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"Application of Statistical and Metaheuristic Techniques with SEM in Abrasive Waterjet Machining of Composite Materials: A Review"

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Abstract: In the era of algorithm-based technologies, researcher explores the scope of optimization of complex real world problems. Abrasive water jet (AWJ) is one of the advance machining processes to cut engineering materials; metals, alloys, and composites, even AWJ machining process can cut hard to machine materials satisfactorily. Recent trends shows augmentation in developments of various types of composite materials. Feature of high strength to weight ratio in composite materials makes it more significant in diversified industries mainly involves defense, aerospace, automobile and sport equipment making industries. Literature provides extensive application of AWJ for cutting, milling, drilling, slotting and turning of composite materials. Real world problems with two or more conflicting objectives requires endeavor to achieve best solutions from the search space of the problem. The paper consolidates study of both statistical and metaheuristic techniques and its applications in complex machining mechanism of composite materials by AWJ in lucid manner. The intrinsic problem in machining of composite materials are structural inaccuracy, delamination, kerf taper and fiber pull out. The paper covers the systematic study of these issues using scanning electron microscopy (SEM).

The paper is worthwhile to the researcher for perceiving various MOO techniques employed so far to solve issues in cut surface of composite material by AWJM. The paper may sensitize the researcher to evolve robust optimisation algorithm to mitigate surface roughness, material removal rate, depth of cut, kerf characteristics and the delamination simultaneously in composite materials as it becomes prime requirements in said industrial application of composite materials.

Keywords*: Abrasive water jet (AWJ), Composite materials, statistical techniques, metaheuristic techniques, scanning electron microscopy (SEM), Multi objective optimization techniques.*

Abbreviations	
ABC	Artificial bee colony
AWJ	Abrasive water jet
AI	Artificial Intelligence
ANN	Artificial neural network
AWJM	Abrasive water jet machining
AFR	Abrasive flow rate
ANOVA	Analysis of variance
APC	Abrasive particle contamination
CMC	Ceramic matrix composite
DOC	Depth of cut
DEAR	Data Envelopment Analysis based Ranking
EA	Evolutionary Algorithms

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EDM	Electrical Discharge Machining
GWO	Grey wolf optimizer
GEP	Genetic expression programming
GRA	Grey relational analysis
GA	Genetic Algorithm
GFRP	Glass fiber reinforced plastic
HAZ	Heat Affected Zone
LBM	Laser Beam Machining
MOO	Multi objective optimization
MOORA	Multi-objective Optimization by Ratio Analysis
MOPSO	Multi objective particle swarm optimization
MRR	Material removal rate
MMC	Metal matrix composites
NSGA-II	Non-dominated sorting genetic algorithm II
PSO	Particle Swarm Optimization
PRMMC	Particle Reinforced Metal Matrix Composite
REPTree	Reduced Error Pruning Tree
RSM	Response surface methodology
SVM	Support vector machine
SEM	Scanning Electron Microscopy
SOD	Stand-off distance
SA	Simulated Annealing
TLBO	Teaching–learning-based optimization
TOPSIS	Technique for order of preference by similarity to Ideal solution
USM	Ultrasonic Machining
WCMFO	Water Cycle and Moth-Flame Optimization
Kt	Kerf Taper
Kb	Kerf width
ϴ	Nozzle angle
P	Pressure of jet water
Ra	Surface roughness
TR	Traverse rate
t	Thickness
T	Temperature

The review paper is designed in five different sections:

Section-I represents introduction to AWJ, its importance in machining of composite materials and optimizing response parameters using multiobjective optimization techniques.

Section-II contains introduction to statistical conventional multiobjective optimization techniques and its application in AWJM of composite.

Section III describes role of advanced multiobjective optimization techniques and its research work performed so far in AWJM of composite

Section-IV represents introduction to scanning electron microscopy (SEM) and work performed by SEM in field of AWJM of composite materials. Concluding remarks and scope of the paper is in the last section.

1. INTRODUCTION

Abrasive water jet machine utilizes flow of mixer of water and abrasive particles at very high speed to machine various kind of ductile and brittle materials. AWJM puts back not only conventional machining process of the materials which are not easy to machine due to their mechanical properties but also unconventional machining viz. Ultrasonic Machining (USM), Laser Beam Machining(LBM) and Electro Discharge Machining(EDM), which have comparatively more machining time including impairment of the cut surface of the material. AWJM is reasonable for cutting of composites materials. **(Momber & Kovacevic, 1998; Rajyalakshmi & Suresh Babu, 2016)** Abrasive waterjet (AWJ) is a well-disposed machining process for difficult-to-machine materials**(Nguyen & Wang, 2019)**.All machining processes have features for which engineers, researcher and other users select them as per their requirements. kerf width on cut surface and quick machining process are common features in AWJM and its far better than other unconventional machining **(S. Kumar et al., 2017).** For preparing micro sized holes and channels, in metals, alloys and composites, AWJM is appropriatre choice as strengthening of cut material is comparatively more than in conventional peening techniques**(Natarajan et al., 2020).** Machining intricate shape in difficult to cut materials in field of medical instruments making, precise mechanical component making, automotive and aerospace industries water jet machining is excellent choice**(X. Liu et al., 2019)**.

Nevertheless, AWJM is suitable for most of the machining engineering materials it renders few cons viz. undesirable taper, striation effect ,heat near to zone of primary contact, reduction in quality of abrasive for reuse and essential to optimize quality of cut surface of composite materials for improving mechanical properties of composites. These cons restrict the use of AWJ machining process**(CIOFU et al., 2019; S. Kumar et al., 2017; Natarajan et al., 2020).**

1.1 Importance of Composites

Composites are combination of two or more than two elements, which are chemically distinct, combined intentionally at macroscopic level to fulfill engineering application**.** Fiber elements deliberately reinforced and oriented in matrix element to achieve desire mechanical properties. Many types of composite materials are available based on different orientation of fibers, types of fiber and matrix. Composite materials are becoming famous since last two decades in very huge field of applications.**(Kulekci, 2002)** suggested that advanced composite materials are becoming more applicable for industries of aircraft, automobile as well as sport equipments. In addition to this usage of application of various composites for making wire glass, laminated glass, optic glass and magnetic materials, which are useful in aircraft, automobile, electronics, medical and manufacturing industries wherein composites are useful. For above reasons it is essential to improve the process parameter using optimization**(Llanto et al., 2021)**.On the other side machining of composite materials using conventional process leads to delamination, removal of fiber, breaking of matrix, heat affected zone (HAZ) in cut surface and tool wear are the dominant difficulties**(Sun et al., 2018).** Developments in composite materials and its applications represents significant need of composite materials in various field of applications.

1.2 importance of AWJM of composite

Review of many literatures revels that AWJ is convenient choice for machining of composite materials.**(Kulekci, 2002)** proved that nonmetal fiber composite materials are difficult to cut due to its structural characteristics but AWJ for machining such materials provides unaffected tool wear compare to conventional machining process. Metal fiber composite cutting in conventional machining process is also not suitable as it offers more noise and dust unlike in AWJM.**(R. Pahuja et al., 2014)** showed cutting of graphene, reinforced titanium (Ti-Gr) composite using AWJM provides surface roughness similar to the cut surface using grinding. Machining of Particle Reinforced Metal Matrix Composites (PRMMCs), Kevlar reinforced composites and Polymer Matrix composites with the help of AWJ showed good experimental results compared to conventional machining**(K.Siva Prasad, 2017).**Tool wear and too life problem during turning operation of metal matrix composites (MMC) can easily solved by AWJ turning**(R Patel & Dr S Srinivas, 2017).** Issue of burr formation and delamination in cut surface of glass fiber reinforced plastic (GFRP) found minimum in water jet machining comparatively**(Abdullah et al., 2019)**.**(Du et al., 2019)** depicted that Cutting of composite materials using unconventional machining provides excellent results over conventional machining. **(H. T. P. Liu, 2020)** represented research papers related to machining of composite in two parts. In second parts of the paper. He deduced that AWJM is suitable for the metals and composites used in aerospace due to cost economy, better machining power and lack of HAZ. According to **(Azmi & Hashim, 2020)**AWJM is more advantageous over LBM, EDM and USM when depth of workpiece is concerned.

1.3 Importance of metaheuristic techniques

When more than one conflicting objectives are to be optimized, Multi objective optimization techniques presents ground for choosing best of them. Multi objective optimization of process parameters is essential in manufacturing industries as values of many parameters like MRR, DOC, production rate expected to be at high extent where on the other hand values of surface roughness, striation marks, kerf width, delamination, fiber pull out, cost of machining desired to be at low extent to achieve satisfactory machining performance in AWJ.

Many literatures available for classical optimization tools and advance optimization tools for the problems to achieve best value of process parameters in AWJ. Conventional optimization tool may not operate efficiently to solve real world problem due to following reasons:

1. Chance of being stuck into local optimum solution rather than global solution in search space.
2. Integer variables sometimes difficult to optimize.
3. Discrete/ discontinuous function is difficult to solve in gradient search method
4. Parallel computing may not possible.
5. Lack of Robust algorithm to solve various type of problem is

(Cui et al., 2017; Debroy & Chakraborty, 2013) Reported limitations of conventional optimization methods a) Optimization is limited to single objective only. b) It may stuck into local best solution and difficult to break away from it. c) In each iteration only one solution is made. d) Accuracy of the solution is dependent on input values. e) Confined application region. The moment when classical optimization fails to solve complex real world problems, one can see the manner by which nature has already solved similar type of problem and can copy the behaviour of the nature in artificial way to solve such problems. In last few years, there are developments in advance searching and optimization techniques to overcome the said problems in conventional techniques. These newly developing techniques proved their usefulness in optimization of problem. Many researcher have integrated both conventional and advance multiobjective optimization together to take the advantages of both simultaneously. Figure 1. Depicts overview of classification of multiobjective optimization.

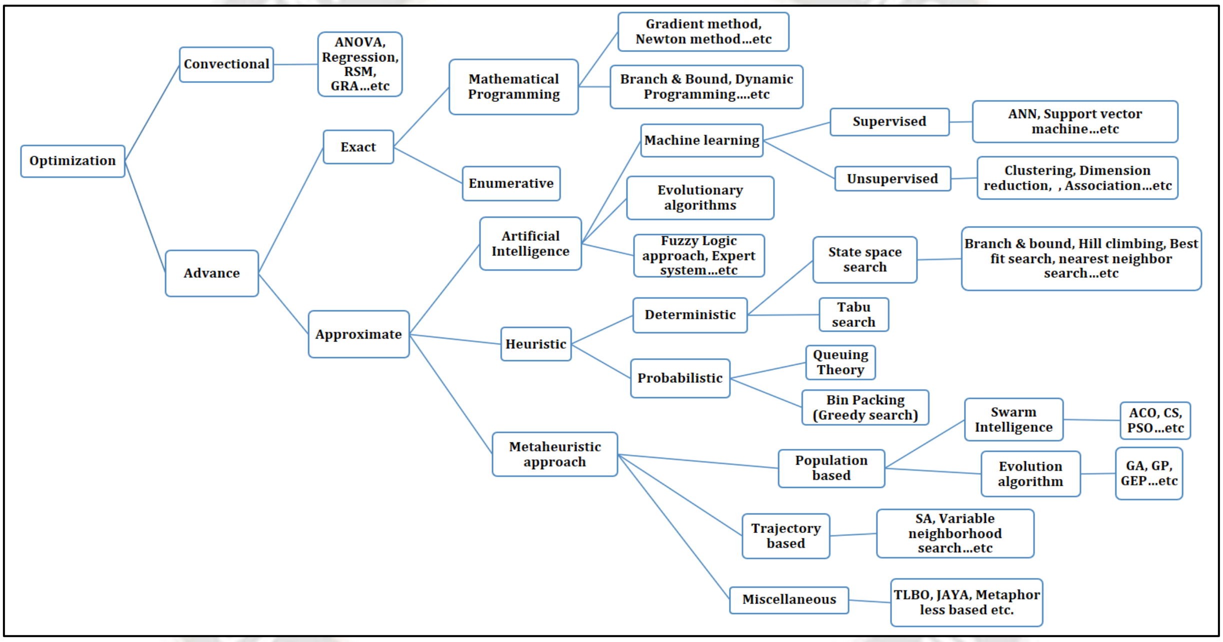

Figure 1. Taxonomy of multiobjective optimisation techniques

It is required to analyse the data using modeling and optimisation to study the nature of the system. **(Duspara et al., 2019)** recommended parametric optimization to control 20%-70% of the total cutting cost in AWJM.

Metaheuristics techniques is being well recognized by researchers due to its salient features. Multi objective optimization finds best global solution without degradation of one-another objective solution while fixing/ correcting the solutions. Most of the newly developed. Metaheuristic techniques can solve most of the optimization problems. These computer aided and customized metaheuristic techniques provides a tool for solving complex engineering problems irrespective of static and dynamic behaviour of the problem. In real world problem there is a need of finding solution of multi objective problem. Metaheuristics techniques for optimization of complex problems is significantly powerful than non-metaheuristic techniques**(Johari et al., 2013)**.

(Desale et al., 2015) reveled concept of heuristic and metaheuristic approach. Heuristic algorithm provides nearly approximate solution to the problems. With the aid of artificial intelligence (AI) and mathematical models, heuristic algorithms solve complex problem faster than classical technique for optimization. As capacity to solve complex real world problem using computer increases the requirement of advance algorithm. Metaheuristic algorithm is an advance version of heuristic algorithm in which searching is carried out irrespective of problem definitions to get near optimum solution through iteration process.

As per the suggestion given by **(Mohd Adnan et al., 2011),** AI yields many methods like Fuzzy logic, Neural Network etc. These are combined togateher to enhance performance of both techniques to solve complex problems in indusries.

(M. R. H. Mohd Adnan, Azlan Mohd Zain, 2013) depicted that AI provides exact prediction for surface roughness and tool wear, which is far better than prediction by non-AI techniques.

(Mirjalili et al., 2014) commneted that it is not possible to do all optimization using only single Meta heuristic technique. One technique may good for particular problem optimization but for other optimization problem it may not so.

(N Riquelme et al., 2015) proved that evolutionary algorithms provides approximate solution of multi-objective optimization of problem in which objective functions are adverse in nature to one another. There are many performance metrics for proper selection of MOO technique suitable for specific problem. Most dominant among them are Hypervolume, generational distance, epsilon indicator and inverted generational distance.

(Weichert et al., 2019) informed about importance of machine learning in problem optimization due to special characteristics of generation and exploration of pattern from the input data,

Justification of making review paper

State of art in review papers were found in field of AWJM of various engineering materials were since last few years. **(Syazwani et al., 2016)** made review paper on research work performed to analyse nozzle wear in AWJM process Review papers based on developments in AWJM and its application are available**(X. Liu et al., 2019; Natarajan et al., 2020).**

Few researcher endeavored to make review paper for AWJ machining of composite materials successfully**(Thakur & Singh, 2020; Bañon et al., 2021; Dhanawade et al., 2014; Khan et al., 2021).**

Machining of Ceramic matrix composite (CMC) with the help of AWJ specifically drilling of hole and slotting is acceptable provided optimization of parameters are handy**(Gavalda Diaz et al., 2019).**

This article reports the detailed study of conventional and advance techniques in multiobjective optimisation problems in AWJ machining of composite materials in very distinct manner.

It also describes research work carried out so far to study surface topography of composite materials and to conceive influence of various process parameters by employing SEM analysis

Extensive research work have performed in AWJM of composite materials so far. Following section of the paper illustrates comprehensive study of conventional and advance techniques in multiobjective optimisation as well as SEM analysis in AWJM of composites.

2. RECENT WORK ON AWJM OF COMPOSITE USING STATISTICAL TECHNIQUES

Diversified tools are available in conventional approach to optimize process parameters mainly includes Taguchi, ANOVA, regression analysis and Response surface methodology (RSM). These conventional techniques utilize mathematical process or statistical analysis for problem optimisation.

2.1 Analysis of variance (ANOVA) & Taguchi

Introduction to ANOVA) & Taguchi

Dr. Genichi Taguchi coined the technique called Taguchi method to lower the fluctuations and cost in process using design of experiment. The mean and variance of various input parameters shows process behaviour. Designed table of orthogonal array provides all available combinations of process parameters to find best significant parameter in limited no of experiments by analyzing set of combinations. Taguchi method is more effective for limited number of variables and single objective optimization**(Peter Woolf et al., 1983)**.

Ronald Fisher developed analysis of variance (ANOVA) method. Its widely used conventional method for performing experimental work to determine significance of independent parameters. **(Tabatabaei et al., 2018)** reported that ANOVA provides approximate solution for the selected set of combinations of process parameters by reduction of operational dimensions in domain search space and establish relations of input variables with their influence on output variables by ignoring less influencing variable. MANOVA is modification in ANOVA for multi objective optimization.

Work

Research work in AWJM of composite materials to optimize process parameters using ANOVA and Taguchi methods carried out by various researcher are described as follows:

(Azmir & Ahsan, 2009) have conducted AWJM of glass FRP using two abrasives Granite & Al2o3 to analyse surface finish.

First time (Siddiqui & Shukla, 2010) performed trepanning operation using AWJM of composite made of kevlar epoxy resin to optimize value of surface roughness and kerf taper.

(Thirumalai Kumaran et al., 2015) Worked on AWJM of AA 6351-SiC-B4C Hybrid Composite using various grain size and found that coarse abrasive has a positive influence on the MRR, while the finer abrasive particle produced less kerf angle and surface roughness value.

(R Pahuja M. Ramulu, 2016) done investigation to predict kerf characteristics of Titanium Graphite (Ti-Gr) composite using AWJM and found better result with less impairment of the cut surface.

(Schwartzentruber et al., 2018) analysed cut surface of CFRP by AWJ considering delamination as moisture uptake and concluded that dominating control parameters for delamination are traverse speed, abrasive flow rate and nozzle diameter.

(Balachandar et al., 2018) carried out experiment to cut MMC (Al6061-T6) composite by AWJ and analysed MRR, Ra and kerf deviations. They found rate of abrasive flow and traverse rate very dominant influence.

(Raj & Kanagasabapathy, 2018) have used three different proportion of reinforcement particle of ZrSiO4. They reported amount of ZrSiO4 increases value of width of kerf, taper angle and surface roughness and fine grit size produces lower kerf taper.

(El-Hofy et al., 2018b) proved that AWJM more economical than conventional milling of CFRP.

(Sasikumar et al., 2018) reported AWJM of Al7075 hybrid MMC by changing volume percentage of titanium carbide (TiC) and boron carbide (B4C) for the prediction of DOC and roughness.

(U. A. Kumar, 2019) carried out AWJM of GFRP to identify the effect of process parameter on Kerf width, and kerf taper angle.

(Edriys et al., 2020) achieved complete understanding of the effects of process variables on kerf characteristics, MRR and Ra of CFRP.

(Ramesha et al., 2019) reported Standoff distance (SOD) as a most significant for MRR in AWJM of GFRP. For top and bottom kerf width, grit size and traverse rate are dominant parameter respectively. For surface roughness, traverse rate is the most Significant followed by SOD.

(Karatas et al., 2019) Conducted experimental analysis of drilling of CGRP by AWJ to analyse surface roughness and delamination and showed that delamination has positive influence with SOD and negative effect with pressure.

(Niranjan et al., 2020) determined Ra, DOC in cut surface of AZ91 MMC and observed scratches, microchips and oxidation on cut region.

(Gawade et al., 2020) Performed AWJM of epoxy fiberglass composite to identify influence of Pressure and SOD on Kerf taper and concluded that it increases with SOD and P.

2.2 Grey Relational analysis (GRA)

Introduction to GRA

GRA is also called as Grey Incidence Analysis. GRA involves following steps : a) pre-processing and normalising of raw data b) determine deviation sequence c) determination of grey relational coefficient for response parameters. and d) determination of grey relational grade for response parameters. It gives optimum condition for MOO by assigning weights to individual response parameters. GRA is more effective for Multi objective optimization

(Julong, 1988) coined first time Grey System theory in 1982. The objective of developing Grey System is to integrate science of social and nature together. Grey system is nothing but the information, which is incomplete for solving; unlike regression analysis, functional model is not required in grey system. Irregularity in raw data is converted into regular sequential data for the modelling real data. It provides suitable solution instead of best solution, which can satisfactorily applicable for actual world problems.

According to **(Ng, 1994)** circumstances in which two conditions conflicting in nature but dependent on each other is the root of grey System.

Work

Research work in AWJM of composite materials to optimize process parameters using GRA techniques carried out by various researcher are described as follows

(Dhanawade & Kumar, 2018) have analysed Ra and Kt to optimize of process parameter in AWJM of Carbon epoxy composite.

(Mogul et al., 2019) carried out experiment on controlled depth milling of Ti6Al4V grade five material to predict of DOC.

(Balamurugan et al., 2019) determined optimum vales of Ra, Kɵ and MRR in AWJM of Lanthanum phosphate/Yttria composite using GRA.

(Deepak & Paulo Davim, 2019) conducted experimental investigation to optimize roughness and kerf geometry in AWJM of Glass FRP composite.

(Thakur et al., 2020)insighted study of influence of process parameter on Ra and Kt for AWJ drilling of hybrid carbon/glass laminate.

(Gnanavelbabu et al., 2020) used integrated approach of Grey-RSM to achieve best value of Ra and Kt of AWJ cut surface of AA6061/B4C/hBN MMC.

2.3 Response surface methodology (RSM)

Introduction to RSM

(Myers et al., 1989) In 1951, Box and Wilson develop RSM. It is set of data analysis tool that improve region of control variables with respect to response variables

(Khuri & Mukhopadhyay, 2010) RSM includes systematic procedure as follows; First statistical & mathematical methods help to generate low degree polynomial equation of approximate relationship between control and response parameter. Second, ascertain hypothesis testing whose level of factor is according to control parameters. Last, detection of excellent set value of control parameters to get optimum response value.

Work

Novel AWJ drilling with threaded nozzle was performed by **(Balasubramanian & Madhu, 2019)** and concluded that pressure and SOD are significant parameters to mitigate delamination and Ra. Due to threaded nozzle improvement in roughness, top kerf width and bottom kerf width found 52%, 29% and 13% respectively using central composite design in RSM.

(Reddy & Venkatesh, 2019) have done AWJ drilling of glass laminate aluminium reinforced epoxy (GLARE) composite by varying thickness of sheet to analyse surface roughness and delamination.

(P. Kumar & Kant, 2019) carried out AWJM of Kevlar (aramid) epoxy composite for investigating roughness and kerf geometry.

(Selvam et al., 2020) performed experimental work on AWJ drilling of hybrid (Carbon, S- Glass fibers and SiC nano particles)) laminated composites to study influence of process parameter on surface roughness and kerf tape, found low kerf taper due to SiC particles and low value of SOD.

(M. Rajesh et al., 2020) developed RSM model for cut surface of Ti-basalt-flax-Ti metal fiber composites to optimize surface finish and kerf ratio.

(Rajamani et al., 2020) investigated AWJM of madar (Calotropis gigantea) fiber reinforced with nano clay filled polyester for evaluating MRR, Kt and Ra. They observed higher value of mechanical as well as machining properties compare to plain polymer composite due to nano clay.

(Uthayakumar et al., 2020) performed experimental work on AWJM of Geopolymers (fly ash, metakaolin and sand).

(Shanmugam et al., 2020) predicted surface roughness and kerf taper using RSM in surface of Al7075 MMC.

Recently **(Kolli et al., 2021)** identified optimum values of MRR, Kt and Ra of hybrid Al 7075/B4C/Gr composite using single objective optimisation RSM ae well as TOPSIS and found improvement in optimum values by integrating RSM-TOPSIS optimization techniques.

2.4 REGRESSION ANALYSIS

Introduction to Regression analysis

(Sykes, 1993) Regression analysis identifies relationship between control and response parameters using statistical analysis. Degree of confidence level states closeness of estimated relationship between control and response parameters.

Work

first time **(Rishi Pahuja & Mamidala, 2020)** considered wavelet packet transform (WPT) factor to compare surface of CFRP cut by both traditional milling and AWJ milling. Ratio of wavelet packet energy to entropy describes surface quality and its relation with process parameters. The WPT factors suggest influence of process parameters to surface roughness. Roughness of cut surface reduces with increase with pressure and decrease with TR in AWJ machining.

(Mohankumar & Kanthababu, 2020) Developed of semi-empirical model of Buckingham's π theorem to predict the depth of cut (DOC) of unreinforced and reinforced MMC cut by AWJM. They done comparison by varying percentage of B4C in Al6063 and analysis of experimental data using regression model.

(Hussien et al., 2021) Performed regression analysis for surface roughness and kerf angle of CFRP cut by AWJ to check influence of TR and P.

Figure 2. Represents major research work on prevalence of classical optimization techniques in AWJM of composite.

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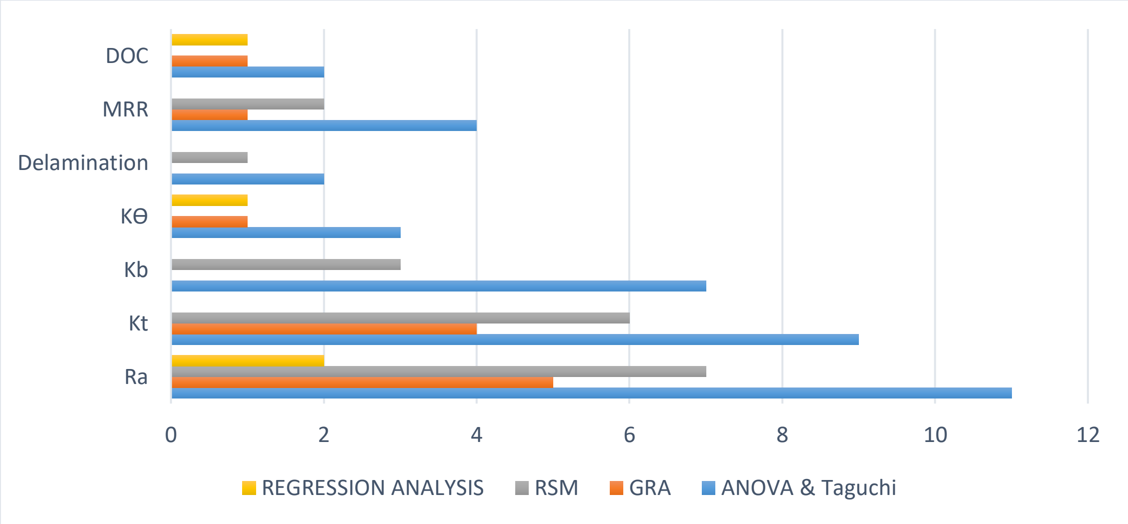

Figure. 2 Prevalence of classical optimization techniques in AWJM of composite

3. RECENT WORK ON AWJM OF COMPOSITE USING ADVANCE MOO TECHNIQUES

In last two decades development in innovations and technologies have imposed researcher to pay attention towards advance multiobjective (vector) optimization techniques for solving complex real world problems. To render significant performance in manufacturing processes it is essential to optimize conflicting parameters using advance techniques and algorithms. Here in the section involves Artificial neural network (ANN), Fuzzy logic, Genetic Algorithm (GA), Non-dominated sorting genetic algorithm II (NSGA-II), Genetic expression programming (GEP). Support vector machine (SVM), Fuzzy approach, Reduced Error Pruning Tree (REPTree), Multi-objective Optimization by Ratio Analysis (MOORA), Metaphor less algorithm, Particle Swarm Optimization (PSO), Grey wolf optimizer (GWO). Water Cycle and Moth-Flame Optimization (WCMFO) and Data Envelopment Analysis based Ranking (DEAR) techniques or in other word, algorithms operated so far in AWJM of composite materials to set optimum values in the machining process are represented.

3.1 Artificial neural network (ANN)

Introduction to ANN

(Sondak & Sondak, 1989) McCulloch and Pitts in 1943 developed a model to analyse neurons of human brain artificially. Neural network was evolved and simulated by Frank Rosenblatt in 1957. Bio neurons are interconnected in parallel and act as a processing unit individually. A system of large number of Bio neurons known as nervous system. Artificial neural network (ANN) is analogous to working principle of nervous system.

(Dongare et al., 2012) ANN is one type of computational algorithm, which mimics human brain consisting many layers of processing units. ANN is made of mainly three layers input layer, hidden layer and output layer. Each processing units gets information from input layer, which performs integration function. Hidden layer containing activation function generates information from previous input layers. The modified information is sent to output layer and estimate error occurred. To achieve desire output, information is sent back to input layer until error is terminated. Supervised or unsupervised learning tools are used to update weight and train the ANN model. This technique is applicable to recognition of pattern, identification and control of system, prediction of data and any more.

Work

Many researcher have performed research work in AWJM for prediction and optimization of process parameters of cutting many materials but a few literature available about AWJM of composite materials.

(Madara et al., 2021) Performed AWJM of Kevlar 49 composite to analyse simultaneous effect of process parameters on optimize surface finish, kerf width and kerf taper and achieved 95 percent more accurate results than ANOVA**.**

3.2 Genetic Algorithm (GA)

Introduction to GA

There are mainly four Evolutionary algorithms viz. genetic algorithms, genetic programming, evolutionary programming and evolutionary strategies. John Holland first coined the Genetic algorithms in 1992.

(Holland, 1992) found that it needs high amount of brain effort and computer programmings to understand unplanned working mechanism of very complex and universal capability of living creatures. Genetic algorithm analogous to Darwin's theory of process selection behaviour of the nature and imitation of it by computer programmings.

(Fonseca et al., 1995) Evolutionary algorithms is a good choice to solve multi objective optimization problems as every individuals pursuit for solving multiple objectives simultaneously and also work well even with complex real world problems. Due to some noticeable parts viz. handling discontinuous, noisy and multi model function evaluations including feasible to disordered space Evolutionary algorithms are dominating others algorithms.

(Chakravarthy & Babu, 2000) investigated that genetic algorithm (GA) combined with fuzzy logic approach is more prominent for selecting optimum set of process parameters in AWJM of any material.

(Sharma, 2013) GA works to find better solution among all solutions in search space. First step in GA is to generate random initial set of population. Followed by encoding of initial population set to genetic string called chromosome. Tournament selection operator picks of the parent solutions for mating according to fitness value.

Reproduction operator and variation operator generate off springs from selected population. Crossover and mutation operators modify offspring solution. Consequently, survival strategy selects best solutions among modified offspring solutions.

Combination of SA-GA techniques improves results with minimum no of iterations for evolution of input variables **(Mohd et al., 2011).**

Work

(Schwartzentruber et al., 2016) concluded that optimum value of delamination using genetic algorithm (GA) is more faster compare to computation fluid dynamics (CFD).

They represented model by adopting genetic algorithm (GA) technique to identify nozzle geometry and machining condition based on abrasive particle energy.

(Azmi & Hashim, 2020) carried out AWJ machining of hybrid MMC of Al7075 made of three different types of reinforcement to achieve best value of kerf width using GA and ascertained minimum top kerf width when volume of reinforced material is more.

3.3 Non-dominated sorting genetic algorithm II (NSGA-II)

Introduction to NSGA-II

(Yusoff et al., 2011)

Non-dominated sorting genetic algorithm II (NSGA-II) is a type of Multi-objectives Genetic Algorithm (MOGA) techniques and extended version of GA in which sorting of data is quicker. In single objective optimization, only one solution is dominant for optimum solution wherein NSGA-II for solving even multi objective problems.

Work

(V. D. P. Rao et al., 2019) done research in AWJM of three different types of composite materials (CFRP, GFRP, CGFR) to predict best value of process parameters for surface finish, Material removal rate and kerf width.

3.4 Genetic expression programming (GEP)

Introduction to GEP

(Kök et al., 2011) genetic expression programming (GEP) is advance version of Genetic programming (GP) wherein encoded entities of linear string of specified length chromosome made of different size and shape representing simple expression tree unlike in GP. At level of chromosome, it uses mutation operators, transportation operators and recombination operators clearly. It can operate multigene to solve complex real world problem divided in subprograms, which makes this technique far better than genetic programming (GP). Transportation operator decodes information beginning from chromosome to expression tree using predefined simple rules. GEP provides user to derive same sequence as in the phenotypes, which is known as Karva code, a type of language for GEP.

WORK

(Kök et al., 2011) analysed machined surface texture of Al7075 alloy composites reinforced with Al2O3 particles cut by AWJM and operated Genetic expression programming (GEP) to predict three surface attributes. Consequently observed that Ra, Rz and mean width of profile (RSm) increased with increasing control variables depth of cut, weight fraction and size particles.

3.5 support vector machine (SVM)

Introduction to SVM

(Vapnik, 1998) In machine learning techniques, support vector machine is one of the type of supervised learning to predict output from given input through training of labelled data set. SVM performs both classification and regression for prediction of data of linear or nonlinear problems. SVM creates parallel hyper planes to separate different class of data ensuring maximum distance between them. The points lies on the hyperplane or boundary is called support vector affects location and orientation of hyper planes. Further, a model is used to measure the distance of unknown sample data in direction of constrained vector.

Support vector machine works based on quadratic programming in which mapping of data into a higher dimensional input space. The solution derived from SVM is independent of input space dimensions. SVM applies various kernel functions like linear, polynomial, spline functions and radial basis function (RBF), sigmoid and Gaussian kernel function to train parameters**(J.A.K.SUYKENS and J. VANDEWALLE, 1999)**.

According to **(Deris et al., 2011),** support vector machine is significant mathematical technique for classification of data, regression analysis, modelling of parameters and data estimation Radial basis function is commonly used kernel function found in parametric modelling of machining.

Work

(S. Rajesh et al., 2021) carried out prediction and modeling to determine influence of control parameter on of surface finish and kerf angle of AWJM of Al- NiTi smart composites by employing hybrid combinations of GRA, Differential evolution (DE), Entropy and SVM techniques and identified 37.8 percent more improvement compare to traditional SVM .

3.6 Fuzzy logic approach

Introduction to Fuzzy logic approach

Researchers have been applying the methodology of fuzzy systems in a wide field of applications. **(GEORGE J. KLIR AND BO YUAN, 1996)** Lotfi Zadeh in 1965 developed the concept fuzzy logic concept, which can handle uncertainty and imprecision in the system using fuzzy inference engine. Affinity of an element to particular class is membership function. Fuzzy inference engine works based on membership function distribution either by linear functions (triangle and trapezoidal) or by nonlinear functions (Gaussian, bell shaped and sigmoid) to determine fuzzy sets of the parameters. Fuzzy expert system involves following steps: 1. Fuzzification (conversion of crisp set into fuzzy set) 2. Determination of membership function based on rule based /data based. 3. Defuzzification (conversion of fuzzy set into crisp set). Fuzzy reasoning is potential tool to solve complex real world problem without extensive mathematical equation to apply in various field of application like fuzzy clustering, fuzzy mathematical programming, fuzzy graph theory etc.

(Singhal et al., 2016) A fuzzy inference system (FIS) applies fuzzy set theory for mapping of input parameters to output parameters by performing fuzzification and defuzzification of the data. Integration of fuzzy system with ANN called ANFIS (adaptive neuro-fuzzy inference system) improves performance of simple fuzzy system. To analyses multi contrary system fuzzy logic system is powerful tool.

(Chakraborty et al., 2018) performed prediction of parameters by hybrid approach of integrating grey relational analysis with fuzzy approach called grey-fuzzy relational grades (GFRG) and operated it to optimize process parameters of both traditional and advance machining processes successfully.

Work

(V. Kumar et al., 2020) performed experimental analysis to prediction of material removal rate, surface finish, and kerf geometry in AWJM of GFRP using Grey relational analysis combined with fuzzy logic called grey-fuzzy relational grades (GFRG) effectively.

(Saravanan et al., 2021) predicted values of surface roughness and kerf width in AWJM of CFRP using fuzzy logic approach.

3.7 Reduced Error Pruning Tree (REPTree)

Introduction to REPTree

(Mohamed et al., 2012) Data mining is the technique to identify irregularities in pattern, classifications and correlations. Decision tree is data mining method in which classification data may not correct to understand the pattern of process due to large size of framed tree. Therefore, solution of the problem is to cut the tree without disturbing accuracy of classification Reduced Error Pruning (REP) tree algorithm is used. REPTree is based on machine learning algorithm called weka (Waikato Environment for Knowledge Analysis). These newly developed classification method can handle intricate tree structure with better accuracy of classification. Best classification algorithms in data mining aims to simple tree structure with great accuracy.

(Vijayaraj et al., 2020) Reduced Error Pruning Tree (REPTree) operates to receive information from origins at various stages of time. The working follows first, development of inference from various trees next to identify best tree to consider as ideal. The algorithm performs pruning to determination of Mean Square Error on tree prediction. This is a fast machine learning decision tree to reduce the error by tree developments. It provides efficient results in various machine-learning algorithms to analyse and simulate complex problems.

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Work

(Vijayaraj et al., 2020) achieved optimum values of material removal rate, surface roughness and Kerf taper in machined surface of AlSi7/SiC composite cut by AWJ. It was found that REPTree has less computational costs due to reduced size of tree.

3.8 Multi-objective Optimization by Ratio Analysis (MOORA)

Introduction to MOORA

(Brauers & Zavadskas, 2006) In MOORA both wanted and unwanted measures are coexistent in ranking. It is applicable for quantitative attributes only. The working involves first normalization of decision matrix containing all alternatives followed by determination of assessment values by multiplying weight criteria to all alternatives and last evaluation of ranking according to assessment values. In process of normalization, dimensionless ratios varies in-between zero to one as ratios are added or subtracted according to wanted or unwanted measures respectively. To provide more weightage to specific objective function substitution of coefficient of importance is necessary.

(Brauers et al., 2008) confirmed the efficiency of MOORA due to many feature viz. fast computational time to solve, simple coding and less mathematical equations.

Work

(Manivannan et al., 2021) performed AWJM of unsaturated polyester composites using 20% Turkey fiber as reinforcement materials to ascertain optimum surface roughness and kerf angle using Multi-objective Optimization by Ratio Analysis (MOORA).

3.9 Metaphor-less optimization

Introduction to Metaphor less algorithm

(R. V. Rao, 2020)

All nature-inspired algorithm requires specific metaphors that are analogous to behaviour of living beings for imitating and simulating them to solve similar type of situation occurred in real world problems. Consequently, metaphor dependent algorithms need to train not only population size and number of iterations but also some parameters according to the nature of the algorithm before using it for optimisation. Metaphor-less algorithms represented as Rao-1, Rao-2 & Rao-3 are simpler and more computationally economical as no need to train any algorithmic dependent parameters. Theses proposed metaphor-less algorithms proved completive to advance metaphor-based algorithms.

Work

(Tripathi et al., 2021) evaluated multi objective optimization of process parameters in AWJM of GFRP to investigate values of MRR, Ra, roundness (Ro), cylindricity (Cy) using metaphor-less algorithms (Rao-1, Rao-2 & Rao-3) and related the result with JAYA & TLBO. Concluded with better result of metaphor-less algorithms.

3.10 Particle Swarm Optimization (PSO)

Introduction to PSO

To solve complex real world problem, **(James Kennedy and Russell Eberhart, 1995)** developed particle swarm optimization metaheuristic algorithm based on nature of swarm of birds searching and beaching the region wherein probability of maximum food and minimum predators available for the survival. Each birds in the swarm follows the survival rule in various locations to search best region identification simultaneously. Optimization of continuous nonlinear functions to search the best region is main quality in PSO algorithm.

(Seixas Gomes de Almeida & Coppo Leite, 2019) PSO is a metaheuristic gradient search based technique converges to optimum objective function within limited number of iterations by imitating swarm of birds for optimization of the problem. Birds are specifically associated with category of creature in which each creatures distribute the information for survival strategy within the group.

Work

(Doğankaya et al., 2020) fabricated ultra-high modulus weight polyethylene (UHMWPE) fiber reinforced polymer composite for different cutting conditions viz. trimming, pocketing, and drilling through AWJ to figure out influence of process parameters on delamination and optimize it using PSO.

3.11 Grey wolf optimizer (GWO)

Introduction to GWO

(Mirjalili et al., 2014) The hunting behaviour of grey wolf inspired to develop algorithm called grey wolf optimizer GWO. Systematical techniques of grey wolves to prey is associated with the ranking based rule of dominance incorporating three important steps for hunting 1. Search for prey 2. Confinement of prey and 3. Striking on prey. Level of dominancy is ranked from alpha, beta, delta and omega to simulate and model the behaviour of grey wolf for hunting. After development of model, it is required to test it using benchmark functions. GWO proved more satisfactory results than other nature inspired algorithms as it doesn't stuck into local optima, better efficiency irrespective of constrained and unconstrained type of problem.

Work

(Chakraborty & Mitra, 2018) reported that due to hierarchical rule for the hunting GWO guides user to not only accumulate best available solutions but also prevent user from stuck into local optima during the process of optimization of the problem. Performance comparison among GWO, SA, GA, and TLBO to optimize of material removal rate and surface roughness depicts result of GWO outperformed other algorithms.

3.12 Water Cycle and Moth-Flame Optimization (WCMFO)

Introduction to WCMFO

(Eskandar et al., 2012) developed novel concept of water cycle algorithm (WCA) adopted the nature of stream of water cycle from river to sea in random manner as well as changing location of stream. They equated outcome of WCA in terms of worst, mean and standard deviation with TLBO and ABC metaheuristic algorithms consequently deduced that WCA can solve different aggregation of problems for the optimization at a cost of less computation.

(Mirjalili, 2015) evolved metaheuristic nature inspired algorithm conceptualized on specific flying behavior of moth in spiral movement called moth-flame optimization (MFO) algorithm. The moth flying linear movement is at specific angle to the moon during absence of sun light. But deviation observed in the movement of the moth due to disturbance of artificial lights in the flying path. In other words, moth gets entrapped in spiral movement instead of travelling long distance path. Mathematical model was evolved to mimic the behaviour of distracted moth to optimize the parameters under restricted condition. Assessment capability or performance of optimization algorithm is necessary through testing their outcomes on standard benchmark functions. MFO algorithms justified its ability to determine complex problem even in concealed domain space.

(Khalilpourazari & Khalilpourazary, 2019) Hybrid technique developed WCMFO algorithm to solve constrained numerical problems adopted to improve strength of water cycle algorithm and proved better effectiveness of the algorithm with various types of benchmark functions than the other hybrid MOO algorithms.

(Tamilarasan et al., 2020) Integration WCA with MFO to assure protection of solution to stuck in local optima using advantages of both algorithm along with random walk operator of WCA and spiral movement of MFO in manipulation of water cycle process. Unlike to simple WCA algorithm steam of water enhances its location with the help of spiral movement of MFO algorithm to improve randomness.

Work

(Tamilarasan et al., 2020) implemented hybrid WCMFO algorithm constitutes a hybrid between the two techniques, comprising the water cycle algorithm (WCA) and moth-flame optimization (MFO) algorithms in AWJM of Pineapple Leaf Fiber reinforced polyester composite (PALFRP).

3.13 Data Envelopment Analysis based Ranking (DEAR)

Introduction to DEAR

Charnes, Cooper and Rhodes in 1978 developed mathematical modelling called Data Envelopment Analysis (DEA) for decision-making.

(Adler et al., 2002) suggested that result in the technique is assessed by given input-output irrespective of objective functions of the problem, which is known as decision-making units (DMU). Suitable weight fraction is assigned to individual DMU after converting into a format of linear programming. The developed model ensures efficiency of DMU relatively with values not more than one. The result in terms of DMU represents best allocations of Pareto solutions (A set of solutions which follow similarity in the set but dominate among rest of set of solutions in the domain of search) that decide whether the results are useful or not according to location of the result on the surface of pareto frontier or pareto solution.

Work

(Manjunath Patel et al., 2020) carried out experiment on AWJM of polymer matrix composites (PMC) to evaluate surface roughness and material removal rate and proved DEAR method as an efficient decision making method for optimum output.

To achieve optimum value of result **(Manjunath Patel et al., 2020)** compared optimization techniques viz. Principal component analysis (PCA), Multi-objective optimization on the basis of ratio analysis (MOORA), Grey relational analysis (GRA), Technique for order preference by similarity to ideal solution (TOPSIS) and Data Envelopment Analysis based Ranking (DEAR). DEAR outperformed other methods considering/ because weight fraction of individual output dependent accuracy in the solution.

In multi-objective optimization problems the set of solution should be not only non-dominated among the set of solution but also be superior to the remaining of solutions in the search

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space. The comparison among various MOO techniques gives a way to decide most suitable techniques for the optimization. Many researched did endeavor to identify best suitable MOO method for machining of alloys, ceramics and composites through AWJ but only a few have shown their effort in AWJM of composite material specially. **(Gulia & Nargundkar, 2019; Shastri et al., 2021; A. Gnanavelbabu and P. Saravanan, 2018)**

(Weck, 2004) suggested that more algorithms in MOO techniques are to be developed to select best one for specific problem.

Figure 3. Represents major research work on prevalence of advance multiobjective optimization techniques in AWJM of composite.

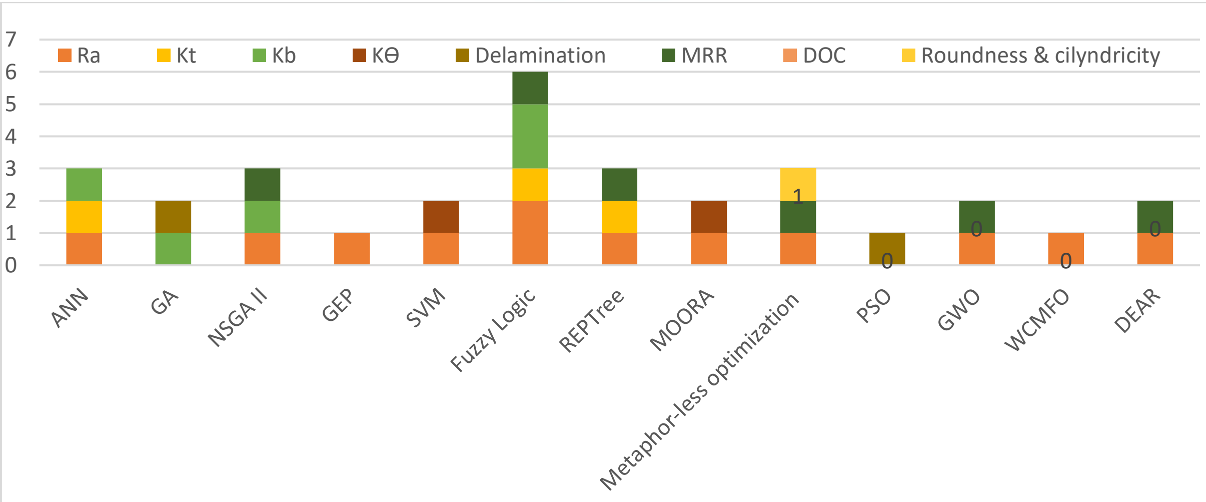

Figure 3. Prevalence of advance multiobjective optimization techniques in AWJM of composite.

4. SURFACE MORPHOLOGY ANALYSES BY SCANNING ELECTRON MICROSCOPY (SEM)

Introduction to SEM analysis /Importance / capabilities/ Characteristics

(Hejjaji et al., 2017) Damage intensity in cut surface of composite materials can form in various structural style viz. embedment of abrasive particles, fiber pull out, impairment of matrix and roughness at micro levels. Study of complex surface morphology in composite materials provides information about damage intensity and consequently responsible parameters for the damage of cut surface can be quantified.

(Mohammed & Abdullah, 2018) Scanning electron microscopy is also called as SEM analysis or SEM technique. This method is applicable to analyse materials at micro level to nanometer due to its very high magnification capability to generate accurate image of extensive range of specimen material surface even in wet surface. Integration of SEM with dispersive X-ray spectroscopy (EDS) and advance software gives results qualitatively.

Work

Many researchers have inspected surface quality of composite materials cut by AWJM to conceive behaviour of complex machining in composite as per the query raised from the industrial point of view. Following are the result claimed in research works carried out using SEM analysis in machined surface of composite to figure out surface roughness, MRR, delamination, kerf geometry and mechanical properties.

(Hejjaji et al., 2017) Investigated influence of process parameters with the help of SEM analysis to know the level of damage in control depth milling of CFRP composite. Concluded that crater volume is significant for strength of composite material.

(R. Pahuja & Ramulu, 2018) conducted experiment using two layer configuration: Ti alloy /CFRP and CFRP/ Ti alloy to analyse surface roughness and kerf geometry by profilometry and SEM.

(Gnanavelbabu et al., 2018) evaluated Kerf angle and surface roughness of Hybrid aluminum alloy composites cut by AWJM and proved that finer abrasives leaves impressions by extracting ductile materials. There is an influence of reinforcement on kerf taper angle and surface roughness. Hybrid metal matrix composite contains both ductile and brittle reinforced particles due to this, characteristics of surface quality analyses becomes more complicate.

(Orbanic et al., 2019) suggested that AWJM is suitable process for cutting intricate shapes of composite materials especially for drilling of composites. SEM results showed delamination when pressure values overcome the binding and tensile strength of composite.

(Sourd, Zitoune, Crouzeix, et al., 2020) carried out AWJ pocketing of CFRP 3D woven composite to predict of DOC & MRR using exponential model & Gauss model and concluded that model 1 is more effective with the experimental values. **(Sourd, Zitoune, Hejjaji, et al., 2020)** influence of parameters on the AWJ milling cut surface of CFRP was interpreted by SEM, X-ray tomography combined with image processing. Crater volume was new criteria to define machined surface quality.

(Li et al., 2020) conducted experimental test on AWJM of CFRP to examine effect of various parameter on 3D morphology and surface roughness. Exact choice of Traverse speed, AFR, pressure, SOD, and sample thickness can control kerf profile. first time **(Youssef et al., 2020)** performed effect of TR and SOD on seven responses (K_{top}, K_{bottom}, Kɵ,$A_{profile}$, VRR, Ra, jet deviation factor) in AWJM of CFRP. The increase in TR value increases the MRR and surface roughness (Ra) and decreases the mean top and bottom kerf width, mean kerf profile area. The increase of SOD increases the mean top and bottom kerf width, area of mean kerf profile, MRR and surface roughness. The increase of both traverse feed and SOD increase the kerf taper.

(M. Rajesh et al., 2020) performed SEM analysis to understand AWJ cutting mechanism of Ti-basalt-flax-Ti metal fiber composites, concluded ductile and brittle behaviour in cutting of Ti ply and basalt fiber ply respectively. Low pressure caused polymer fade out and reveled fibers.

(Ceritbinmez & Yapici, 2020) compared AWJ drilling of pure and doped composite (multi-walled carbon nanotubes (MWCNTs)-doped composite).The entry–exit hole diameter, kerf, delamination, splintering, burring, thickness and hardness were investigated. As TR increases rotational slip, cutting start point, circularity in hole, inlet and outlet dimensions, and circular error increases but delamination decreases. Surface hardness increased with adding more nano particles.

(Sumesh & Kanthavel, 2020) Carried out AWJM of hybrid composites made of fly ash from bio waste materials viz. Bagasse (BGFA), Banana (BFA) and Coir (CFA) and Pineapple (P)/Sisal (S). it is observed that low MRR and high surface roughness due to addition of more percentage of fly ash filler. SEM results showed lesser cracks and matrix breakages due to fly ash filler.

(D. Kumar & Gururaja, 2020)

Analysed interface damage factor, kerf taper ratio and surface roughness in AWJM of Aerospace grade five (Ti6Al4V) based MMC. Damage factor, which defines, cut quality decreased with increase in pressure, traverse speed and SOD. Results of SEM of surface showed that debonding, pullout of fiber, matrix washout, and delamination reduced with less pressure.

(Ramraji et al. 2021) done comparative study by varying layers of fabrics made of Glass and Basalt Woven Polymer Composites. They found that configuration of top and bottom layers of basalt in-between seven flax fiber layers composite have more tensile strength and flexural properties. Concise summary of above research work in pictorial view to represent prevalence of SEM analysis in AWJM of composite as shown in Figure 4.

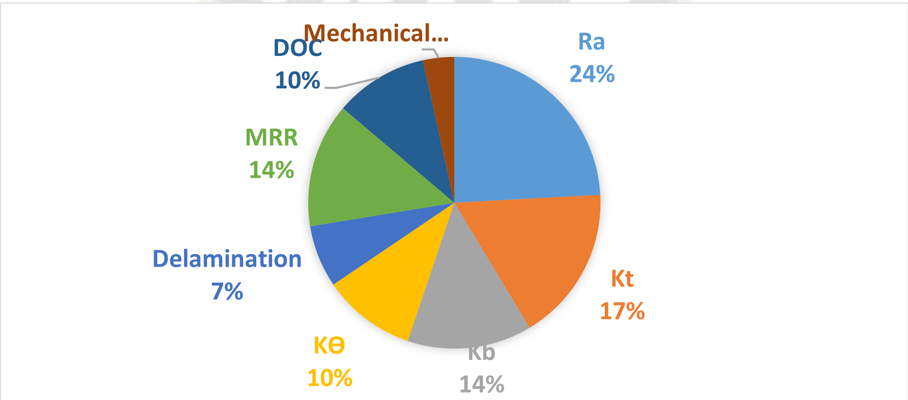

Figure. 4 Prevalence of SEM analysis in AWJM of composite.

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Research work performed on AWJM of composite materials employing conventional as well advance multiobjective optimization techniques and SEM analysis listed in section 2, 3 and 4 are summarized to reveal overall details in tabular form below as Table 1.

Table 1. Overview of research work in AWJM of composite.

Authors & year	**Work material**	**t (Thickness, in mm)**	**process parameters**	**Response parameters**	**Proposed algorithm/ Tool for analysis**
Azmir & Ahsan, 2009	Fibre glass/epoxy laminates	t= 5.4 mm	P, TR, SOD, AFR, ϴ, Abrasive type	Ra, Kt,	ANOVA
Orbanic et al. 2010	carbon fiber plate	t = 2 mm	P, AFR, abrasive delay time	Area of pierced hole	----
Siddiqui and Shukla 2010	Kevlar epoxy composites	t=6mm	P, AFR and QL Grit size	Ra	Taguchi
Kök et al., NSG	Al 7075 reinforced with α-Al2O3 paticles	t=140 mm	weight fraction of particle, size of particle, depth of cut	Ra, Rz,Rsm	Genetic expression programming (GEP)
Thirumalai Kumaran et al., 2015	AA (6351)-SiC-B4C Hybrid Composite	-------	G.S, P,TR,SOD	Kϴ, MRR, Ra	ANOVA
R Pahuja M. Ramulu, 2016	Titanium Graphite (TiGr) Laminates	t =7.56, 10.5 mm	P, TR, AFR	Kt, Ra	ANOVA
P Rajesh and S Srinivas, 2017	Al-si Carbide Metal Matrix	di= 22	%, Si, TR, ϴ (5, 10, 15% of SiC in AL alloy)	MRR, Ra	RSM
(Hejjaji et al., 2017)	CFRP	t=3.12 mm	P,TR,SOD, scan step	Ra. DOC, MRR, Surface waviness	SEM
El-Hofy et al., 2018	Multi directional CFRP	t=10.4mm	P,TR,SOD, 2 Lay up configuration	Kb, Kt, Ra , M.I (machinability index)	ANOVA
Sasikumar et al., 2018	Al 7075 -MMCs with 5%,10% 15% vol of TiC and B4C	t=10 mm	P,TR,SOD,	Kb, Kt, Ra	ANOVA
Schwartzentruber et. al 2018	Carbon epoxy composite	t=1.2mm	P,TR,AFR,SOD, do, ,fibre orientation	delamination	Taguchi
S Chakraborty & Ankan Mitra 2018	---------	--------------	P,TR, AFR, SOD, nozzle angle	MRR, Ra	GWO

Dhanawade & Kumar, 2018	Carbon epoxy composite	t=22mm	P, TR, AFR, SOD	Ra, Kt	GRA
M. El. Hofy et.al 2018	Multi directional CFRP	t=10.4mm	P,TR,SOD, Lay up configuration	Kb, Kt, Ra	ANOVA
Balachandar et.al. 2018	Al 6061-T6 magnesium with AZ 31 and rock dust Reinforcement.	t = 10 mm	AFR, TR, SOD	Ra, MRR, Kw	ANOVA
Balasubramania n & S Madhu 2018	CFRP	t = 3 mm	P, SOD, dn, Grit size	Delamination, Ra	RSM
R. Pahuja & Ramulu, 2018	Ti6Al4Vl 2.8 mm-MD CFRP	12.7 mm stacks	P,TR, Stacking configuration	Kerf geometry	SEM
Balamurugan et.al 2018	Lanthanum phosphate/ Yttria composite	t=7mm	P, TR, SOD	Ra, Kɵ, MRR	GRA
Karatas et al. 2019	CFRP	t = 4,8,12	P, D, SOD	Ra	Taguchi
Manjunath Patel et. al. 2019	polymer matrix composites PMC	t = 6 mm	P, TR, AFR,SOD, Grit size	MRR, Ra	DEAR
D Kumar & S Gururaja 2019	Ti/CFRP/Ti laminate	t = 3.5 mm	P, TR, SOD	MRR, Damage factor, Ra, Taper Ratio	RSM
Ramraji et al. 2019	Glass and Basalt Woven Polymer Composites	t = 7.2 mm	P, TR, SOD	Ra, Kt	SEM
Puneet Kumar and Ravi Kant 2019	Kevlar epoxy composite	t = 14 mm	P,TR,AFR,SO D	Ra,Kt	RSM
D. Deepak & J. Paulo Davim 2019	Glass FRP	t = 3 mm	P,AFR, Abrasive concentratio n, SOD	Ra & Kerf ratio(BKW /TKW)	GRA
Ramesha et. al. 2019	Glass FRP	t = 6 mm	TR,SOD, Abr con., Grit size	MRR, Kb, Ra	Taguchi
Shanmugam et.al. 2019	Al7075 MMC	t= 10mm	P,TR,SOD	Ra,Kt	RSM
V.Durga Prasada Rao et.al. 2019	CFRP, GFRP, CGFRP	t= 8 mm	TR, AFR, SOD	Ra, Kw, MRR	NSGA-II
V Reddy & B Venkatesh 2019	Glass laminate aluminium reinforced epoxy (GLARE)	t = 4,8,12 mm	P, TR, AFR, SOD	Ra, Delamination	RSM

Thakur et.al. 2019	hybrid carbon/glass laminate	t = 6mm	P, TR, SOD	Ra, Kt	GRA
Azmi & Hashim, 2020	Hybrid Metal Matrix Composites (MMC) Al7075	t =10 mm	P, TR,SOD,	Top Kb	GA
Gnanavelbabu and Saravanan 2020	Grade 5 Ti-6Al-4V	t = 5 mm	P, TR,AFR, grit size	Ra, Kɵ	RSM, PSO, CSA, SA
Ashok Kumar et al. 2020	Glass fiber reinforced polymer GFRP	t = 5 mm	P, TR, AFR, SOD	Kw, Kɵ	----
Tamilarasan et.al. 2020	Pineapple Leaf Fiber reinforced polyester composite (PALFRP)	---------	P, TR,SOD	Ra	Hybrid WCMFO algorithm
Gawade et.al.2020	Epoxy Resin Glass Fibre	t = 5 mm	P, SOD,	Kɵ	ANOVA
Doğankaya et.al.2020	Ultra High Modulus Weight Polyethylene (UHMWPE) FRP	t= 4 mm	P,TR,SOD, Sand ratio	Ra , Dimensional error	RSM, MOPSO
Edriys et.al. [2020]	CFRP	t = 4,8,12	t, P, TR,AFR, SOD	Ra, Kt, Kw, Kɵ, MRR	Taguchi
Niranjan et.al. [2020	AZ91/Al2O3 nano-composites	t = 25 mm	P, TR,AFR, grit size , Dn	Ra, DOP	Taguchi
Pahuja & ramulu 2020	HexMC t =11 mm	P,AFR, TR	WPT indicator , Rz		AWJ milling
Rajamani et.al. 2020	NFR nano clay filled green Composites	t = 10 mm	P, TR, SOD, % of nano clay	Ra , MRR, Kt	RSM
Rajesh et.al.2020	Ti-basalt-flax fiber laminate	t = 5 mm	P,TR, AFR, SOD	Ra, Kerf ratio	RSM
Rajesh et.al.2020	Al- NiTi smart composites	-------	P,TR, SOD, grit size, % of reinforcement	Ra, Kɵ	Ra, Kɵ
Rajamani et. al. 2020	natural fiber reinforced Nano clay filled polyester	t =10 mm	Wt % of Nano clay , P, TR, SOD	Ra, MRR, Kt	RSM,

Selvam et.al. 2020	hybrid-laminated composites	t= 5 mm	P,TR,SOD, AFR	Ra,Kt	RSM
Sumesh and Kanthavel [2020]	Sisal/Pineapple epoxy hybrid composites	--------	P,TR,SOD, % of fly ash filler	MRR, Ra	SEM
Sourd et.al. [2020]	CFRP 3D woven composite	t = 9.75 mm	Pth, Peff, TR, Scan Step	DOC, MRR	SEM
Ceritbinmez & Yapici, 2020	MWCNTs-Doped GFRP Composite	t=1.6 mm	TR, Pure composite , 0.1 wt% MWCNT doping,	entry–exit hole diameter, kerf, delamination, splintering, burring, change in thickness and change in hardness	---------
Uthayakumar et. al. 2020	Geopolymers (flyash, metakaolin and sand	----------	P, TR, SOD	Kt,MRR	ANOVA
Vijayaraj et al., 2020	AlSi7/SiC composite	t =120 mm	P, TR, SOD	KΘ, MRR, Ra	REPTree
V. Kumar et al., 2020	GFRP	t =8 mm	P, TR, SOD, AFR	Kb, KΘ, MRR, Ra	Grey-fuzzy logic approach
Xin Li et.al.2020	CFRP	t = 2.2, 4.5,6.8, 8.8,11	t , P, TR, AFR, SOD	Ra, Kerf Profile	----
Youssef et.al. [2020]	CFRP	t = 10.4 mm	TR, SOD	Ktop, Kbottom, Kθ,Aprofile, VRR, Ra, JDF (jet deviation factor)	---
Gnanavelbabu et al., 2020	AA7075-ZrSiO4-hBN Hybrid MMC	t =5 mm	P, TR,AFR, Grit size	Kt, Ra	Grey-RSM
Hussien et al., 2021	CFRP	t =7 mm	P, TR	Kt, Ra	Regression
Manivannan et al., 2021	polyester resin with turkey Fibre composites	t =3 mm	P, TR, SOD	KΘ, Ra	MOORA
Saravanan et al., 2021	CFRP	t =5 mm	TR,SOD	Kb, KΘ , Ra	Fuzzy Logic
Tripathi et al., 2021	GFRP	t =10.25 mm	TR, AFR	MRR, Ra, roundness (Ro), cylindricity (Cy)	metaphor-less optimization
Madara et al., 2021	Kevlar 49 Composite	-------	P,TR,AFR,SOD	Kb, Kt, Ra	BPNN

Kolli et al., 2021	hybrid Al 7075/B4C/Gr composite	t=10 mm	P,TR,SOD,	MRR, Kt, Ra	RSM-TOPSIS

5. Concluding remarks.

- The literature involves three aspects in AWJM of composite 1. Basic introduction of conventional and advance multiobjective optimization techniques. 2. Application of MOO techniques in AWJM of composite materials.. 3. Scanning electron microscopy analysis in AWJM of composite materials.

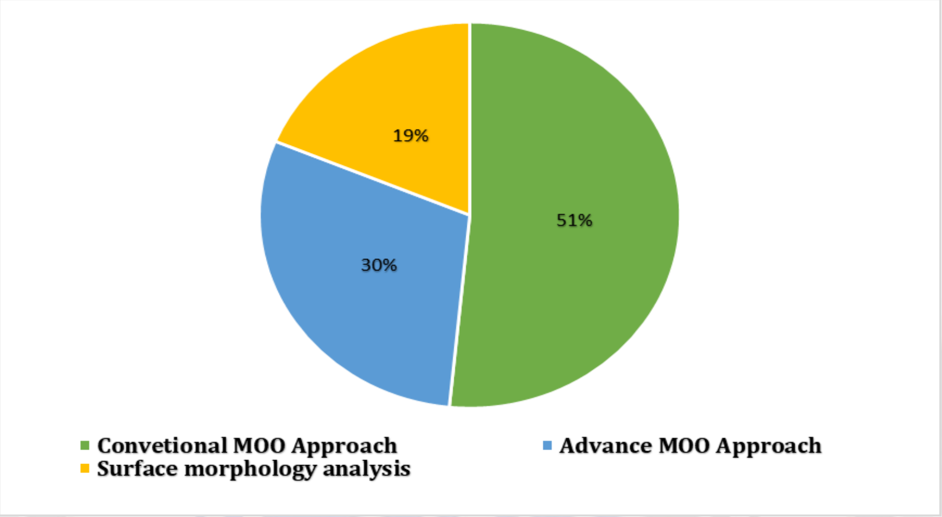

Figure. 5 overall contribution of techniques in AWJM of composite.

- Figure.5 represents overall contribution of conventional & advance multiobjective optimization techniques including SEM analysis employed so far in AWJM of composite. Conventional multiobjective optimization techniques remain dominant followed by advance multiobjective optimization techniques and SEM analysis.
- Research in experimental investigation shows that AWJM of composite is quite suitable than conventional machining. Researchers endeavors to improve cut quality and performance using AWJM of various types of composite
- It is identified that garnet abrasive particles is most commonly used in AWJM of composite materials to achieve better performance over other types of abrasives.
- AWJM of composites revels issue like structural inaccuracy, delamination, kerf taper, fiber pull out in machined surface, which need to overcome by selecting best set of process parameters.
- To mitigate the problem of delamination in AWJM of composite one can need to optimize the process parameters using development of MOO techniques.
- It is clearly noticed from Figure. 2 and 3 that delamination, depth of cut, kerf angle and MRR in composite materials cut by AWJM have been given less attention by the researcher employing both classical as well as advance multiobjective optimization techniques.
- Surface Morphology analyses by Scanning electron microscopy is employed to evaluate delamination, surface roughness, kerf geometry, depth of cut and to assess mechanical properties in composite materials
- Selection of any optimization technique fairly depends on the need of the problem. The user has to adjust the method of optimization techniques to accommodate it with specific problem solving.
- Research literature recognized considerably need of hybrid multiobjective optimization techniques to prepare impressive algorithm for enhancing study of influence of various process parameters on complex response parameters in AWJM of composite and also to reduce computational cost in solving MOO algorithms..
- With the aid of optimization techniques many operations viz. analysis, prediction of data, simulation, numerical computation, programming etc. are being performed using MATLAB software.

6. Scope marks / Future scope /opportunities

- More research work needs to understand delamination, kerf geometry and depth of cut in composite materials through multiobjective optimization techniques.
- There is always scope remains to develop new algorithm and compare it with existing algorithm to get most suitable optimization tool among them for particular manufacturing process.
- Many nature inspired optimization algorithms are yet to analyse delamination, surface roughness, kerf geometry and MRR in AWJM of composite. Most famous advance algorithms are bat algorithm, fireworks algorithm, differential evolution, society and civilization algorithm, Weighted principal components analysis (WPCA) , Shuffled frog leaping algorithm (SFLA), Adaptive harmony search (etc. are still remained to be scratched for parametric optimization in AWJM of composite.
- It is recommended to integrate algorithms like K mean- AFSO, Hybrid GRA-PCA Approach, parse Auto encoder–Adaptive Network-Based Fuzzy Inference System (RSAE–ANFIS), etc. to improve performance of algorithm and to get optimum output as well.

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