Modelling & Optimization of Machining Parameters for Micro-Textured Cutting Tools

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Dissertation

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By

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The project entitled **"MODELLING & OPTIMIZATION OF MACHINING PARAMETERS FOR MICRO-TEXTURED CUTTING TOOLS "**submitted by **Mr. Manish Meena (ME/17/10), Mr. Kautillya Saragadam (ME/17/17) and Dharmendra Meena (ME/17/23)** is presented in a satisfactory manner to warrant in acceptance as a pre- requisite for the degree of bachelor of mechanical engineering of the National Institute of Technology, Arunachal Pradesh. It is understood that by this approval the undersigned do not necessarily endorse or approve any statement made, opinion expressed and conclusion drawn there in, but only for the purpose for which it has been submitted.

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Certificate from Supervisor

This is to certify that the dissertation entitled **"MODELLING & OPTIMIZATION OF MACHINING PARAMETERS FOR MICRO-TEXTURED CUTTING TOOLS "**submitted by **MR. MANISH MEENA (ME/17/10), MR. KAUTILLYA SARAGADAM (ME/17/17) AND DHARMENDRA MEENA (ME/17/23)** to the department of mechanical engineering of the national institute of Arunachal Pradesh, as a partial fulfilment of their Bachelor of Technology Degree in Mechanical Engineering of the National Institute of Technology, Arunachal Pradesh is absolutely based upon their own work , carried out during the period from July 2020- May 2021 under my supervision. Neither this dissertation nor any part of it has been submitted for the award of any other degree of this institute or any other institute/university.

Dr. SHUBHAJIT DAS

B. Tech project supervisor

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ABSTRACT

Machining is an integral part of a manufacturing industry. It is highly valuable to get the best surface characteristics and gives smoothness and texture to finished products. This is very important in the longevity and the use of the product and machining is essential to every product design in terms of cost and reliability. Conventional Machining has exhausted it prime time and with the advent of technology these days, Non-Traditional Machining techniques are making their way into the markets for high profile finishing. Electro Discharging Machines is one such technique which performs no contact machining. As it very expensive to perform EDM, we have to optimize the working parameters and give them the best working conditions to effectively gain profits and time in EDM. Therefore, experimental values have been modelled using various mathematical techniques and predict the values along with contour analyzing them. Neural Networks, Fuzzy logic and Response Surface Methodology has been employed in mathematical modelling. They help in functionalizing the process parameters which can be further used to optimize using evolutionary computational techniques Evolutionary techniques can deal with random problems better than classical ones and have higher convergence to non-linear equations as compared to classical optimization techniques. In this context, Genetic Algorithm has been used in the function optimization of the mathematical models from above three methods. Lastly, Pareto plot is obtained from GA for each of the WEDM texture.

Keywords: Wire Electric Discharging Machining (WEDM), Artificial Neural Network (ANN), Response Surface Methodology (RSM), Genetic Algorithm (GA).

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NOMENCLATURE

ACRONYM	DESCRIPTION
EDM	Electro-Discharge Machining
EA	Evolutionary Algorithms
GA	Genetic Algorithm
PGSA	Parallel Genetic Simulated Annealing
BPN	Back Propagation Network
CNC	Computer Numerical Control
ANN	Artificial Neural Network
RSM	Response Surface Methodology
WEDM	Wire Electric Discharging Machining
MRR	Material Removal Rate
SR	Surface Roughness
SS	Stainless Steel
SiC	Silicon Carbide
T_{off}	Time Off
T_{on}	Time On
WT	Wire Tension
WF	Wire Feed
DFA	Desirability Function Analysis
Ni-Ti	Nickel Titanium Alloy
TWR	Tool Wear Rate
ANOVA	Analysis of Variance
Cu-MWCNT	Copper–multi-walled carbon nanotube

ACRONYM	DESCRIPTION
PAC	Plasma Arc Cutting
CCD	Central Composite Design
DRSM	Desirability Based Response Surface Methodology
DI	Desirability Index
BA	Bat Algorithm
ABC	Ant Bee Colony
HSS	High Speed Steel
B_4C	Boron Carbide
MOPSO	Multi Objective Particle Swarm Optimization
mm	Millimeter
Rpm	Revolutions Per Minute
FLM	Fuzzy Logic Model
COA	Centre of Area
NNTOOL	Neural Network Toolbox
MSE	Mean Squared Error

NOTATIONS

F: Fahrenheit HZ: Hertz

Ra: Surface Roughness (μm)

WR: Wear Rate (mm3 /m)

COF: Coefficient of Friction

S/N: Signal to Noise ratio

SS: Sliding Speed (rpm)

SD: Sliding distance (m)

CHAPTER 1

1.1 NEED FOR OPTIMIZATION IN ENGINEERING

Engineering is the application of scientific theory and mathematical theorems in the design of products intended to make human lives easier. These devices are mostly worked on because of the requirement, necessity of them in simplifying our lives, to put less efforts on routine jobs. The invention of the bulb gave us more time, due to which we can live at night. Vehicle, automobiles save considerable amount of time, effort and let us go anywhere in the world. All these are a result of innovatively engineered inventions that got better over time. In order to make these devices and products available for everyone, the cost considerations are needed to be cut down along with the quality and productivity of the device being intact. This demands for efficient, time effective processes and operations to obtain the final product. Therefore, an industrial and production engineers lay emphasis on the optimization of the various processes employed by involving newer methods which ultimately bring down the costs, runtime, wastages while improving efficiency, productivity, quality.

Optimization is a method through which we can obtain a desirable maximum or minimum of an objective function, using a set of decision variables and under a set of given constraint equalities and inequalities. Manufacturing is the process or processes by which we convert raw materials into finished goods. So, Manufacturing is only about getting a desired product without considering about easy or difficult it might be, but when manufacturing is coupled with optimization, we will able to get desired product with the maximum efficiency and minimum costs, waste. So, it is clear that to be able to make these products, devices or services available to everyone and still make an efficient, profitable, useful machines, optimization plays a big role and hence is one of the most sought out studies in recent times. Optimization is applied in almost every branch of engineering.

1.2 HISTORICAL DEVELOPMENTS OF OTIMIZATION TECHNIQUES

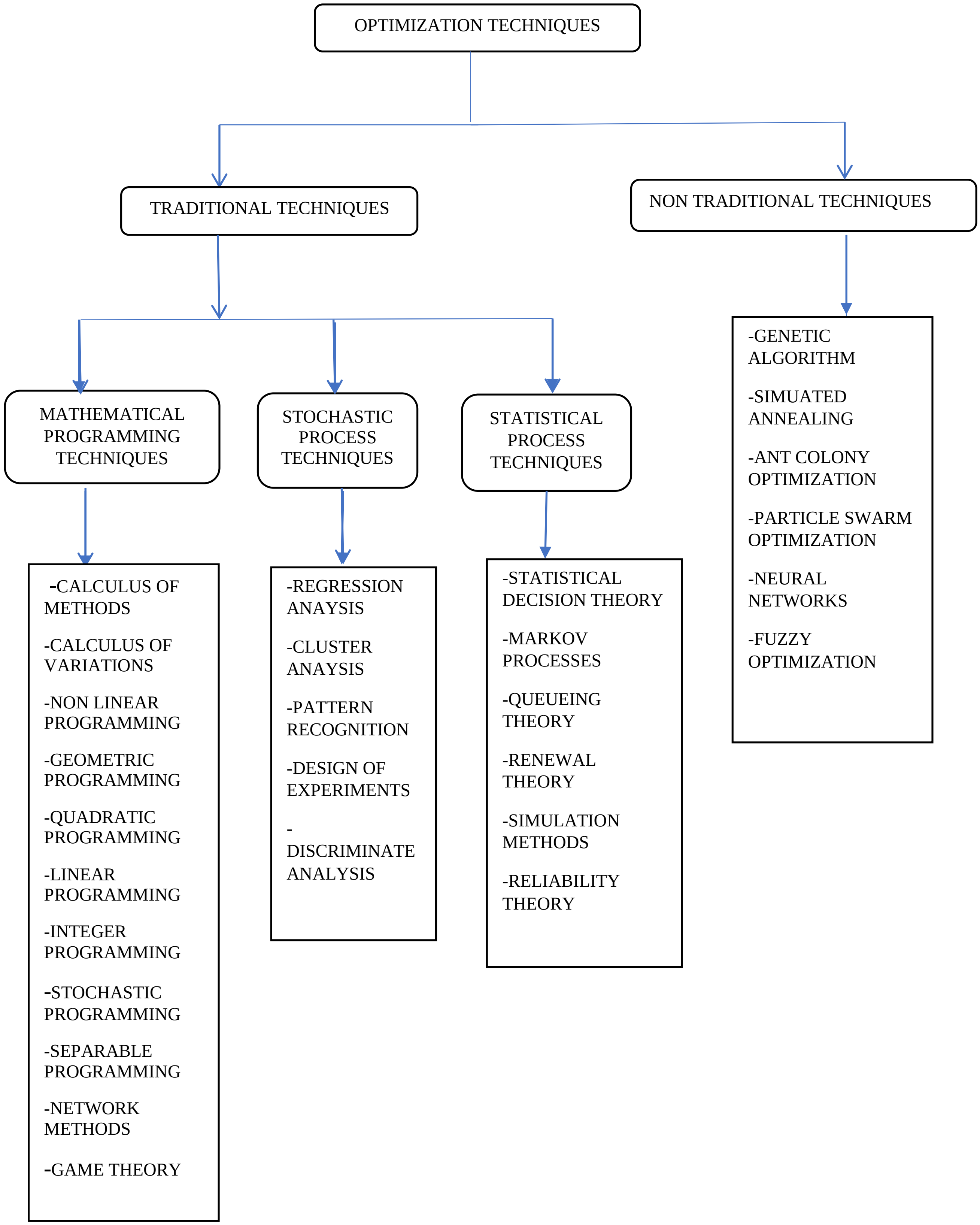
Though rigorous mathematical analysis of the optimization problems was carried out during the 20th century, the roots can be traced back to about 300 B.C., when the Greek mathematician Euclid evaluated the minimum distance between point and a line. Another Greek mathematician, Zenedorous, showed in 200 B.C. that a figure bounded by a line that has a maximum area for a given perimeter is a semicircle.

In the 17th century, Pierre de Fermat, a French mathematician, laid the foundation of calculus. He showed that the gradient of a function vanishes at the maximum or minimum point. The development of differential calculus methods of optimization was possible because of the contributions of Newton and Leibnitz to calculus. The foundations of calculus of variations, which deals with the minimization of functionals, were laid by Bernoulli, Euler, Lagrange, and Weirstrass. The method of optimization for constrained problems, which involves the addition of unknown multipliers, became known by the name of its inventor, Lagrange. Cauchy made the first application of the steepest descent method to solve unconstrained minimization problems. Despite these early contributions, very little progress was made until the middle of the twentieth century, when high-speed digital computers made implementation of the optimization procedures possible and stimulated further research on new methods. Spectacular advances followed, producing a massive literature on optimization techniques. This advancement also resulted in the emergence of several well-defined new areas in optimization theory. It is interesting to note that the major developments in the area of numerical methods of unconstrained optimization have been made in the United Kingdom only in the 1960s.

The development of the simplex method by Dantzig in 1947 for linear programming problems and the annunciation of the principle of optimality in 1957 by Bellman for dynamic programming problems paved the way for development of the methods of constrained optimization. Work by Kuhn and Tucker in 1951 on the necessary and sufficiency conditions for the optimal solution of programming problems laid the foundations for a great deal of later research in nonlinear programming. The contributions of Zoutendijk and Rosen to nonlinear programming during the early 1960s have been significant. Although no single technique has been found to be universally applicable for nonlinear programming problems, work of Carroll and Fiacco and McCormick allowed many difficult problems to be solved by using the well-known techniques of unconstrained optimization. Geometric programming was developed in the 1960s by Duffin, Zener, and Peterson. Gomory did pioneering work in integer programming, one of the most exciting and rapidly developing areas of optimization. The reason for this is that most real-world applications fall under this category of problems. Dantzig and Charnas and Cooper developed stochastic programming techniques and solved problems by assuming design parameters to be independent and normally distributed. The desire to optimize more than one objective or goal while satisfying the physical limitations led to the development of multiobjective programming methods. Goal programming is a well-known technique for solving specific types of multiobjective optimization problems. The goal programming was originally proposed for linear problems by Charnas and Cooper in 1961. The foundations of game theory were laid by von Neumann in 1928 and since then the technique has been applied to solve several mathematical economics and military problems. Only during the last few years has game theory been applied to solve engineering design problems.

The modern optimization methods, also sometimes called nontraditional optimization methods, have emerged as powerful and popular methods for solving complex engineering optimization problems in recent years. These methods include genetic algorithms, simulated annealing, particle swarm optimization, ant colony optimization, neural network-based optimization, and fuzzy optimization. The genetic algorithms are computerized search and optimization algorithms based on the mechanics of natural genetics and natural selection. The genetic algorithms were originally proposed by John Holland in 1975. The simulated annealing method is based on the mechanics of the cooling process of molten metals through annealing. The method was originally developed by Kirkpatrick, Gelatt, and Vecchi. The particle swarm optimization algorithm mimics the behavior of social organisms such as a colony or swarm of insects (for example, ants, termites, bees, and wasps), a flock of birds, and a school of fish. The algorithm was originally proposed by Kennedy and Eberhart in 1995. The ant colony optimization is based on the cooperative behavior of ant colonies, which are able to find the shortest path from their nest to a food source. The method was first developed by Marco Dorigo in 1992. The neural network methods are based on the immense computational power of the nervous system to solve perceptional problems in the presence of massive amount of sensory data through its parallel processing capability. The method was originally used for optimization by Hopfield and Tank in 1985. The fuzzy optimization methods were developed to solve optimization problems involving design data, objective function, and constraints stated in imprecise form involving vague and linguistic descriptions. The fuzzy approaches for single and multiobjective optimization in engineering design were first presented by Rao in 1986.

1.3CLASSIFICATION OF OPTIMIZATION TECHNIQUES



1.4 NEED FOR EVOLUTIONARY COMPUTATIONAL CONCEPTS IN OPTIMIZATION

Evolutionary computation, describes the field of investigation that concerns all evolutionary algorithms and offers practical advantages to several optimization problems. The advantages include the simplicity of the approach, its robust response to changing circumstances, and its flexibility and so on. This section briefs why there is a need for evolutionary computation techniques and what are some of its features which make them superior and effective compared to traditional optimization techniques.

1.4.*1 Conceptual Simplicity*

A key advantage of evolutionary computation is that it is conceptually simple. Figure 1.7 shows a flowchart of an evolutionary algorithm applied for function optimization. The algorithm consists of initialization, iterative variation and selection in light of a performance index. In particular, no gradient information needs to be presented to the algorithm. Over iterations of random variation and selection, the population can be made to converge to optimal solutions. The effectiveness of an evolutionary algorithm depends on the variation and selection operators as applied to a chosen representation and initialization.

1.4.2 Broad Applicability

Evolutionary algorithms can be applied to any problems that can be formulated as function optimization problems. To solve these problems, it requires a data structure to represent solutions, to evaluate solutions from old solutions. Representations can be chosen by human designer based on his intuition. Representation should allow for variation operators that maintain a behavioral link between parent and offspring.

1.4.3 Hybridization with Other Methods

Evolutionary algorithms can be combined with more traditional optimization techniques. This is as simple as the use of a conjugate-gradient minimization used after primary search with an evolutionary algorithm. It may also involve simultaneous application of algorithms like the use of evolutionary search for the structure of a model coupled with gradient search for parameter values. Further, evolutionary computation can be used to optimize the performance of neural networks, fuzzy systems, production systems, wireless systems and other program structures.

1.4.4 Parallelism

Evolution is a highly parallel process. When distributed processing computers become more popular are readily available, there will be increased potential for applying evolutionary computation to more complex problems. Generally, the individual solutions are evaluated independently of the evaluations assigned to competing solutions. The evaluation of each solution can be handled in parallel and selection only requires some serial operation. In effect, the running time required for an application may be inversely proportional to the number of processors. Also, the current computing machines provide sufficient computational speed to generate solutions to difficult problems in reasonable time.

1.4.5 Robust to Dynamic Changes

Traditional methods of optimization are not robust to dynamic changes in the environment and they require a complete restart for providing a solution. In contrary, evolutionary computation can be used to adapt solutions to changing circumstances. The generated population of evolved solutions provides a basis for further improvement and in many cases, it is not necessary to reinitialize the population at random. This method of adapting in the face of a dynamic environment is a key advantage.

1.4.6 Solves Problems that have no Solutions

The advantage of evolutionary algorithms includes its ability to address problems for which there is no human expertise. Even though human expertise should be used when it is needed and available; it often proves less adequate for automated problem-solving routines. Certain problems exist with expert system: the experts may not agree, may not be qualified, may not be self-consistent or may simply cause error. Artificial intelligence may be applied to several difficult problems requiring high computational speed, but they cannot compete with the human intelligence.

CHAPTER 2

LITERATURE REVIEW AND RESEARCH OBJECTIVES

2.1 LITERATURE REVIEW

2.1.1 Optimization of manufacturing processes using genetic algorithm

This chapter will briefly elaborate the work that has been done from the past few years and discusses the current trend and direction of the research going on in evolutionary computation in manufacturing technologies.

Lungxuan Zhang et al., [1] focused on minimizing processing time and tool wear of a micro EDM process. Here, the input parameters considered were discharge peak current, pulse duration, pulse off time, capacitance, electrode rotating speed and servo reference speed. A support vector machine has been used to relate the input and output parameters. The output parameters were processing time and tool wear. The more the processing time, more would be the tool wear and obtaining a minimum of both these process parameters presents a Pareto optimal problem. To overcome this problem, a non-dominated sorting which uses a multi-objective optimization genetic algorithm was proposed. These results have been compared with the experimental results and it has been found that a precise, efficient and stable solutions were obtained.

Wang et al., [2] presented a hybrid Genetic Algorithm on multi pass milling operations. Genetic Algorithms are very general and random that there is a necessity to improve data collecting and data processing techniques of which, directed simulated annealing is an option. Therefore, a parallel genetic simulated annealing was applied to try and improve the solutions and minimize errors. Finally, the results of PGSA turned out to be more accurate than the one with normal genetic programming techniques.

Rituparna Dutta et al., [3] worked on optimizing the machining parameters of a turning operation. Optimal parameters considered were cutting speed, feed and depth of cut. Objective parameters were production time, production cost and surface roughness. A classical mathematical formulation and also a genetic algorithm with multi objective

U. Deepak et.al., [4] discussed Particle Swarm Optimization and Genetic Algorithm techniques are used for Optimizing the machining parameters like depth of cut, feed rate and cutting speed. This will help in better optimization of milling operation. A genetic algorithm (GA) is a search heuristic that mimics the process of natural evolution. This heuristic is routinely used to generate useful solutions to optimization and search problems. Genetic algorithms belong to the larger class of Evolutionary Algorithms (EA), which generate solutions to optimization problems using techniques inspired by natural evolution, such as inheritance, mutation, selection, and crossover. Particle Swarm Optimization (PSO) is a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality.

K. Kalita et. al., [5] presented, an empirical model is developed based on the extensive experiments performed on polyester composite reinforced with chopped fiberglass. To account for the various parameters a Box-Behnken design of experiments is conducted for four parameters (material thickness, drill diameter, spindle speed, and feed rate) each having three distinct levels. Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) techniques are then used for predicting the global optimum (minimum delamination factor). The performance of both GA and PSO in terms of predicting the global optimum is found to be same. However, PSO converged much faster and required far lesser computational time.

D. Venkatesan et al., [6] studied optimizing machining parameters using artificial neural network mathematical model and implemented by genetic algorithms. Turning operation is considered where depth of cut, feed and speed have been selected as process parameters. Roughness, force, power and tool life equations are developed as they are chosen as objective functions. BPN is used to train the data with a hidden layer. The weights have been calculated using genetic algorithm. After working on this, it has been found that we need a minimum of 500 iterations to reduce the error and bridge the gap between the experimental values and predicted values using optimization and minimize the error

Kulankara Krishnakumar et al., [7] has used parallel genetic algorithm in the fixture layout optimization in machining. This paper slightly differs from other papers which deal with direct machining parameters. It takes into consideration the effects of fixture layout. Mostly, this is implemented using a finite element model but in this genetic algorithm is used because of the reason that no direct relationship exists between machining error and fixture layout. Locator pins and clamps are taken as the process parameters. Then, population of values are selected, crossover done on them and they are finally mutated to find a global optimum.

Girish Kant et al., [8] has developed a predictive modelling of the process parameters in turning operations to optimize the surface roughness (objective function) and the cutting speed, feed, depth of cut and flank wear as design variables. A feel forward BPN has been used to train the model. Predicted values are obtained and compared with experimental results. There is a minute error involved which has been computed a shown using performance graphs.

Pavel A Borisovsky et al., [9] worked on a non-machining problem. The objective of the paper was to produce reconfigurable machining lines. A genetic algorithm is proposed and a permutation of operations using different CNC machines with various operations are considered. The manufacturing line has a particular order which it follows to perform its intended operations. A mixed integer programming model is suggested for an optimal design of workstations. A perfect evaluation of the proposed GA on large scale tests

G C Onwubolu et al., [10] proposes a new optimization technique based on genetic algorithms for determination of the cutting parameters in multi-pass rough machining and finish machining. The optimum machining parameters are determined by minimizing the unit production cost subject to twenty practical constraints. The cutting model formulated is a non-linear, constrained programming problem. Experimental results show that the proposed genetic algorithm-based approach is both effective and efficient. (Multi pass turning operations optimization based on genetic algorithm)

S. Marichamy et al., [11] presented is used to determine the optimal parameters with the help of Artificial Neural Network (ANN) model and genetic algorithm during EDM of ἀ-β brass. Based upon the different machining conditions, training and verification of the model was done. The optimal combination of parameter is found by genetic algorithm. The experimental and ANN model results were compared and it is found that the optimal values lie within the limits

V.N. Gaitonde et al., [12] presented RSM models were combined with genetic algorithm to determine the optimal process parameters for a given frill diameter that results in minimum burr height and thickness. The simulation results reveal that point angle and cutting speed have significant effects in minimizing burr sizeYanming Liu et al., [13] modified genetic algorithm is used for the optimisation of milling parameters and simulation and experimental results show an improved performance

Doriana M et al., [14] presented deals with a novel approach to optimize the machining parameters during turning process, by basing on the use of cognitive paradigms. In order to find optimal cutting parameters during a turning process, the genetic algorithm has been used as an optimal solution finder. Since the genetic algorithm-based approach can obtain near optimal solution, it can be used for machining parameter selection of complex machined parts that require many machining constraints. It has been integrating with an intelligent manufacturing system that will lead to reduction in production cost, reduction in production time, flexibility in machining parameter selection, and improvement of product quality.

2.1.2 Various machining processes using WEDM

S. Ujjaini Kumar et al., [15] has worked on the multi objective optimization of Wire EDM with pulse on time, pulse off time and wire tension values. Material removal rate and surface roughness are the objective functions which have been independently optimized. For both of the objective functions, it has been found that pulse on time is a critical parameter that modifies the output values (MRR & SR). Taguchi –Grey methodology was used to optimize the process parameters.

Urgasen Ga et al., [16] has worked on EDM optimal process parameters on SS304 with molybdenum as a tool electrode. Control parameters of EDM such as pulse on time, pulse off time, Rate, Dimensional Error, Electrode Wear and also Surface Roughness. It has been concluded that current primarily effects accuracy, bed speed on MRR. Taguchi's L_{27} array.

Ranjan et.al., [17] many optimization techniques have been investigated to optimize the process of WEDM and to obtain the suitable parameters to have the best machining outputs. Response surface methodology and Particle swarm optimization are the most researched techniques among them. this paper analyses the effect of different parameters such as Pulse on time, Pulse off time, Peak current and Gap voltage along-with the powder particle size and its concentration on MRR and SR while machining Inconel 718. SiC and

Al_2O_3 powders are investigated. Regression analysis has been done to model responses and then their optimization is performed through PSO.

M. Satheesh et.al., [18] has addressed the application of desirability function approach combined with fuzzy logic analysis to optimize the multiple quality characteristics (bead reinforcement, bead width, bead penetration and dilution) of submerged arc welding process parameters of SA 516 Grade 70 steels (boiler steel). Experiments were conducted using Taguchi's L27 orthogonal array with varying the weld parameters of welding current, arc voltage, welding speed and electrode stick out. By analysing the response table and response graph of the fuzzy reasoning grade, optimal parameters were obtained. Solutions from this method can be useful for pressure vessel manufacturers and operators to search an optimal solution of welding condition.

Himadri Majumder et al., [19] has done an experimental investigation, desirability function analysis (DFA), a multi-attribute decision making was utilized to find out the optimum input parameter setting during wire electrical discharge machining (WEDM) of Ni-Ti shape memory alloy. Four critical machining parameters, namely pulse on time (TON), pulse off time (TOFF), wire feed (WF) and wire tension (WT) were taken as machining inputs for the experiments to optimize three interconnected responses like cutting speed, kerf width, and surface roughness. Confirmation test has been done to validate the optimum machining parameter combination which affirmed DFA was a competent approach to select optimum input parameters for the ideal response quality for WEDM of Ni-Ti shape memory alloy.

Arun Pratap Singh et al., [20] experimented with the micro-EDM using pulse on, pulse off as process parameters and MRR & TWR as objective functions. A three level RSM model has been used and a regression multi response optimization was performed to obtain maximum MRR and TWR. After the application of this optimization model, except for input current, for all other parameters MRR first increases and then starts to descend. For input current, MRR always increases. The TWR increases proportionally with pulse off and decreases with pulse off time. The validation of this result is confirmed as the error in it has been minimized to the least possible extent after repeating iterations.

Gurudev Singha et al., [21] has worked on similar experiment as above (Arun Pratap Singh), considered a micro-EDM machining wherein TWR & MRR were response factors for pulse on time, pulse off time, duty cycle and gap voltage process parameters. Taguchi mathematical model is applied which is verified by ANOVA analysis. MRR & TWR are largely effected by pulse on time as mentioned above. But, mainly for TWR, gap voltage has more effect than other parameters.

Rafał Swiercz et.al., [22] has done, an analytical and experimental investigation of the influence of the EDM parameters: Surface integrity and MRR Analysis of variance (ANOVA) was used to establish the statistical significance parameters. The calculated contribution indicated that the discharge current had the most influence (over the 50%) on the Sa, WL, and MRR, followed by the discharge time. The multi-response optimization was carried out using the desirability function for the three cases of EDM: Finishing, semi-finishing, and roughing. The confirmation test showed that maximal errors between the predicted and the obtained values did not exceed 6%.

Prosum Mandal et al., [23] has experimented the machining performance of an EDM process using (electrode wear resistance) EWR and Material Removal Rate MRR. The variably controlled independent variables were pulse on time, duty cycle, discharge current and gap voltage. This has been applied on Cu-MWCNT (Copper–multi-walled carbon nanotube). Particle Swarm multi objective optimization using a Taguchi L9 Orthogonal array was used to find non dominated and pareto solutions. The experimental results have confirmed with the predicted ones.

2.1.3 Other Evolutionary Optimization techniques used in machining

Ali R. Yildiz et al., [24] has investigated the cutting parameters in milling operations. This paper studies the optimization of milling using various techniques already existed like ant colony algorithm, hybrid particle swarm, hybrid immune algorithm and feasible direct methods. They suggested the cuckoo search algorithm and used it to try and improve solution methods mentioned above. CS algorithm has been found to be more effective than the rest of the methods prescribed above.

Dun Liu et al., [25] performed a thorough analysis of abrasive jet machining. The objective of the paper is to effect of depth of penetration on the roughness of the surface. Transverse direction, strain, standoff distance, inclination angle, surface speed and abrasive flow were considered as the operating parameters and Response Surface Methodology is used to optimize, investigate the major parameters that influence penetration depth. It has been found that transverse direction, tilt angle, abrasive flow rate were major influences in this regard.

Ram Singh et.al., [26] in this study the Bat algorithm BA, Ant bee colony ABC and PSO algorithm is applied to determine the optimal parametric combinations for three turning processes for achieving better and higher machining performance and to get greater efficiency. The experiments are performed on Al5083 metal matrix composite reinforcement of 7%B_4C. The turning process is carried out by using HSS single point cutting tool under the dry condition. In the present experiment the turning parameters such as cutting speed, feed rate and depth of cut are being optimized by considering constant length of material being machined. In the metal cutting process, the proper cutting parameter will affect the quality of the finished product, In Ex-situ form B4C particle used for reinforcing the material. The reinforced aluminium matrix composites have some special properties which make them use for various purposes. The presence of B4C particle in Al matrix makes them difficult in machining, for the achieving of industrial requirement. The influence of B4C particle in Al5083 was studied experimentally and optimal machining condition is studied in this experiment. The investigation shows that MRR increases with increases in speed and depth of cut and shows intermittent effect with an increase. in feed-rate. Surface roughness increases with increase in depth of cut and feed-rate and shows intermittent effect with speed. Change in temperature increases with increase in speed and depth of cut and shows intermittent effect with feed-rate. When the comparison is done between different population-based optimization algorithms, like BA, ABC and PSO it is observed that the PSO algorithm gives better results.

2.2 INFERENCES DRAWN FROM LITERATURE REVIEW

- The predicted value of experimental data proposed by the ANN model is much more significant than the regression model for every response parameter in the milling of these AMMCs.
- Genetic Algorithm is a generalised stochastic search method and it needs to be coupled with other techniques to bring optimal solutions for particular problems.
- Particle Swarm Optimization converges quickly as compare to normal genetic algorithm and to enhance this, Genetic Algorithms are hybridised.
- The Taguchi technique, through an orthogonal array, led to reduced experiments. This technique assisted in optimizing parameters with a satisfaction level of 95%.
- The Taguchi method, the ratio Signal/Noise is a measure of the variation of response relative to the target or nominal value for different noise conditions.
- Of all the non-traditional measuring techniques, machine vision and AE have proved better in measuring response parameters to optimize machining
- All the non-dominant solutions od multi objective optimization are solved by MOPSO optimization technique.

2.3 RESEARCH OBJECTIVES

1. Perform mathematical model and analysis on WEDM textured inclined, parallel and cross patterns.

2.Comparison of mathematical models obtained by RSM, ANN and Fuzzy logic. Find the method which predicts near accurate solutions among them and find error percentage.

3.Apply genetic algorithm to the results obtained by RSM. Firstly, perform single objective optimization of MRR and TWR separately. Then, perform a multi objective GA optimization of both TWR AND MRR to find a feasible solution and improve process parameters.

2.4 METHODOLOGY

(FLOWDIAGRAM)

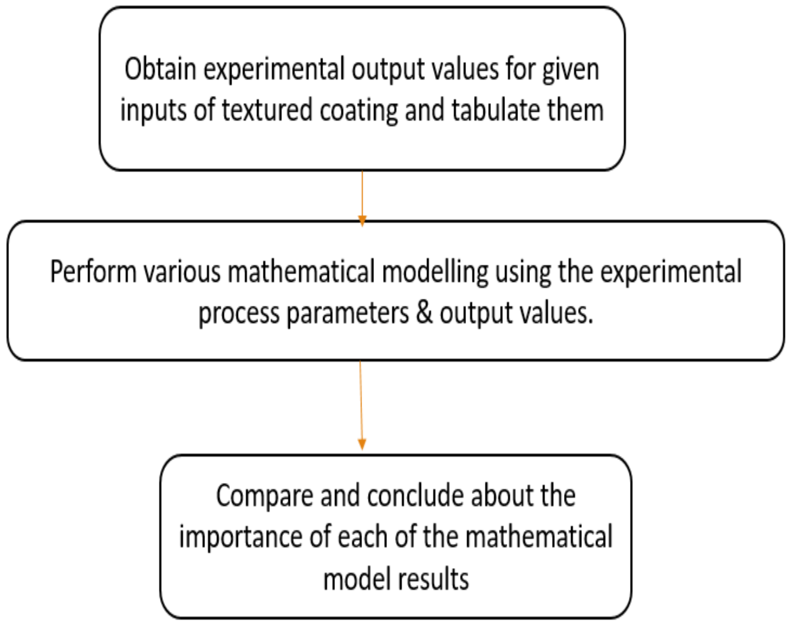


FIGURE 2.1: Flowchart of the entire work

The overview of the entire thesis has been represented using a flow diagram as shown above.

CHAPTER 3

3.1EXPERIMENTAL DETAILS

3.1.1Selection of tool materials (HSS)

High speed steel is a highly alloyed tool steel capable of maintaining hardness even at elevated temperatures. High speed steel tools are so named primarily because of their ability to machine materials at high cutting speeds. High speed steel has unusually high resistance to softening at temperatures up to6000 °C. It is called red hardness. They are complex iron-base alloys of carbon, chromium, vanadium, molybdenum or tungsten, or combinations thereof, and in some cases substantial amounts of cobalt. The carbon and alloy contents are balanced at levels to give high attainable hardening response, high wear resistance, high resistance to the softening effect of heat, and good toughness for effective use in industrial cutting operations. Especially suited to applications involving complicated tool shapes; drills, taps, milling cutters, and broaches.

3.1.2Techniques to create textures

Textures can be successfully created using electrical discharge machining (EDM) that implements electrical sparks to form a metal shape. In this process, the desired shape is cut from the metal when current discharge or sparks occurs between two electrodes; where the sparking occurs, cuts are made into the metal, creating the desired shape and detaching it from the metal sheet. There are two main types of EDM – wire and sinker- and several others less common. During the EDM process, a metal part is placed into dielectric fluid, and a wire is fed through the submerged metal component. An electrical signal is sent through the part to create the sparks that will ultimately help form the desired shape of the component. When the distance separating the electrodes narrows, it increases the intensity of the electric field, and thus increases the strength of the dielectric fluid. The current more easily passes between the two electrodes under these conditions, leading to the separation of the component from the metal sheet with each spark. After the current have passed through and the desired shape has been achieved, manufacturers will sometimes perform a process called “flushing”, using a dielectric liquid to help remove any leftover material or waste from the finished product. Wire EDM is most commonly used in mold and dies manufacturing process, particularly for extrusion dies and blanking punches. EDM can be used in everything from prototypes to full production runs, and is most often used to manufacturing metal components and tools. The process is best suited for applications requiring low level of residual stress. In our present work the textures on the HSS cutting tool were created using WEDM (Model: Tool Master 6S, make: Electronica Hi-tech) as shown in Figure 3.1.

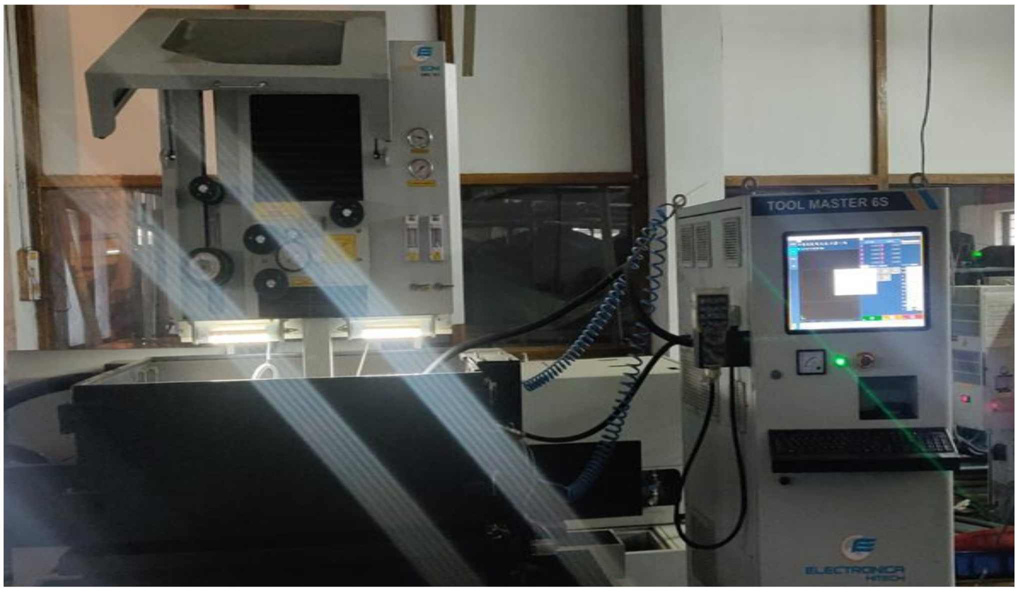
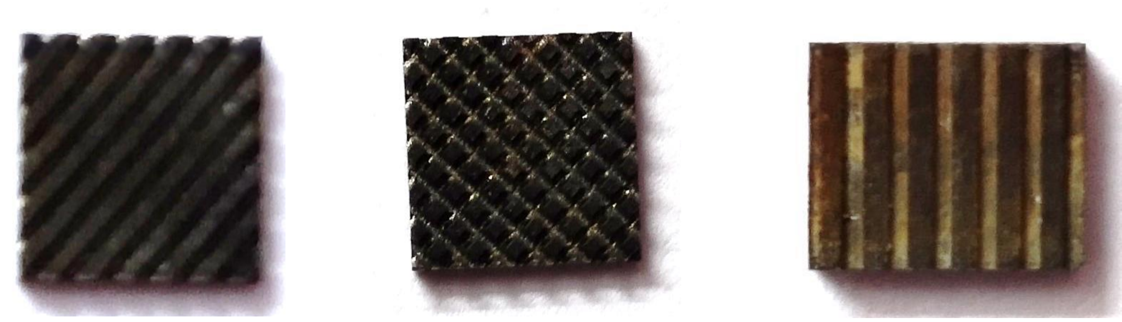


Figure 3.1: Wire electric discharge machining

The three different textures created on the HSS cutting tools using WEDM are shown in Figure3.2.



(a) Inclined texture (b) Cross texture (c) parallel texture

Figure 3.2: Textures: (a) Inclined texture, (b) Cross texture, (c) parallel texture

3.1.3Machining investigation

The turning operations were carried out in a conventional lathe with HSS single point cutting tool having three different textures, viz. parallel, inclined and cross patterns, on its rake surface. Circular mild steel rods having a diameter of 20.5 mm and a length of 50 mm was selected as work piece materials. The material removal rate (MRR) is expressed in equation 3.1 as:

$$MRR = \frac{\frac{\pi}{4}\left(Di^2 - Df^2\right)L}{Machining\ time} \tag{3.1}$$

The tool wear rate during machining can be investigated using the equation 3.2:

$$Tool\ wear\ rate = \frac{Wi - Wf}{tm\rho} \tag{3.2}$$

where, W_i = Initial Weight of the cutting tool insert (g)

W_f = Final Weight measured of the cutting tool insert (g)

ρ = Density of the cutting tool materials (g/mm^3)

t_m = Machining time in minute

Introduce three levels of values individually for each of the process parameters namely, spindle speed (rpm), feed rate(mm/rev) and depth of cut (mm). They are tabulated as given below.

Table 1: Input process parameters and their levels for machining investigation.

Factors	Parameters	Levels		
		Level 1	Level 2	Level 3
A	Spindle Speed(rpm)	290	480	700
B	Feed rate (mm/rev)	0.06	0.14	0.2
C	Depth of cut (mm)	0.2	0.4	0.6

Corresponding to the three levels of process parameters, we obtain nine sets of input values for which output (MRR &TWR) are calculated for each of the three textures. These tables are given below.

Case 1

Table 2: Results of MRR and TWR for HSS cutting tools with **inclined texture**

Exp. No.	A	B	C	MRR (mm^3/min)	TWR (mm^3/min)
1	290	0.06	0.2	341.969	1.838
2	290	0.14	0.4	1259.020	5.551
3	290	0.2	0.6	2213.422	0.365
4	480	0.06	0.4	1075.367	1.528
5	480	0.14	0.6	3553.508	0.271
6	480	0.2	0.2	1048.185	1.190
7	700	0.06	0.6	2306.153	0.838
8	700	0.14	0.2	882.283	1.435
9	700	0.2	0.4	1349.831	1.682

Case 2

Table 3: Results of MRR and TWR for HSS cutting tools with **cross texture**

Exp. No.	A	B	C	MRR (mm^3/min)	TWR (mm^3/min)
1	290	0.06	0.2	178.807	0.467
2	290	0.14	0.4	1305.028	0.222
3	290	0.2	0.6	2486.410	0.417
4	480	0.06	0.4	346.410	2.908
5	480	0.14	0.6	3747.222	0.205
6	480	0.2	0.2	721.369	0.427
7	700	0.06	0.6	1819.608	1.079
8	700	0.14	0.2	1243.571	2.946
9	700	0.2	0.4	2388.573	2.323

Case 3

Table 4: Results of MRR and TWR for HSS cutting tools with **parallel texture**

Exp. No.	A	B	C	MRR (mm^3/min)	TWR (mm^3/min)
1	290	0.06	0.2	366.186	1.648
2	290	0.14	0.4	913.310	0.347
3	290	0.2	0.6	2566.085	2.814
4	480	0.06	0.4	760.567	3.489
5	480	0.14	0.6	2147.719	1.869
6	480	0.2	0.2	666.475	2.269
7	700	0.06	0.6	1509.957	0.243
8	700	0.14	0.2	808.617	1.178
9	700	0.2	0.4	2124.118	0.901

Using these tabular input and output parameter values, we can apply mathematical models which can predict values, model them and also show plots and graphs which can further be used to optimize and find one accurate value.

3.2 Modeling of experimental results

3.2.1 Fuzzy Logic Modelling

Due to the complex and non-linear relationship between the input parameters and output performance measures, it is quite difficult to develop a process model for EDM. Unfortunately, no efficient, generalized approach to model the EDM process has been reported for studying and predicting MRR and TWR. The fuzzy inference system or fuzzy model is a computing framework based on fuzzy set theory, fuzzy if-then rules and fuzzy reasoning. The fuzzy inference system consists of three components, namely rule base, data base and reasoning mechanism. A fuzzy logic unit consists of a fuzzifier, membership functions, a fuzzy rule base, an inference engine, and a defuzzifier. The input and output values are fuzzified using membership functions. The fuzzy reasoning works on fuzzy rules to generate a fuzzy value to be used by inference engine. Finally, fuzzy value is converted into a crisp output by defuzzifier. Generally, defuzzification is done according to the Centre of Area (COA) method. Fuzzy logic tool box was used to build the FLM of EDM process.

The first step in generating a fuzzy logic is to identify the ranges of input and output variables. Then, the range of each process variable is divided into groups of fuzzy subsets. Each fuzzy subset is given a proper name and assigned a membership function. The membership function is assigned without depending on the results of the experiments. In general, membership functions are classified into trapezoidal, triangular and square or their combinations. Based on the number of trials, Gaussian membership functions were selected for this study. The notations used in fuzzy subsets were as follows: L - Low, M - Medium, H - High. For all inputs, three input functions were considered, namely low, medium and high, represented by L, M, H respectively. Similarly, for output variables, three different functions were considered, namely extreme low, medium, and high, represented by L, M, H respectively.

The relationship between input and output in a fuzzy system is characterized by a set of linguistic statements. There are no systematic tools for forming the rule base of the FLM. The fuzzy control rules can be derived from experience and knowledge of control engineering.

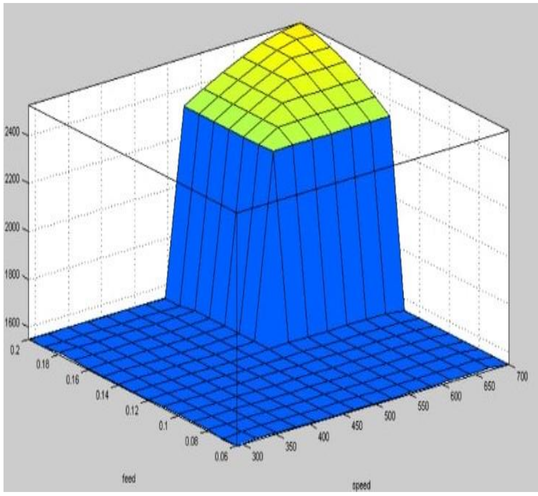
One experiment result in one fuzzy rule. If all the fuzzy rules are saved in a data base, a fuzzy rule base is established. The number of fuzzy rules in a fuzzy system is related to the number of fuzzy sets for each input variable. In this study, 9 fuzzy rules were established as shown in Table.

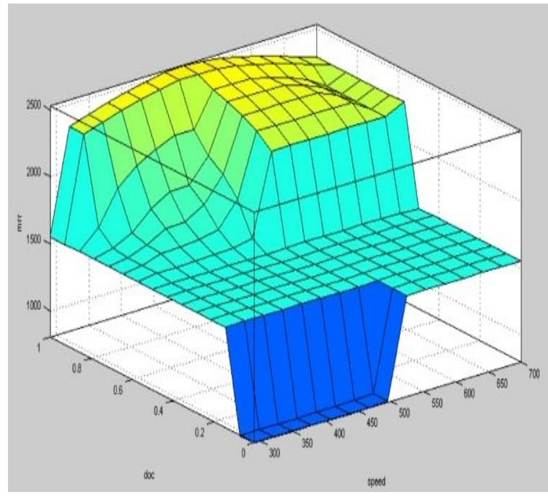
Table5: The below table represents the truth table for the 3 levels of the experimental values.

INPUT RANGE | OUTPUT RANGE

S. No	SPEED (rpm)	FEED (mm/s)	DEPTH OF CUT (mm)	MRR (mm^3/min)	TWR (mm^3/min)
1.	L	L	L	L	L
2.	L	M	M	L	L
3.	L	H	H	H	H
4.	M	L	M	M	M
5.	M	M	H	H	H
6.	M	H	L	H	M
7.	H	L	H	M	H
8.	H	M	L	M	M
9.	H	H	M	H	M

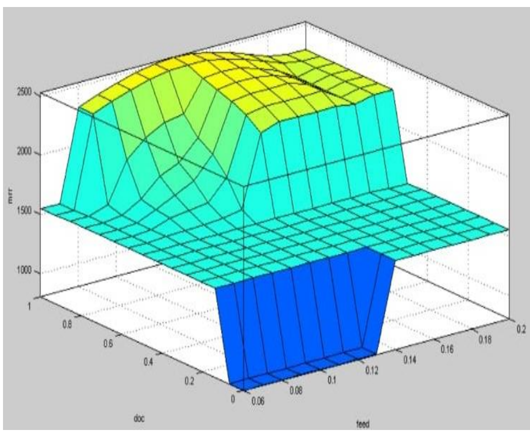
The output responses of the fuzzy process can be viewed only in fuzzy values and they need to be defuzzified. We need to choose the outputs which have high (H) MRR and low (L)/ medium (M) TWR S.no 6 satisfies this condition and gives us an optimized performance of the machining.

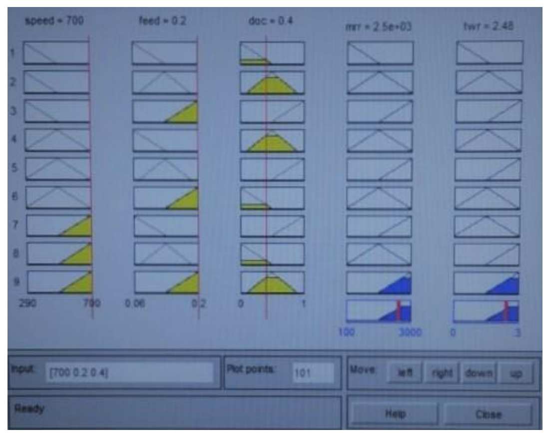




a) Inclined MRR Plot

b) Cross MRR Plot





c) Parallel MRR Plot

d) Rules Veiw

Figure 3.3 Various plots obtained from fuzzy logic .

The above figure represents the plots that have been used to find the range of the truth tables given in table number 5

3.2.2 Artificial Neural Networks

Artificial neural networks (ANNs), usually simply called neural networks (NNs), are computing systems vaguely inspired by the biological neural networks that constitute animal brains.

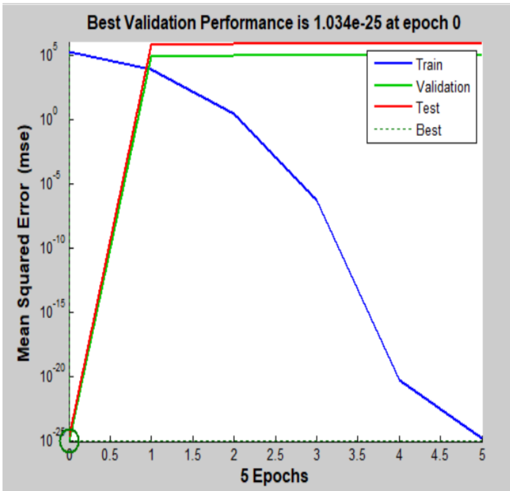
An ANN is based on a collection of connected units or nodes called artificial neurons which loosely model the neurons in a biological brain. Each connection, like the synapses in a biological brain, can transmit a signal to other neurons. An artificial neuron that receives a signal then processes it and can signal neurons connected to it. The "signal" at a connection is a real number, and the output of each neuron is computed by some non-linear function of the sum of its inputs. The connections are called *edges*. Neurons and edges typically have a weight that adjusts as learning proceeds. The weight increases or decreases the strength of the signal at a connection. Neurons may have a threshold such that a signal is sent only if the aggregate signal crosses that threshold. Typically, neurons are aggregated into layers. Different layers may perform different transformations on their inputs. Signals travel from the first layer (the input layer), to the last layer (the output layer), possibly after traversing the layer multiple times.

In the present work, ANNs have been implemented using a MATLAB NNTOOL BOX, in which input process parameters were given along with the target values and they have been trained.

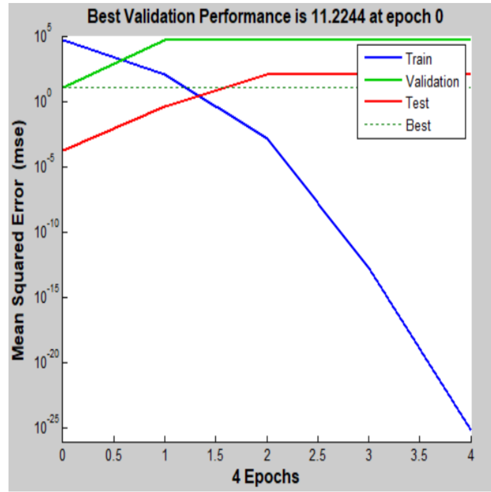
The network chosen for modelling data is a two layered Levenberg-Marquardt backpropagation (TRAINLM) which uses an adaptive gradient descent and bias learning (LEARNGDM) performed on a mean squared error (MSE).

Inputs, target and output variables are exported to the network and a training model is created.

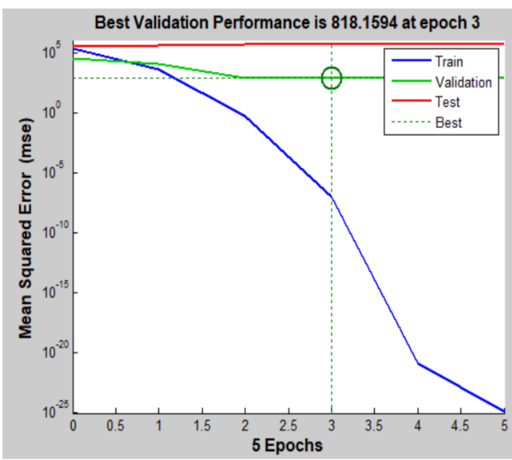
The results obtained from the training model are given as follows:



a) inclined texture graph



b) parallel texture graph



c) cross texture graph

Figure 3.4; Performance curves for a) inclined texture b) parallel texture c) cross texture

As you can see from the above figures, the MSE for each of the textures have reduced with more epochs which means that as the model got trained more and more, we were able to obtain predicted values with minimum errors. The predicted values for these textures are given below.

Table 6: Predicted values obtained after simulating and training the above data

a) Inclined texture b) Parallel texture c) Cross texture

MRR (mm^3/min)	**TWR** (mm^3/min)
825.7180	1.7633
1.6466e+03	5.4205
1.6884e+03	2.0705
1.3409e+03	2.2086
2.8410e+03	3.0059
964.8414	1.4115
2.3007e+03	1.0522
2.2316e+03	1.1633
2.2115e+03	-0.0495

a) Inclined texture values

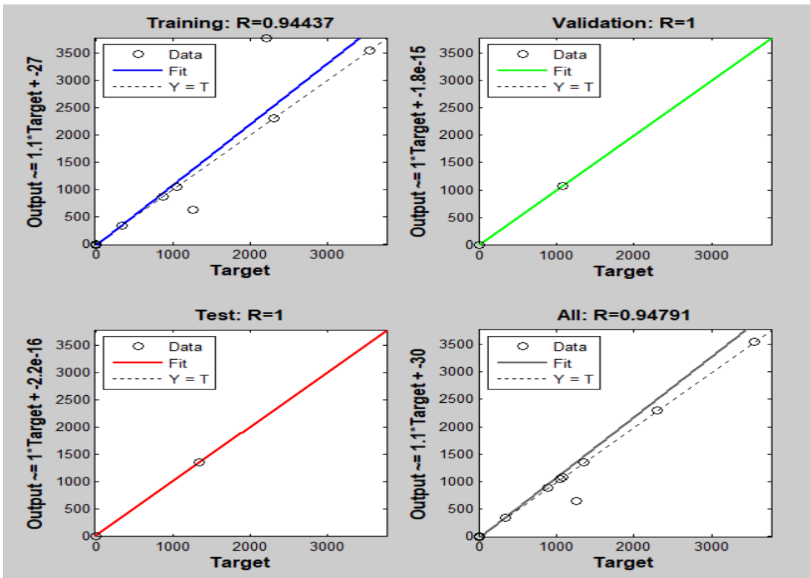
MRR (mm^3/min)	**TWR** (mm^3/min)
341.9690	1.8380
640.5395	2.8829
3.7658e+03	-0.9166
1.0754e+03	1.5280
3.5535e+03	0.2710
1.0482e+03	1.1900
2.3062e+03	0.8380
882.2830	1.4350
1.3498e+03	1.6820

b) Parallel texture values

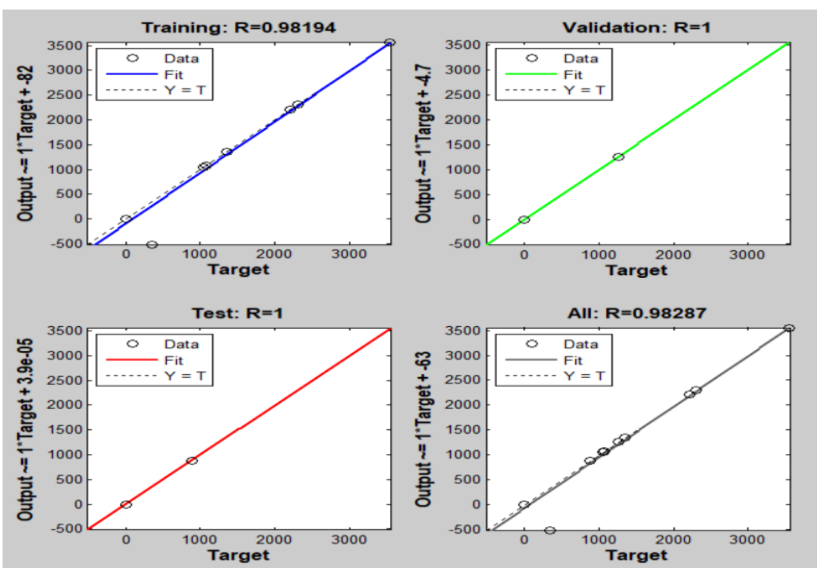
MRR (mm^3/min)	**TWR** (mm^3/min)
-508.7066	2.0981
1.2593e+03	0.8238
2.2134e+03	0.3652
1.0754e+03	1.5273
3.5536e+03	0.2710
1.0479e+03	1.1903
2.3059e+03	0.8382
882.2635	1.4350
1.3498e+03	1.6820

c) Cross texture values

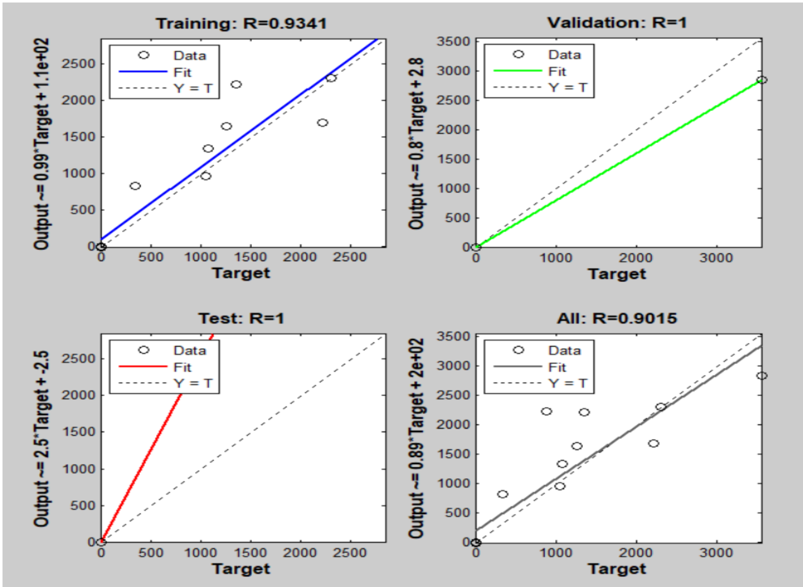
For the same model, a regression plot also has been prepared in the ANN models to compare the test, training and validation of the above trained network. They have been shown below.



a) Inclined texture



b) Parallel texture



c) Cross texture

figure 3.5: the above plots are the regression plots of the ANN model comparing the training, testing and validation of the three textures.

3.2.3 RSM modelling

➢ Response Surface Methodology (RSM) explores the relationships between several explanatory variables and one or more response variables. The method was introduced by George E. P. Box and K. B. Wilson in 1951. The main idea of RSM is to use a sequence of designed experiments to obtain an optimal response. Response Surface Methodology (RSM) uses various statistical, graphical, and mathematical techniques to develop, improve, or optimize a process, also use for modelling and analysis of problems if our response variables in influenced by several independent variables.

➢ Main objectives are as follow.

- Optimize
- Develop
- Improve.

RSM is used in different fields of real life. Like Industries, Agriculture, Electronics, Medical field and many other like this. It is use where we want to get optimum response.

The regression equation in uncoded units obtained of MRR and TWR on modeling using Minitab are: -

Case 1: Inclined Texture

Regression Equation in Uncoded Units is given by equation 3.3

MRR (mm^3/min) = -1837- {9.055 Spindle Speed (rpm)* 27118 Feed rate (mm/rev)}
- 8543Depth of cut (mm) - {0.01218 Spindle Speed (rpm)
*Spindle Speed (rpm)} - {118464 Feed rate (mm/rev)
*Feed rate (mm/rev)} + {14798 Depth of cut (mm)
*Depth of cut (mm)} + {14.29 Spindle Speed (rpm)
*Feed rate (mm/rev)} + {4.213*Spindle Speed (rpm)
*Depth of cut (mm)} (3.3)

Regression Equation in Uncoded Units is given by equation 3.4

TWR (mm^3/min) = -2.818 - 0.02830 Spindle Speed (rpm) + {140.8 Feed rate (mm/rev)
+ 29.11Depth of cut (mm)} + {0.000024 Spindle Speed (rpm)
*Spindle Speed (rpm)} - {369.5 Feed rate (mm/rev)
*Feed rate (mm/rev)} - {61.41 Depth of cut (mm)
*Depth of cut (mm)} - {0.07845Spindle Speed (rpm)
*Feed rate (mm/rev)} + {0.02988 Spindle Speed (rpm)
*Depth of cut (mm)} (3.4)

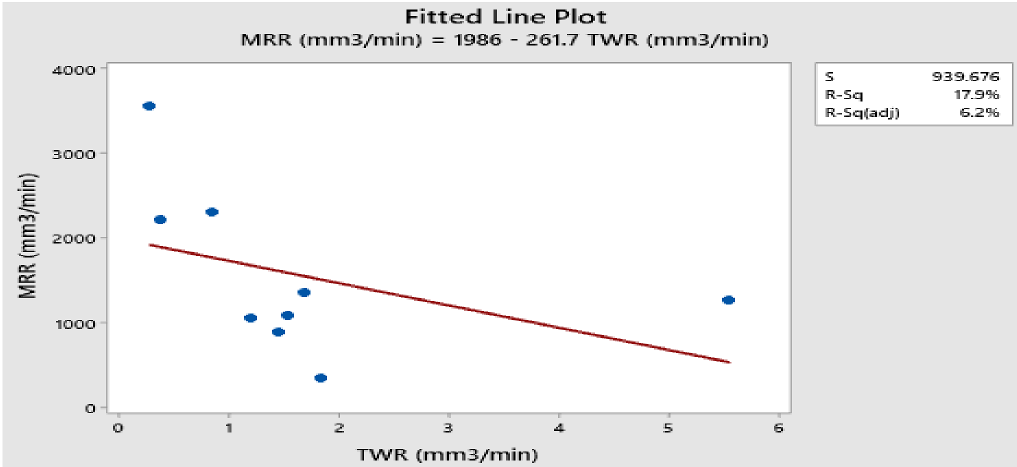


Figure 3.6; plot obtained between MRR and TWR for inclined texture

The final regression equations obtained is the regression equation is given by equation 3.5

$$MRR\ (mm^3/min) = 1986 - 261.7\ TWR\ (mm^3/min) \quad (3.5)$$

The figure shows the linear variation of MRR and TWR according to the regression equation. i.e., as the value of MRR decreases the value of TWR increases.

Case 2: Parallel Texture

MRR Regression Equation in Uncoded Units is given by equation 3.6

MRR (mm^3/min) = 921.8-5.043 Spindle Speed (rpm)+ 20265 Feed rate (mm/rev)
-7757 Depth of cut (mm) - {0.001262 Spindle Speed (rpm)
*Spindle Speed (rpm)} – {148606 Feed rate (mm/rev)
*Feed rate (mm/rev)} + {17827 Depth of cut (mm)
*Depth of cut (mm)} + {53.77 Spindle Speed (rpm)
*Feed rate (mm/rev)} + {0.8175 Spindle Speed (rpm)
*Depth of cut(mm)} (3.6)

TWR Regression Equation in Uncoded Units is given by equation 3.7

TWR (mm^3/min) = -4.351-0.01520 Spindle Speed (rpm) – {66.76 Feed rate (mm/rev) +30.98 Depth of cut (mm)} - {0.000000 Spindle Speed (rpm) *Spindle Speed (rpm)} + {163.3 Feed rate (mm/rev) *Feed rate (mm/rev)} – {18.50 Depth of cut (mm) *Depth of cut (mm)} + {0.02299 Spindle Speed (rpm) *Feed rate (mm/rev)} – {0.03492 Spindle Speed (rpm) *Depth of cut (mm)} (3.7)

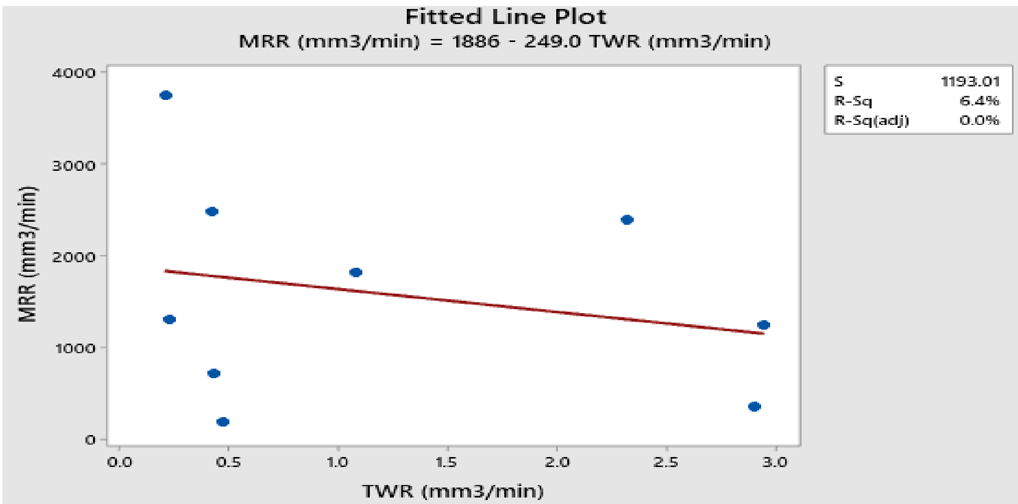


Figure 3.7 plot obtained between MRR and TWR for cross texture

The final regression equations obtained is the regression equation is given by equation 3.8:

MRR (mm^3/min) = 1886 - 249.0 TWR (mm^3/min) (3.8)

The figure shows the linear variation of MRR and TWR according to the regression equation of cross texture. i.e., as the value of MRR decreases the value of TWR increases but it is less inclined than inclined texture.

Case 3: Cross Texture

Regression Equation in Uncoded Units is given by equation 3.9

MRR (mm^3/min) = 1965-5.535 Spindle Speed (rpm) - {24232 Feed rate (mm/rev)
+2178 Depth of cut (mm)} + {0.004366 Spindle Speed (rpm)
*Spindle Speed (rpm)} + {48973 Feed rate (mm/rev)
*Feed rate (mm/rev)} + {7446 Depth of cut (mm)
*Depth of cut (mm)} + {32.79 Spindle Speed (rpm)
*Feed rate (mm/rev)} – {6.685 Spindle Speed (rpm)
*Depth of cut (mm)} (3.9)

Regression Equation in Uncoded Units is given by equation 3.10

TWR (mm^3/min) = -3.385-0.03951 Spindle Speed (rpm)- 101.6 Feed rate (mm/rev)
+12.46 Depth of cut (mm) - {0.000032 Spindle Speed (rpm)
*Spindle Speed (rpm)} + {302.4 Feed rate (mm/rev)
*Feed rate (mm/rev)} + {7.186 Depth of cut (mm)
*Depth of cut (mm)} + {0.02929 Spindle Speed (rpm)
*Feed rate (mm/rev)} –{0.03524 Spindle Speed (rpm)
*Depth of cut (mm)} (3.10)

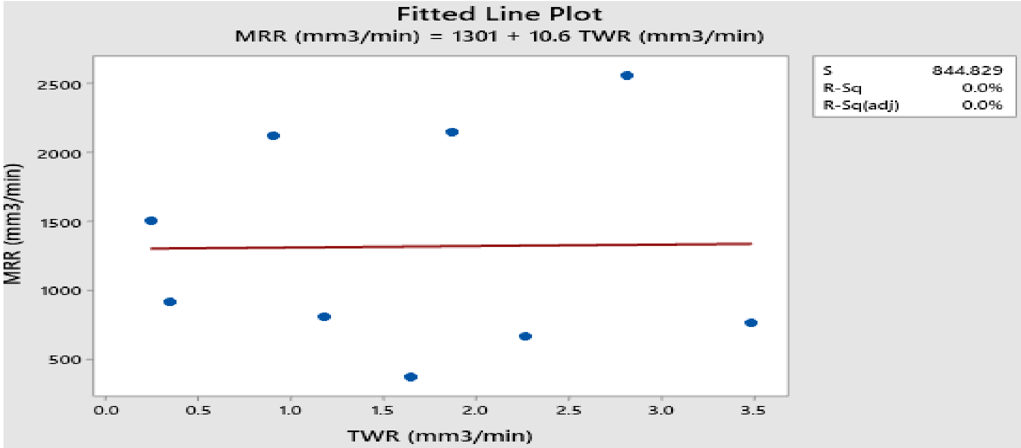


Figure 3.8: plot obtained between MRR and TWR for cross texture

The final regression equations obtained is the regression equation is given by equation 3.11-

MRR (mm^3/min) = 1301 + 10.6 TWR (mm^3/min) (3.11)

The figure shows the linear variation of MRR and TWR according to the regression equation of parallel texture. i.e., the value of MRR increases the value of TWR increase but the increment the value of TWR is very less hence the variation is almost parallel.

3.2.4 Comparison of different Modeling techniques

RSM is a statistical method that uses quantitative data from the related experiment to determine regression model and to optimize a response (output variable) which is influenced by several independent variables (input variables). Fuzzy models or sets are mathematical means of representing vagueness and imprecise information (hence the term fuzzy). These models have the capability of recognizing, representing, manipulating, interpreting, and utilizing data and information that are vague and lack certainty. An ANN is a computational model that establishes a relationship between process factors and output variables. Artificial neurons are combined through weights, which work as adjustable coefficients.

CHAPTER 4:

OPTIMIZATION OF EXPERIMENT RESULTS

4.1 ABOUT CHAPTER

This chapter presents the results and discussion of optimization using genetic algorithm and different mathematical modelling done on hss tool of the non-textured and textured high-speed steel (HSS) single point cutting tools. experiments were performed using three input variables spindle speed, feed, depth of cut.

4.2 STEPS INVOLVED IN EXECUTING THE OPTIMIZATION IN GENETIC ALGORITHM

Step-1

This step starts with guessing of initial sets of a and b values which may or may not include the optimal values. These sets of values are called as 'chromosomes and the step are called 'initialize population'. Here population means sets of a and b [a, b]. Random uniform function is used to generate initial values of a and b.

Step-2

In this step, the value of the objective function for each chromosome is computed. The value of the objective function is also called fitness value. This step is very important and is called 'selection' because fittest chromosomes are selected from the population for subsequent operations.

Based on the fitness values, more suitable chromosomes who have possibilities of producing low values of fitness function (because the value of our objective function needs to be 0) are selected and allowed to survive in succeeding generations. Some chromosomes are discarded to be unsuitable to produce low fitness values.

One of the most widely used selection methods in GA is 'roulette wheel method'. Roulette wheel method is discussed in detail below.

Roulette wheel method

Roulette wheel is a pie plot where the value of each pie is expressed in terms of fitness probability. Note that fitness value and fitness probability are two different terms. In this optimization problem, chromosome which produces low fitness value has high fitness probability. Fitness probability of each chromosome is computed from fitness values. Chromosome having high fitness probability will have higher chance of getting selected.

Step — 3

This step is called 'crossover'. In this step, chromosomes are expressed in terms of genes. This can be done by converting the values of a and b into binary strings which means the values need to be expressed in terms of 0 or 1.

What is crossover?

Crossover is 'the change of a single (0 or 1) or a group of genes (e.g. [1,0,1])' occurred because of mating between two parent chromosomes. The new chromosome produced after crossover operation is called 'offspring'.

Step — 4

This step is called 'mutation'. Mutation is the process of altering the value of gene i.e., to replace the value 1 with 0 and vice-versa. For example, if offspring chromosome is [1,0,0,1], after mutation it becomes [1,1,0,1]. Here, 2nd value of the offspring chromosome is decided to get mutated. It has got changed to 1 from 0. The mutation parameter decides how many genes to be mutated. If mutation parameter is 0.1 (usually kept low values). Then 0.1 times the total genes are allowed to mutate.

After mutation, binary chromosomes are converted into integer form and fitness values are calculated. If any one of the chromosomes produces target fitness value equal to 0, we stop there. Otherwise, the process will be repeated from step — 2 to step — 4 by equating mutated chromosomes with new population

4.3 MULTI OBJECTIVE GA IN MATLAB

In this section, we will show the actual code and the settings given to the GA toolbox in MATLAB and show the pareto front plot obtained from it.

Firstly, we create a function with inputs and output. The output functions obtained from the regression equation in section 3.2.3 for the three textures are used in this section to obtain the pareto plot. This function is imported to the GA TOOLBOX window and the input bounds are given. The population is chosen as a double vector and selection is done based on the TOURNAMENT. After all this, the algorithm is started until it goes through the required generations and gives a pareto plot.

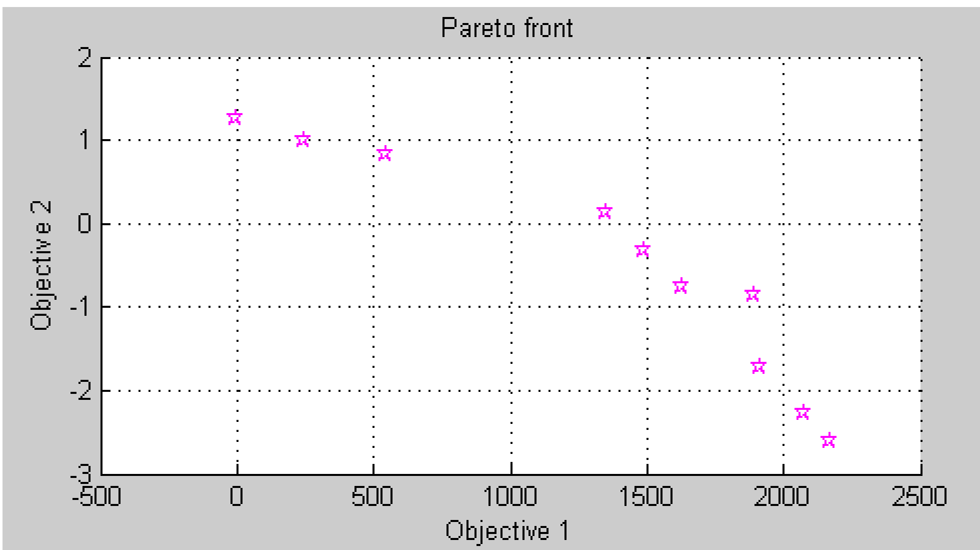


Figure: 4.1 Inclined Texture Pareto Plot of MRR (Objective 1) & TWR (Objective 2)

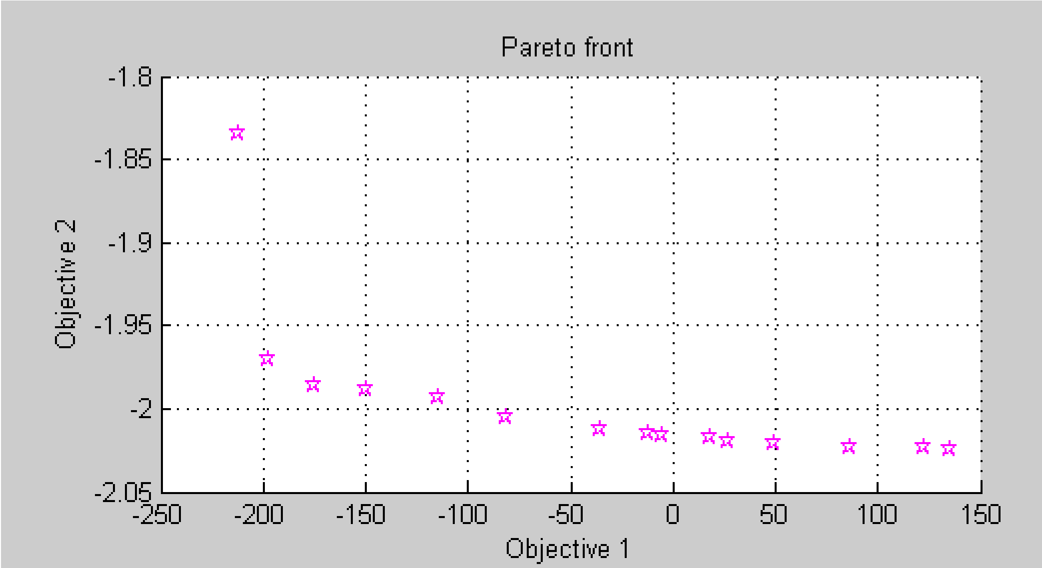


Figure 4.2: Parallel Texture Pareto Plot of MRR (Objective 1) & TWR (Objective 2)

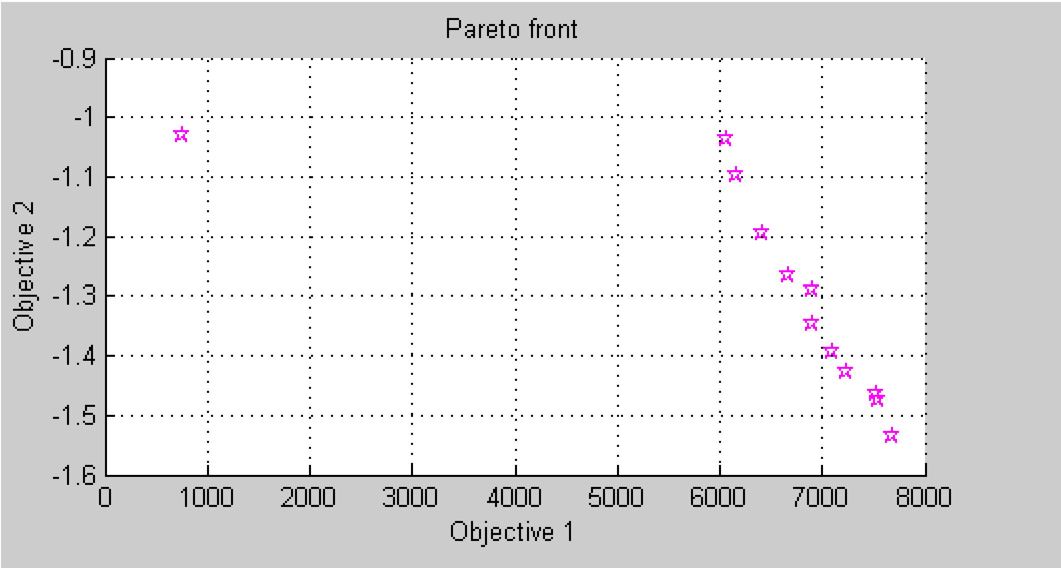


Figure 4.3: Cross Texture Pareto Plot of MRR (Objective 1) & TWR (Objective 2)

From the above pareto plots of the different textures, we find out that the inclined texture had better result as compared to parallel and cross textures.

CHAPTER 5:

5.1 Conclusion and future scope

•The results obtained by fuzzy logic are linguistic and they give the extent to which a value obeys. Therefore, fuzzy logic is a qualitative mathematical model. It specifies a range of values. Deterministic models are not possible with the fuzzy logic modelling.

But, this model works quite well with a layman and can give a brief idea of the working process parameters and there is nothing complicated about this model.

•The results obtained by RSM models give the curvature of the plot that can be specify graphical points, areas and contours which are better for representation purposes. Also, this model provides us with a regression equation which can be further employed in optimization and give us the best working parameters.

•The results obtained by ANN models can use the experimental data to create a black box and predict values with minimum errors. Although, its parameterization is still the work of user and its efficiency depends on the user's skill, it was quite effective in predicting the models by training states and spare us with more experimental analysis.

•Overall, these models have their own unique advantages and can be used according to the context and requirements.

• The future of this mathematical modelling and optimization looks interesting as new evolutionary computational techniques, hybrid techniques for specific problem sets are being formulated. The Neural Network efficiencies have been improving over the years and obtaining predictive values with minimum data set of the experiments can reduce experimental costs and time too.

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