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Multi Objective Optimization of Drilling Process Variables Using Genetic Algorithm for Precision Drilling Operation

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Abstract:- The aim of this paper is to utilise genetic algorithm approach to investigate the effect of CNC drilling process variables such as spindle speed, drill diameter, material thickness, and feed rate on thrust force and torque generated during the drilling of mild steel plate using H.S.S drill. To find out the relationship between drilling process variable on thrust force and torque generated to the jig and work table, multiple regression model is used. Regression model is generated with the help of SPSS-19. Statistical validity, explanatory power and significance of the regression model is tested at 95% confidence interval. High degree of correlation between drilling parameters and thrust force/torque has been found with almost negligible interaction amongst the drilling process parameter. Regression model is found to be significant and valid. Optimum combination of process variable to explain thrust force and torque generated is found with the help of MATLAB solver using genetic algorithm. Sensitivity analysis investigates the change in the solutions resulting from making changes in parameters of the GA model. In this research, sensitivity analysis shows how sensitive of solutions and decision variables to changes in weights in objective functions. It shows that the solutions of an aggregation method are affected by weight adjustment. Thus, in case of aggregation method, if the weights are not appropriately assigned, the GA may not give out good solutions. On the other hand, for the proposed Pareto method, it is not sensitive to weigh, so incorrect weights do not affect the solution outcome of Pareto based MOGA.
Key words:- Twist drill, High speed steel, Mild steel, CNC, VMC, Multiple regression, R square, Adjusted R square, Multicollinearity, Multiobjective optimization, Genetic algorithm, MOGA, Pareto front, mutation, cross over etc.

INTRODUCTION

Drilling is one of the most commonly used machining processes in the shaping of Mild steel. It has considerable economical importance because it is usually among the finishing steps in the fabrication of industrial mechanical parts. The word steel is used for many different alloys of iron. These alloys vary both in the technique they are made and in the extent of the materials added to the iron. All steels, though, contain small amounts of carbon and manganese. In other words, it can be said that steel is a crystalline alloy of iron, carbon and several other elements, which hardens above its critical temperature. There are several types of steels, which are (among others) plain carbon steel (Mild steel), stainless steel, alloyed steel and tool steel. Mild steel is extensively used as a main engineering material in various industries such as aircraft, aerospace, and automotive industries where weight is probably the most important factor. These materials are considered as easy to machining and possess superior machinability.

The performance of these products is mainly dependant on surface quality and dimensional accuracy of the drilled hole. The quality of the hole drilled is affected by thrust force and torque generated on to the jig and work table which is subjective to the cutting conditions, such as cutting speed, drill diameter, feed rate, material thickness, tool material and geometry. The efficiency of drilling operation is directly proportional to the material removal rate but it is done at the cost of drilling quality, which is not effective. It has been a great challenge for most of the researcher worldwide how to increase the productivity of drilling process which the multiplier effect of efficiency and effectiveness by optimizing the drilling process parameters. In a precision drilling operation quality of drilling hole is very important which is greatly influenced by thrust force and torque generated. Higher the value of thrust force and torque lesser will be the accuracy of the drilling. Many researchers over the years worldwide tried to minimize thrust force and torque generated during the precision drilling operation in particular.

Optimization of machining & geometric parameters is usually a tricky work, where the following aspects are required like knowledge of machining, empirical equations relating the study undertaken, specification of machine tool capabilities and knowledge of mathematical and numerical optimization techniques also is required. Selection of the proper machining parameters using own experience or from the handbooks on the part geometry, technological requirement, machine tool, a cutting tool and the part material is rarely gives you the optimum results.

To select the optimum parameters it is necessary to determine them at first for the given machining situation. There are several techniques available to determine the optimum values of these parameters, such as, nomograms, graphical techniques, performance envelope, linear programming, geometrical programming, search procedures, approaches based on mathematical optimization etc. In all the above methods, empirical equations are used which involves a number of factors, thus requiring a large amount of data to be handled. The most frequently method used to find empirical relationship between problem undertaken and its explanatory variables is regression analysis.

In this paper drilling parameters, cutting speed, feed, material thickness, drill diameter and geometric parameter drill point angle are considered. A relational model is formed using multiple regression to explain the thrust force and torque generated. ANOVA is applied for testing the statistical validity and significance of the empirical relationship. The trials are then carried out in Ashok Leyland Limited, Bhandara (India) using CNC vertical machining centre .The empirical relationship obtained for both trust force and torque is optimize using genetic algorithm. There are various approaches to multiobjective such as, goal programming, particle swarm optimization, ant colony optimization and evolutionary genetic algorithm. In this paper pareto based multiobjective optimization has been used. A solution can be considered Pareto optimal if there is no other solution that performs at least as well on every criteria and strictly better on at least one criteria. Thus, a Pareto-optimal solution cannot be improved upon without hurting at least one of the criteria.

LITERATURE REVIEW

The principal amount of money spent on any one class of cutting tools is spent on drills. Therefore, from the perspective of cost and productivity, modeling and optimization of drilling processes are exceptionally important for the manufacturing industry [1]. Amongst traditional machining processes, drilling is one of the most important metal cutting operations, comprising 33% of all metal cutting operations [2]. Although modern metal cutting methods have tremendously improved in the manufacturing industry, conventional drilling process still remains one of the most common processes.

Product quality of the work piece has been an issue of primary apprehension to the manufacturing industry. From the various factors that affect the product quality, tool wear is the most significant one. Drilling is one of the usual material removal processes which almost account for 40% of all machining processes. Drill wear is characterized as flank wear, chisel wear, corner wear and crater wear. Flank wear is the most significant of all. Drill wear has a negative effect on the surface finish and dimensional correctness of the work piece. Generally thrust force and torque are developed in the operations which try to unclamp the job and create vibrations. As the flank wear increases, for the same set of speed and feed the forces will increase which is not desired at all. For long these cutting parameters which give minimum flank wear with minimum thrust force and torque are decided by experience and the optimum parameters could not be guaranteed and taken for granted. Now-a-days software packages have come out for help. Researchers have tried implementing software and found out exceptional results and the literature is quite rich. Thrust force and torque were established as a function of material hardness, average flank wear and feed rate by Cook et.al [3], Jalai et.al [4] observed that when machining the last hole, the thrust force and torque are 50% larger than while machining the first hole. These results show that both thrust force and torque increases as the drill wear increases. Lin and Ting [5] studied the effect of drill wear as well as other cutting parameters on current force signals and established the relationship between the force signals and drill wear with other cutting parameters.

N.Baskar et al. [6] found out optimization procedures for processes like, milling, grinding, and drilling etc. A specific case in milling operation was taken and solved by using three different non-traditional optimization techniques which comprises of: 1. Global search algorithm (genetic algorithm),2. Local search algorithm (local hill climbing), 3. Memetic algorithm. Results obtained in this work are intended for use by NC machines. However they also be used for manually operated machines. It is also observed that the procedures described in this work can be applied to similar machining operations as well as other non-linear optimization problems. H. Li et al. [7] studied the tool wear propagation and cutting force variations in the end milling of Inconel 718 with coated carbide insert and results showed that significant flank wear was the predominant failure mode affecting the tool life. The tool flank wear propagation in the up milling operations was more rapid than that in the down milling operations and the significant flank wear was the predominant failure mode affecting tool performance and tool life. J.Zhang et al. [8] studied the Taguchi design application to optimize surface quality in a CNC face milling operation and ANOVA analyses were carried out to identify the significant factors affecting surface roughness, and the optimal cutting combination and confirmed that the Taguchi design was successful in optimizing milling parameters for surface roughness. It was found that the effects of spindle speed and feed rate on surface were larger than depth of cut for milling operation. This was accomplished with a relatively small number of experimental runs. R. Jalili Saffar et al. [9] made an attempt to optimize machining parameters using Genetic Algorithm (GA) so as to minimize tool deflection. The algorithm considers tool deflection as the objective function while surface roughness and tool life are the constraints. With increasing feed rate and depth of cut, the tool deflection is increased. Optimization of machining parameters is successfully achieved using Genetic Algorithm. P Tandon et al. [10] explains the geometry of cutting flutes and the surfaces of end mill as one of the crucial parameters affecting the quality of the machining in the case of end milling. These are usually represented by two-dimensional models. The geometric definition of the end mill is developed in terms of surface patches; flutes as helicoidally surfaces, the shank as a surface of revolution and the blending surfaces as bicubic Bezier and biparametric sweep surfaces. The method described in this paper offers a simple and intuitive way of generating high-quality flat end mill models for use in machining process simulations. V. Astakhov et al. [11] has discussed that, when the optimal cutting temperature is considered, the influence of the cutting feed, depth of cut, and work piece (bore) diameter on tool wear becomes clear and straightforward. The obtained results reveal that there are least five independent factors that determine the influence of the cutting feed on tool wear. Among them, the length of the tool path and the cutting temperature are of prime importance. As a result, the influence of the cutting feed on the tool wear rate is different at different cutting speeds.

V.Gadakh et al. [12] has shown the application of multi objective optimization on the basis of ratio analysis (MOORA) method for solving multiple criteria (objective) optimization problem in milling process. Six decision making problems which include selection of suitable milling process parameters in different milling processes are considered. As this method is based only on simple ratio analysis, it involves the least amount of mathematical calculations, which may be quite useful and helpful to the decision makers who may not have a strong background in mathematics. Also, the computation time of the MOORA method would obviously be less. R. Sardiñas et al. [13] have used a multi-objective optimization technique, based on genetic algorithms, to optimize the cutting parameters in turning processes: cutting depth, feed and speed. Two conflicting objectives, tool life and operation time, are simultaneously optimized using micro genetic algorithm and Pareto frontier graphics.

In quest of the meaningful relationship between the process variables and the cutting force in drilling has been an dynamic area of research since several decades. Marques et al. found that as the feed rate increases, the thrust force increases, whereas the effect of the speed on the thrust force is negative up to certain limit than it starts to rise with the increase in speed. Madhavan et.al.[14] suggest that as the spindle speed increases, the cutting torque also decreases for a certain limit of speed, beyond which it increases with the increase in speed. Wen-Chou-Chen [15] established that the thrust force increases as point angle increases, while the cutting torque decreases with the increase in drill point angle. Mansheel Cheong et al. [16] found that the drill diameter is having a positive relationship with both the thrust and torque generated. Panda et al. investigated the effect of drill diameter on the thrust force and found positive relationship between the two. Abrao et al.[17] suggested positive relationship between thrust force and the thickness of the material to be drilled. Based on the present-day research, there are number of factors have been recognized, which are likely to affect the thrust force and torque. The important factors are as follows-

- Material thickness
- Drill point angle
- Drill diameter
- Speed
- Feed rate

2.1 Overview of Genetic Algorithms

In the last decades, several Evolutionary Computation methodologies have emerged and gained popularity. These include evolutionary programming, evolution strategy, genetic programming and genetic algorithm. Genetic Algorithm was firstly introduced by J. H. Holland (1975) in 1975. The Genetic Algorithm has been applied to variety types of problems such as machine learning, optimization. Genetic Algorithm is a stochastic search techniques based on the process of natural selection and genetics. Genetic Algorithm is distinctive from conventional optimization techniques in the way that it is initialized by a set of random generated solutions called population. Each individual, i.e. one solution, in the population is called chromosome. A chromosome is subdivided into genes. A gene represents a single factor for a control factor. Each factor in the solution set corresponds to gene in the chromosome. The chromosome represents the genotype, i.e., raw genetic information. The phenotype is an expression of the chromosome in terms of an objective function as shown in figure 1-

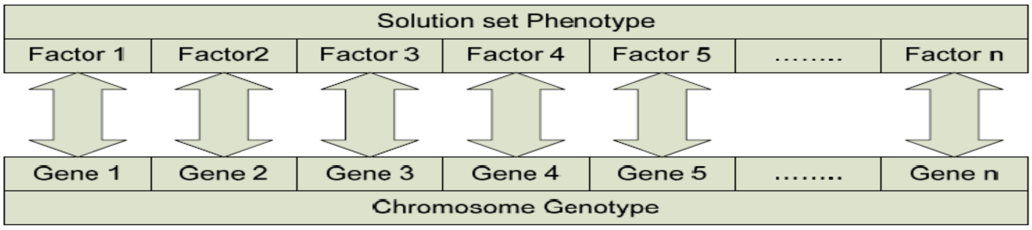

Figure 1 representation of genotype and phenotype of an individual chromosome adapted from Sivanandam and Deepa (Sivanandam and Deepa 2008)

A chromosome, in the final stage, will give out solutions to the objective function which is called fitness function in Genetic Algorithm. The chromosome is a string of variables that is usually, but not necessary, a binary string. The chromosome evolves through successive iterations which are called generations. During each generation, the chromosomes are evaluated their fitness. Some of the fittest chromosomes are selected to generate the next generation or offspring via recombination process.

Differences between Genetic Algorithms and conventional optimization techniques:
Genetic Algorithm differs from conventional optimization and search techniques in the following ways:

- Genetic Algorithm works with coding of solution set instead of the solutions themselves.
- Genetic Algorithm searches from population of solutions rather than a single solution found in conventional methods
- Genetic Algorithm uses fitness function for evaluation rather than derivatives or other auxiliary knowledge.
- Genetic Algorithm uses probabilistic transition rules while conventional methods use deterministic transition rules.

Advantages of Genetic Algorithms:
There are main three main advantages when applying Genetic Algorithm to optimization problems which are:

- Genetic Algorithm does not have many mathematical requirements related to the optimization problems. Because of its evolutionary nature, Genetic Algorithm searches for solutions without any regard to the specific internal structure of the problem. Genetic Algorithm can handle any kind of objective function and any kind of constraint (e.g. linear vs nonlinear) defined on discrete, continuous or mixed search space.
- The ergodicity of evolution operators makes Genetic Algorithm very effective at performing a global search (in probability). The traditional approaches perform a local search by a convergent stepwise procedure, which compares the values of nearby points, and moves to the relative optimal points. Global optima can be found only if the problem possesses certain convexity properties which essentially guarantee that any local optimum is a global optimum.
- Genetic Algorithm provides us with a great flexibility to hybridize with domain dependent heuristics to make an efficient implementation for a specific problem . There are also additional advantages to the three main ones mentioned above as follows:
- Genetic Algorithm can scan thru solution sets quickly, and is not affected by bad proposals. Bad proposals are simply discarded by the algorithm.
- Genetic Algorithm is self inductive in nature, so it does not need to know any prior rules or data (domain knowledge). Genetic Algorithm works by its own internal rules.Therefore, Genetic Algorithm is good for complex or loosely defined problems.
- Genetic Algorithm searches problem space efficiently, so it is more likely to converge toward global optima.
- Genetic Algorithm can handle linear as well as non-linear problems
- Genetic Algorithm does not need to compute partial derivatives, so it saves some computational time
- Genetic Algorithm handles noisy search space better than stochastic hill climbing that sometimes get stuck in a local optimum.

2.2 Existing research in multi objective optimization of drilling process variables using MOGA:

Neural networks and fuzzy sets have been used for the prediction of surface finish and tool life while optimisation for various goals is carried out using real coded GA by D.K. Ojha et.al [18] in a turning operation. A neuro-fuzzy model was developed by S.S.Roy[19] for a drilling operation which can produce optimal knowledge base of fuzzy system for predicting tool life, torque and thrust force in drilling operation. In a workby P. Bhattacharyya et.al [20] combinations of signal processing techniques for real-time estimation of tool wear in face milling using cutting force signals are presented. Optimization techniques of GA like Multiobjective genetic algorithm (MOGA) is applied for reactive power optimization by P.Aruna Jeyanthy[21] effectively. In latest researches in this field S.N.Joshi et.al [22] integrated finite element method (FEM) with neural networks and GA to optimize the process parameters in a electric discharge machining (EDM). B.Latha et.al [23] used multi-objective optimization of genetic algorithm with neural networks to optimise the process parameters of a composite drilling. All these research activities are done in sophisticated computer numerical controlled (CNC) machines.

2.3 Multi-objective Optimization and Genetic Algorithms:

The multi-objective Optimization Problem (MOP) is also called in other names such as multicriteria optimization, multiperformance or vector optimization problem. It can be defined as the problem of finding a vector of decision variables which satisfies constraints and optimizes a vector function whose elements represent the objective functions. These functions form a mathematical description of performance criteria which are usually in conflict with each other. Therefore, the term, "optimize," means finding such a solution which would give the values of all objective functions acceptable to the decision maker [24]. When dealing with real-life problems, especially in engineering design field, the optimal design cannot usually be expressed in terms of a single objective. In general, there is more than one objective to be satisfied in the design. Also, the objectives are usually in conflict in a multi objective model. Therefore, there is no one solution exists that is optimal for all objectives. In this kind of problem, the notion of optimality is replaced by that of non-dominance or non-inferiority. A non-inferior solution is one in which an improvement in any one objective results in degradation of at least one of the other objective's values. Hence, a multi-objective model is used to generate various non-inferior solutions to the problem rather than to identify a single optimal solution .To deal with a multi-objective optimization problem, it is common practice to combine multiple objectives to one objective. Then, a single objective optimization algorithm can be used to obtain the solution. This method is called aggregation method. It is done by translating multiple objectives into a single objective that is a convex combination of the original objective functions. This convex combination is determined by assigning relative weights to the original objectives and combining them. As mentioned before, the "good" weights are difficult to obtain without prior knowledge to the solutions. The other method is the constraint method. The constraints method identifies non-inferior solutions by optimizing one of the original objectives subjected to constraints on the value for the other objectives. Various non-inferior solutions are generated by varying the bounds on the other objectives. These approaches are less than ideal without prior knowledge how objectives interact with one another. The last method to obtain a set of solutions for MOP is through the use of Pareto Optimal Theory. The multi-objective problems require a decision maker to make a choice of preferred solutions. The selection is essentially a tradeoff of one complete solution over another in multi-objective space. The definition of Pareto optimal in a minimization problem is that "x" is Pareto optimal if there exists no feasible vector x which would decrease some criterion without causing a simultaneous increase in at least one other criterion. The concept of Pareto Optimality is integral to the theory and the solving of MOPs . In the other words, a solution can be considered Pareto optimal if there is no other solution that performs at least as well on every criteria and strictly better on at least one criteria. Thus, a Pareto-optimal solution cannot be improved upon without hurting at least one of the criteria. Solutions that are Pareto-optimal are also known in various literatures as nondominated, noninferior or Pareto-efficient. A solution is not Pareto-optimal if one criterion can be improved without degrading any others. This solution is known as a dominated or inferior solution. Multi-objective optimization algorithms find these solutions by approximating the true Pareto optimal front that involves three objectives.

- Minimize the distance between solutions and the Pareto front
- Maximize the diversity of the non-dominated solutions to represent as much of the Pareto front as possible
- Maintain already found non-dominated solutions

Pareto optimality is named after an Italian economist, Vilfredo Pareto (1906). It is a measure of efficiency in multi-criteria situations. The concept has wide applicability in economics, game theory, multicriteria optimization, multicriteria decision-making, and the social sciences generally. Multi-objective problems are those in which there are two or more criteria measured in different units, and no agreed-upon conversion factor exists to convert all criteria into a single metric. Multi-objective optimization is concerned only with the generation and selection of noninferior solution points, i.e., Pareto optima. (Genetic Algorithm and Direct Search Toolbox 2, user's guide).

Genetic Algorithms have recently become more widely used for their performance with large-scale, multi-objective problems. Genetic Algorithm is recognized as well suited to multiobjective optimization since their early development. Multiple individuals can search for multiple solutions in the same time, eventually taking advantage of any similarities available in the family of possible solutions to the problem. The ability to handle complex problems that involes features such as discontinuity, multimodality, disjoint feasible spaces and noisy function evaluation strengthen the potential effectiveness of Genetic Algorithm in multi-objective optimization. This is where Genetic Algorithm, including evolutionary computation, distinguishes itself from the competition [25].

RESEARCH APPROACH AND METHODOLOGY

3.1 Problem Statement

In precision drilling operation thrust force and torque generated is having significant influence over the quality of drilled hole. Trust force and torque generated are dependent on drilling parameters such as cutting speed, feed rate, material thickness, drill diameter tool geometry-drill point angle angle. Research problem is to find some empirical relation between thrust force/torque and drilling process variables. There after to find out optimum combination of drilling process variables that minimize both thrust force and torque generated.

Research Objective

This research aims to determine drilling process variables that minimize not only thrust force but also torque generated. Because of the hard combinatorial nature of process variable design problems together with multi-objective characteristics of real world optimization problems, the author decided to apply a nonconventional optimization method to obtain solutions. Ant Colony Optimization (ACO) was first explored. A few Ant Colony Optimization approaches exist that try to approximate the set of Pareto-optimal solutions (Dorigo and Stutzle 2004). Therefore, the other nonconventional techniques including Genetic Algorithm (GA) were surveyed. Finally, Genetic algorithm was selected instead of Ant Colony Optimization previously studied due its inherent multiple objective performance and available published researches at the time. Genetic Algorithm technique is used to obtain the solutions from a multi-objective drilling process design model (MODPDM) to reduce computational requirement of a traditional mixed integer linear programming (MILP) solver for NP-hard problems. The formal statement of research objectives are as follows:

- Determination of empirical relationship between drilling process variables and thrust force/torque.
- Testing statistical validity and significance of the found empirical relationships.
- Determination of multiobjective fitness function using the found empirical relationships.
- Minimization of the fitness function using genetic algorithm.
- To perform sensitivity analysis of found results

Research Hypothesis

Thrust Force (H1): Ho1: There is no significant relationship between drilling process variables and thrust force. Ha1: There is a significant relationship between drilling process variables and thrust force.

Torque (H2): Ho2: There is no significant relationship between drilling process variables and torque. Ha2: There is a significant relationship between drilling process variables and torque.

Research Methodology:

- Define decision variables from the objectives.
- Explore decision variables with the help of experiments.
- All experiments were performed using B.M.W vertical machining centre at Ashok Leyland Bhandara, India
- Develop empirical relationship between thrust force/torque using multiple regression model.
- Examine statistical validity and significance of regression model at 95% confidence interval.
- Conclude framed hypothesis.
- Construct objective functions. There are two objectives to be minimized.
  The first objective is minimizing thrust force and second one is minimizing torque generated.
- Formulation of multiobjective fitness function.
- Set suitable parameters for multiobjective optimization using genetic algorithm.
- Run data through the Multi-objective Genetic Algorithms model (MOGA)
- Evaluate results.

3.2 Experimental Process:

Drilling operation performed on Mild steel workpiese.mild steel are soft, ductile and easily machined The composition of mild conation carbon(0.05%to0.3%) and small quantities of manganese(Mn), silicon(Si), phosphorus (P) sulphur(S). Table1 shows the material related properties. Experiments were performed using a CNC vertical drilling machine. Figure2 depicts schematically the experimental set-up. A rectangular piece of mild steel was selected for the experiment.

Elastic modulus	kN/cm^2	21,000
Compressive strength	kN/cm	30

Table 1 Material parameters of mild steel

Tools for the CNC drilling operation will be twist drill made of the high speed steel.
HSS grades generally display high hardness The composition of high speed steel are carbon (0.6%to0.75%), tungsten (14%to20%),Chromium (3%to5%), vanadium (1%to1.5%), Cobalt (5%to10%) and remaining is iron.

Elastic modulus	kN/cm^2	21,000
Compressive strength	kN/cm	72

Table 2 Material parameters (HSS)

Technical specifications of B.M.W VMC are as follows: number of tools in a magazine- 16 , spindle speed (programmable) ranges from 50-3000 r.p.m, maximum feed rate on X and Y axis- 1500 mm/min and maximum feed rate on Z axis-1000 mm/min.

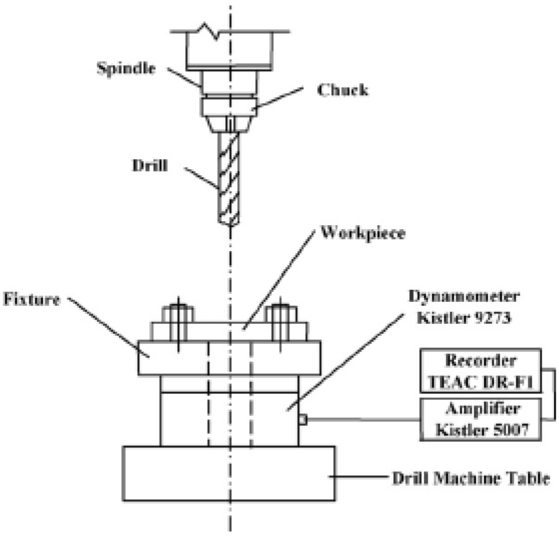

Fig.2: Line diagram of experimental set up

Design of Experiment:

In the present study drill point angle (X1-degree), drill diameter (X2-mm), material thickness (X3-mm), spindle speed (X4-mm) and feed (X5-mm/rev) have been selected as design factor. while other parameter have been assumed to be constant over the Experimental domain This Experiment focuses the observed values of thrust force (N) and torque generated (N-M). Each experimental trial was performed by setting the different values of design variables. Total 112 trials were conducted.

Control variable	Minimum	Intermediate	Maximum
Drill point angle	90	103	118
Drill diameter	6	8	10
Material thickness	8	10	12
Spindle speed	900	1200	1500
Feed rate	75	110	150

Table 3: Design scheme of experiment of Parameters and levels

3.3 Multi-objective Genetic Algorithm model (MOGA):

The Multi-objective Genetic Algorithm model attempts to create a set of Pareto optima for a multi-objective minimization. First, bounds and constraints on decision variables have to be defined. MOGA uses the genetic algorithm for finding local Pareto optima. As in the generic Genetic Algorithm, an initial population is randomly generated according to creation function specified by the users.

Genetic representation:

Genetic or chromosome representation is an important step in the design of Genetic Algorithm. Appropriate representation of candidate solutions greatly affects the efficiency and complexity of the search algorithm. In this model, vectors of real numbers are used to represent chromosomes. Each gene in the chromosome represents a solution to each decision variable.

Define fitness function:

In the Darwinian model of evolution, individuals with the best characteristics have the best chance to survive and to reproduce. A mathematical function, namely fitness function, is used to quantify how good the solution represented by a chromosome is in order to determine the ability of an individual to survive. The genetic operators such as cross-over, mutation and selection make use of the fitness evaluation of the chromosomes. For example, selection operators are more likely to choose the most fit parents for cross-over while mutation is inclined towards the least fit individuals.In the methodology, there are two objectives to be satisfied. The first one is minimizing thrust force. The second one is minimizing torque generated. The objective function can be described as follow.

Minimize: objective function1
Z1= constant+a1*X1+b1*X2+c1*X3+d1*X4+e1*X5
Z1=thrust force
Variables:
X1: drill point angle
X2: drill diameter
X3: material thickness
X4: spindle speed
X5: feed rate
a1,b1,c1,d1 and e1 are the coefficient of these variables
Minimize: objective function2
Z2= constant+a2*X1+b2*X2+c2*X3+d2*X4+e2*X5
Z2= torque generated
Variables:
X1: drill point angle
X2: drill diameter
X3: material thickness
X4: spindle speed
X5: feed rate
a2,b2,c2,d2 and e2 are the coefficient of these variables
Constraints:
X1>= 90, X2<=118
X2>=6, X2<=10
X3>=8, X2<=12
X4>=900, X4<=1500
X5>=75, X4<=150
Fitness function
Minimize Z=Z1+Z2

Run multi objective Genetic Algorithm (MOGA) to obtain solutions

1. Run MOGA with parameters set as:
   • Population type: double vector
   • Population size: 75 (15*number of genes)
   • Creation function: feasible population creation function
   • Selection: tournament selection with tournament size = 2
   • Crossover fraction = 0.8, mutation fraction = 0.2
   • Mutation: adaptive feasible
   • Crossover: intermediate with crossover ratio of 1.0
   • Migration direction: forward with fraction of 0.2 and interval of 20
   • Distance measure function: distance crowding
   • Pareto front population fraction = 0.90
   • Termination criteria: 1000 generations, stall generations or function tolerance set default value.
2. Perform population initialization
   Initial population is generated by assigning a random value from the allowed domain to each of genes in chromosomes according to creation function defined in parameter setting. The generation is completed when a population size is reached. The population size remains constant throughout the algorithm.
3. Perform selection process
   At the end of each generation, a new population of candidate solutions is selected to serve as the new population of the next generation. Tournament selection is used for this multiobjective problem. Tournament selection randomly picks out individuals from the population to form a sub group of population specified by tournament size. The scaled fitness of each individual in the subgroup is compared, and the best one is selected. The new population is generated through cross-over, mutation and elitism operators. In crossover,

the superior individuals have more opportunities to be chosen to reproduce to ensure that offspring contain genes from the best. In mutation, selection focuses on weak individuals in light that mutation will introduce better traits to increase the chance of survival. In elitism, the best individuals are selected and passed onto the next generation.

4. Perform reproduction process
   - Cross-over operation produces new offspring from two selected parents. Crossover process creates a new individual by combining genetic material selected from parents. For this model, intermediate cross-over method is used as specified in parameter settings.
   - Mutation operation randomly changes the value of genes in a chromosome to increase genetic diversity. Adaptive feasible method is used as specified in parameter settings.
5. Evaluate fitness

   Fitness of each individual in the new generation is calculated for the selection process for the next generation.
6. Terminate algorithm

   Algorithm is repeated until one of termination conditions that are previously defined in parameter settings is met. They can be a combination of generations, time, stall generations, stall time and function tolerance.
7. Evaluate solutions

   The non-dominated solutions are ranked by value of each objective function from low to high, so a decision maker can choose the solutions according to organization's goal.

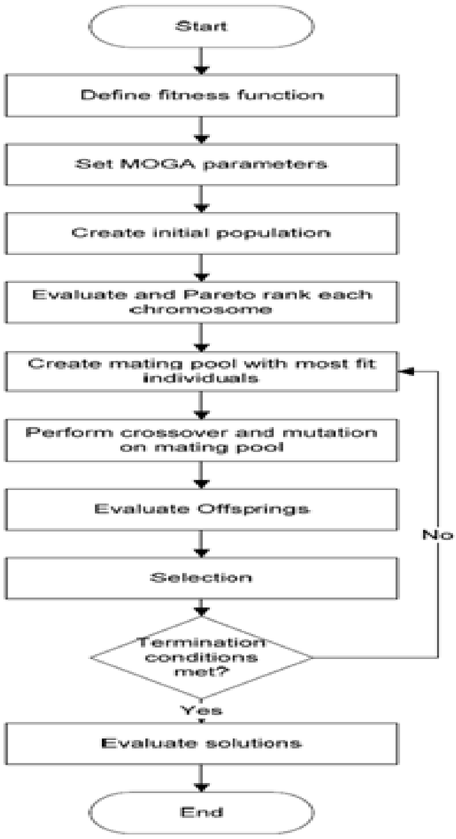

Figure3. Flowchart of Pareto based Multi-objective Genetic Algorithms (MOGA)

DATA INTERPRETATION AND ANALYSIS

4.1 Regression analysis

SPSS output

	Mean	Std. Deviation	N
Thrust	45.6588	3.42614	112
Diameter	12.00	4.018	112
Angle	102.81	11.613	112
Speed	1200.00	200.899	112
Thickness	9.86	1.604	112
Feed	112.50	23.152	112

Table-4 Descriptive Statistics

		Thrust	Diameter	Angle	Speed	Thickness	Feed
Pearson Correlation	Thrust	1.000	.614	.211	-.374	.251	.405
	Diameter	.614	1.000	.000	1.000	.078	.000
	Angle	.211	.000	1.000	.000	.009	.941
	Speed	-.374	1.000	.000	1.000	.078	.000
	Thickness	.251	.078	.009	.078	1.000	-.010
	Feed	.405	.000	.941	.000	-.010	1.000
Sig. (1-tailed)	Thrust	.	.000	.000	.000	.004	.000
	Diameter	.000	.	.500	.000	.206	.500
	Angle	.000	.500	.	.500	.462	.000
	Speed	.000	.000	.500	.	.206	.500
	Thickness	.004	.206	.462	.206	.	.460
	Feed	.000	.500	.000	.500	.460	.
N	Thrust	112	112	112	112	112	112
	Diameter	112	112	112	112	112	112
	Angle	112	112	112	112	112	112
	Speed	112	112	112	112	112	112
	Thickness	112	112	112	112	112	112
	Feed	112	112	112	112	112	112

Table-5 Correlations

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.952(a)	.906	.896	.45798	.896	1526.313	4	107	.005

a Predictors: (Constant), Feed, Speed, Thickness, Angle, Diameter
b Dependent Variable: Thrust

Table-6 Model Summary

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1280.524	4	320.131	1526.313	.005(a)
	Residual	22.442	107	.210		
	Total	1302.967	111			

a Predictors: (Constant), Feed, Speed, Thickness, Angle,Diameter
b Dependent Variable: Thrust

Table-7 ANOVA

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	20.175	.682		51.566	.002
	Angle	.209	.011	.370	9.831	.001
	Speed	-.031	.000	-.637	-50.076	.003
	Thickness	.642	.027	.300	23.574	.004
	Feed	.043	.006	.360	9.572	.005
	Diameter	1.28	.009	.480	13.789	.007

Table-8 Coefficients

	Mean	Std. Deviation	N
Torque	31.6545	10.61538	112
Diameter	12.00	4.018	112
Angle	102.81	11.613	112
Speed	1200.00	200.899	112
Thickness	9.86	1.604	112
Feed	112.50	23.152	112

Table-9 Descriptive Statistics

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	12427.618	4	3106.904	4126.059	.007(a)
	Residual	80.571	107	.753		
	Total	12508.188	111			

a Predictors: (Constant), Feed, Speed, Thickness, Angle, Diameter
b Dependent Variable: Torque

Table-10 ANOVA

Table- **11**

		Torque	Diameter	Angle	Speed	Thickness	Feed
Pearson Correlation	Torque	1.000	.981	-.098	-.281	.233	.515
	Diameter	.981	1.000	.000	000	.078	.000
	Angle	-.098	.000	1.000	.000	.009	.941
	Speed	-.281	000	.000	1.000	.078	.000
	Thickness	.233	.078	.009	.078	1.000	-.010
	Feed	.515	.000	.941	.000	-.010	1.000
Sig. (1-tailed)	Torque	.	.000	.346	.000	.007	.437
	Diameter	.000	.	.500	.000	.206	.500
	Angle	.346	.500	000	.500	.462	.000
	Speed	.000	.000	.500	.	.206	.500
	Thickness	.007	.206	.462	.206	000	.460
	Feed	.437	.500	.000	.500	.460	.
N	Torque	112	112	112	112	112	112
	Diameter	112	112	112	112	112	112
	Angle	112	112	112	112	112	112
	Speed	112	112	112	112	112	112
	Thickness	112	112	112	112	112	112
	Feed	112	112	112	112	112	112

Table-11 Correlation

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R quare Change	F Change	df1	df2	Sig. F Change
1	.934 (a)	.872	.870	.86775	.994	4126.059	4	107	.007

a Predictors: (Constant), Feed, Speed, Thickness, Angle, Diameter
b Dependent Variable: Torque

Table-12 Model Summary

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	5.153	1.292		22.470	.007
	Angle	-.129	.021	-.232	-10.108	.003
	Speed	-.010	.000	-.968	-4.432	.008
	Thickness	.120	.052	.162	20.749	.001
	Feed	.180	.011	.205	8.925	.005
	Diameter	3.070	.048	.652	5.625	.003

Table-13 Coefficients

To understand the relationship between thrust force, torque generated and the drilling process and its statistical significance, regression analysis has been done. In regression analysis the 5 drilling process variables namely drill point angle, drill diameter, material thickness and spindle speed are taken as independent variables and thrust force, torque generated as dependent variable. Statistical veracity of the model has been tested using 5% level of significance

From table-8, it can be observed that p value =.005, which is less than .05. Hence the proposed regression model for explaining thrust force is highly significant. The value of adjusted R-square is 89.6%, means regression model explain 89.6% variation and only 10.4% is unexplained (Table-7). Since the value of adjusted R-square and R-square is almost same, hence the phenomenon of multicollinearity is ruled out and no interaction amongst the independent variables.

With the help table-9, the proposed regression model can be framed as-

Z1= 20.135+.209*X1+1.28*X2+.642*X3-.031*X4+.043*X5

Z1= Thrust force
X1= Drill point angle
X2= Drill diameter
X3= Material thickness
X4= Spindle speed
X5= Feed rate

From table11, it can be observed that p value =.007, which is less than .05. Hence the proposed regression model for explaining torque generated is highly significant. The value of adjusted R-square is 87%, means regression model explain 87% variation and only 13% is unexplained (Table-13). Since the value of adjusted R-square and R-square is almost same, hence the phenomenon of multicollinearity is ruled out and no interaction amongst the independent variables.

With the help table-14, the proposed regression model can be framed as-

Z2= 5.153-.129*X1+3.070*X2+.120*X3-.010*X4+.180*X5

Z1= Torque generated
X1= Drill point angle
X2= Drill diameter
X3= Material thickness
X4= Spindle speed
X5= Feed rate

4.2 Multi-objective optimization (MOGA):

MATLAB Output

Problem formulation and Genetic representation

This multi-objective optimization problem (MOP) is solved to obtain solutions by multiobjective genetic algorithm employed by matlab on a Pentium Core 2 Duo 2.4 GHz with 3 GB of ram. A multi-objective fitness function can be formulated in a form as:

```
function f = mymulti1(x)
f(1) =20.135+.209*x(1)+1.28*x(2)+.642*x(3)-.031*x(4)+.043*x(5);
f(2) =5.153-.129*x(1)+3.070*x(2)+.120*x(3)-.010*x(4)+.180*x(5);
```

Where f(1) =Thrust force and f(2) = Torque generated.

Parameters of the multi-objective genetic algorithm are set as follow:

- Population type: double vector
- Population size: 75 (15*number of genes)
- Creation function: feasible population creation function
- Selection: tournament selection with tournament size = 2
- Crossover fraction = 0.8, mutation fraction = 0.2
- Mutation: adaptive feasible
- Crossover: intermediate with crossover ratio of 1.0
- Migration direction: forward with fraction of 0.2 and interval of 20
- Distance measure function: distance crowding
- Pareto front population fraction = 0.90
- Termination criteria: 1000 generations, stall generations or function tolerance set default value.

X1	X2	X3	X4	X5	F2	F1
103.709	6.003	8.031	1440.995	84.101	12	13.596
103.429	6.004	8.029	1440.996	84.105	12.04	13.537
103.047	6.004	8.03	1441.009	84.103	12.087	13.457
102.733	6.002	8.028	1441.029	84.105	12.123	13.388
102.482	6.004	8.023	1441.029	84.104	12.159	13.335
102.017	6.004	8.024	1441.010	84.12	12.222	13.239
101.541	6.001	8.024	1441.028	84.111	12.272	13.135

Table-14 Top 7 chromosome ranked by objective function F2 values from lowest to highest

X1	X2	X3	X4	X5	F2	F1
97.933	6.006	8.013	1441.031	84.345	12.790	12.39
98.293	6.006	8.016	1441.036	84.297	12.734	12.464
98.317	6.007	8.011	1441.034	84.240	12.724	12.466
98.726	6.005	8.019	1441.03	84.328	12.683	12.558
99.082	6.005	8.011	1441.023	84.236	12.618	12.622
99.663	6.004	8.024	1441.02	84.115	12.522	12.747
100.112	6.004	8.017	1441.017	84.114	12.462	12.835

Table-15 Top 7 chromosome ranked by objective function F1 values from lowest to highest

```
function [x,fval,exitflag,output,population,score] =
project(nvars,lb,ub,PopulationSize_Data,ParetoFraction_Data)
% This is an auto generated M-file from Optimization Tool.
 % Start with the default options
options = gaoptimset;
% Modify options setting
options = gaoptimset(options,'PopulationSize' ,PopulationSize_Data);
options = gaoptimset(options,'ParetoFraction' ,ParetoFraction_Data);
options = gaoptimset(options,'Display' ,'off');
options = gaoptimset(options,'OutputFcns' ,{ [] });
[x,fval,exitflag,output,population,score] = ...
gamultiobj(@mymulti1,nvars,[],[],[],[],lb,ub,options);
```

Diagnostic information.

Fitness function = @mymulti1
Number of variables = 5
Number of objectives = 2
0 Inequality constraints
0 Equality constraints

0 Total number of linear constraints

Modified options:

options.PopulationSize = 75
options.ParetoFraction = 0.9
options.Display = 'diagnose'
options.OutputFcns = { [] @gamultiobjtooloutput }

End of diagnostic information.

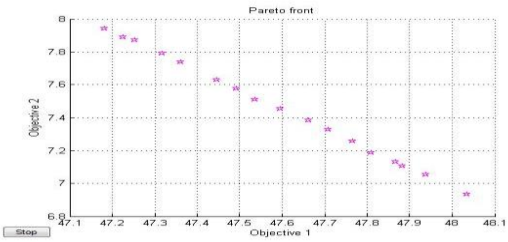

Figure 4. Pareto front plot showing objective function values for all non inferior solutions**.**

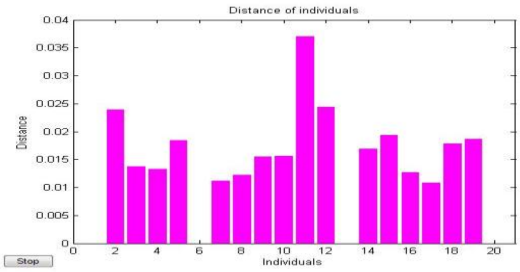

Figure 5. Average Pareto distance plot showing the average distance measure between individuals

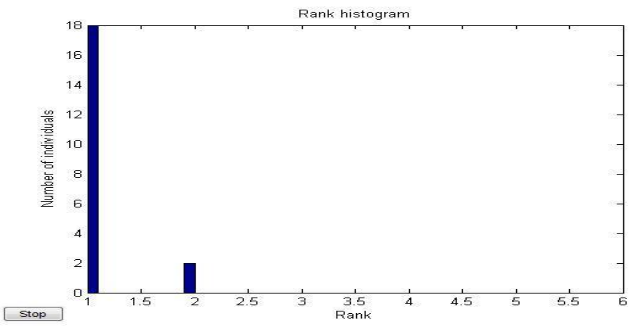

Figure 6. Rank histogram plot showing the fraction of individuals in each Pareto tier. Rank 1 individuals are best, rank 2 individuals are dominated only by rank 1 individuals, etc.

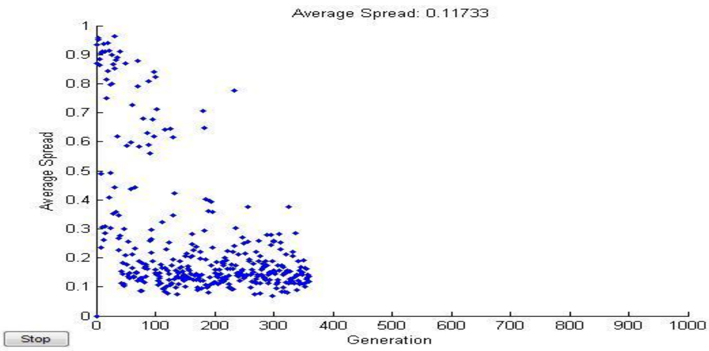

Figure 7. Average Pareto spread plot showing the change in distance measure of individuals with respect to the previous generation.

4.3 Sensitivity Analysis:

Sensitivity analysis is performed for data analysis purpose. Sensitivity analysis investigates the change in the solutions resulting from making changes in parameters of the GA model. In this research, sensitivity analysis shows how sensitive of solutions and decision variables to changes in weights in objective functions. It shows that the solutions of an aggregation method are affected by weight adjustment. Thus, in case of aggregation method, if the weights are not appropriately assigned, the GA may not give out good solutions. On the other hand, for the proposed Pareto method, it is not sensitive to weigh, so incorrect weights do not affect the solution outcome of Pareto based MOGA.

A sensitivity analysis for weighted aggregation method is done by varying weight w1 and w2 in the equation below to determine changes in decision variables, X1 to X5 in GA solutions.

Z= w1*Z1 + w2*Z2

Case 1: Z= 0.999 *Z1+ 0.001*Z2

Case 2: Z= 0.99 *Z1+ 0.01*Z2

Case 3: Z= 0.90 *Z1+ 0.1*Z2

Case 4: Z= 0.50 *Z1+ 0.50*Z2

Case 5: Z= 0.1 *Z1+ 0.9*Z2

Case 6: Z= 0.01 *Z1+ 0.99*Z2

Case 7: Z= 0.001 *Z1+ 0.999*Z2

The decision variables and objective function values are obtained as shown in table…

Case	X1	X2	X3	X4	X5	Z
Case1	97.933	6.006	8.013	1441.031	84.345	12.39
Case2	98.293	6.006	8.016	1441.036	84.297	12.46
Case3	98.317	6.007	8.011	1441.034	84.240	12.49
Case4	98.726	6.005	8.019	1441.03	84.328	12.62
Case5	99.082	6.005	8.011	1441.023	84.236	12.61
Case6	99.663	6.004	8.024	1441.02	84.115	12.52
Case7	100.112	6.004	8.017	1441.017	84.114	12.46

Table-16 Decision variables and objective function values for each case

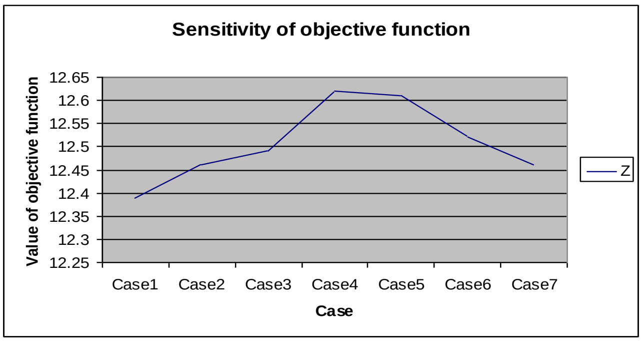

Figure 8. A sensitivity analysis of objective function value (Z) in aggregation method.

In the case of Pareto based MOGA, the definition of optimization is changed from finding optimal solutions to finding Pareto optimal solutions-compromise solution belong to the set of non-dominated solutions. Weights are assigned to z1 and z2 to generate 7 cases. It is apparent that the Pareto based MOGA does not affected by weight changes as the aggregation method. Therefore, the Pareto based MOGA is more robust and does not need prior knowledge for defining a weight of each objective in multi-objective optimization problems.

CONCLUSION

It is evident from the data analysis, the found empirical relationship between thrust force, torque generated and drilling process variables are statistically significant. The null hypothesis there is no significant relationship between thrust force, torque generated and drilling process variable can be rejected.

In real world problems, there are multiple objectives to be considered and they are usually in conflict. An aggregation method that is usually used to transform multiple objectives to single objective does not provide good solutions if the weights are not properly assigned. Prior domain knowledge is also required in order to obtain appropriate weights. Pareto based method, employing dominance ranking schemes, can be used to achieve nondominated solutions which optimally balance the trade-offs among objectives. In addition, Genetic Algorithms can obtain good quality solutions in short time and are suitable for the multi-objective environment due to its population based nature. The Pareto based multiobjective Genetic Algorithms model are constructed and sensitivity analysis are also performed. The proposed model utilizes Pareto based Genetic Algorithms to solve multiple objective problems in drilling parameter design. The Pareto based method is designed to obtain non-dominated solutions from multiple objective problems coupled with genetic algorithms which can obtain good quality solution efficiently. A sensitivity analysis was conducted to compare robustness and stability between aggregation based multi-objective genetic algorithms and Pareto based multi-objective genetic algorithms. The results show that

Pareto based method is not susceptible to inappropriate weight assignment. Therefore, it is more robust for multi-objective environment. Furthermore, Genetic Algorithms can find solutions more efficiently than conventional optimization techniques.

Limitation and future work:

- The linear relationship amongst the explained and explanatory variables can be questioned and need some further analysis.
- Maximization of material removal rate, minimization of cost of drilling should be considered along with minimization of thrust force and torque generated.
- Analytical Hierarchy Process (AHP) might be used to evaluate non-dominated/ noninferior/ Pareto optima instead of the ranking procedure if more than two objectives are considered.
- Apply other evolution computation algorithms such as Differential Evolution (DE) to the multi-objective optimization. DE is a population based search strategy similar to standard genetic algorithms. DE main difference from GA occurs in reproduction step where are created from three parents utilizing an arithmetic crossover operator.

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