum_{j=1}^{n} w_j = 1$

Step 4: Determine the ideal (best) and negative ideal (worst) solutions:

a) The ideal solution:

$$A^+ = \left\{ \left(\max_i y_{ij} \middle| j \in J \right), \left(\min_i y_{ij} \middle| j \in J' \middle| i = 1,2,.........,m \right) \right\} \qquad (2.5)$$

$$= \left\{ y_1^+, y_2^+, ..., y_j^+, ...y_n^+ \right\}$$

b) The negative ideal solution:

$$A^- = \left\{ \left(\min_i y_{ij} \middle| j \in J \right), \left(\max_i y_{ij} \middle| j \in J' \middle| i = 1,2,........,m \right) \right\} \qquad (2.6)$$

$$= \left\{ y_1^-, y_2^-, ..., y_j^-, ...y_n^- \right\}$$

Here,

$J = \{ j = 1,2,.......,n | j \}$: Associated with the beneficial attributes

$J' = \{ j = 1,2,.......,n | j \}$: Associated with non-beneficial attributes

Step 5: Determine the distance measures. The separation of each alternative from the ideal solution is given by n- dimensional Euclidean distance from the following equations:

$$S_i^+ = \sqrt{\sum_{j=1}^{n} \left(y_{ij} - y_j^+ \right)^2} \quad i = 1,2,.........,m \qquad (2.7)$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} \left(y_{ij} - y_j^-\right)^2} \quad i = 1,2,.........,m \tag{2.8}$$

Step 6: Calculate the Overall performance coefficient closest to the ideal solution:

$$C_i^+ = \frac{S_i^-}{S_i^+ + S_i^-}, \; i = 1,2,........,m; 0 \le C_i^+ \le 1 \tag{2.9}$$

2.4.2 Deng's Similarity Based Method

Deng's similarity-based method is a modified form of TOPSIS methodology based on concept that ideal solution is used in such manner so that most preferred alternative should have the highest degree of similarity to the positive ideal increasing or decreasing values. It proposed for evaluating the conflicting index between two alternatives to show the degree conflict between the alternatives (Safari et al., 2013; Refer Fig. 2.1-2.2).

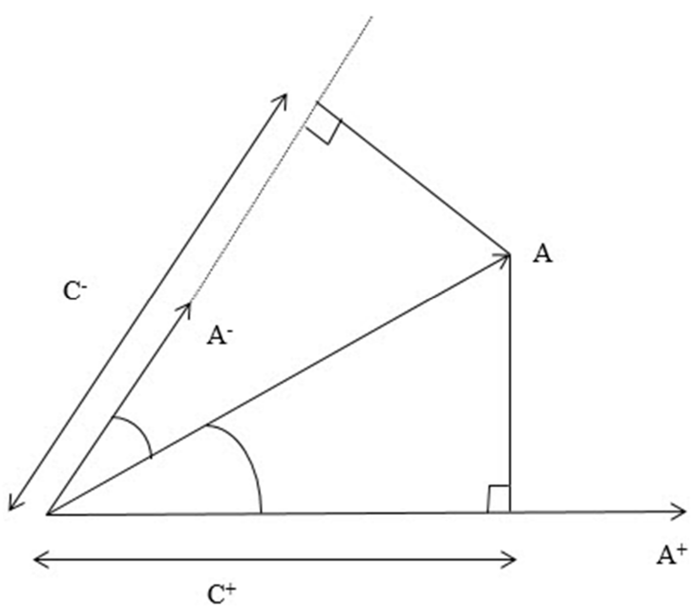

Fig. 2.1: Degree of conflict between A_i and $A^{\pm}$

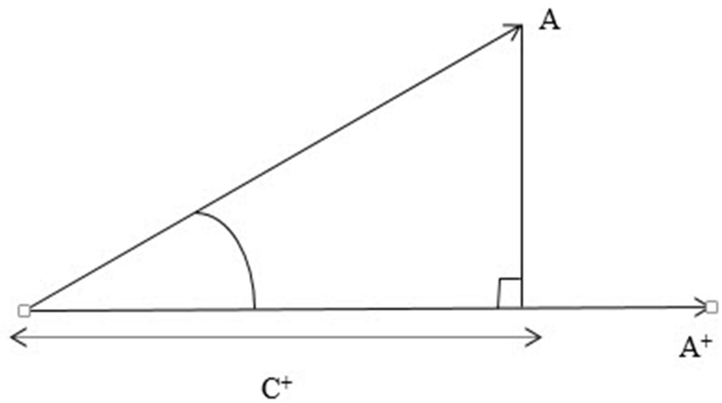

Fig. 2.2: Degree of conflict between A_i and A^+

Steps involved in Deng's Similarity-Based Method

Step 1: Formulation of decision matrix

Step 2: Normalization of decision matrix

Step 3: Determination of weighted decision matrix

Step 4: Evaluation of Positive ideal and negative ideal solution

Step 5: Estimation of conflict between each alternative and the positive and the negative ideal solution:

$$A_i, A^{\mp} = |A_i||A^{\mp}| \cos\theta^{\mp} \tag{2.10}$$

$$A_i, A^{\mp} = \sum y_{ij} y_j^{-+} \tag{2.11}$$

$$|A_i| = \left(\sum_{j=1}^{m} y_{ij}^{\;2} \right)^{0.5} \tag{2.12}$$

$$A^{\mp} = \left(\sum_{j=1}^{m} y_{ij}^{\mp 2} \right)^{0.5} \tag{2.13}$$

$$\cos\theta_i^{+} = \frac{\sum_{j=1}^{m} y_{ij} y_j^{+}}{\left(\sum_{j=1}^{m} y_{ij}^{\;2} \right)^{0.5} \left(\sum_{j=1}^{m} y_{ij}^{+2} \right)^{0.5}} \tag{2.14}$$

$$\cos\theta_i^- = \frac{\sum_{j=1}^{m} y_{ij} y_j^-}{\left(\sum_{j=1}^{m} y_{ij}^{\ 2}\right)^{0.5} \left(\sum_{j=1}^{m} y_{ij}^{-2}\right)^{0.5}} \tag{2.15}$$

Step 6: Assessment of the degree of similarity between each alternative and the positive and the negative ideal solution

$$\left|C_i\right| = cos\,\theta_i^{-\,+} \times \left|A_i\right| \tag{2.16}$$

$$\left|C_i\right| = \frac{\sum_{j=1}^{m} y_{ij} y_j^{-\,+}}{\left(\sum_{j=1}^{m} y_{ij}^{\prime\ 2}\right)^{0.5} \left(\sum_{j=1}^{m} y_{ij}^{-\,+2}\right)^{0.5}} \times \left(\sum_{j=1}^{m} y_{ij}^{\ 2}\right)^{0.5} \tag{2.17}$$

$$S_i^{-\,+} = \frac{\left|C_i\right|}{\left|A^{-+}\right|} = \frac{cos\,\theta^{-+} \times \left|A1\right|}{\left|A^{-+}\right|} = \frac{cos\,\theta^{-+} \times \left(\sum_{j=1}^{m} y_{ij}^{\ \ 2}\right)^{0.5}}{\left(\sum_{j=1}^{m} y_{ij}^{-+2}\right)^{0.5}} \tag{2.18}$$

Step 7: Evaluation of overall performance index:

$$P_i = \frac{S_i^+}{S_i^+ + S_i^-},\ i = 1,2,........,n \tag{2.19}$$

Step 8: Determine the optimum process variable by optimization OPI using Taguchi method

The optimum process parameter combination ensures highest OPI value. The closeness coefficient value is optimized using Taguchi method. For calculating S/N ratio (corresponding to the values of closeness coefficient); Higher-the-Better (HB) criterion is to be considered. As larger the value of closeness coefficient, better is the proximity to the ideal solution.

2.5 Results and Discussions

Experimental data presented in Table 2.3 have been analyzed by following aforesaid procedures. Two different techniques have been applied utilizing these output response characteristics. Individual experimental runs (parameters settings) have been dealt as the alternatives and the normalized decision matrix have been calculated and presented in the Table 2.4. Assuming equal priority weight of the responses (20%), the weighted normalized matrix has thus been computed and presented in Table 2.5. According to TOPSIS philosophy, the positive ideal and negative-ideal solutions have been determined and shown in Table 2.6. The degree of conflict between each alternative and the positive and the negative ideal solution has been determined and tabulated in Table 2.7. Table 2.8 presents the overall performance coefficient that has been evaluated by using all these two methodologies: TOPSIS and Deng's similarity method.

Finally, the Taguchi method has been applied on the overall performance coefficient (OPI) to assess the optimal machining parameter by using S/N ratio plot of OPI. Higher the value of closeness coefficient, the corresponding parameter combination is said to be close to the optimal solution. Fig. 2.5-2.6 show the optimal parametric combination obtained by these different methodologies and it has been noticed that predicted S/N ratios values for these optimal combination individually represent highest value than that obtained for corresponding S/N ratios as depicted in Table 2.9.

2.6 Concluding Remarks

The present study investigates the influence of drilling parameters based on parametric appraisal and optimization (minimization) of thrust forces, torque, surface roughness, damage factor and thereby attaining defect controlled drilling of GFRP composites using TiAlN coated solid Carbide drill bits, according to the L_{16} orthogonal array experiments. Optimal parametric combination obtained from TOPSIS and Deng's similarity methods are found similar to each other. Experimental approach illustrates the feasibility and effectiveness of these proposed methodologies for optimizing the drilling parameters to achieve better quality holes in GFRP composites.

2.7 Bibliography

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3.1 Coverage

The metal matrix composite (MMC) Aluminum silicon carbide has widespread application in aerospace, automotive and electronics engineering due to its excellent properties like high toughness, low weight to volume ratio, high strength, etc. Drilling is one of most common conventional machining processes being applied on MMCs. For obtaining high product quality and satisfactory process performance yield it is indeed necessary to control and optimize several drilling parameters. Taguchi's philosophy has been mainly concerned with optimization of single objective function, whereas drilling involves multi-response characteristics viz. thrust force, torque and circularity at entry and exit; hence exploration of an appropriate multi-objective optimization technique is certainly essential. To this end, the present work reports application of (i) PCA-Grey analysis integrated with Taguchi method and (ii) Grey-TOPSIS combined with Taguchi method in order to obtain appropriate (optimal) parametric combination in drilling of Al-20%SiCp composites.

3.2 Background and Rationale

Literature depicts that metal matrix composite has widespread applications because of its excellent properties like high strength, fracture toughness and stiffness. Recently, more emphasis has been given for development of lighter MMCs using Aluminum matrix and SiC as reinforcement due to the significant potential improvement in the thrust-to-weight ratio; suitable for aerospace and automobile applications. Hence, it is important to know the machinability behavior of these composites. Researchers highlighted the effect of drilling parameters such as drill speed, feed rate, drill diameter, type of drill etc. on several drilling performance yields during composite drilling and examined to get an optimal parametric combination to improve the machining performances of these composites as well as to improve productivity in an economic way.

Sardinas et al. (2006) proposed a multi-objective optimization module for the drilling process of a laminate composite material. Here, material removal rate and delamination factor were the two mutually conflicted objectives, optimized by using a micro-genetic algorithm. A posteriori approach was used to obtain a set of optimal solutions. Finally, the obtained outcomes were arranged in graphical form (Pareto's front) and analyzed to make the proper decision for different process preferences. Ahamed et al. (2010) focused on drilling of Al-5% SiCp-5% B_4Cp hybrid composite with high-speed steel (HSS), PCD, or carbide drills to explore the viability of the process. It was found that drilling of Al-5%SiC-5%B_4C composites with HSS drills was possible with lower speed and feed combination. The cutting conditions for minimized tool wear and improved surface finish were also recognized. An approach for characterization of tool wear and surface integrity was also carried out. Tosun (2011) carried out statistical analysis of process parameters for surface roughness in drilling of Al/ SiCp metal matrix composite. Spindle speed, feed rate, drill type, point angle of drill and heat treatment were taken as cutting parameters for the experiment. It was found that the feed rate and tool type were more significant factors than other. Hayajneh et al. (2011) predicted torque and thrust force using feed forward back propagation neural network in dry drilling of aluminium-copper/silicon carbide composites produced by stir casting method. Somasundaram et al. (2011) carried out comprehensive analysis on friction drilling of Al/SiCp metal matrix composites. The composition of work piece, work piece thickness, spindle speed, and feed rate were taken as the input parameters. Experimental design matrix was used for analysing the effect of parameters on roundness errors and empirical relation between the process parameters and roundness error was established using response surface methodology. Analysis of variance was used for analysing the results. The influences of individual input process parameters on roundness error were analyzed as well. Altunpak et al. (2012) investigated the influence of cutting parameters on cutting force and surface roughness in drilling of Al/20%SiC/5%Gr and Al/20%SiC/10%Gr hybrid composites fabricated by vortex method. The drilling experiments were conducted with carbon coated cutting tools. The outcomes showed that inclusion of graphite in Al/SiCp reinforced composite reduced cutting force and found that the feed rate was the main factor influencing the cutting force in both composites. Huang et al. (2012) experimentally investigated the influences of the cutting speed and feed rate on the drilling performance of SiCp/Al composites with 56% SiC particles. Drilling forces, tool wear, and the surface quality of drilled-hole were taken as the output performance parameters. The result showed that the feed rate was one of the main cutting parameters that affect the drilling performance, while the cutting speed had no significant effect on the thrust force. Rajmohan and Palanikumar (2011) proposed an approach based on grey relational analysis and the Taguchi method in order to optimize machining parameters with multiple performance characteristics in drilling hybrid Al356/SiC-mica composites. L_9, 3-level orthogonal array was chosen for experiment. Spindle speed, feed rate, drills and wt% of SiC, were taken as the input parameters and drilling characteristics were evaluated in terms of thrust force, surface roughness and torque. Experimental results indicated that the feed rate and the type of drill were the most significant factors which affect performance. Kumar and Venkataramaiah (2013) focused on selection of optimal parameters in drilling of Aluminium Metal Matrix Composites (AMMC) using "Desirable-Fuzzy" approach. Taguchi orthogonal array L_{27} experimental design was used to conducting drilling on the AMMC. Drilling performance parameters were evaluated in terms of thrust force, temperature and surface roughness. Outcomes results were analyzed using Desirable-Fuzzy approach and optimal parameters combination was identified. Rajmohan and

Palanikumar (2013) examined machining characteristics in terms of the thrust force, surface roughness, burr height, and tool wear using carbide, coated carbide, and polycrystalline diamond drills in the drilling of hybrid metal matrix composites using the response surface methodology. Tapkesen et al. (2013) investigated the interactions and effects of the machining parameters such as cutting speed, feed rate, cutting-tool and material particle fraction on the thrust force and cutting torque in drilling of aluminum-based composites reinforced with boron-carbide (B_4C) particles with three different types of drills under dry cutting conditions. Experimental data analysis was carried out with Taguchi's approach and it was found that the particle fraction and feed rate were the most affecting factors for the cutting forces.

The present case study highlights the application of Grey-TOPSIS coupled with Taguchi method for obtaining optimal machining condition in drilling of MMC composites.

3.3 Experimentation

Work Material

In this work aluminium alloy (Al2265) reinforced with abrasive grade SiC particles of average size 37μm with 10g in weight made up by the powder metallurgy method, having 25 mm diameter are used for the experimentation.

Tool Material

Drilling tests are performed by using TiN coated HSS twist drills.

Experimental Set Up

Drilling tests have been conducted on CNC drilling machine [MAXMILL 3 axis CNC machine with FANUC Oi Mate MC Controller, Model No. CNC 2000EG] under dry conditions. Experimental setup has been shown in Fig. 3.1.

Design of Experiment (DOE)

The present study concentrates on the effects of drilling parameters such as drill speed, feed rate and drill diameter; each varied in three different levels, (as shown in Table 3.1) on different drilling characteristics namely thrust force, torque and entry-exit circularity of the drilled hole. In this experimentation, Taguchi based three-level L_9 orthogonal array has been used as shown in Table 3.2.

Response Measurement

Thrust force and torque has been measured with the help of Digital Drilling Tool Dynamometer [Make: Medilab Enterprises, Chandigarh, INDIA], whereas circularity at inlet and the exit of the hole have been evaluated by using optical microscope.

3.4 Proposed Methodologies

3.4.1 PCA-Grey Integrated with Taguchi Method

Multiple responses always contain some extent of correlations; the PCA has been initially performed on the (Signal-to-Noise ratio) S/N values obtained from each response to reduce the dimension of multiple responses to a less number of uncorrelated indices called principal components (PCs). Quality loss estimates has been derived based on the deviation of individual PCs from their ideal value.

Step 1: Collection of Experimental data

Aforesaid machining performance evaluation characteristics viz. thrust force, torque, circularity at entry and exit has been obtained for each experimental run.

Step 2: Data pre-processing

As optimal value of a quality characteristic is too enormous; experimental data should be normalized to eliminate these types of effects. Normalization can be done according to the following equation:

Higher-the-Better (HB)

$$X_i^* = \left(\frac{\hat{y} - y_{min}}{y_{max} - y_{min}} \right) \tag{3.1}$$

Lower-the-Better (LB)

$$X_i^* = \left(\frac{\hat{y} - y_{max}}{y_{min} - y_{max}} \right)$$

(3.2)

(Here y_{min} denotes the lower experimental value of $\hat{y}$, the y_{max} represents the upper experimental value of $\hat{y}$.

Step 3: Application of PCA (Liao, 2006; Abhishek, 2012)

PCA is a multivariate mathematical procedure which explores an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of uncorrelated indices called principal components (PCs). Each PC has the property of explaining the maximum possible amount of variance obtained in the original dataset. The PCs, which are expressed as linear combinations of the original variables which can be used for effective representation of the system under investigation, with a lower number of variables in the new system of variables being called scores, while the coefficient of linear combination describes each PCs, i.e. the weight of each PCs.

(a) Checking for correlation between each pair of quality characteristics

Let, $Q_i = \{X_0^*(i), X_1^*(i), X_2^*(i), \ldots\ldots\ldots\ldots\ldots\ldots, X_m^*(i)\}$ (3.3)

Where,

$i = 1,2,3,\ldots\ldots\ldots\ldots, n.$

It is the normalized series of the i^{th} quality characteristic. The correlation coefficient between two quality characteristics is calculated by the following equation:

$$\rho_{jk} = \frac{Cov(Q_j, Q_k)}{\sigma_{Q_j} \times \sigma_{Q_k}} \tag{3.4}$$

$$\begin{aligned} &here, \\ &j = 1,2,3,\ldots\ldots\ldots\ldots,n \\ &k = 1,2,3,\ldots\ldots\ldots\ldots,n \\ &j \neq k \end{aligned}$$

Here, ρ_{jk} is correlation coefficient, σ_{Q_j} and σ_{Q_k} denotes standard deviation of the quality characteristics j and quality characteristics of k respectively.

(b) Calculation of the principal component score

1) Compute the Eigen value λ_k and the corresponding Eigen vector β_k $(k = 1,2,3,\ldots\ldots\ldots n)$ from the correlation matrix formed by all the quality characteristics.
2) Compute the principal component scores of the normalized reference sequence and comparative sequences using the equation shown below:

$$Y_i(k) = \sum_{j=1}^{n} X_i^*(j)\beta_{kj}, i = 0,1,2\ldots\ldots\ldots,m, k = 1,2,3\ldots\ldots\ldots\ldots,n \tag{3.5}$$

Here, $Y_i(k)$ is the principal component score of the kth element in the ith series. Let, $X_i^*(j)$ be the normalized value of the jth element in the ith sequence, and β_{kj} is the j^{th} element of the Eigen vector β_k.

(c) Estimation of quality loss $\Delta_{0,i}(k)$

Loss estimate $\Delta_{0,i}(k)$ is defined as the absolute value of the difference between desired (ideal) value and i^{th} experimental value for k^{th} response. If responses are correlated then instead of using [$X_o(k)$ $X_i(k)$]; [$Y_0(k)$ $Y_i(k)$] should be used for computation of $\Delta_{0,i}(k)$.

$$\Delta_{0,i} = \begin{Bmatrix} \left| X_0(k) - X_i(k) \right| \\ \left| Y_0(k) - Y_i(k) \right| \end{Bmatrix} \tag{3.6}$$

Step 4: Application of Grey Analysis for evaluating overall Grey relation grade:

Individual grey coefficient has been assessed by using as:

$$\gamma_{ij} = \frac{\Delta_{min} + \tau \Delta_{mx}}{\Delta_{0i}(j) + \tau \Delta_{max}} \tag{3.7}$$

Here,

$\Delta_{0i}(j) = \left| y_0(j - y_i(j)) \right|,$

$\Delta_{min} = min_i \, min_j \, \Delta_{0i}(j),$

$\Delta_{max} = max_i \, max_j \, \Delta_{0i}(j), i = 1,2,........, m$

$j = 1,2,.......n$

$\tau \in [0,1]$ the distinguishing coefficient, usually, $\tau = 0.5$

The overall grey relational grade computed as:

$$R_i = \frac{1}{n} \sum_{j=1}^{n} \gamma_{ij} \tag{3.8}$$

Step 5: Determine the optimum process variable by optimization OPI using Taguchi method

The optimum process parameter combination ensures highest OPI value. The closeness coefficient value is optimized using Taguchi method. For calculating S/N ratio (corresponding to the values of closeness coefficient); Higher-the-Better (HB) criterion is to be considered. As larger the value of closeness coefficient, better is the proximity to the ideal solution.

3.4.2 Grey-TOPSIS Integrated with Taguchi Method

TOPSIS has been applied to determine the positive-ideal and negative-ideal solution and thus, closeness coefficient. The closeness coefficient has been treated here as OPI. Optimal factorial combination (parameter setting) has been evaluated finally by optimizing OPI using Taguchi method.

Step 1: Determination of S/N ratio for the corresponding responses.

Larger the better

$$S / N ratio = -10 \log_{10}\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{x_{ij}^{2}}\right) \tag{3.9}$$

Smaller the better

$$S / N ratio = -10 \log_{10}\left(\frac{1}{n}\sum_{i=1}^{n}x_{ij}^{2}\right) \tag{3.10}$$

$i = 1,2,3,...,n$ $\qquad$ $j = 1,2,3,...,m$

n = no. of experimental data,

x_{ij} = observed response value,

m = no. of responses

Step 2: Normalization of the S/N ratio can be obtain by using the following equation.

$$Y_{ij} = \frac{x_{ij} - min(x_{ij})}{max(x_{ij}) - min(x_{ij})}, \text{ for larger the better manner} \tag{3.11}$$

$$Y_{ij} = \frac{\max(x_{ij}) - x_{ij}}{\max(x_{ij}) - \min(x_{ij})}, \text{ for smaller the better manner} \tag{3.12}$$

Step 3: Application of Grey Analysis for evaluating individual Grey relation grade:

Individual grey coefficient has been assessed by using as:

$$\gamma_{ij} = \frac{\Delta_{min} + \tau\Delta_{mx}}{\Delta_{0i}(j) + \tau\Delta_{max}}$$

(3.13)

Here,

$\Delta_{0i}(j) = \left| y_0(j - y_i(j)) \right|,$

$\Delta_{min} = min_i \, min_j \, \Delta_{0i}(j),$

$\Delta_{max} = max_i \, max_j \, \Delta_{0i}(j),$

$i = 1,2,........, m \quad j = 1,2,.......n$

$\tau \in [0,1]$ is the distinguishing coefficient, usually, $\tau = 0.5$

Step 4: Application of TOPSIS for determining OPI:

The individual grey coefficients that have been evaluated are treated as decision matrix in TOPSIS. Further steps of TOPSIS has been carried out which are earlier discussed in Chapter 2.

Step 5: Parametric optimization of OPI using Taguchi method

The optimum process parameter combination ensures highest OPI value. The closeness coefficient value is optimized using Taguchi method. For calculating S/N ratio (corresponding to the values of closeness coefficient); Higher-the-Better (HB) criterion is to be considered. As larger the value of closeness coefficient, better is the proximity to the ideal solution.

3.5 Results and Discussions

Experimental data presented in Table 3.3 have been analyzed by following aforesaid procedures. In PCA-Grey method experimental data has been normalized firstly (Table 3.4) and in Grey-TOPSIS method first S/N ratio is calculated (Table 3.10) then S/N ratio values has been normalized to convert all response dimensions into a common scale within the range 0 to 1 (Table 3.11). For the thrust force and torque; Lower-is-Better (LB) has been considered whereas for circularity Higher-is-Better (HB) has been taken in consideration. Now, principal component analysis has been implemented for checking the correlation among the responses. Eigen value and Eigen vector has been computed and it has been noticed from Table 3.5 that first three principal component has major contribution and fourth principal component has negligible effect. The principal components for each experimental run has been calculated and shown in Table 3.6. The quality loss has been determined and shown in Table 3.7. After that, grey relation theory has been implemented to obtain individual grey relation coefficient which is shown in Table 3.8. Table 3.9 represents the overall grey relation grade; Finally, Taguchi has been adopted for evaluating the optimal machining condition as $N_{1000} f_{100} d_5$ (shown in Fig. 3.2). It has been observed that predicated S/N ratio has highest value among all computed S/N ratios (Table 3.9). Now, in Grey-TOPSIS method Individual grey coefficient has been evaluated by using Eq. 3.13 and tabulated in Table 3.12. These calculated grey coefficients are treated individual alternatives of decision matrix in TOPSIS. Here, equal weightage has been given to each alternative. The ideal positive and anti-ideal solution has been determined by using Eq. 2.5, 2.6 and tabulated in Table 3.14. Now, separation distance measure has been evaluated from both positive ideal and negative ideal solution by using Eq. 2.7, 2.8 and tabulated in Table 3.15. Over all coefficients have been evaluated by using Eq. 2.9 and tabulated in Table 3.16. Finally Taguchi method has been implemented to determine favorable machining condition. The optimal machining condition has been determined as $N_{500} f_{50} D_6$ and it has been observed from Table 3.16 that predicted S/N ratio for this setting has higher value as compare to corresponding S/N ratios.

3.6 Concluding Remarks

The present study accomplishes with the two different Multi-Attribute Decision Making (MADM) methodologies for the optimization of the cutting parameters in drilling of Al-20%SiCp composites. Experiments were conducted on Al-20%SiCp composites using TiN-coated carbide drills, the drilling responses were collected under different drilling conditions for various combination of cutting speed, feed rate, and drill diameter. The objective of the present work is to investigate the optimal drilling parameters setting based on minimum of the thrust forces, torque and maximum of the entry and exit circularity in context with by using two different methodologies i.e. PCA integrated with Grey-Taguchi approach and Grey integrated with TOPSIS-Taguchi approach. PCA has been adopted to eliminate the correlation among the responses, whereas grey relational analysis technique simplifies the optimization problem by converting the multiple performance characteristics into single performance characteristics and TOPSIS has the characteristic to evaluate the solution which is closest to ideal solution. It has been observed that PCA-Grey provides better results as compare Grey TOPSIS to obtain optimal machining condition (Fig. 3.4).

3.7 Scope for Future Work

In this present research, an emphasis has been given to determine the optimal solution in drilling of composite by using only one tool material. In future present effort can be extended to examine the effect of using different tool materials and tool geometry on the quality of drilled hole and varying different machining parameters at the same time. Also different orientation of fiber in FRP and types of FRP's and MMCs can be used with or without consideration of tool wear. Some analytical model can also be developed to evaluate the output responses.

The limitations of this research are as follows:

1. Interaction effect of machining parameters has been neglected.
2. The composite with 90^0 fiber orientation has been studied only.
3. Tool geometry variation, tool material has not been considered.
4. Machine tool vibration has been ignored.
5. Tool wear is not considered.

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Appendix

Table 2.1: Domain of Experiments

Factors	Unit	Level 1	Level 2	Level 3	Level 4
Spindle Speed	RPM	800	1200	1600	2000
Feed rate	mm/rev	100	150	200	250
Plate Thickness	mm	5	6	7	8
Drill diameter	mm	8	10	_	_

Table 2.2: Design of Experiment (L_{16}) orthogonal array

Sl. No.	Drill Speed (RPM)	Feed rate (mm/rev)	Plate Thickness (mm)	drill diameter (mm)
1.	800	100	5	8
2.	800	150	6	8
3.	800	200	7	10
4.	800	250	8	10
5.	1200	100	6	10
6.	1200	150	5	10
7.	1200	200	8	8
8.	1200	250	7	8
9.	1600	100	7	8
10.	1600	150	8	8
11.	1600	200	5	10
12.	1600	250	6	10
13.	2000	100	8	10
14.	2000	150	7	10
15.	2000	200	6	8
16.	2000	250	5	8

Table 2.3: Experimental Data

Sl. No.	Torque (N-m)	Thrust (N)	R_a (μ-m)	F_{in}	F_{out}
1	2.943	0.99081	5.098	1.1772395	1.172444785
2	6.867	1.14777	5.036	1.1881515	1.177239452
3	10.4967	1.15758	8.901667	1.2097903	1.175348039
4	17.7561	1.51074	11.30967	1.1709568	1.193944732
5	10.3986	0.81423	5.453	1.1791573	1.198997318
6	13.6359	0.84366	4.816667	1.259549	1.297853424
7	7.9461	1.40283	3.272667	1.1963851	1.109518919
8	13.6359	1.57941	4.471	1.2203253	1.186828785
9	3.7278	0.74556	6.282333	1.1867957	1.196385052
10	1.2753	0.93195	7.266333	1.1282016	1.061241587
11	7.7499	0.96138	8.732333	1.2403968	1.198309532
12	7.4556	0.86328	5.244333	1.251904	1.220927131
13	16.9713	0.42183	10.56633	1.2748655	1.216959131
14	10.4967	0.48069	8.170667	1.1973572	1.159052785
15	3.8259	0.87309	4.725	1.1868288	1.220325318
16	12.8511	1.03986	6.964667	1.2059744	1.206933318

Table 2.4: Normalized Decision Matrix

Sl. No.	Torque	Thrust	R_a	F_{in}	F_{out}
1	0.070683392	0.23956731	0.18167812	0.244206972	0.246715508
2	0.164927914	0.27751857	0.17946862	0.246470561	0.247724441
3	0.252104097	0.27989053	0.31722991	0.250959327	0.247326434
4	0.426456464	0.36528086	0.40304424	0.242903693	0.251239704
5	0.249747984	0.19687215	0.1943293	0.244604815	0.252302911
6	0.327499715	0.20398801	0.17165222	0.261281293	0.273105028
7	0.190845158	0.33918937	0.11662848	0.248178542	0.233474128
8	0.327499715	0.38188453	0.15933363	0.253144719	0.249742308
9	0.089532296	0.18026847	0.22388435	0.246189327	0.251753216

10	0.03062947	0.22533559	0.25895129	0.234034539	0.223315213
11	0.186132932	0.23245145	0.31119534	0.257308351	0.252158181
12	0.179064592	0.20873192	0.18689301	0.259695409	0.256917563
13	0.407607559	0.10199401	0.37655374	0.264458549	0.256082584
14	0.252104097	0.11622573	0.29117917	0.248380207	0.243897452
15	0.091888409	0.21110387	0.16838547	0.246196186	0.256790924
16	0.308650811	0.25142708	0.24820078	0.250167756	0.253972869
Weightage	0.2	0.2	0.2	0.2	0.2

Table 2.5: Weighted Normalized Matrix

Sl. No.	Torque	Thrust	R_a	F_{in}	F_{out}
1	0.014136678	0.047913463	0.036335624	0.04884139	0.0493431
2	0.032985583	0.055503714	0.035893723	0.04929411	0.04954489
3	0.050420819	0.055978105	0.063445983	0.05019187	0.04946529
4	0.085291293	0.073056171	0.080608849	0.04858074	0.05024794
5	0.049949597	0.03937443	0.03886586	0.04892096	0.05046058
6	0.065499943	0.040797602	0.034330443	0.05225626	0.05462101
7	0.038169032	0.067837873	0.023325696	0.04963571	0.04669483
8	0.065499943	0.076376906	0.031866727	0.05062894	0.04994846
9	0.017906459	0.036053695	0.044776871	0.04923787	0.05035064
10	0.006125894	0.045067119	0.051790259	0.04680691	0.04466304
11	0.037226586	0.046490291	0.062239067	0.05146167	0.05043164
12	0.035812918	0.041746383	0.037378601	0.05193908	0.05138351
13	0.081521512	0.020398801	0.075310747	0.05289171	0.05121652
14	0.050420819	0.023245145	0.058235834	0.04967604	0.04877949
15	0.018377682	0.042220774	0.033677093	0.04923924	0.05135818
16	0.061730162	0.050285416	0.049640157	0.05003355	0.05079457

Table 2.6: Positive Ideal Solution and Negative Ideal Solution

	Torque	Thrust	R_a	F_{in}	F_{out}
A+	0.006125894	0.020398801	0.023325696	0.04680691	0.04466304
A-	0.085291293	0.076376906	0.080608849	0.05289171	0.05462101

Table 2.7: Conflict between each alternative and the positive and the negative ideal solution

Sl. No.	$Cos\,\theta^{+}$	$Cos\,\theta^{-}$
1.	0.956784401	0.88288183
2.	0.913967031	0.941753645
3.	0.85893116	0.987059298
4.	0.75420841	0.999410383
5.	0.889306762	0.964534138
6.	0.84795811	0.953349907
7.	0.860547359	0.916868942
8.	0.7970471	0.956446437
9.	0.965862544	0.897162582
10.	0.933085585	0.866712618
11.	0.901531141	0.962307259
12.	0.937588695	0.940829538
13.	0.766488592	0.939852085
14.	0.867479458	0.94743711
15.	0.968353392	0.888921559
16.	0.845382672	0.986782609

Table 2.8: Overall Performance Index (OPI)

Sl. No.	OPI by TOPSIS	OPI by Deng's Similarity Method
1.	0.735714028	0.705737476
2.	0.609318215	0.682315862
3.	0.388134092	0.658213474
4.	0.059093032	0.625483138
5.	0.567107	0.671103732
6.	0.487739182	0.663120971
7.	0.567172173	0.675022134
8.	0.391085254	0.648413601
9.	0.744386219	0.704364506
10.	0.706415709	0.704365556
11.	0.512669447	0.67461764
12.	0.649762985	0.688031776
13.	0.380252326	0.643475641
14.	0.544262978	0.6695644
15.	0.760079881	0.706816501
16.	0.406552098	0.654691051

Table 2.9: Corresponding S/N Ratios (of OPIs) and Predicted S/N Ratios

Sl. No.	TOPSIS	Deng's Similarity Method	Predicted S/N Ratio (TOPSIS)	Predicted S/N Ratio (Deng's Similarity Method)
1.	-2.665819266	-3.027136405	2.57546	-2.76218
2.	-4.303116778	-3.320290647		
3.	-8.220364172	-3.632664631		
4.	-24.56927458	-4.075687874		
5.	-4.926699846	-3.464206925		
6.	-6.23624708	-3.568144746		

7.	-4.925701694	-3.413639726		
8.	-8.154571168	-3.762957687		
9.	-2.564033512	-3.044050735		
10.	-3.018793036	-3.044037795		
11.	-5.803251274	-3.418846144		
12.	-3.744900657	-3.247830082		
13.	-8.398562404	-3.829357779		
14.	-5.283824123	-3.484152901		
15.	-2.382815263	-3.013866409		
16.	-7.817675863	-3.679271905		

Table 3.1: Domain of Experiments

Factors	Unit	Level 1	Level 2	Level 3
Spindle Speed (N)	RPM	500	750	1000
Feed rate (f)	mm/min	50	100	150
Drill diameter (D)	mm	5	6	8

Table 3.2: Design of Experiments

Sr. No.	Speed (RPM)	Feed (rev/mm)	Diameter (mm)
1	500	50	5
2	500	100	6
3	500	150	8
4	750	50	6
5	750	100	8
6	750	150	5
7	1000	50	8
8	1000	100	5
9	1000	150	6

Table 3.3: Experimental Data

Sl. No.	Thrust force (N)	Torque (Nm)	Circularity (in)	Circularity (out)
1.	1.5092	2.45	0.899563319	0.92139738
2.	3.136	2.4206	0.925190311	0.914893617
3.	3.6162	6.664	0.9269264	0.910740691
4.	4.116	1.8718	0.893270188	0.923538073
5.	2.499	6.272	0.969112282	0.969411255
6.	3.6848	6.86	0.894751739	0.941456307
7.	2.254	7.938	0.9328	0.89528
8.	2.1364	6.958	0.95610766	0.989500022
9.	2.0482	2.254	0.882489704	0.941998336

Table 3.4: Normalization of Experimental Data

Sl. No.	Thrust force	Torque	Circularity (in)	Circularity out
Ideal	1	1	1	1
1.	1	0.904684976	0.197101	0.277196
2.	0.37593985	0.909531502	0.49295	0.208168
3.	0.191729323	0.210016155	0.512992	0.164091
4.	0	1	0.124451	0.299916
5.	0.620300752	0.274636511	1.00000	0.786789
6.	0.165413534	0.177705977	0.141555	0.49009
7.	0.714285714	0	0.580799	0
8.	0.759398496	0.161550889	0.849873	1
9.	0.793233083	0.936995153	0	0.495843

Table 3.5: Eigen value, Eigen vector, AP and CAP

	PC1	PC2	PC3	PC4
Eigen value	1.8911	1.0644	0.7134	0.0657
Eigen vector	$\begin{vmatrix} -0.262 \\ 0.531 \\ 0.645 \\ 0.482 \end{vmatrix}$	$\begin{vmatrix} 0.777 \\ 0.508 \\ 0.152 \\ -0.340 \end{vmatrix}$	$\begin{vmatrix} 0.559 \\ -0.322 \\ -0.076 \\ 0.760 \end{vmatrix}$	$\begin{vmatrix} -0.126 \\ .0.597 \\ -0.745 \\ 0.271 \end{vmatrix}$
AP	0.473	0.266	0.178	0.083
CAP	0.473	0.739	0.917	1.000

Table 3.6: Major Principal Components for L_9 experimental run

Sl. No.	PC1	PC2	PC3
Ideal	1.396	1.097	0.921
1.	0.479126	1.172293	0.46338
2.	0.802755	0.758298	0.038025
3.	0.471257	0.277846	0.125274
4.	0.75583	0.424945	-0.10352
5.	1.007548	0.505981	0.780275
6.	0.37855	0.073687	0.396955
7.	0.187473	0.643281	0.355145
8.	0.916989	0.461301	1.067894
9.	0.528712	0.923748	0.518546

Table 3.7: Quality loss (Δ_{ok})

Sl. No.	Δ_{01}	Δ_{02}	Δ_{03}
1.	0.916874	0.075293	0.45762
2.	0.593245	0.338702	0.882975
3.	0.924743	0.819154	0.795726
4.	0.64017	0.672055	1.024522
5.	0.388452	0.591019	0.140725
6.	1.01745	1.023313	0.524045

7.	1.208527	0.453719	0.565855
8.	0.479011	0.635699	0.146894
9.	0.867288	0.173252	0.402454

Table 3.8: Individual grey coefficients (γ_{ij})

Sl. No.	γ_1	γ_2	γ_3
1.	0.916874	0.075293	0.45762
2.	0.593245	0.338702	0.882975
3.	0.924743	0.819154	0.795726
4.	0.64017	0.672055	1.024522
5.	0.388452	0.591019	0.140725
6.	1.01745	1.023313	0.524045
7.	1.208527	0.453719	0.565855
8.	0.479011	0.635699	0.146894
9.	0.867288	0.173252	0.402454

Table 3.9: Over all Grey coefficient (R_i), Corresponding S/N ratio and Predicted S/N ratio

Sl. No.	R_i	SNRA1	PSNRA1
1.	0.775293	-2.21068	-1.34604
2.	0.662411	-3.57745	
3.	0.529844	-5.51704	
4.	0.572828	-4.83951	
5.	0.844098	-1.47214	
6.	0.541545	-5.32731	
7.	0.587097	-4.62580	
8.	0.806204	-1.87111	
9.	0.748483	-2.51636	

Table 3.10: Corresponding S/N ratio of experimental data

Sl. No.	Thrust force	Torque	Circularity (in)	Circularity (out)
1.	-3.574935931	-7.783321687	-0.919365237	-0.71106054
2.	-9.92752108	-7.678460579	-0.67537848	-0.772588047
3.	-11.16504884	-16.47469977	-0.659094969	-0.812105183
4.	-12.28950732	-5.445188859	-0.980343198	-0.69090392
5.	-7.955325123	-15.94812099	-0.272518048	-0.269838847
6.	-11.32827841	-16.72648231	-0.965948977	-0.523996616
7.	-7.059078234	-17.99422189	-0.604229252	-0.960822345
8.	-6.593651386	-16.84968849	-0.389864048	-0.091683836
9.	-6.227447236	-7.059078234	-1.085807056	-0.518997287

Table 3.11: Normalized S/N ratio

Sl. No.	Thrust force	Torque	Circularity (in)	Circularity (out)
1.	0	0.18632	0.795347	0.712633
2.	0.728961284	0.177964	0.495347	0.783424
3.	0.87096801	0.878913	0.475325	0.828891
4.	1	0	0.870324	0.689441
5.	0.502651134	0.836952	0	0.204979
6.	0.889698659	0.898977	0.852625	0.497404
7.	0.399806502	1	0.407864	1
8.	0.346398614	0.908795	0.144286	0
9.	0.304376565	0.128607	1	0.491652

Table 3.12: Individual Grey Coefficient

Sl. No.	Thrust force	Torque	Circularity (in)	Circularity (out)
1.	0.333333	0.38061	0.709569375	0.63502781
2.	0.648476	0.378204	0.497684374	0.697762967
3.	0.794872	0.80504	0.487959786	0.745035787
4.	1	0.333333	0.794059488	0.616858558
5.	0.501329	0.754093	0.333333333	0.38609408
6.	0.819267	0.831915	0.772350444	0.498705251
7.	0.454466	1	0.457818386	1
8.	0.433425	0.84573	0.368809278	0.333333333
9.	0.418192	0.364593	1	0.495860423

Table 3.13: Weighted Normalized matrix (TOPSIS)

Sl. No.	Thrust force	Torque	Circularity (in)	Circularity (out)
1.	0.083333	0.095152531	0.177392344	0.15875695
2.	0.162119	0.094551107	0.124421093	0.17444074
3.	0.198718	0.201260117	0.121989946	0.18625895
4.	0.25	0.083333333	0.198514872	0.15421464
5.	0.125332	0.188523165	0.083333333	0.09652352
6.	0.204817	0.207978768	0.193087611	0.12467631
7.	0.113616	0.25	0.114454597	0.25
8.	0.108356	0.211432616	0.092202319	0.08333333
9.	0.104548	0.091148176	0.25	0.12396511

Table 3.14: Positive and negative ideal solution

	Thrust force	Torque	Circularity (in)	Circularity out
A^+	0.083333	0.083333333	0.198514872	0.25
A^-	0.25	0.25	0.083333333	0.08333333

Table 3.15: Separation Distance

Sr. No.	S^+	S^-
1	0.094399	0.257471
2	0.132409	0.204637
3	0.192716	0.130742
4	0.192231	0.214636
5	0.222824	0.139626
6	0.214547	0.132524
7	0.189106	0.217593
8	0.236888	0.147068
9	0.13801	0.275352

Table 3.16: Overall Performance Index (OPI) and Predicted S/N Ratio

Sl. No.	D_i	S/N ratio of OPI	Predicted S/N Ratio
1.	0.731722225	-2.71308	-1.91904
2.	0.607148551	-4.33410	
3.	0.404200955	-7.86805	
4.	0.527534356	-5.55499	
5.	0.385228113	-8.28564	
6.	0.381835493	-8.36247	
7.	0.535022829	-5.43255	
8.	0.383034125	-8.33525	
9.	0.666128944	-3.52883	

Fig. 2.3: GFRP epoxy work pieces after machining

Fig. 2.4: Drill bits $(\phi 8, \phi 10)$ used during experimentation

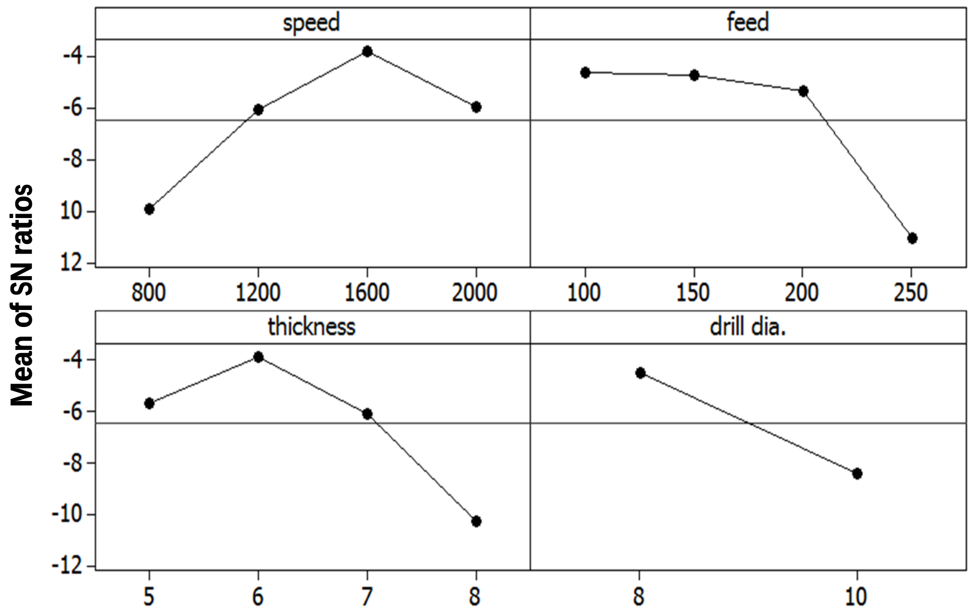

Fig. 2.5: Evaluation of optimal parametric combination by using TOPSIS based Taguchi method $\left(N_{1600}\, f_{100} t_6 d_8\right)$

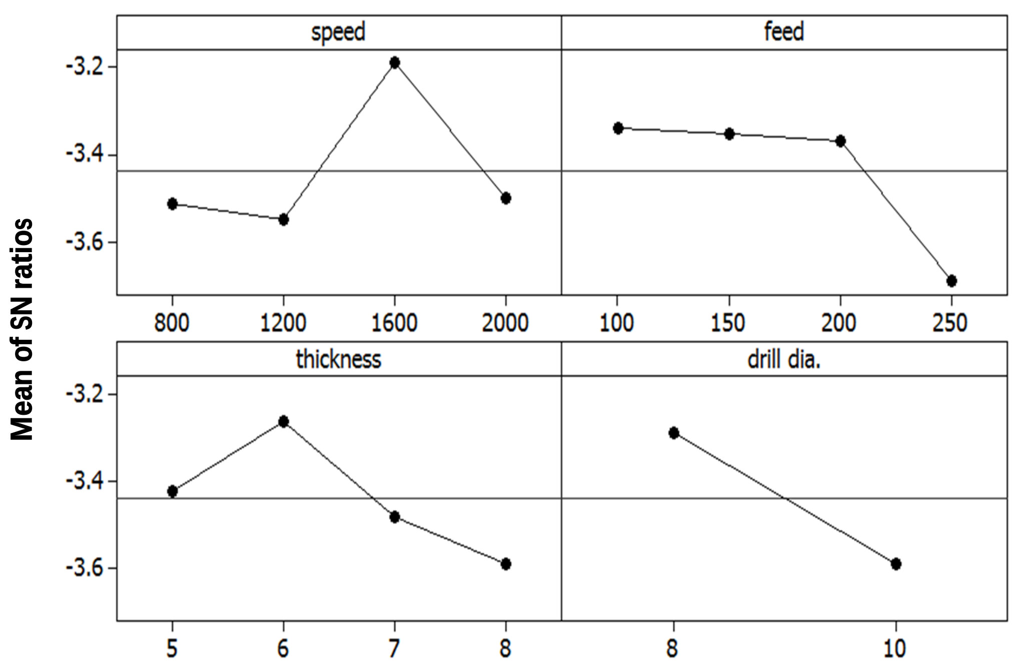

Fig. 2.6: Evaluation of optimal parametric combination by using Deng's Similarity Based Method in conjugation with Taguchi approach $\left(N_{1600}\, f_{100} t_6 d_8\right)$

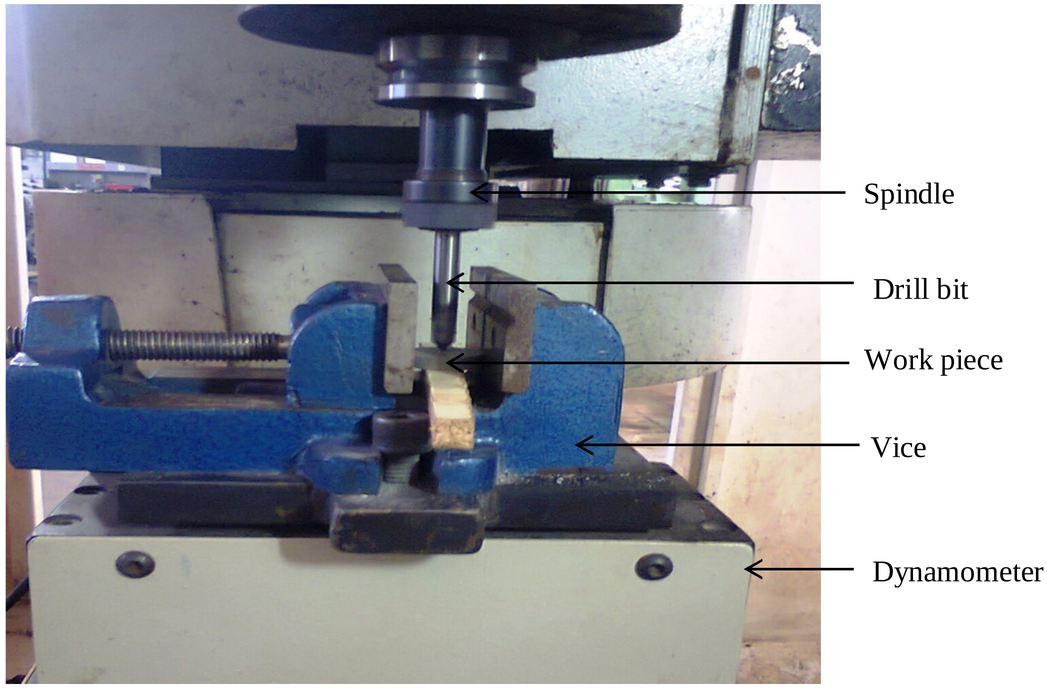

Fig. 3.1: Experimental setup for drilling of Al20%SiCp Composite

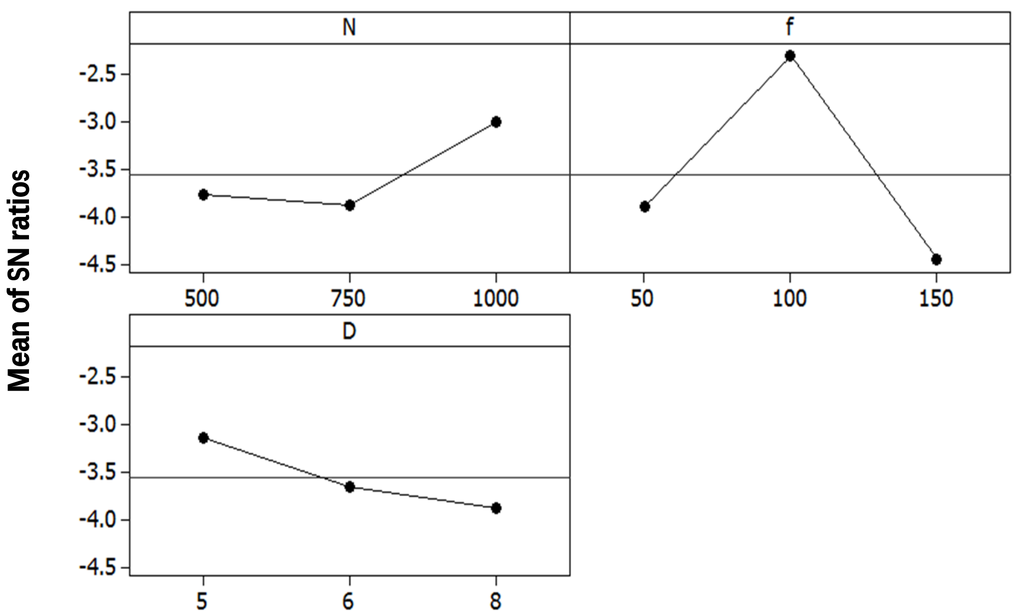

Fig. 3.2: Evaluation of optimal parametric combination by PCA-Grey integrated with Taguchi methodology

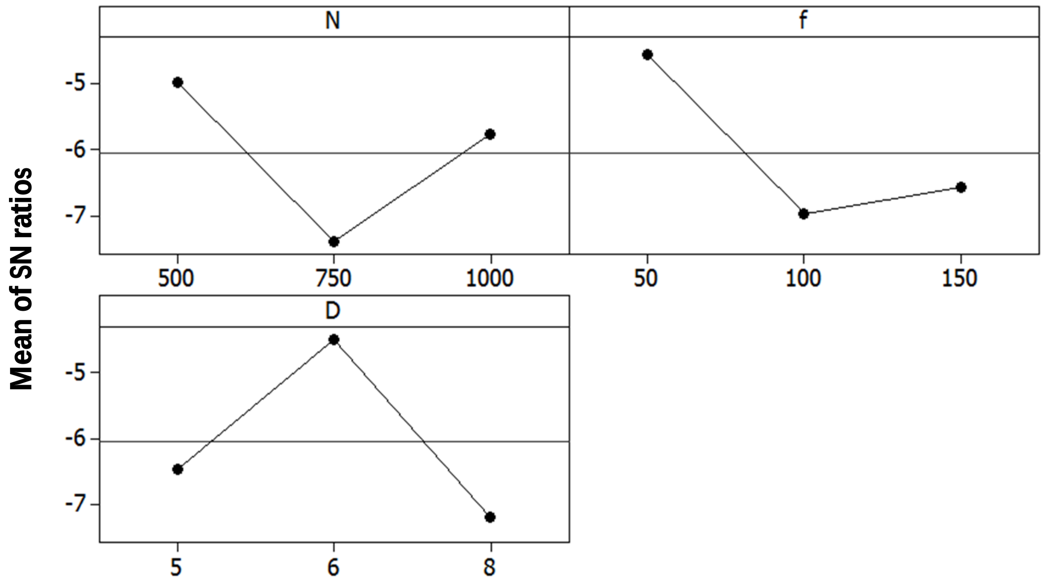

Fig. 3.3: Evaluation of optimal parametric combination by Grey -TOPSIS integrated with Taguchi methodology

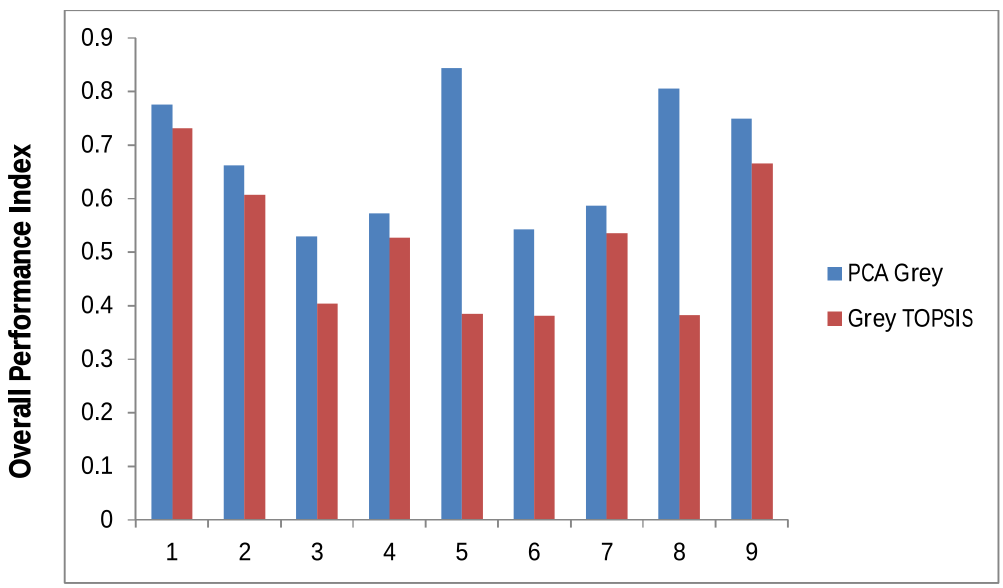

Fig. 3.4: Graphical comparison between PCA-Grey and Grey-TOPSIS integrated with Taguchi method on basis of OPIs

List of Publications

1. **Vikas Sonkar,** Kumar Abhishek, Saurav Datta, Siba Sankar Mahapatra, "*Multi-Objective Optimization in Drilling of GFRP Composites: A Degree of Similarity Approach*", **International Conference on Materials Processing and Characterisation (ICMPC 2014),** organized by Department of Mechanical Engineering, **Gokaraju Rangaraju Institute of Engineering and Technology, Hyderabad, Andhra Pradesh (India)**.

2. **Vikas Sonkar**, Kumar Abhishek, Saurav Datta, Siba Sankar Mahapatra, "*Optimization in drilling of Al-20%SiCp Composites by using Grey TOPSIS*", **International Mechanical Engineering Congress (IMEC 2014)**, June 13-15, 2014, organized by Department of Mechanical Engineering, **National Institute of Technology, Tiruchirappalli, Tamil Nadu (India).**

3. Kumar Abhishek, **Vikas Sonkar,** Saurav Datta, Siba Sankar Mahapatra, "*Optimization in drilling of MMC Composites: A case research*", **Recent Advances in Manufacturing (RAM- 2014)**, 26-28 June, 2014, organized by Department of organized by Department of Mechanical Engineering, **National Institute of Technology, Surat, Gujarat (India)**. **(Under Review)**