AN INTEGRATED EVOLUTIONARY APPROACH FOR MODELLING AND OPTIMIZATION USING MGGP AND MULTI OBJECTIVE GENETIC ALGORITHM

A dissertation

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MASTER OF TECHNOLOGY IN COMPUTER INTEGRATED MANUFACTURING

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DECLARATION

I declare that this written submission represents my ideas in my own words and where others ideas or words have been included, I have adequately cited and referenced the original sources. I also declare that I have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in my submission. I understand that any violation of the above will cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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NOMENCLATURES

MGGP	Multi Gene Genetic Programming
MOGA	Multi Objective Genetic Algorithm
GP	Genetic Programming
MRR	Material removal rate
R_a	Average Surface Roughness
GA	Genetic Algorithm
NSGA	Non Sorted Genetic Algorithm
RSM	Response Surface Methodology
BH	Bead Height
BW	Bead Width
BP	Bead Penetration
GPTIPS	Genetic Programming Toolbox
DOE	Design of Experiment
ANOVA	Analysis of variance
OA	Orthogonal array

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ABSTRACT

This Experimental Study presents an application of an integrated evolutionary approach for modelling and optimization of Several Manufacturing and Production processes. Three case Studies have been included from International Journals whose Mathematical Modelling and Optimization is to be done. The proposed methodology consists of two parts. In the first part, a novel application of MGGP (Multi Gene genetic programming (GP)) using GPTIPS is proposed. GP is an evolutionary modelling algorithm which uses principles similar to genetic algorithms to model highly non-linear and complex processes using Multi Gene Symbolic Regression, resulting in accurate and reliable models. Design of experiments is used to conduct the experiments. Several aspects of Production performance of different processes, are modelled based on experimental data using GP in terms of prominent input variables. The effect of input parameters on the performance measures is also reported. In the second part, as the chosen manufacturing performances are opposite in nature, the problem under consideration is formulated as a multi-objective optimization problem and solved using an efficient evolutionary optimization algorithm, Multi Objective genetic algorithm. The outcome of Pareto optimal solutions is presented. The work presents a fully fledged evolutionary approach for optimization of the process.

Keywords: MGGP; GPTIPS; Symbolic Regression; DOE; Taguchi Technique; Multi Objective Genetic Algorithm; Modelling; Optimization.

CHAPTER 1

INTRODUCTION

1.1 Introduction

Genetic programming [5] is a biologically machine learning technique that evolves pc programs to perform a task. It does this by generating a population of pc programs (represented by tree structures) so mutating and crossover the best performing trees to form a replacement population. This method is iterated till the population contains programs that (hopefully) solve the task well.

When the task is building an empirical mathematical model of information inheritable from a method or system, the GP is usually referred to as symbolic regression. In contrast to traditional multivariate analysis (in that the user should specify the structure of the model), GP mechanically evolves each the structure and the parameters of the mathematical model. Symbolic regression has had each in educational and industrial applications. [6]

A free open supply MATLAB toolbox known as GPTIPS [4] that was written for the specific purpose of activity for symbolic regression. GPTIPS employs a novel sort of symbolic regression

known as multigene symbolic regression [7], [8] that evolves linear combinations of non-linear transformations of the input variable.

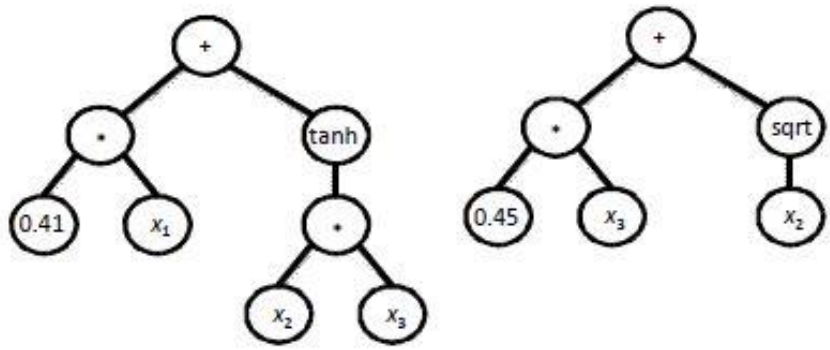
When the transformations are forced to be low order (by limiting the general practitioner tree depth) this, in distinction to "standard" symbolic regression, permits the evolution of accurate, comparatively compact mathematical models of predictor – response (input – output) information sets, even when there are an oversized variety of input variables.

1.2 Multigene Symbolic Regression

Typically, symbolic regression is performed by GP to evolve a population of trees, each of which develops a mathematical equation that predicts a (N × 1) vector of outputs y employing corresponding (N × M) matrix of inputs X where N is the no of observations of the response variable and M is the no of input (predictor) variables i.e. the ith column of X includes the N input values for the ith input variable and should be selected as input variable x_i.

In distinction, in multigene symbolic regression every symbolic model (and every member of the GP population) is a weighted linear combination of the outputs from variety of GP trees, where every tree can be considered to be a "gene". For example, the multigene model shown in Fig. 1 predicts an output variable using input variables x_1, x_2 and x_3.

This model structure contains non-linear terms (e.g. the hyperbolic tangent) however is linear in parameters with respect to the coefficients d_0, d_1 and d_2. In usual practice, the user specifies the utmost number of genes G_{max} a model is allowed to possess and maximum tree depth D_{max} any gene may have and therefore will exert control over the maximum complexity of the evolved models. The weights d_0, d_1 and d_2 are automatically obtained by least squares.



$$y = d_0 + d_1(0.41x_1 + \tanh(x_2x_3) + d_2(0.45x_3 + \mathrm{sqrt}(x_2))$$

Fig. 1 Multigene Model

In GPTIPS, the initial population is made by making individuals that contain randomly generated GP trees with between one and G_{max} genes. Throughout a GPTIPS run, genes are acquired and deleted employing a tree crossover operator referred to as two point high level crossover.This enables the exchange of genes between individuals and it's employed in addition to the "standard" Gp recombination operators. If the i_{th} gene in an individual is labeled G_i then a 2 point high level crossover is performed as within the following example. Here, the first parent individual contains the genes (G1 G2 G3) and also the second contains the genes (G4 G5 G6 G7) wherever G_{max} =5. Two randomly selected crossover points are created for every individual. The genes enclosed by the crossover points are denoted by < …>

(G1 < G2 > G3) (G4 < G5 G6 G7 >)

The genes enclosed by the crossover points are then exchanged resulting in the two new individuals below

(G1 G5 G6 G7 G3) (G4 G2)

Two point high level crossover permits the acquisition of new genes for both individuals however also permits genes to be removed. If an exchange of genes ends up in an individual containing more genes than G_{max} then genes are haphazardly selected and deleted till the individual contains G_{max} genes. In GPTIPS, standard GP subtree crossover is referred to as low level crossover. during this case, a gene is chosen randomly from every parent individual, standard subtree crossover is performed and also the resulting trees replace the parent trees in the otherwise

unaltered individual within the next generation. GPTIPS also provides many ways of mutating trees.

The user can set the relative probabilities of each of these re-combinative processes. These processes are grouped into categories called events. The user can then specify the probability of crossover events, direct copy events and mutation events. These should total to one. The user will also specify the probabilities of event subtypes, e.g. the probability of a a pair of point high level crossover happening once a crossover event has been chosen, or the chance of a subtree mutation once a mutation event has been chosen.

1.3 Steps to Perform Genetic Programming

1) Randomly produce an initial population of individual pc programs composed of the available functions and terminals.

2) Iteratively perform the subsequent sub-steps (called a generation) on the population -
A: - Execute every program within the population and ascertain its fitness (explicitly or implicitly) exploitation the problem's fitness measure.

B: - choose one or 2 individual program(s) from the population with a probability based on fitness to participate within the genetic operations.

C: - produce new individual program(s) for the population by applying the following genetic operations-
(I) Reproduction: Copy the chosen individual program to the new population.
(II) Crossover: produce new offspring program(s) for the new population by recombining randomly chosen components from 2 selected programs.
(III) Mutation: produce one new offspring program for the new population by randomly mutating a randomly chosen a part of one selected program.

1.4 GP Life Cycle in Short: The Pseudo Code

1. Produce an initial population of pc programs.
2. Evaluation.
3. Selection.
4. Reproduction.
5. Analysis.
6. Replacement.
7. Continue from 3.

1.5 Genetic Programming Example

- max(x∗x , x + 3∗y)

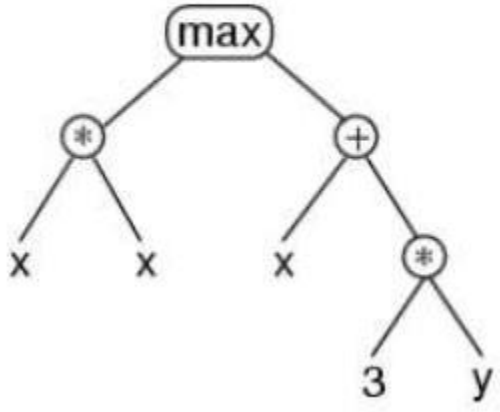


Fig. 2 Basic tree like program Representation used in GP

1.5.1 Selection

- Roulette Wheel Selection – Fitness Proportionate Selection.
- Tournament Selection.

1.5.2 Crossover

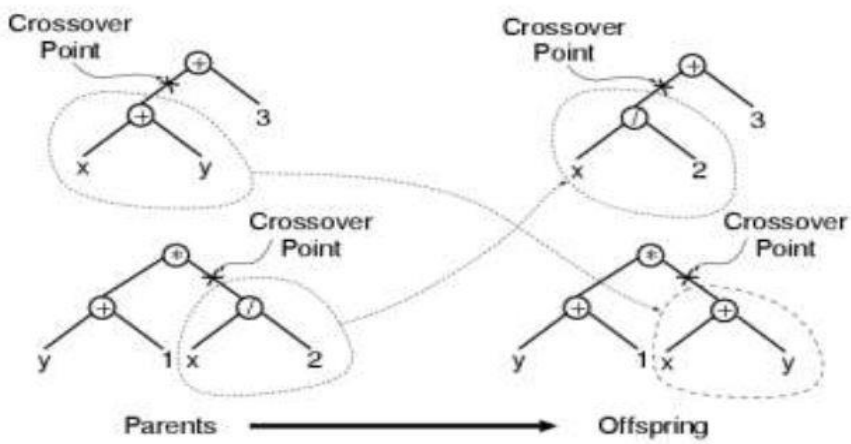


Fig. 3 Example of two child crossover between syntax trees

1.5.3 Mutation

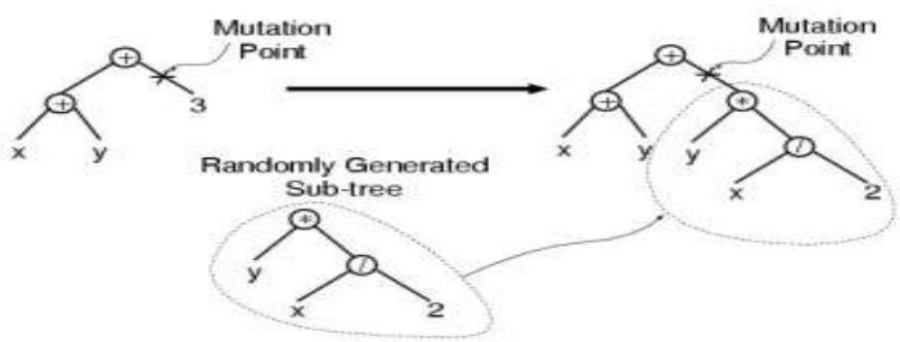


Fig. 4 Example of Sub Tree Mutation

1.5.4 Survival

- Elitism
- Replacement

1.5.5 Fitness Evaluation

- Mean Root Squared Error(MRSE)
- Chi Squared Error
- Scaled Mean Squared Error

1.6 What Is GPTIPS

GPTIPS is a genetic programming (GP) tool for use with MATLAB. GPTIPS provides variety of convenient functions for exploration of the population of evolved models, investigating model behavior, post-run model simplification and export to fully completely different formats, e.g. graphics file, Latex expression, standalone m file. One of the significant feature of GPTIPS is that it is designed to evolve multigene individuals. Simpler more correct models can be evolved by exploitation of this feature.

One of the most the main features of GPTIPS is that it will be organized to evolve multigene individuals. Simpler, a lot of correct models will be created by exploitation this feature.

1.7 GENERAL GP FEATURES

- Multiple tree (multigene) individuals.
- Tournament selection & lexicographic tournament selection.
- Standard subtree crossover operator.
- Elitism.

- Early run termination criterion.
- Graphical population browser showing best and non-dominated individuals (fitness & complexity).
- Graphical summary of fitness over GP run.
- 6 different mutation operators.

1.7.1 GPTIPS RUN SETTINGS

A GPTIPS run with the following settings:

- Population size.
- Number of generations.
- Tournament size (with lexicographic selection pressure).
- $D_{max, Gmax}$ values.
- Elitism = % of population.
- Function node set = {plus, minus, times, tanh, sin}, Terminal node set.
- Random constants in the range Specified.

1.7.2 SYMBOLIC REGRESSION FEATURES

- It has facility of four symbolic regression demos.
- Graphical results of symbolic regression.
- Statistical analysis of multigene symbolic regression models.
- Multigene regression model reduction exploitation “gene knockouts”.
- Rendering to PNG file of evolved symbolic regression models.
- Conversion of evolved multigene models to Latex format.
- Conversion of evolved multigene models to symbolic mathematical objects file to be used outside GPTIPS.
- Conversion of evolved multigene models to M file to be used outside GPTIPS.

- Mathematical simplification of evolved multigene symbolic regression models.
- Runtime validation facility on ‘holdout’ information set.

1.8 Requirements for GP

A relatively recent version of (MATLAB 7.6.0) was used and testing of GPTIPS was done in Matlab. No toolboxes are needed for basic practicality, however the Symbolic math toolbox is exceptionally helpful for the simplification and visualization of the evolved models using GPTIPS for symbolic regression. The Statistics toolbox is additionally helpful for computing statistical data about multigene models.

1.9 Symbolic Regression Implementation

GPTIPS was written chiefly for the needs of multigene symbolic regression. The multigene Approach (i.e. linear combination of ‘smaller’ low depth trees) typically provides simpler models than evolving models consisting of 1 monolithic GP tree.

1.10 Demos

There are four symbolic regression demos included within GPTIPS. Have a glance at these files to visualize how to configure, access and display info from a run.

- gpdemo1: runs standard GP symbolic regression on Koza’s 1992 quadratic polynomial problem [9].
- gpdemo2: runs multigene GP symbolic regression on a data set generated from a non-linear mathematical function comprising one output (y) and four inputs (x1… x4). A separate check data set is employed to evaluate the evolved models

- gpdemo3: runs multigene GP symbolic regression on a data set obtained from a simulation of a non-linear pH neutralization method. This also contains i) one output (pH) and four inputs. A test data set is used to evaluate the evolved models. Each testing & training data is noise free.
- gpdemo4: runs multigene GP symbolic regression on a "real life" data set comprising one output and eight inputs. A holdout validation data set and a testing data set are used to evaluate the evolved models.

1.11 How Multigene Symbolic Regression Works

In multigene symbolic regression, each prediction Y of the output variable y is formed by the weighted output of each of the trees/genes in the multigene individual plus a bias term. Each tree is a function of 0 or more of the N input variables $X_1 \ldots X_N$.
Mathematically, a multigene regression model can be written as:

$$\mathbf{Y = d0 + d1 \times tree1 + \ldots + d_M \times treeM}$$

Where d0 = bias (offset) term and d1, …, dM are the gene weights and M is the no. of genes (i.e. trees) comprising the present individual. The weights (regression coefficients) are determined by a statistical method of Least Squares for every multigene individual.

The number and structure of the trees is evolved automatically throughout a run (subject to user defined constraints) using training data, i.e. a collection of existing input values and corresponding output values. Testing data (another set of input and corresponding output values from the method or system you're modelling) can be used, after the run, to evaluate the evolved models.
The testing data isn't used to evolve the models and serves to give a sign of how well the models generalize to new data.
In GPTIPS, the fitness function regressmulti_fitfun.m implements multigene symbolic regression and is employed by gpdemo2, gpdemo3 and gpdemo4. Exploiting this fitness function GPTIPS tries to minimize the root mean square error (RMSE) between the output y and therefore

the predicted output .In the following section it's outlined however you can use this fitness function for your own symbolic regression issues.

1.12 Using GPTIPS for Multigene Symbolic Regression

An example of a simple configuration file my_config.m for multiple gene symbolic regression is shown below.

It is presumed that whole data is found inside the file (mydata.mat) and contains the training input (xtrain), the training output (ytrain) as well as testing data set (xtest and ytest). The data-set should be organized within columns, e.g. the nth column of xtrain should coincide with the observations of the nth input variable.

```
function gp = my_config(gp);
% Example of a GPTIPS configuration file for multiple gene symbolic regression.
%Define population size, number of generations, fitness function name and
%optimisation type.
gp.runcontrol.pop_size = 100;
gp.runcontrol.num_gen = 100;
gp.fitness.fitfun = @regressmulti_fitfun;
gp.fitness.minimisation = true;
%Load the variables xtrain, ytrain, xtest and ytest and assign to gp structure
load mydata
gp.userdata.xtrain = xtrain;
gp.userdata.ytrain = ytrain;
gp.userdata.xtest = xtest;
gp.userdata.ytest = ytest;
%Define the number of inputs
gp.nodes.inputs.num_inp = size (gp.userdata.xtrain, 2);
%Enable multiple gene mode, set tree depth and set max number of genes per individual.
gp.genes.multigene = true;
```

```
gp.genes.max_genes = 4;
gp.treedef.max_depth = 5;
%Define function nodes
gp.nodes.functions.name = {'times','minus','plus'};
```

In this example, only a couple of GPTIPS settings are specified. The total list of user parameters may be found in Appendix one. Any user parameters not explicitly set automatically use the default values. However, the user should at least specify the fitness function, the input and output information and therefore the function nodes to be utilized in their configuration file.

This configuration file initial sets population size = 100 and number of generations =100. The fitness function regressmulti_fitfun.m is then specified as is the proven fact that this is an error minimization problem.

Next, the user file mydata.mat is loaded and also the variables within this file (here known as xtrain, ytrain, xtest and ytest however they may be called anything) are assigned to the gp.userdata field. Note that the training information inputs should be assigned to gp.userdata.xtrain and the outputs to gp.userdata.ytrain. It is not a requirement that testing information must be provided once using regressmulti_fitfun.

Finally, the function nodes times, minus and and plus are mentioned. All function nodes should be MATLAB m files (or built in functions) on the MATLAB path. Furthermore, all function nodes accept settle for a fixed range of input arguments. E.g. The MATLAB rand function isn't allowed to be a function node in GPTIPS as it is known in numerous forms, rand(1), rand(1,1) etc.

Note that the configuration file should take the structure gp as an input argument and return it as an output argument.

This configuration can be run using gp = rungp (‘my_config’). Once the run is completed the data structure GP is shown in MATLAB workspace.

There are functions provided in GPTIPS to analyze the results of GP runs and some functions specifically to be used with multigene symbolic regression.

1.13 Post Run Analysis

You can enter runtree (gp,'best') to examine the behavior of the best individual from the run on your fitness function.

Alternatively, you'll be able to also enter runtree (gp, 2) to examine the behavior of the individual with index = 2 within the current population on your fitness function (note: this is simply an index and not the second best individual within the population).

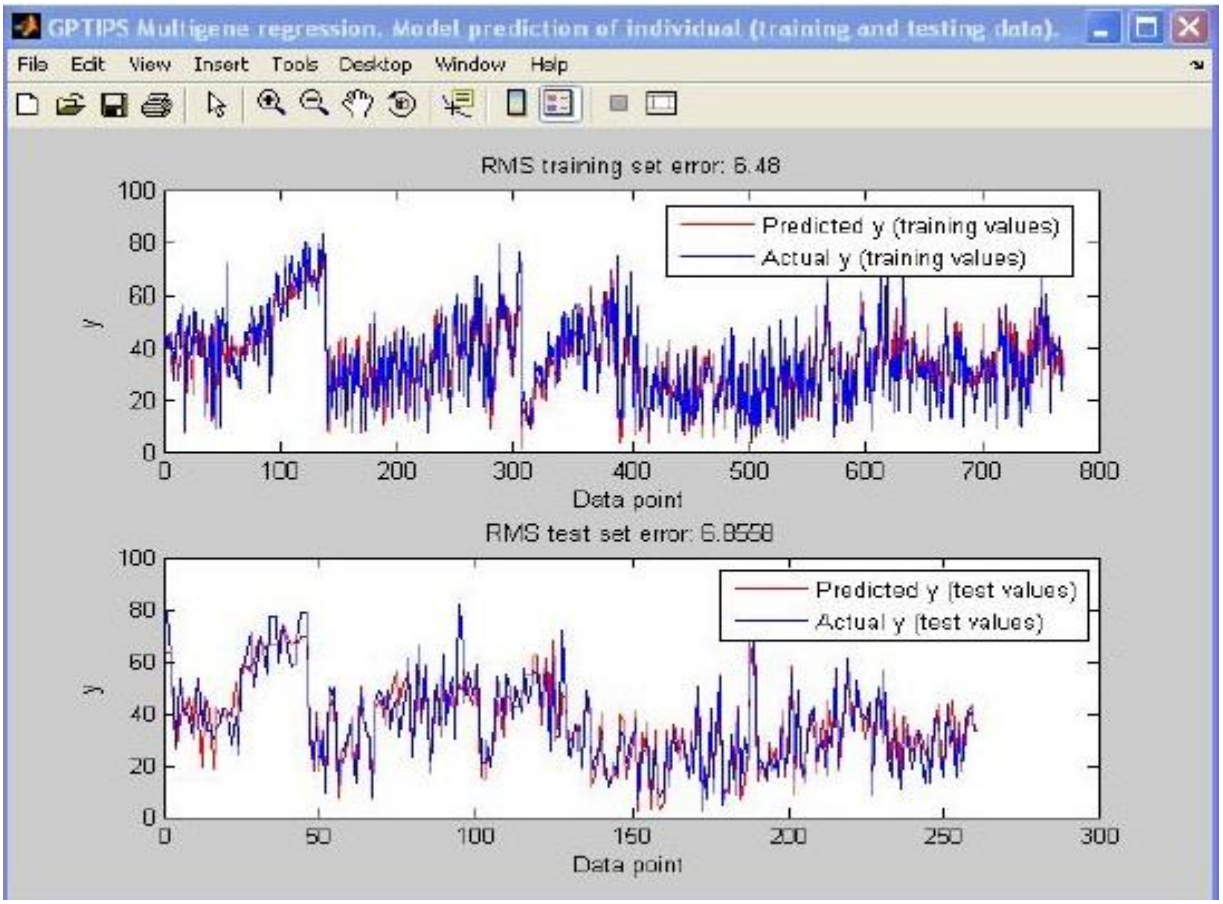


Fig. 5 Result of run tree on a GP structure returned when running multiple gene symbolic regression with gpdemo4.

1.13.1 VALIDATION

As well as training and testing information sets, a further 'holdout' validation data set may be specified to assist mitigate against overfitting. GPTIPS evaluates the "best" individual at every generation against the validation data set and so tracks the results over the run. This doesn't have an effect on the GP run as such however it allows user to identify, once the run has completed, which individual performed best on a data set which was not utilized to build the model. Typically this can be often not the individual that performed best on the training information and it may generalize better to unseen data.

Here Validation has been performed in MS excel by selecting a validation data from experimental data by finding percentage error between MGGP value and Experimental value to ensure that MGGP equation is conforming the output pattern on the basis of input parameters. Validation can also be performed inside GPTIPS with a holdout validation data set by writing the following MATLAB code.

```
function gp = my_config2(gp);
% Example of a GPTIPS configuration file for multiple gene symbolic regression % using training, testing and holdout validaton data sets.

%Define population size, number of generations, fitness function name and
%optimisation type.
gp.runcontrol.pop_size = 100;
gp.runcontrol.num_gen = 100;
gp.fitness.fitfun = @regressmulti_fitfun;
gp.fitness.minimisation = true;
%Load the variables xtrain, ytrain, xtest and ytest and assign to gp structure
load mydata2
gp.userdata.xtrain = xtrain;
```

```
gp.userdata.ytrain = ytrain;
gp.userdata.xtest = xtest;
gp.userdata.ytest = ytest;
gp.userdata.xval = xval;
gp.userdata.yval = yval;
%Tell GPTIPS to call validation set once per generation
gp.userdata.user_fcn = @regressmulti_fitfun_validate;
%Define the number of inputs
gp.nodes.inputs.num_inp = size(gp.userdata.xtrain,2);
%Enable multiple gene mode, set tree depth and set max number of genes per individual.
gp.genes.multigene = true;
gp.genes.max_genes = 4;
gp.treedef.max_depth = 5;
%Define function nodes
gp.nodes.functions.name = {'times','minus','plus'};
```

After a run using holdout validation has completed, the individual with the best performance on the validation data is run using:

```
runtree(gp,'valbest')
```

1.14 Applications

- Black art problems" like automated synthesis of analog electrical circuits, controllers, antennas etc.
- "Programming the unprogrammable" involves creation of pc programs for unconventional computing devices.
- Commercially useful new inventions (CUNI) involves the utilization of genetic programming as automatic "invention machine" for automated new inventions.
- In regression and classification.
- ➢ Regression or Classification of nonlinear issues.

- In Telecommunications: Speech quality estimation.
- In computer Networks: Network cryptography.
- In Finance: In evolving effective bidding ways.
- In Clinical: Cancer detectors, seizure detectors, mental
- Health diagnosis etc.

1.15 Motivation for the project work

After studying most of the research papers and journals I found for Mathematical Modelling they have applied Response Surface Methodology and Taguchi Optimization Techniques in which after validation the percentage error between RSM value and Experimental value is more as compared to percentage error between MGGP value and Experimental value. Multi Gene Genetic Programming for symbolic Regression has been used seldom by Researchers in there Research papers so I tried to include 3 case studies of basic Manufacturing Processes in industries, one based on Surface Roughness and Material Removal Rate parameters, second based on Drilling parameters and last based on MAG welding parameters and applied MGGP for mathematical Modelling using Symbolic Regression with application of Multi objective Genetic Algorithm for parameters Optimization.

CHAPTER 2

LITERATURE SURVEY

2.1 Literature Review

The Literature survey is mainly focused on 3 case studies based on basic Manufacturing Processes in industries, one case study is based on Surface Roughness and Material Removal Rate parameters, second based on Drilling parameters and last based on MAG welding parameters.

2.1 Literature Survey Based on Machining Parameters

- Surface finish (Ra) of produced parts is a very important aspect in mechanical design, and it is also used as an indicator for quality measurement of manufacturing processes, which is, in return, necessary for proper part geometries [10]. It was found that surface finish in turning is influenced by several factors such as feed, work material characteristics, workpiece hardness, coolants, cutting speed, depth of cut, tool nose radius and tool cutting edge angles [11]-[12].

- The effect of cutting speed, feed, and depth of cut on attained surface roughness of machined work pieces have been investigated by many researchers [13]-[17].

- Benardos and Vosniakos [18] presented various methodologies and practices that were employed for the prediction of surface roughness. The approaches listed in their review paper were classified into those based on machining theory, experimental investigation, designed experiments and artificial intelligence (AI).

- Choudhury and EI-Baradie [19] mentioned the development of surface roughness prediction models for turning EN 24T steel (290 BHN) utilizing response surface methodology. A factorial design technique was accustomed to study the consequences of the main cutting parameters like cutting speed, feed, and depth of cut, on surface roughness.

2.2 Literature Survey Based on Drilling Parameters

- Bishop and Gindy, 1990 [20] performed an investigation on drilling of ballistic Kevlar composites and concluded that drill point angle influenced thrust force and was maximum

at 180. The removal of drill web achieved a further reduction in angle and increase in the rake angle reduced the torque, varying point angle had a lesser effect on torque.

- Sunny et al., 2014 [21] carried out experiments on GFRP composites by Taguchi Method L25 using three different tools viz., twist drill, end mill and Kevlar drill. The study revealed that feed rate is the most influential parameter and high spindle speed and low feed rate decreased the delamination.

- Mohan et al., 2005 [22] carried out experiments with glassefibre polyester reinforced composites and noted that minimum thrust force could be obtained by lower feed rate, less specimen thickness and drill diameter, and higher speed. Also, minimum torque force could be obtained by higher speed, medium feed, low specimen thickness and high drill diameter.

- Tsao and Hocheng, 2004[23] performed Taguchi analysis on various drill bits of composite material and found that feed rate and drill diameter made the most significant contribution. Twist drill caused more delamination than candlestick drill and saw drill.

- TsKhashaba et al., 2010 [24] conducted an experiment on machinability analysis in drilling the woven GFR/epoxy composites and noted that as the feed rate and drill diameter increased, thrust force also increased. The increase in cutting speed also increased the surface roughness.

- Kilickap, 2010 [25] conducted experiments on GFRP composite at drill point angles of 118 and 135 and concluded that feed rate is a most important factor and drill point angle at 118 produced less damage and delamination.

- Gaitonde et al., 2008 [26] showed that apart from spindle speed, drill point angle and low feed minimized the delamination in drilling of CFRP composites.

- Saravanana M., et al., 2012 [27] carried out multiobjective optimization of drilling parameters using GA. The variation of parameters was approached by both GA and finite

element method and concluded that GA approach was much better than the finite element method.

2.3 Literature Survey Based on Welding Parameters

- Wells [28] estimated weld bead width by considering conduction heat transfer.

- Christensen et al. [29] derived non dimensional factors to relate bead dimensions with operational parameters.

- Chandel et al[30] conferred predictions of impact of current, electrode polarity, electrode diameter, and electrode extension on melting rate, bead height, bead breadth and weld penetration in submerged arc welding.

- Markelj & Tusek [31] mathematically modeled current and voltage in TIG welding.

- Kim et al [32] conducted a sensitivity analysis of a robotic GMAW (gas metal arc welding) process employing non-linear multiple regression analysis (RA) for modeling process and quantified respective effects of process parameters on weld bead geometry (WBG) parameters.

- Kim et al [33] did comparison of experimental GMAW weld bead geometry results with those obtained from heat-transfer and regression models parameters for optimum weld pool geometry in TIG welding of stainless steel.

- Tarng et al [34], [35] determined optimum process parameters for submerged arc welding (SAW) in hard facing using grey-based Taguchi method.

- New trend in producing processes parameters optimization is to use evolutionary algorithms like genetic algorithm (GA) [36] and simulated annealing (SA) [37].

2.4 Multi-parameter optimization

➢ Multi Objective Genetic Algorithm

Mitchell et al. [38] has done work in this complex approach genetic algorithm (GA) where an artificially developed form of natural process of selection is used. Here the problem comes from the bigger club of evolutionary algorithms. The GA are conventionally used to develop high-quality results to optimize and solve problems by depending on the bio-inspired operators such as mutation, crossover and selection. Eventually, here in context of current thesis work the genetic algorithms are computer programs that replace the processes of biological evolution in order to solve problems and to model evolutionary systems. Optimization of the process parameters has assumed significant research interest in machining operations (including turning operations) [39, 40, 41], since for given set of constraint(s), it has the capability to recommend optimal parametric combination and hence useful for industry [42].

The MOGA employed is a hybrid variant of the popular NSGA-II (Non-dominated Sorted Genetic Algorithm-II) based on controlled elitism ideas. It supports every kind of input parameters. The pareto ranking scheme is completed by a quick, non-dominated sorting technique that's an order of magnitude quicker than traditional pareto ranking strategies. The constraint handling uses a similar non-dominance principle because the objectives, thus penalty functions and Lagrange multipliers are not required. This also ensures that the possible solutions are always hierarchic on top of the unfeasible solutions.

The first pareto front solutions are archived during a separate sample set internally and are distinct from the evolving sample set. This ensures marginal disruption of pareto front patterns already available from earlier iterations. You’ll control the selection pressure (and, consequently, the elitism of the process) to avoid premature convergence by fixing the utmost Allowable pareto percentage property.

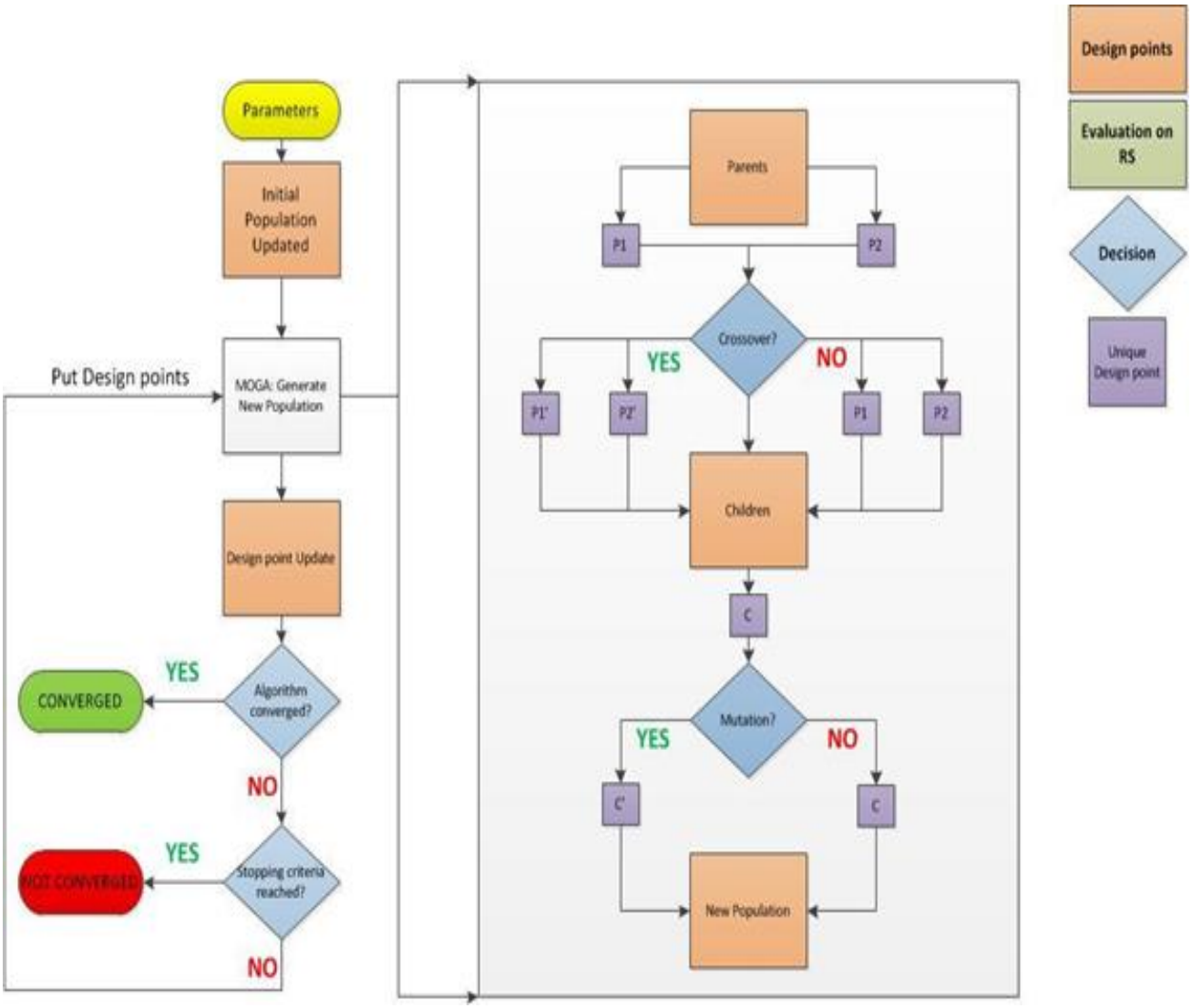


Fig. 6 The workflow of the MOGA optimization method is shown above

CHAPTER 3

PROBLEM FORMULATION AND RESEARCH OBJECTIVE

3.1 Problem formulation

The literature survey reveals that particular efforts were devoted to determine the most accurate models for manufacturing input processes parameters. These empirical models were utilized as objective functions and were optimized to obtain the machining conditions for the required input control parameters. Also the literature shows that the predominant modelling and optimization tools used to date have been Taguchi-based regression analysis, response surface methodology, and ANNs. However, the accuracy and possibility of determining the global optimum solution depend on the type of modelling technique used to express the objective function and constraints

as functions of the decision variables [43]. Therefore, effective, efficient, and economic utilization of these manufacturing processes necessitates an accurate modelling and optimization procedure.

In most conventional deterministic approaches such as multiple regression and response surface methodology, a prediction model has to be determined in advance and a set of coefficients has to be found. The pre specified size and shape of the model mean that these are not adequate to capture a complex relation between the influencing variables and output parameters. Like the aforementioned approaches, although ANNs have also been used extensively in the literature for modelling, they have the drawback of not being able to quantify explicitly the relationships between inputs and outputs. So we have applied MGGP and MOGA for Mathematical Modelling using Symbolic Regression Method and parameters optimization since this method gives an accurate modelling and optimization procedure.
Most of the Research Papers have employed ANN, RSM, ANNOVA and Taguchi Optimization Techniques for mathematical Modelling and parameter Optimization. The overall objective of this research is to apply a new process modelling and optimization methodology for the highly non-linear and complex manufacturing process.

3.2 Objective of the Project

After doing the gap analysis, the aim of the work is to study journals employing Taguchi based Regression Analysis, RSM, ANN etc. approaches for modelling and optimization of various manufacturing processes, to achieve this work following objective are there:

- Choosing Experimental Data (preferably L_{54} Orthogonal Arrays) from different Journal papers depicting various input parameters based on a particular manufacturing process and there effect on output parameters.

- Central Composite full factorial designs along with ANOVA from International Journal Papers will be used in order to maximize or minimize the output parameters.

- Develop Regression model using Multi Gene Genetic programming for Multigene Symbolic Regression on input and output parameters.

- Optimization of parameters using Multi Objective Genetic Algorithm.

- To reduce Percentage Error between Experimental value and MGGP value relative to Experimental value as compared to other Regression Analysis based methods like RSM, ANN etc.

  Relative Error (%) = $\frac{MGGP\ VALUE - EXPERIMENTAL\ VALUE}{EXPERIMENTAL\ VALUE} \times 100$

CHAPTER 4

CASE STUDY 1
An integrated evolutionary approach for modelling and optimization of turning parameters (MRR, Surface Roughness)

4.1 Introduction

The aim of this analysis is to evaluate surface roughness and develop a multiple regression model for surface roughness as a function of cutting parameters throughout the turning of flame hardened medium carbon steel with TiN-Al2O3-TiCN coated inserts [44]. The planned methodology consists of 2 elements. In the 1st half, a completely unique application of genetic programming (GP) is proposed. GP is an evolutionary modelling algorithm that uses principles

like genetic algorithms to model highly non-linear and complicated processes, leading to accurate and reliable models. 2 important aspects of machining performance, particularly metal removal rate and surface roughness, are modeled based on experimental data using GP in terms of 3 prominent input variables. The effect of machining parameters on the performance measures is additionally reported. In the second half, as the chosen machining performances are opposite in nature, the problem under consideration is developed as a multi-objective optimization problem and resolved using an efficient evolutionary optimization algorithm, MOGA. The end result of Pareto optimum solutions is presented.

Machining processes play a significant role in manufacturing industry where cost and quality are the main driving forces. One of the most investigated areas of machining is process modelling and optimization as this results in both reduced production cost and improved product quality.

However, experimental optimization of any machining process is costly and time consuming owing to the complex, coupled, and non-linear nature of the input–output variables of machining processes [2]. Briefly, owing to the highly complicated interactions between process parameters, current analytical models and analyses cannot provide accurate process prediction for better quality control and higher throughput. Therefore, an efficient method is needed to determine the optimal machining parameters. the most significant performance indicators are metal removal rate (MRR) and surface finis the most significant performance indicators are metal removal rate (MRR) and surface finish productivity while surface roughness (Ra) is a measure of work quality/ Moreover, the performance measures, namely MRR and Ra, are conflicting in nature as it is desirable to have higher MRR with lower value of surface roughness. The overall objective is to apply a new method which can handle highly non-linear and complex manufacturing processes. With this aim, accurate prediction models to estimate MRR and Ra were developed from the experimental data using a potential evolutionary modelling algorithm called genetic programming (GP). The developed models were used for optimization of the process. As the chosen objectives, MRR and Ra, are conflicting in nature, the problem was formulated as a multi-objective optimization problem.

4.2 Methodology

In this case study, a novel approach is conferred for modelling of material removal rate and surface roughness using GP. The distinctive aspect of GP as compared to traditional approaches is it doesn't make any presumption concerning the formulation to be created also the generated model helps directly to get an interpretation of the parameters affecting the method. The models developed by GP were afterward used for optimization. In the current study, the optimization problem of turning parameters was explicitly formulated as a multi objective optimization problem, as the determination of the optimal machining conditions involves a conflict between maximizing MRR and minimizing the surface roughness. It can be noted that the classical optimization methods (weighted sum methods, goal programming, min–max methods, etc.) are not efficient for handling multi-objective optimization problems because they do not find multiple solutions in a single run, and therefore it is necessary for them to be applied as many times as the number of desired Pareto-optimal solutions. The above-mentioned difficulty of classical optimization methods is eliminated in evolutionary algorithms, as they can find the multiple solutions in a single run. As a result, a most commonly used evolutionary approach, the MOGA is proposed for multi-objective optimization. Genetic algorithm (GA)-based multi-objective optimization methodologies have been widely used in the literature to find Pareto-optimal solutions [15–18]

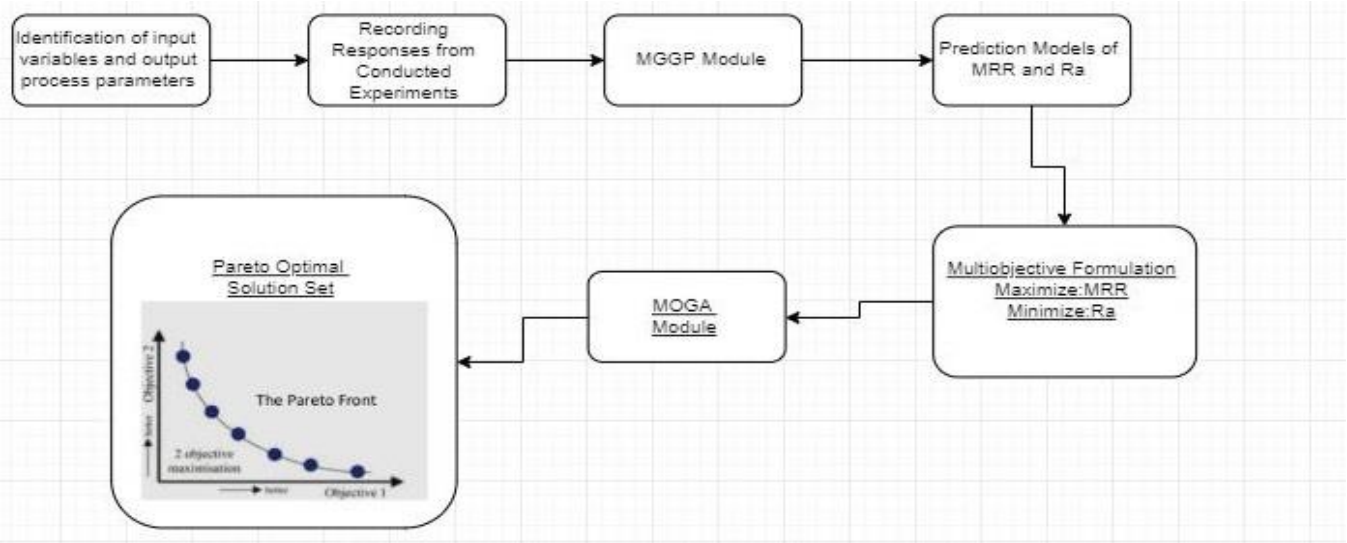


Fig. 7 Proposed Methodology

4.3 Experimental Design and Software Setup

Based on this journal paper the aim of the experiments was to analyze the effect of turning parameters on the surface roughness of hardened AISI 1055 steel, apart from this MRR parameter was also included for mathematical modelling[44].Based on Taguchi principles, an L54 orthogonal array was set up. Below table shows the number and levels of control parameters used.

CONTROL FACTORS LEVELS OF FINISH TURNING PROCESS

Code	Control factors	Levels		
		1	2	3
A	Depth of cut (mm)	0.4	0.8	1.2
B	Cutting speed (m/min)	40	98	177
C	Feed (mm/rev)	0.1	0.2	0.3

Table 4.1 Control Factors of Turning Process

Exp. No.	A	B	C	Ra(μm)	MSD	ζ	MRR(mm^3/min)
1	1	1	1	0.88	0.7744	-1.1	2392.38
2	1	2	1	0.81	0.6561	1.46	5861.33
3	1	3	1	1.03	1.0609	0.78	10586.29
4	1	1	1	1.34	1.7956	-1.1	2392.38
5	1	2	1	0.88	0.7744	1.46	5861.33
6	1	3	1	0.78	0.6084	0.78	10586.29
7	2	1	1	1.38	1.9044	-1.1	4769.52
8	2	2	1	0.58	0.3364	3.55	11685.33
9	2	3	1	0.72	0.5184	1.6	21105.14
10	2	1	1	0.81	0.6561	-1.1	4769.52
11	2	2	1	0.74	0.5476	3.55	11685.33
12	2	3	1	0.93	0.8649	1.6	21105.14
13	3	1	1	1.16	1.3456	-0.9	7131.43
14	3	2	1	0.89	0.7921	-1.8	17472
15	3	3	1	1.02	1.0404	-0.6	31556.57
16	3	1	1	1.05	1.1025	-0.9	7131.43
17	3	2	1	1.5	2.25	-1.8	17472
18	3	3	1	1.11	1.2321	-0.6	31556.57
19	1	1	2	2.19	4.7961	-7.1	4784.76
20	1	2	2	1.53	2.3409	-4.7	11722.67
21	1	3	2	1.66	2.7556	-4.5	21172.57
22	1	1	2	2.32	5.3824	-7.1	4784.76
23	1	2	2	1.89	3.5721	-4.7	11722.67
24	1	3	2	1.68	2.8224	-4.5	21172.57
25	2	1	2	2.35	5.5225	-9.7	9539.05
26	2	2	2	1.48	2.1904	-5.6	23370.67
27	2	3	2	1.67	2.7889	-5.6	42210.29
28	2	1	2	3.65	13.3225	-9.7	9539.05
29	2	2	2	2.25	5.0625	-5.6	23370.67
30	2	3	2	2.12	4.4944	-5.6	42210.29
31	3	1	2	1.88	3.5344	-5.8	14262.86
32	3	2	2	1.83	3.3489	-5.9	34944
33	3	3	2	2.35	5.5225	-6.6	63113.14
34	3	1	2	2.02	4.0804	-5.8	14262.86
35	3	2	2	2.12	4.4944	-5.9	34944
36	3	3	2	1.91	3.6481	-6.6	63113.14
37	1	1	3	4.94	24.4036	-14	7177.14
38	1	2	3	4.57	20.8849	-13	17584
39	1	3	3	2.84	8.0656	-12	31758.86
40	1	1	3	4.59	21.0681	-14	7177.14
41	1	2	3	4.25	18.0625	-13	17584
42	1	3	3	4.51	20.3401	-12	31758.86
43	2	1	3	4.83	23.3289	-13	14308.57
44	2	2	3	3.95	15.6025	-13	35056
45	2	3	3	4.1	16.81	-12	63315.43
46	2	1	3	4.52	20.4304	-13	14308.57
47	2	2	3	5.27	27.7729	-13	35056
48	2	3	3	4.24	17.9776	-12	63315.43
49	3	1	3	5.02	25.2004	-13	21394.29
50	3	2	3	4.61	21.2521	-12	52416
51	3	3	3	3.64	13.2496	-12	94669.71
52	3	1	3	4.23	17.8929	-13	21394.29
53	3	2	3	3.1	9.61	-12	52416
54	3	3	3	4.02	16.1604	-12	94669.71

Table 4.2 L_{54} Orthogonal Array and Calculated Values

4.4 Implementation of MGGP

Experimental Data is divided into three data sets:

- Training: 38 values
- Testing: 12 values
- Validation: 4 values(will be done from outside in Excel after running MGGP code)

4.4.1 Training Dataset for MRR and Ra

S.No	x1	x2	x3	Ra	MRR
1	0.4	40	0.1	0.88	31758.86
2	0.4	98	0.1	0.81	14308.57
3	0.4	177	0.1	1.03	35056
4	0.4	40	0.1	1.34	63315.43
5	0.4	98	0.1	0.88	21394.29
6	0.4	177	0.1	0.78	94669.71
7	0.8	40	0.1	1.38	21394.29
8	0.8	98	0.1	0.58	52416
9	0.8	177	0.1	0.72	5861.33
10	1.2	40	0.1	1.16	10586.29
11	1.2	98	0.1	0.89	4769.52
12	1.2	177	0.1	1.02	31556.57
13	1.2	40	0.1	1.05	7131.43
14	1.2	98	0.1	1.5	17472
15	1.2	177	0.1	1.11	23370.67
16	0.4	40	0.2	2.19	42210.29
17	0.4	98	0.2	1.53	9539.05
18	0.4	177	0.2	1.66	35056
19	0.8	40	0.2	2.35	63315.43
20	0.8	98	0.2	1.48	31556.57
21	0.8	177	0.2	1.67	4784.76
22	0.8	40	0.2	3.65	23370.67
23	0.8	98	0.2	2.25	11722.67
24	0.8	177	0.2	2.12	21172.57
25	1.2	40	0.2	1.88	9539.05
26	1.2	98	0.2	1.83	42210.29
27	1.2	177	0.2	2.35	14262.86
28	0.4	40	0.3	4.94	34944
29	0.4	98	0.3	4.57	63113.14
30	0.4	177	0.3	2.84	7177.14
31	0.4	40	0.3	4.59	17584
32	0.4	98	0.3	4.25	17584
33	0.4	177	0.3	4.51	2392.38
34	0.8	40	0.3	4.83	5861.33
35	0.8	98	0.3	3.95	10586.29
36	0.8	177	0.3	4.1	11685.33
37	1.2	40	0.3	5.02	21105.14
38	1.2	98	0.3	4.61	7131.43

Table 4.3 Training Dataset

4.4.2 Testing Dataset

S.No	x1	x2	x3	Ra	MRR
1	1.2	98	0.2	0.81	34944
2	1.2	177	0.3	0.74	94669.71
3	0.4	40	0.1	0.93	2392.38
4	0.8	98	0.1	2.32	11685.33
5	0.8	177	0.1	1.89	21105.14
6	0.8	40	0.1	1.68	4769.52
7	1.2	98	0.1	2.02	17472
8	0.4	98	0.2	2.12	11722.67
9	0.4	177	0.2	1.91	21172.57
10	0.4	40	0.2	4.52	4784.76
11	1.2	177	0.2	5.27	63113.14
12	1.2	40	0.2	4.24	14262.86

Table 4.4 Testing Dataset

4.5 MGGP Matlab Implementation

GP Control Parameters:

- Population Size: 100
- Number of Generations: 100
- Terminal set: {x1, x2, x3}
- Function set: {+, −, ×}
- Selection Method: Tournament Selection
- Crossover probability (%): 85
- Mutation probability (%): 5
- Reproduction probability (%): 10
- Fitness Measure: Root Mean square Error(R^2 value)
- Maximum Tree Depth: 4
- Maximum Genes: 12
- Constant Range: [-10 10]

4.5.1 MGGP Matlab Code (Configuration File)

```
function gp=Y1_config(gp)
%Surface Roughness- Y1
gp.runcontrol.pop_size=100;
gp.runcontrol.num_gen=100;
gp.runcontrol.verbose=20;
gp.fitness.fitfun=@regressmulti_fitfun;
gp.fitness.minimisation=true;
gp.runcontrol.showBestInputs = true;
gp.runcontrol.runs = 1;

gp.selection.method='tour';
gp.selection.tournament.size=15;
gp.selection.elite_fraction = 0.3;

%Load the variables xtrain, ytrain, xtest and ytest and assign to gp structure
load mydataY1;
gp.userdata.xtrain=xtrain;
gp.userdata.ytrain=ytrain;
gp.userdata.xtest=xtest;
gp.userdata.ytest=ytest;

%Define the number of inputs
gp.nodes.inputs.num_inp = size(gp.userdata.xtrain,2);

%Enable multiple gene mode and set max number of genes per individual.
gp.genes.multigene=true;
gp.genes.max_genes=12;
gp.genes.max_depth=6;
```

```
%Define function nodes
gp.nodes.functions.name={'times','minus','plus'};
End
```

Note: Here we are not using Fitness Function (R^2 value) as a Termination Criteria but we are using Number of Generations as Termination Criteria.

4.5.2 MGGP Matlab Code (Run File)

```
%run MGGP on Experiment data for Surface Roughness
clear;
clc;
disp('>>gp=rungp(@Y1_config);');
disp('Press a key to continue');
disp(' ');
pause;
gp = rungp(@Y1_config);
disp(' ');
disp('Evaluate the best individual of');
disp('the runs on the fitness function using:');
disp('>>runtree(gp,"best");');
disp('Press a key to continue');
disp(' ');
pause;
runtree(gp,'best');
if gp.info.toolbox.symbolic

    disp(' ');
    disp('Next, use the the GPPRETTY command on the best individual: ');
    disp('>>gppretty(gp,"best")');
    disp('Press a key to continue');
```

```
    disp(' ');
    pause;
    gppretty(gp,'best');
     disp(' ');
end
disp('Next, use the the DRAWTREE command: ');
disp('>>drawtrees(gp,"best")');
disp('Press a key to continue');
disp(' ');
pause;
drawtrees(gp,'best');
disp(' ');
    pause;
if gp.info.toolbox.symbolic
    disp('Finally, an HTML report listing the models on the Pareto optimal front');
    disp('of model expressional complexity and performance can be generated using');
    disp('the PARETOREPORT function.');
    disp('>>paretoreport(gp)');
    disp(' ');
    disp('Press a key to continue');
    disp(' ');
    pause;
    paretoreport(gp);
    disp('end');
end
```

Above Run file was executed for several times and for 100 Generations which resulted in following Multigene Regression expression for Ra, found to have the largest fitness value.

4.5.3 Regression Equation for Ra (Surface Roughness)

Ra=0.01279*x(1)^3*x(2)+85.63*x(1)^2*x(3)^2-29.69*x(1)^2*x(3)-1.179*x(1)^2+0.001308*x(1)*x(2)^2*x(3) - 0.0002235*x(1)*x(2)^2 - 0.5726*x(1)*x(2)*x(3)^2-40.09*x(1)*x(3)^2+17.34*x(1)*x(3) + 3.293*x(1) - 0.0009345*x(2)^2*x(3) + 0.0002235*x(2)^2 + 0.3806*x(2)*x(3)^2 - 0.001532*x(2)*x(3) - 0.02367 x(2) + 46.97*x(3)^2 - 3.795*x(3)+0.4373

Similarly Regression Equation for MRR was obtained by making certain modifications in above Configuration file and Run file.

4.5.4 Regression Equation for MRR (Material Removal Rate)

0.1234*x(2)- 575.0*x(1) - 749.5*x(3) + 2145.0*x(1)^2*x(3)^2 - 0.2846*x(1)*x(2) +2447.0*x(1)*x(3) -0.5074*x(2)*x(3) + 0.1447*x(1)^2*x(2) - 3159.0*x(1)*x(3)^2 - 2569.0*x(1)^2*x(3) + 749.3*x(1)^3*x(3) + 749.3*x(1)^2 - 294.8*x(1)^3 +1583.0*x(3)^2 - 0.1234*x(1)*x(2)*x(3)^2 - 0.002399*x(1)*x(2)*x(3)*(x(1) - 1.0*x(2)) +137.3

A comparison of the predicted models and the experimental values for the Training and Testing datasets of Ra and MRR are shown in Figs 8 and 9 respectively.

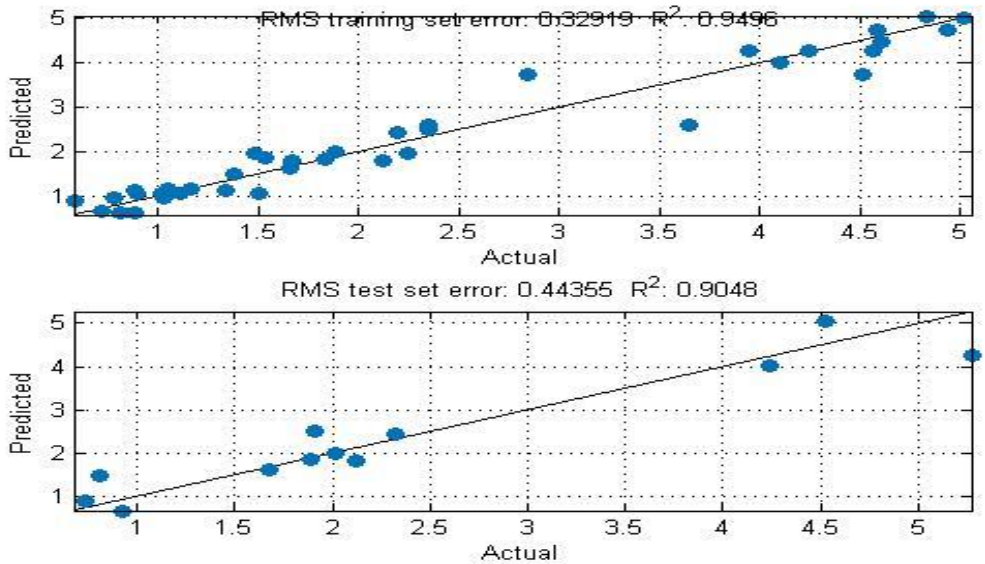


Fig. 8 Scatter Plot for Ra

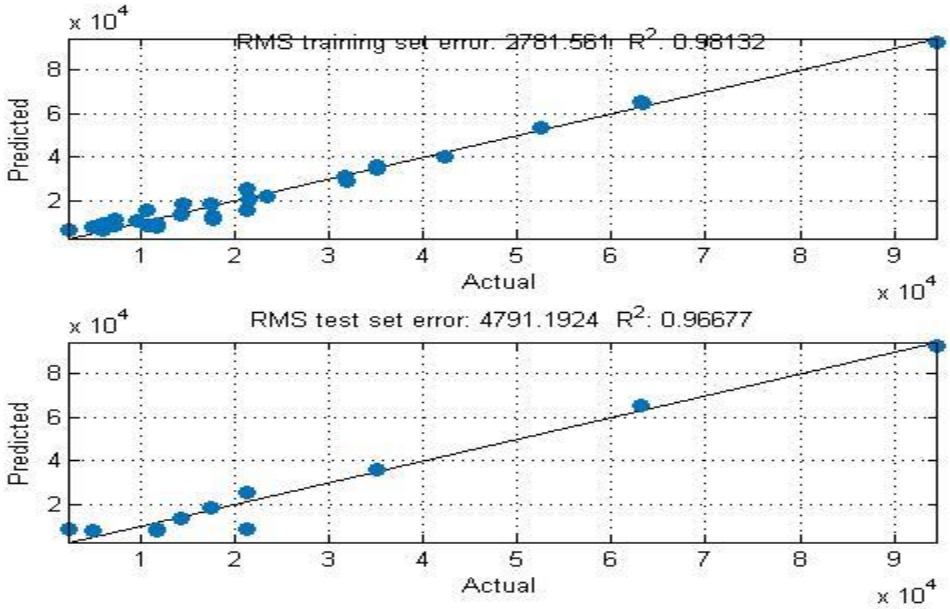


Fig. 9 Scatter Plot for MRR

While developing the above models, the correlation coefficient R^2 was taken as the fitness measure. GP was continued until a value as close as possible to the maximum value of R^2 was obtained. R^2 was used as the fitness measure in order to check whether the fitted models actually describe the experimental data. Below figures show the convergence graphs of the models predicted by the proposed algorithm. The fitness measures for MRR and Ra have gradually

improved with the number of generations and finally converged to 0.98132 and 0.9496 respectively. This shows that the models can explain the variation in the MRR and Ra up to the extents of 98.13% and 94.96 percent respectively. On the basis of the high values of R^2 it can be said that the models are adequate in representing the process.

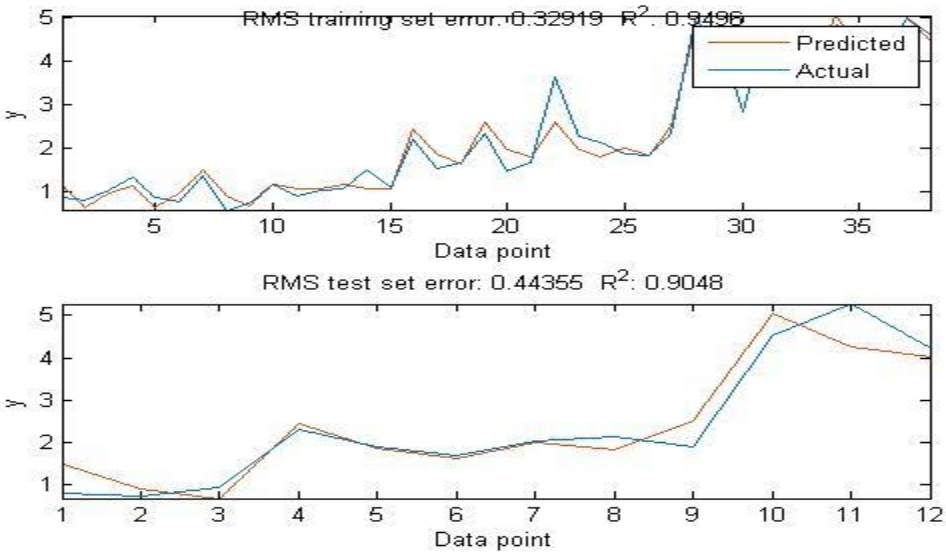


Fig. 10 Comparison Graph for Ra

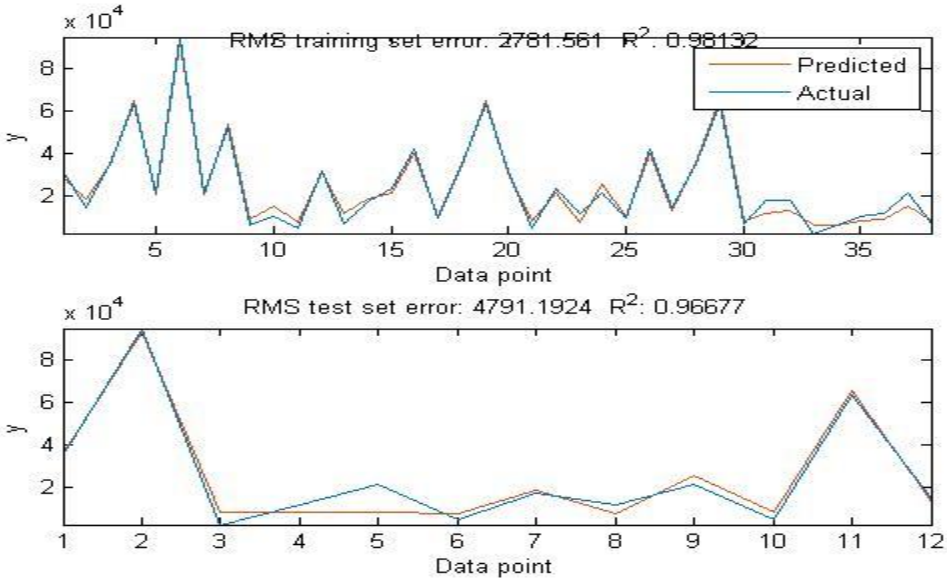


Fig. 11 Comparison Graph for MRR

4.6 Optimization using Multi Objective Genetic Algorithm

MOGA Control Parameters:

- Population Size:100
- Selection Function: Tournament selection
- Tournament Size: 2
- Crossover fraction: 0.8
- Crossover function: 1
- Mutation: Constraint Independent
- Stopping Criteria: Generations(200*no. of variables)

4.6.1 Multi Objective Genetic Algorithm Settings in Matlab

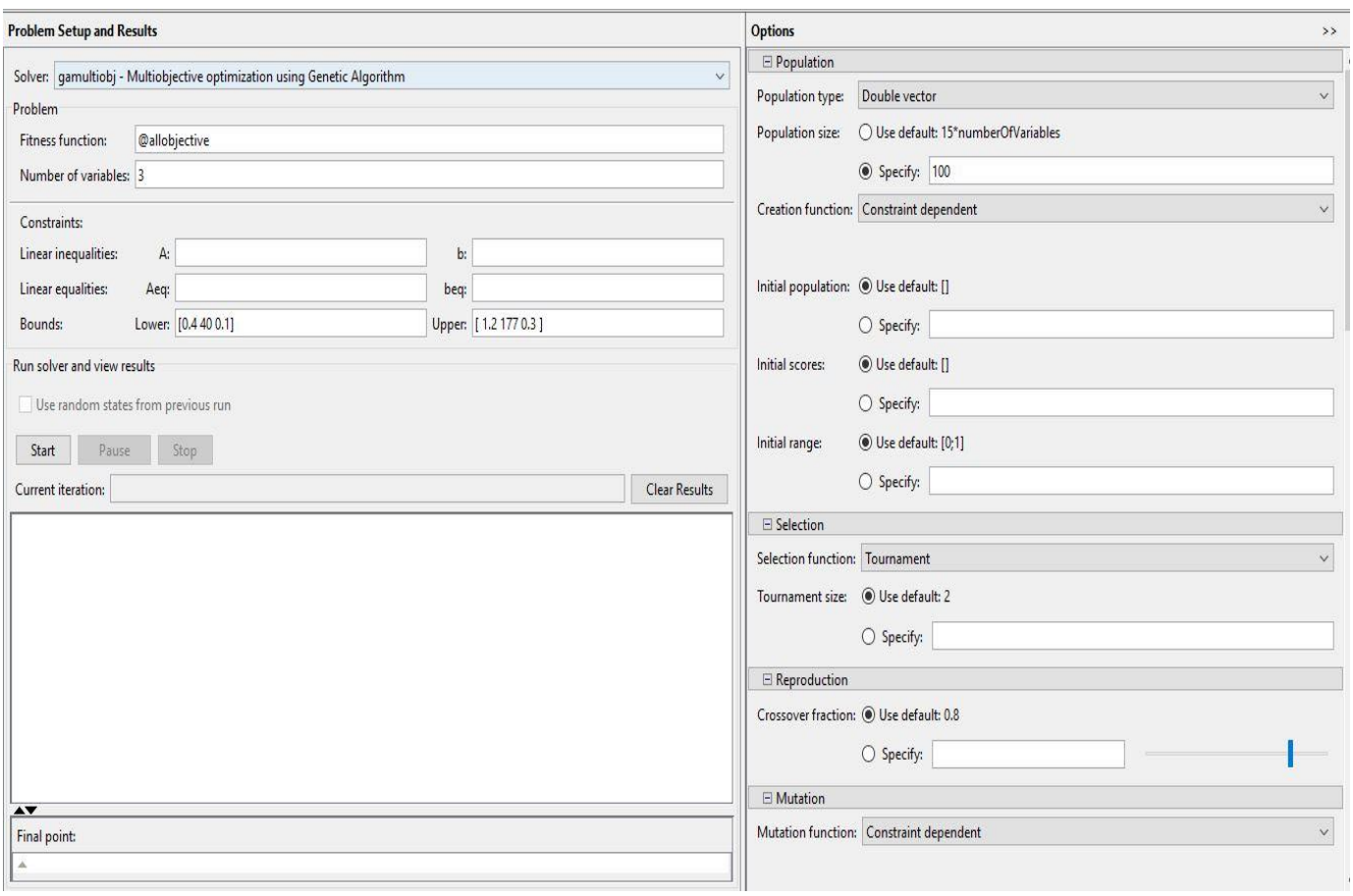


Fig. 12 MOGA Settings Matlab

4.6.2 Optimal Solutions through MOGA

After running MOGA with desired settings we got Optimal Solutions which are all good Solutions and we can select any combination of Optimal Solutions depending upon a particular Manufacturing Process.

S.No	x1	x2	x3	Ra	MRR
1	1.199778	172.9633	0.295173	2.84	190752.4
2	0.738006	171.4973	0.101001	3.57	68347.86
3	1.196356	172.2967	0.166813	1.7	152260.1
4	0.727441	171.7637	0.106192	1.98	69208.62
5	1.125462	171.8767	0.112362	2.66	121112.6
6	1.180224	172.572	0.209821	1.23	163777.7
7	1.191921	171.893	0.138814	1.45	141427.9
8	1.043495	171.9205	0.108862	1.27	107490.8
9	0.895045	170.5974	0.103901	1.57	84951.49
10	1.064011	171.8924	0.110385	2.66	111024.4
11	1.162631	171.9796	0.124353	1.42	131604.2
12	1.196249	168.7232	0.293807	3.23	183104
13	0.738006	171.4973	0.101001	1.91	68347.86
14	1.196982	172.9025	0.16059	2.22	151169
15	1.086988	171.9012	0.119884	1.36	118011.3
16	1.17683	172.2	0.124645	2.7	134324.2
17	1.177578	172.0298	0.155605	2.92	145082.6
18	1.189477	171.7987	0.1959	1.48	159772.7
19	1.19219	172.4964	0.182625	2.49	157041.1
20	1.139953	172.5254	0.133411	3.58	131953.7
21	0.852441	171.6387	0.106192	2.25	81783.99
22	1.185144	172.8824	0.138164	1.59	141462.4
23	0.993356	171.3007	0.1158	1.55	102403.4
24	1.107804	171.4476	0.127688	1.39	123490.5
25	1.174016	172.1694	0.147656	1.71	141973.1
26	0.957685	170.7835	0.10919	2.94	94742.1
27	1.194454	172.1502	0.196994	2.29	161421.8
28	0.938025	171.8154	0.106545	3.12	92254.3
29	1.097257	171.3428	0.115877	1.29	117416.5
30	1.17968	171.6509	0.161619	3.59	146915.6
31	0.770459	171.3593	0.108403	2.8	73690.75
32	1.035665	171.7713	0.115607	1.45	108728.7
33	0.811471	171.5025	0.1059	1.4	77138.46
34	1.19219	172.5589	0.182625	1.2	157133.8
35	1.196982	172.84	0.172309	2.51	154970.3

Table 4.6.1 Optimal Solutions

4.6.3 Results and Discussions

- The source code of the proposed optimization algorithm was run on a Core i5 processor using C++ programming language on a Windows 10 platform. The control parameters required for implementation of the algorithm are listed in Table 4.6.1. The algorithm found the Pareto optimal front of the conflicting objective functions with good diversity of the solutions, as shown in Fig.12. The optimal input variables and their corresponding objective function values are presented in Table 4.6.1. By analyzing the Pareto front, some decisions could be taken, depending upon specific requirements of the process. For instance, at point 1, a component can be machined with the best surface quality but with minimum MRR. On the other extreme of the front, i.e. at point 2, the highest material removal rate can be achieved but it will be of the worst surface quality. All the other points are in between cases. As can be observed from the graph, no solution in the front is better than any other as they are non-dominated solutions. The choice of a solution has to be made purely based on production requirements. For example, if a manufacturing engineer chooses to machine a component with a surface quality of 1.57 µm, the set of input variables may be selected from the 9th row of Table 4.6.1.

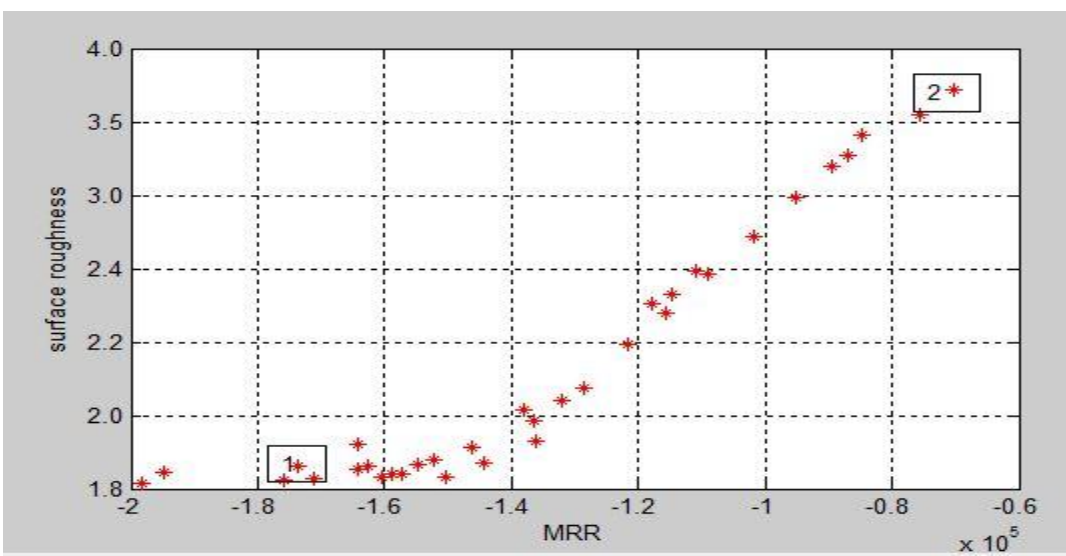


Fig. 13 Pareto Optimal Front

- Here in this study we got predicted R^2 value through MGGP as 94.96 % for Surface Roughness and 98.13% for MRR. So the predicted values of Ra and MRR of MGGP

model closely matched with the experimental values which signified the accuracy of the developed model. In the actual journal they got R^2 value for Ra through RSM as 87.9% but through MGGP we are getting R^2 as 94.96% for Ra which proves that MGGP is more effective in Multiple Symbolic Regression as compared to RSM.

4.7 Validation

Validation was performed from outside in MS Excel by finding out the percentage error between MGGP value and Experimental value w.r.t Experimental value. MGGP value was calculated by using the Regression Equation which was obtained by performing Multi Gene Genetic Programming symbolic Regression.

$$\text{Relative Error (\%)} = \frac{MGGP\ VALUE - EXPERIMENTAL\ VALUE}{EXPERIMENTAL\ VALUE} \times 100$$

s.no.	x1	x2	x3	y1 Exp	y1 MGGP	%error	y1 Rsm	%error
1	0.4	177	0.3	2.84	2.724002	4.08	3.83755	35.12
2	0.4	40	0.3	4.59	4.730482	3.06	4.3102	6.09
3	0.8	40	0.3	4.52	4.655927	3.01	4.3314	4.17
4	1.2	98	0.3	4.61	4.462442	3.2	4.1525	9.92

Table 4.7.1 Validation based on Surface Finish

Here we can see that % error in MGGP value for Ra is less as compared to % error in RSM value which confirms that MGGP is more efficient in conforming the actual Experimental conditions.

s.no.	x1	x2	x3	Y2 EXP	Y2 MGGP	%error
1	0.4	177	0.3	31758.86	29230.95	7.9
2	0.4	40	0.3	7177.14	7267.24	1.25
3	0.8	40	0.3	14308.57	14689.83	2.66
4	1.2	98	0.3	14308.57	14808.87	3.49

Table 4.7.2 Validation based on MRR

4.8 Conclusion

Many manufacturing industries machine intricate shapes of electrically conductive materials irrespective of their hardness. However, the selection of the right combination of input variables for optimal performance is not possible by the trial-and-error method. The present work proposes a novel approach based on the integration of two evolutionary approaches, namely, GP and MOGA. GP is such powerful tool that it can extract any complex quantitative relationship between input variables and output parameters effectively, whereas MOGA is a widely used potential tool for multi-objective optimization.

In this work, the most important machining per-romances namely MRR and surface finish, are considered. Initially, GP was used to model the mathematical relations for the chosen machining performances. Then, the models developed by GP were tested for their suitability using statistical methods. Later, the validated mathematical models of GP were used by MOGA to find the multiple sets of optimal solutions so as to enable a manufacturing engineer to choose a particular optimal set of input.

CHAPTER 5

CASE STUDY 2

An integrated evolutionary approach for modelling and optimization of drilling parameters (Thrust Force, Torque Force)

5.1 Introduction

Aramid Fibre strengthened Plastic composites are difficult to be drilled due to anisotropic material properties. Currently, soft computing techniques are used as alternatives to traditional mathematical models that is strong and might cope with inaccuracy and uncertainty. In this case study, drilling of Aramid Fibre strengthened Plastics (AFRPs) was applied and carried out using Taguchi L54 experimental layout. Drilling tool employed in this experiment was solid carbide. The aim of this study was to seek out optimum combination of drilling parameters to get

minimum thrust and torque force to reduce the delamination. Also, this study proposed a prediction model of Multi gene Genetic Programming optimized by Multi Objective Genetic algorithm (MGGP-MOGA). Moreover, RSM technique was used to measure the influence of process parameters (spindle speed, feed rate, drill point angle and drill diameter on thrust force and torque. The investigation demonstrated that drill point angle is the primary factor affecting thrust force and drill diameter influences the torque force on the drill bit.

Overall, this study recommends the use of high speed and low feed combination and drill point angles of 90° 118° to reduce the delamination of the materials in the drilling of AFRP composites. Overall, this study recommends the use of high speed and low feed combination and drill point angles of 90° 118° to reduce the delamination of the materials in the drilling of AFRP composites.

The materials used in construction, aerospace, automotive industries, etc. need to have high specific stiffness, high damping, high strength, high thermal resistance and low thermal expansion. Further, these materials should be corrosion & wear resistant and dimensionally stable. Composites such as Aramid Fibre Reinforced Plastics/Polymers (AFRP) exhibit such distinct properties and hence find broad applications in cryogenics, sports equipment, ropes & cables, ballistic applications, building construction, breaks, armor, aerospace, etc. Composite materials are two or more chemically different constituents combined synergistically and macroscopically to yield a useful material that is different in physical form and chemical composition of the parent materials. The purpose of having two or more constituents is to get rid of the inferior properties of the constituents and to gain benefits of the superior features of all the constituents. However, due to the presence of the two or more different phases AFRP composites pose various kinds of machining problems. Thus, the machining mechanism of composite materials is different from that of the homogeneous conventional materials [45, 46, 47, and 48].

The distinctive difficulties like delamination, fibre pull out, melting of the matrix, adhesion of materials to drill etc., are found while drilling of AFRP composites. These failures adversely affect the quality of the AFRP composites. Lamination, resin type, fibres, reinforcing materials all these factors also significantly modify the properties of AFRP composites. Therefore, it is necessary to control the factors affecting the drilling of AFRP composites [49, 50, 51, 52, and

53]. Various researchers used different and innovative ways to control the factors affecting the drilling of composites.

5.2 Methodology

In this case study, a novel approach is conferred for modelling of Thrust Force and Torque Force using GP. The distinctive aspect of GP as compared to traditional approaches is it doesn't make any presumption concerning the formulation to be created also the generated model helps directly to get an interpretation of the parameters affecting the method. The models developed by GP were afterward used for optimization. In the current study, the optimization problem of drilling parameters was explicitly formulated as a multi objective optimization problem, as the determination of the optimal working conditions are conflicting as Thrust force and Torque Force has to be kept minimum. It can be noted that the classical optimization methods (weighted sum methods, goal programming, min–max methods, etc.) are not efficient for handling multi-objective optimization problems because they do not find multiple solutions in a single run, and therefore it is necessary for them to be applied as many times as the number of desired Pareto-optimal solutions. The above-mentioned difficulty of classical optimization methods is eliminated in evolutionary algorithms, as they can find the multiple solutions in a single run. As a result, a most commonly used evolutionary approach, the MOGA is proposed for multi-objective optimization. Genetic algorithm (GA)-based multi-objective optimization methodologies have been widely used in the literature to find Pareto-optimal solutions.

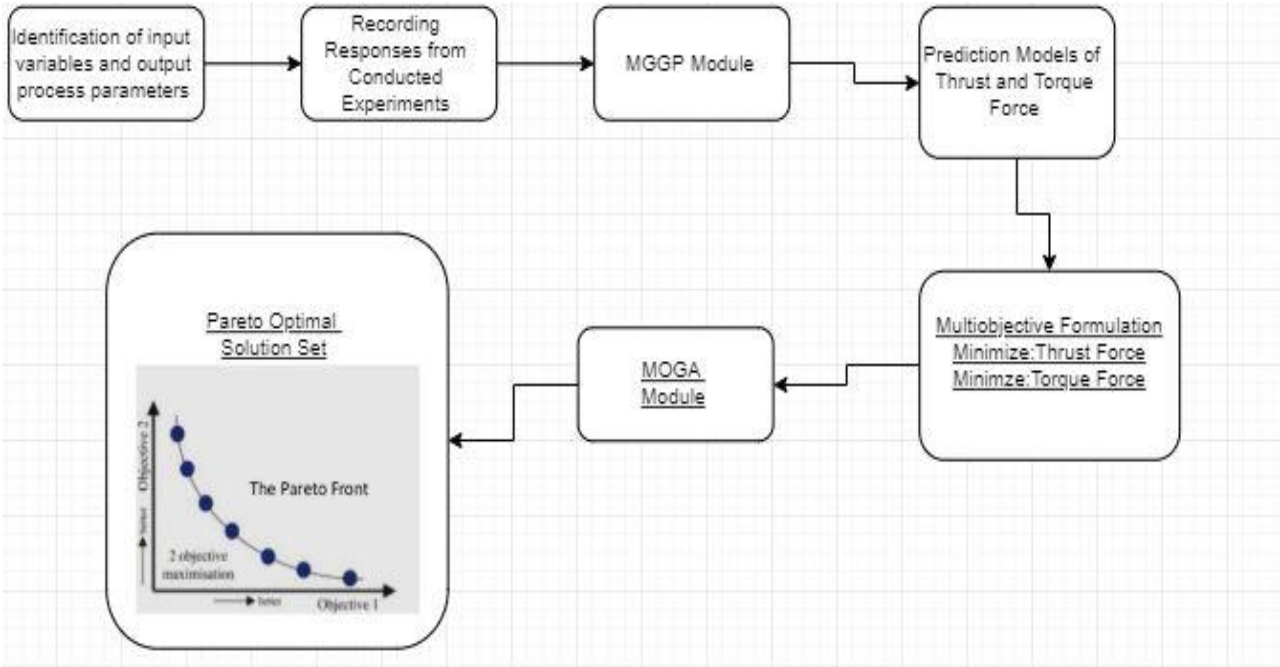


Fig. 14 Proposed Methodology

5.3 Experimental Design and Software Setup

AFRP values were analyzed with the Taguchi method. In this study, drill point angle, drill diameter, spindle speed and feed rate were selected. The drill parameters and levels are shown in Table 5.1. The experiments were conducted according to Taguchi's L54 Orthogonal Array, shown in Table 5.2. The drill diameter, speed, and feed have three levels, and drill point angle had two levels. In this work, Taguchi's L54 orthogonal array was considered, as the L8 array was insufficient to handle the data. In the current case study, fifty-four sets of experiments were conducted using standard design matrix of factorial design. Drill parameters concerning thrust and torque forces were measured using S-N ratio. Below table 5.1 shows the number and levels of control parameters used.

Factor	Type	Level	Values
DA (Drill Point Angle)	Fixed	2	90°, 118°.
DD (Drill Diameter)	Fixed	3	6 mm, 8 mm, 10 mm.
SPEED (Spindle Speed)	Fixed	3	600 rpm, 900 rpm, 1200 rpm.
FEED (Feed Rate)	Fixed	3	50 mm/min, 75 mm/min, 100 mm/min.

Table 5.1 Control Factors of Drilling Process

Taguchi's L54 Orthogonal Array, shown in Table 5.2 below.

Test no.	DA	DD	SPEED	FEED	THRUST	TORQUE
1	90	6	600	50	98.32	20.82
2	90	6	600	75	100.61	20.64
3	90	6	600	100	101.45	20.24
4	90	6	900	50	87.59	17.41
5	90	6	900	75	91.75	18.20
6	90	6	900	100	94.49	18.03
7	90	6	1200	50	74.68	15.99
8	90	6	1200	75	86.03	16.79
9	90	6	1200	100	86.77	16.91
10	90	8	600	50	112.44	22.09
11	90	8	600	75	114.43	20.01
12	90	8	600	100	111.52	20.33
13	90	8	900	50	98.57	16.19
14	90	8	900	75	102.92	17.55
15	90	8	900	100	102.40	18.39
16	90	8	1200	50	91.84	16.56
17	90	8	1200	75	93.50	17.41
18	90	8	1200	100	94.26	17.28
19	90	10	600	50	107.55	25.39
20	90	10	600	75	108.32	26.14
21	90	10	600	100	109.03	25.75
22	90	10	900	50	98.45	26.68
23	90	10	900	75	96.28	27.80
24	90	10	900	100	97.64	27.45
25	90	10	1200	50	87.94	24.43
26	90	10	1200	75	88.72	25.72
27	90	10	1200	100	90.33	24.44

28	118	6	50	122.31	18.33
29	118	6	75	126.76	16.66
30	118	6	100	129.44	16.16
31	118	6	50	120.04	17.02
32	118	6	75	113.78	17.80
33	118	6	100	118.49	17.83
34	118	6	50	102.06	15.59
35	118	6	75	104.72	16.51
36	118	6	100	113.07	15.57
37	118	8	50	137.37	17.30
38	118	8	75	137.72	17.75
39	118	8	100	138.87	18.22
40	118	8	50	128.59	18.02
41	118	8	75	130.06	17.90
42	118	8	100	132.54	17.68
43	118	8	50	114.84	16.19
44	118	8	75	121.71	17.26
45	118	8	100	123.73	16.93
46	118	10	50	134.29	23.62
47	118	10	75	135.65	24.80
48	118	10	100	136.48	23.80
49	118	10	50	125.43	23.89
50	118	10	75	126.62	24.86
51	118	10	100	124.15	24.49
52	118	10	50	112.14	21.99
53	118	10	75	118.67	23.12
54	118	10	100	120.11	23.29

Table 5.2 Taguchi's L54 Orthogonal Array and Calculated Values

5.4 Implementation of MGGP

Experimental Data is divided into three data sets:

- Training: 34 values for Thrust Force and 38 values for Torque Force
- Testing: 16 values for Thrust Force and 12 values for Torque Force
- Validation: 4 values(will be done from outside in Excel after running MGGP code)

5.4.1 Training Dataset

Training Dataset for Thrust Force:

S.No	x1	x2	x3	x4	THRUST
1	90	6	900	75	91.75
2	90	6	900	100	94.49
3	90	6	1200	50	74.68
4	90	6	1200	75	86.03
5	90	6	1200	100	86.77
6	90	8	600	50	112.44
7	90	8	600	75	114.43
8	90	8	600	100	111.52
9	90	8	900	50	98.57
10	90	8	900	75	102.92
11	90	8	900	100	102.4
12	90	8	1200	50	91.84
13	90	8	1200	75	93.5
14	90	8	1200	100	94.26
15	90	10	600	50	107.55
16	90	10	600	75	108.32
17	90	10	600	100	109.03
18	118	6	600	50	122.31
19	118	6	600	75	126.76
20	118	6	600	100	129.44
21	118	6	900	50	120.04
22	118	6	900	75	113.78
23	118	6	900	100	118.49
24	118	6	1200	50	102.06
25	118	6	1200	75	104.72
26	118	6	1200	100	113.07
27	118	8	600	50	137.37
28	118	8	600	75	137.72
29	118	8	600	100	138.87
30	118	8	900	50	128.59
31	118	8	900	75	130.06
32	118	8	900	100	132.54
33	118	8	1200	50	114.84
34	118	8	1200	75	121.71

Table 5.3 Training Dataset for Thrust Force

Training Dataset for Torque Force:

S.No	x1	x2	x3	x4	TORQUE
1	90	6	600	50	20.82
2	90	6	600	75	20.64
3	90	6	600	100	20.24
4	90	6	900	50	17.41
5	90	6	900	75	18.2
6	90	6	900	100	18.03
7	90	6	1200	50	15.99
8	90	6	1200	75	16.79
9	90	6	1200	100	16.91
10	90	8	900	50	16.19
11	90	8	900	75	17.55
12	90	8	900	100	18.39
13	90	8	1200	50	16.56
14	90	8	1200	75	17.41
15	90	8	1200	100	17.28
16	90	10	600	50	25.39
17	90	10	600	75	26.14
18	90	10	600	100	25.75
19	90	10	1200	50	24.43
20	90	10	1200	75	25.72
21	90	10	1200	100	24.44
22	118	6	600	50	18.33
23	118	6	600	75	16.66
24	118	6	600	100	16.16
25	118	6	900	50	17.02
26	118	6	900	75	17.8
27	118	6	900	100	17.83
28	118	8	600	50	17.3
29	118	8	600	75	17.75
30	118	8	600	100	18.22
31	118	8	900	50	18.02
32	118	8	900	75	17.9
33	118	8	900	100	17.68
34	118	8	1200	50	16.19
35	118	8	1200	75	17.26
36	118	8	1200	100	16.93
37	118	10	900	50	23.89
38	118	10	900	75	24.86

Table 5.4 Training Dataset for Torque Force

5.4.2 Testing Dataset

Testing Data for Thrust Force:

S.No	x1	x2	x3	x4	Thrust
1	90	6	600	50	98.32
2	90	6	600	75	100.61
3	90	6	600	100	101.45
4	90	6	900	50	87.59
5	90	10	900	50	98.45
6	90	10	900	75	96.28
7	90	10	900	100	97.64
8	90	10	1200	50	87.94
9	90	10	1200	75	88.72
10	90	10	1200	100	90.33
11	118	8	1200	75	121.71
12	118	8	1200	100	123.73
13	118	10	600	50	134.29
14	118	10	600	75	135.65
15	118	10	600	100	136.48
16	118	10	900	50	125.43

Table 5.5 Testing Dataset for Thrust Force

Testing Data for Torque Force:

S.No	x1	x2	x3	x4	Torque
1	90	8	600	50	22.09
2	90	8	600	75	20.01
3	90	8	600	100	20.33
4	90	10	900	50	26.68
5	90	10	900	75	27.8
6	90	10	900	100	27.45
7	118	6	1200	50	15.59
8	118	6	1200	75	16.51
9	118	6	1200	100	15.57
10	118	10	600	50	23.62
11	118	10	600	75	24.8
12	118	10	600	100	23.8

Table 5.6 Testing Dataset for Torque Force

5.5 MGGP Matlab Implementation

GP Control Parameters:

- Population Size: 100
- Number of Generations: 100
- Terminal set: {x1, x2, x3,x4}
- Function set: {+, −, ×}
- Selection Method: Tournament Selection
- Crossover probability (%): 85
- Mutation probability (%): 5
- Reproduction probability (%): 10
- Fitness Measure: Root Mean square Error(R^2 value)
- Maximum Tree Depth: 4
- Maximum Genes: 12
- Constant Range: [-10 10]

5.5.1 MGGP Matlab Code (Configuration File)

```
function gp=Y1_config(gp)
%Thrust Force- Y1
gp.runcontrol.pop_size=100;
gp.runcontrol.num_gen=100;
gp.runcontrol.verbose=20;
gp.fitness.fitfun=@regressmulti_fitfun;
gp.fitness.minimisation=true;
gp.runcontrol.showBestInputs = true;
gp.runcontrol.runs = 1;

gp.selection.method='tour';
gp.selection.tournament.size=15;
```

```
gp.selection.elite_fraction = 0.3;

%Load the variables xtrain, ytrain, xtest and ytest and assign to gp structure
load mydataY1;
gp.userdata.xtrain=xtrain;
gp.userdata.ytrain=ytrain;
gp.userdata.xtest=xtest;
gp.userdata.ytest=ytest;

%Define the number of inputs
gp.nodes.inputs.num_inp = size(gp.userdata.xtrain,2);

%Enable multiple gene mode and set max number of genes per individual.
gp.genes.multigene=true;
gp.genes.max_genes=12;
gp.genes.max_depth=6;

%Define function nodes
gp.nodes.functions.name={'times','minus','plus'};
End
```

Note: Here we are not using Fitness Function (R^2 value) as a Termination Criteria but we are using Number of Generations as Termination Criteria.

5.5.2 MGGP Matlab Code (Run File)

```
%run MGGP on Experiment data for Surface Roughness
clear;
clc;
disp('>>gp=rungp(@Y1_config);');
disp('Press a key to continue');
disp(' ');
pause;
gp = rungp(@Y1_config);
disp(' ');
disp('Evaluate the best individual of');
disp('the runs on the fitness function using:');
disp('>>runtree(gp,"best");');
disp('Press a key to continue');
disp(' ');
pause;
runtree(gp,'best');
if gp.info.toolbox.symbolic

    disp(' ');
    disp('Next, use the the GPPRETTY command on the best individual: ');
    disp('>>gppretty(gp,"best")');
    disp('Press a key to continue');
    disp(' ');
    pause;
    gppretty(gp,'best');
     disp(' ');
end
disp('Next, use the the DRAWTREE command: ');
disp('>>drawtrees(gp,"best")');
```

```
disp('Press a key to continue');
disp(' ');
pause;
drawtrees(gp,'best');
disp(' ');
   pause;
if gp.info.toolbox.symbolic
  disp('Finally, an HTML report listing the models on the Pareto optimal front');
  disp('of model expressional complexity and performance can be generated using');
  disp('the PARETOREPORT function.');
   disp('>>paretoreport(gp)');
   disp(' ');
   disp('Press a key to continue');
   disp(' ');
   pause;
   paretoreport(gp);
   disp('end');
end
```

Above Run file was executed for several times and for 100 Generations which resulted in following Multigene Regression expression for Thrust Force, found to have the largest fitness value.

5.5.3 Regression Equation for Thrust Force:

- 0.0001804*x(1)^2*x(2) + 0.003846*x(1)^2 - 0.02163*x(1)*x(2)^2 + 0.0000902*x(1)*x(2)*x(3) + 0.0006395*x(1)*x(2)*x(4) + 0.2426*x(1)*x(2) - 0.0006343*x(1)*x(3) - 0.003974*x(1)*x(4)- 0.2565*x(1) -0.00007464*x(2)*x(3)*x(4) - 0.003868*x(2)*x(3) - 0.0001198*x(2)*x(4) - 0.003194*x(2)*x(4)+10.2*x(2) - 0.000002592*x(3)^2 + 0.0007154*x(3)*x(4) - 0.01372*x(3) + 0.01709*x(4)+0.4381

Similarly Regression Equation for Torque Force was obtained by making certain modifications in above Configuration file and Run file by changing Training Data and Testing Data for Torque Force.

5.5.3 Regression Equation for Torque Force:

0.1708*x(4) - 13.07*x(2) - 0.02377*x(3) - 0.3506*x(1) + 0.001061*x(4)*(x(2) + x(3))+ 0.0005219*(x(2) - 1.0*x(4))*(x(2)+2.0*x(3)+x(4)) + 0.07021*x(1)*x(2) - 0.0002754*x(1)*x(3)- 0.003669*x(1)*(x(2)^2+x(4)) - 0.0001363*x(2)^3*(x(1) + x(4)) + 0.07807*x(2)^3+0.0003904*x(1)*(x(3) + 3.0*x(4)) + 0.0002754*x(1)*x(2)*x(4) +91.1

A comparison of the predicted models and the experimental values for the Training and Testing datasets of Thrust Force and Torque Force are shown in Figs 15 and 16 respectively.

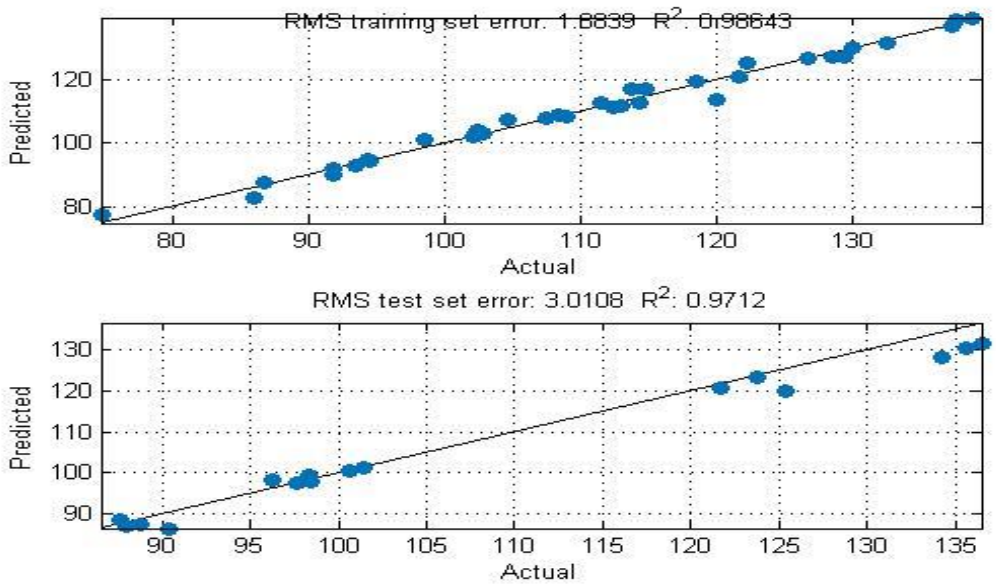


Fig. 15 Scatter Plot for Thrust Force

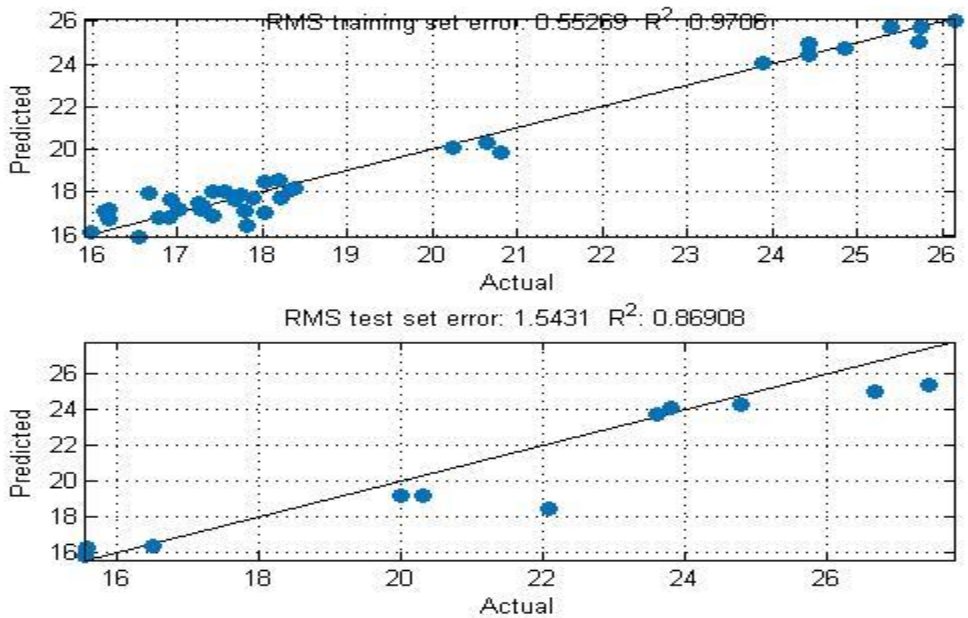


Fig. 16 Scatter Plot for Torque Force

While developing the above models, the correlation coefficient R^2 was taken as the fitness measure. GP was continued until a value as close as possible to the maximum value of R^2 was

obtained. R^2 was used as the fitness measure in order to check whether the fitted models actually describe the experimental data. Below figures show the convergence graphs of the models predicted by the proposed algorithm. The fitness measures for Thrust Force and Torque Force have gradually improved with the number of generations and finally converged to 0.98643 and 0.9712 respectively. This shows that the models can explain the variation in the Thrust Force and Torque Force up to the extents of 98.64% and 97.12% respectively. On the basis of the high values of R^2 it can be said that the models are adequate in representing the process.

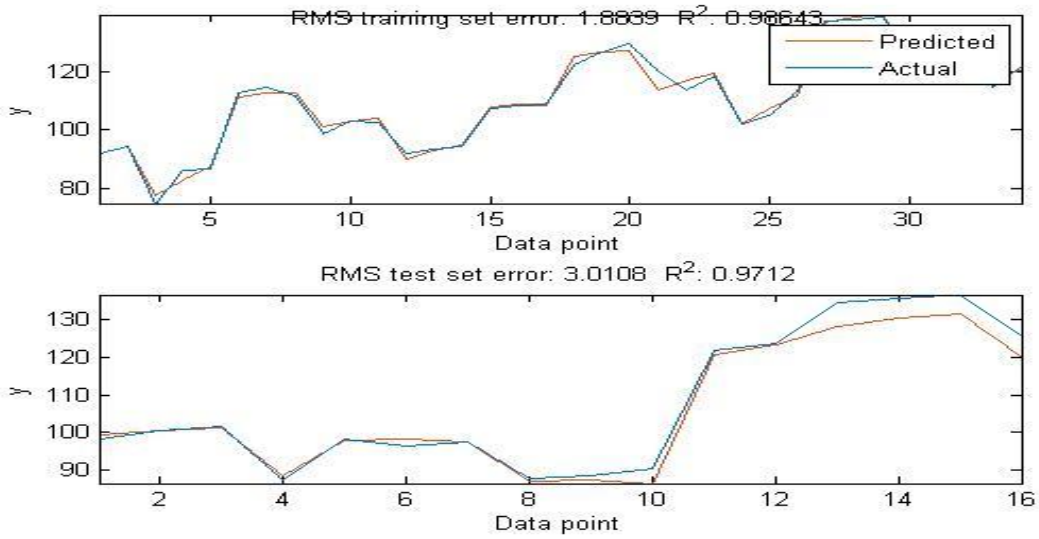


Fig. 17 Comparison Graph for Thrust Force

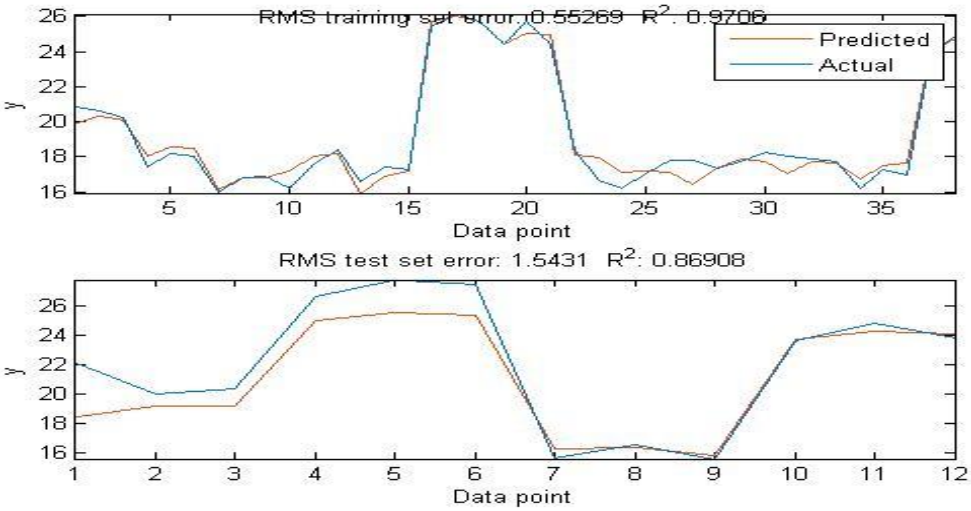


Fig. 18 Comparison Graph for Torque Force

5.6 Optimization using Multi Objective Genetic Algorithm

MOGA Control Parameters:

- Population Size:100
- Selection Function: Tournament selection
- Tournament Size: 2
- Crossover fraction: 0.8
- Crossover function: 1
- Mutation: Constraint Independent
- Stopping Criteria: Generations(200*no. of variables)

5.6.1 Multi Objective Genetic Algorithm Settings in Matlab

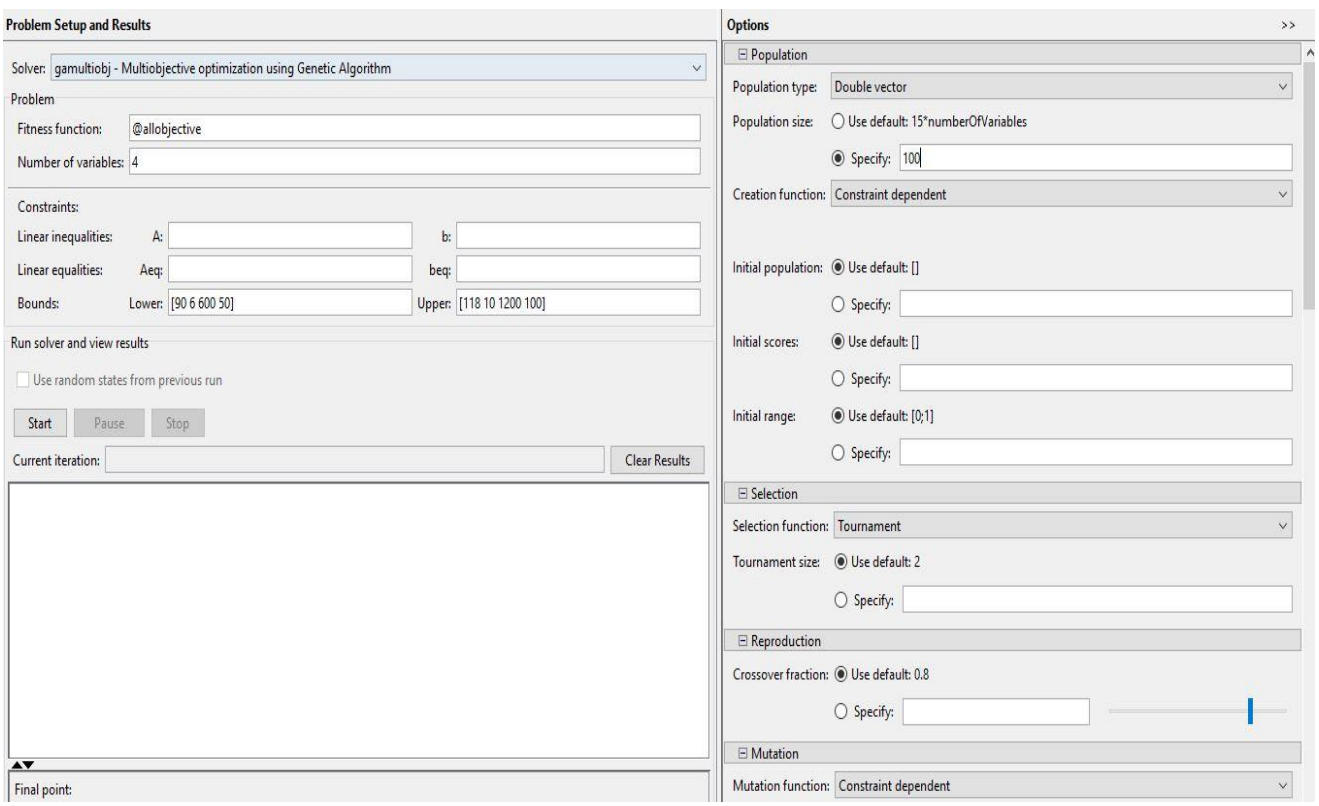


Fig. 19 MOGA Settings Matlab

5.6.2 Optimal Solutions through MOGA

After running MOGA with desired settings we got Optimal Solutions which are all good Solutions and we can select any combination of Optimal Solutions depending upon a particular Manufacturing Process.

S.No	x1	x2	x3	x4	THRUST	TORQUE
1	90.02368	7.109752	1164.234	50.00572	89.72642	15.28306
2	90.03626	6.801033	1164.154	50.01885	87.6418	15.36673
3	90.06905	7.011196	1164.251	50.05539	89.14758	15.29383
4	90.04511	6.049147	1164.087	50.07984	80.99701	16.24595
5	90.03814	6.856491	1164.156	50.02614	88.05026	15.33973
6	90.05836	7.048199	1164.214	50.04786	89.37892	15.28854
7	90.04023	6.519998	1164.153	50.01327	85.40732	15.58655
8	90.05373	6.472456	1164.128	50.09786	85.03461	15.64088
9	90.05942	6.976904	1164.153	50.07301	88.91922	15.30178
10	90.0553	6.197392	1164.1	50.0469	82.48495	16.00087
11	90.04558	6.180109	1164.109	50.01532	82.29821	16.02616
12	90.03472	6.612941	1164.193	50.05905	86.18744	15.50077
13	90.05454	6.034802	1164.06	50.05887	80.85073	16.27062
14	90.05188	6.662091	1164.113	50.16569	86.62982	15.4659
15	90.05127	6.103821	1164.121	50.15392	81.58178	16.15503
16	90.0642	6.228966	1164.09	50.22135	82.84932	15.96067
17	90.05647	6.000212	1164.064	50.15774	80.51954	16.3368
18	90.05815	6.164983	1164.066	50.15796	82.20249	16.0561
19	90.05722	6.250746	1164.127	50.16759	83.03556	15.92626
20	90.06228	6.778957	1164.163	50.06731	87.51238	15.38175
21	90.04973	6.401129	1164.089	50.11921	84.40919	15.7243
22	90.04691	6.078355	1164.109	50.01812	81.27976	16.19271
23	90.04882	6.351236	1164.117	50.03624	83.93156	15.78299
24	90.02515	7.095064	1164.241	50.01281	89.63767	15.28339
25	90.05495	6.45291	1164.094	50.07985	84.86127	15.66204
26	90.05168	6.22021	1164.125	50.13286	82.72762	15.96973
27	90.05039	6.429264	1164.123	50.07163	84.64572	15.68859
28	90.05133	6.263219	1164.125	50.21332	83.16278	15.91021
29	90.04169	6.090825	1164.107	50.05256	81.41293	16.17287
30	90.04891	6.336181	1164.115	50.06969	83.80289	15.80407
31	90.04187	6.376191	1164.136	50.11302	84.1743	15.75439
32	90.04949	6.296474	1164.127	50.15257	83.45752	15.86098
33	90.05213	6.152116	1164.083	50.13874	82.06381	16.07563
34	90.05321	6.502602	1164.183	50.16069	85.30987	15.61105
35	90.02899	6.41289	1164.207	50.15022	84.50135	15.71062
36	90.05647	6.013395	1164.08	50.17337	80.66201	16.31338
37	90.04778	6.675469	1164.11	50.06123	86.70375	15.4508
38	90.02949	6.061598	1164.087	50.07984	81.11279	16.22418
39	90.07093	6.209599	1164.109	50.0469	82.61631	15.98232

Table 5.6.1 Optimal Solutions

5.6.3 Results and Discussions

- The source code of the proposed optimization algorithm was run on a Core i5 processor using C++ programming language on a Windows 10 platform. The control parameters required for implementation of the algorithm are listed in Table 5.6.1. The predicted values of thrust force and torque of MGGP model closely matched with the experimental values which signified the accuracy of the developed model. The algorithm found the Pareto optimal front of the conflicting objective functions with good diversity of the solutions, as shown in Fig.12. The optimal input variables and their corresponding objective function values are presented in Table 5.6.1. By analyzing the Pareto front, some decisions could be taken, depending upon specific requirements of the process. As can be observed from the graph, no solution in the front is better than any other as they are non-dominated solutions. If we see point 1 at that point Thrust Force is maximum and Torque Force is minimum but at point 2 Thrust Force is minimum and Torque Force is maximum so the choice of a solution has to be made purely based on production requirements, if we want both forces to be minimum we have to take some intermediate values between 1 and 2 from Table 5.6.1.

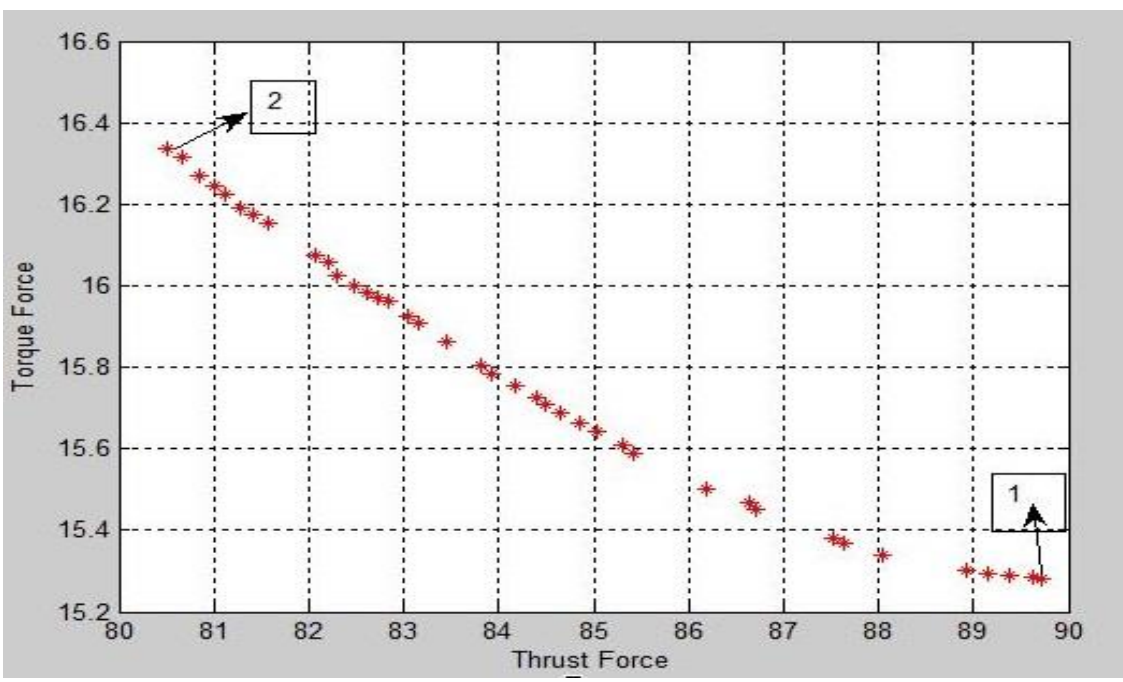


Fig. 20 Pareto Optimal Front

- Here in this Journal they got predicted R^2 value through RSM as 97.93% for Thrust Force and 91.33% for Torque Force. Predicted R^2 value through MGGP is 98.64% for Thrust Force and 97.06% for Torque Force. So the predicted values of thrust force and torque of MGGP model closely matched with the experimental values which signified the accuracy of the developed model as compared through RSM method.

5.7 Validation

Validation was performed from outside in MS Excel by finding out the percentage error between MGGP value and Experimental value w.r.t Experimental value. MGGP value was calculated by using the Regression Equation which was obtained by performing Multi Gene Genetic Programming symbolic Regression.

$$\text{Relative Error (\%)} = \frac{MGGP\ VALUE - EXPERIMENTAL\ VALUE}{EXPERIMENTAL\ VALUE} \times 100$$

s.no.	x1	x2	x3	x4	y1 Exp	y1Mggp	%error	y1 Rsm	%error
1	118	10	900	100	124.15	126	1.49	126.5528	1.93
2	118	10	1200	50	112.14	115	2.55	113.6244	1.32
3	118	10	1200	75	118.67	120	1.12	116.464	1.85
4	118	10	1200	100	120.11	122	1.57	118.3436	1.47

Table 5.7.1 Validation based on Thrust Force

Here we can see that % error in MGGP value of Thrust Force is less as compared to % error in RSM value for 2 levels and approximately near to other 2 levels which confirms that MGGP is more efficient in conforming the actual Experimental conditions as compared to RSM technique.

s.no.	x1	x2	x3	x4	y2 Exp	y2 Mggp	%error	y2Rsm	%errror
1	118	10	900	100	24.49	25	2.08	27.58581	12.64
2	118	10	1200	50	21.99	23	4.59	17.9604	18.32
3	118	10	1200	75	23.12	23	0.51	23.41656	1.28
4	118	10	1200	100	23.29	25	7.34	28.12021	20.73

Table 5.7.2 Validation based on Torque Force

Here we can see that % error in MGGP value for Torque Force is less as compared to % error in RSM value which confirms that MGGP is more efficient in conforming the actual Experimental conditions as compared to RSM technique.

CHAPTER 6

CASE STUDY 3

An integrated evolutionary approach for modelling and optimization of welding parameters (Bead Height, Bead Width, Bead Penetration)

6.1 Introduction

Welding in the current situation of in industries is becoming progressively popular. Right from the man metal arc welding method to beam welding method welding endure tremendous technological innovations over the years. Weld ought to be sound enough to fulfill the purposeful demand of the welded structure. The most quality characteristics are weld bead geometry like weld penetration, HAZ, fusion and met and mechanical properties of the welded joints. Weld bead geometry is especially depends upon the kind of welding method. The necessity of weld

quality in every applications are totally different that leads to the invention of advanced welding technologies. Generally, weld quality is evaluated in terms of weld bead geometry, microstructure of weld, hardness, tensile strength and aesthetic look of weld. Weld bead geometry primarily includes depth of fusion, fusion breadth, bead height and HAZ breadth. In most of the cases, weld penetration ought to be maximum whereas fusion breadth, bead height and HAZ breadth ought to be minimum so as to get the required strength of the welded joint.

Lack of penetration is one in all the significant issue affecting fatigue lifetime of the weld joint [28].Changes in weld penetration can reflect in fatigue life of the joint. Lack of penetration permits a natural stress raiser from that a crack might propagate [28]. Quantity of heat input is one in all the main parameter that influences the depth of penetration. Spare heat input is needed to attain the penetration. In most of the conventional arc welding processes heat input is directly proportional to the depth of fusion. On the opposite hand, if heat input will increase, fusion area and HAZ area will increase. Increase in fusion area ends up in increase in distortion. Microstructure and mechanical property of heat affected zone differs from weld metal and base material. Typically, hardness of the HAZ are above weld metal and base material. As increase in hardness results in increase in brittleness of the weld joint completely utterly unfavorable for load carrying structure. Increase in bead height or excess bead will increase the strain in weld toe region. Stress in weld toe region clearly results in fatigue failure. On the opposite hand, lack of weld reinforcement reduces the fatigue strength of the weld joint. So, manufacturing weld joint with most penetration and minimum fusion and HAZ breadth is really a tricky task for welding engineers. Generally, the conventional arc welding processes famous for its high heat input. Advanced welding processes are available which might deliver maximum penetration with minimum fusion and HAZ area at low heat input.

About Weld Bead Geometry:

Most important weld bead geometry parameters are depth of fusion, bead width, bead height and HAZ space.

- Depth of fusion - It is because the distance that fusion extends into the bottom material.
- Bead dimension – It outlined because the most dimension of the deposited weld metal.
- Bead height -It is outlined because the bead height on top of the surface of the plate.
- Heat affected zone - It outlined because the non-melted space that experiences changes in material**.**

This case study proposed a good approach to determine relationships between method parameters (inputs) and responses (outputs) in metal active gas (MAG) welding using MGGP technique carried out on data collected as per Taguchi design of experiments.

6.2 Methodology

In this case study, a novel approach is conferred for modelling of Bead Height, Bead Width and Bead Penetration using GP. The distinctive aspect of GP as compared to traditional approaches is it doesn't make any presumption concerning the formulation to be created also the generated model helps directly to get an interpretation of the parameters affecting the method. The models developed by GP were afterward used for optimization. In the current study, the optimization problem of welding parameters was explicitly formulated as a multi objective optimization problem, as the determination of the optimal working conditions are conflicting as Bead Penetration has to be maximum and Bead Height, Bead Width has to be minimum. It can be noted that the classical optimization methods (weighted sum methods, goal programming, min–max methods, etc.) are not efficient for handling multi-objective optimization problems because they do not find multiple solutions in a single run, and therefore it is necessary for them to be applied as many times as the number of desired Pareto optimal solutions. The above-mentioned difficulty of classical optimization methods is eliminated in evolutionary algorithms, as they can find the multiple solutions in a single run. As a result, a most commonly used evolutionary approach, the MOGA is proposed for multi-objective optimization. Genetic algorithm (GA)-

based multi-objective optimization methodologies have been widely used in the literature to find Pareto optimal solutions [15–18].

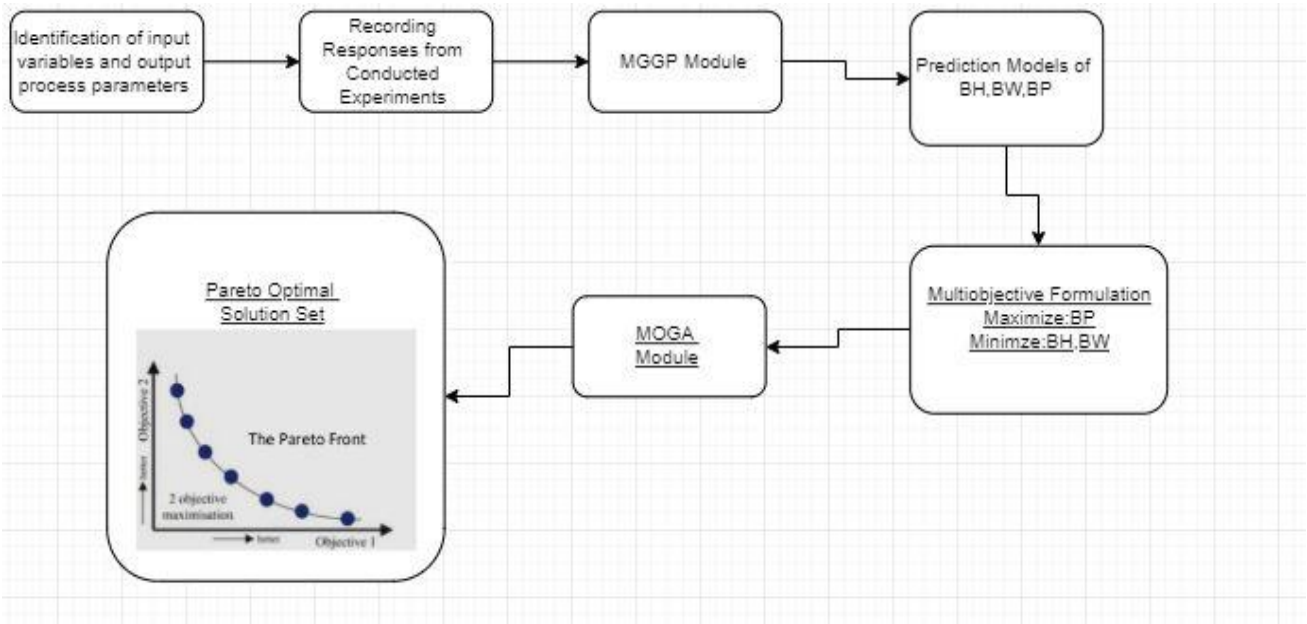


Fig. 21 Proposed Methodology

6.3 Experimental Design and Software Setup

For modeling and improvement of Metal arc gas welding method (shown in Figure 20), a consumable electrode is employed as filler with an active gas shielding to guard molten metal from reaction. Vital input parameters in mag are welding speed (S), welding voltage (V), wire feed rate (F), nozzle-to-plate distance (D) and torch angle (A), whereas output parameters (responses) are bead height (BH), bead breadth/width (BW) and bead/weld penetration (BP). 3 levels were thought of for input process parameters as shown in table 6.1 and fifty four combinations (L_{54} Orthogonal Array) of input method parameters were considered for Taguchi Design of Experiments.

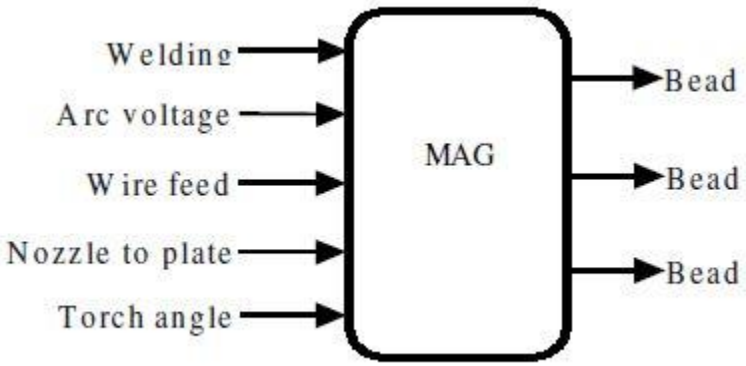


Fig. 22 Input and Output Parameters for MAG welding Process

Factor	Level -	Level 0	Level +
Welding speed (S), cm/m	10	17	24
Arc voltage (V), V	27	32	37
Wire feed rate (F), m/min	4	5.5	7
Torch angle (A), °	70	85	100
Nozzle-plate distance (D), cm	1	-	1.5

Table 6.1 Control Factors for GMAW welding Process

In combined optimization, evolutionary algorithms (MGGP and MOGA) were used. Multigene symbolic regression was used to develop to model relationships between process variables and weld bead geometry in gas metal arc welding. MOGA approach is proposed to determine optimal values for process parameters with respect to any given bead geometry. Planned solution is developed in such manner that it will accurately determine best process variables through minimization of an error function relative to any desired weld bead specifications.

Taguchi's L54 Orthogonal Array, shown in Table 6.2 below

No.	D	A°	F	S	V	BH	BW	BP
	cm		m/min	cm/min	v	mm	mm	mm
1	1	70	4	10	27	3.3	7.06	0.85
2	1	70	5.5	17	32	2.75	6.32	1.45
3	1	70	7	24	37	2.2	8.95	2.6
4	1	85	4	10	32	2.35	9.85	1.1
5	1	85	5.5	17	37	2.25	11.35	1.95
6	1	85	7	24	27	3.15	5.48	1.6
7	1	100	4	17	27	2.6	5.48	1.05
8	1	100	5.5	24	32	1.8	7.52	1.8
9	1	100	7	10	37	2.65	15.08	1.55
10	1.5	70	4	24	37	1.6	7.37	1.5
11	1.5	70	5.5	10	27	4.25	7.57	0.45
12	1.5	70	7	17	32	3.2	8.42	1.35
13	1.5	85	4	17	37	2.1	9.03	1.5
14	1.5	85	5.5	24	27	2.8	4.92	0.95
15	1.5	85	7	10	32	4.1	10.38	0.9
16	1.5	100	4	24	32	1.95	5.57	1.1
17	1.5	100	5.5	10	37	2.65	12.9	1.3
18	1.5	100	7	17	27	3.9	5.97	0.5
19	1	70	4	10	27	3.4	7.07	0.75
20	1	70	5.5	17	32	2.65	8.2	1.3
21	1	70	7	24	37	2.4	9.25	2.4
22	1	85	4	10	32	2.55	10.25	0.8
23	1	85	5.5	17	37	2.15	11.47	1.55
24	1	85	7	24	27	2.95	5.55	1.3
25	1	100	4	17	27	2.55	5.3	0.9
26	1	100	5.5	24	32	2.2	6.3	1.6
27	1	100	7	10	37	3.2	15.2	1.7
28	1.5	70	4	24	37	1.7	6.92	1.1
29	1.5	70	5.5	10	27	4	7.63	0.5
30	1.5	70	7	17	32	3.3	7.38	1.35
31	1.5	85	4	17	37	2.05	8.4	1.65
32	1.5	85	5.5	24	27	2.8	4.85	1.1
33	1.5	85	7	10	32	4.15	11.12	1
34	1.5	100	4	24	32	2	5.77	1.3
35	1.5	100	5.5	10	37	3.1	12.8	1.2
36	1.5	100	7	17	27	3.8	5.47	0.6
37	1	70	4	10	27	3.5	7.13	0.6
38	1	70	5.5	17	32	2.3	8.48	1.35
39	1	70	7	24	37	2	9.87	2.2
40	1	85	4	10	32	3	9.34	1.05
41	1	85	5.5	17	37	2.2	11.36	1.85
42	1	85	7	24	27	3.1	5.36	1.25
43	1	100	4	17	27	2.65	5.4	0.8
44	1	100	5.5	24	32	2.05	7.2	1.5

45	1	100	7	10	37	3.05	15.05	2
46	1.5	70	4	24	37	1.9	7.25	1.15
47	1.5	70	5.5	10	27	4.1	7.41	0.45
48	1.5	70	7	17	32	3.4	7.77	1.35
49	1.5	85	4	17	37	2.05	8.94	1.8
50	1.5	85	5.5	24	27	2.85	4.57	1
51	1.5	85	7	10	32	3.8	10.36	1.35
52	1.5	100	4	24	32	2.05	6.23	0.9
53	1.5	100	5.5	10	37	3.35	13.7	0.9
54	1.5	100	7	17	27	3.55	6.2	0.8

Table 6.2 Taguchi's L54 Orthogonal Array and Calculated Values

6.4 Implementation of MGGP

Experimental Data is divided into three data sets. Training and testing used directly in the evolution of mathematical model.

Training is used to develop or evolve the model and testing is used to check the goodness of the model after each generation.

- Training: 38 values for Bead Height, Bead Width and 34 values for Bead Penetration.
- Testing: 12 values for Bead Height, Bead Width and 16 values for Bead Penetration.
- Validation: 4 values(will be done from outside in Excel after running MGGP code)

6.4.1 Training Dataset

Training Dataset for Bead Height and Bead Width

S.No	x1	x2	x3	x4	x5	BH	BW
1	1	70	4	10	27	3.3	7.06
2	1	70	5.5	17	32	2.75	6.32
3	1	70	7	24	37	2.2	8.95
4	1	85	4	10	32	2.35	9.85
5	1	85	5.5	17	37	2.25	11.35
6	1	85	7	24	27	3.15	5.48
7	1	100	4	17	27	2.6	5.48
8	1	100	5.5	24	32	1.8	7.52
9	1	100	7	10	37	2.65	15.08
10	1.5	85	4	17	37	2.1	9.03
11	1.5	85	5.5	24	27	2.8	4.92
12	1.5	85	7	10	32	4.1	10.38
13	1.5	100	4	24	32	1.95	5.57
14	1.5	100	5.5	10	37	2.65	12.9
15	1.5	100	7	17	27	3.9	5.97
16	1	70	4	10	27	3.4	7.07
17	1	70	5.5	17	32	2.65	8.2
18	1	70	7	24	37	2.4	9.25
19	1	100	4	17	27	2.55	5.3
20	1	100	5.5	24	32	2.2	6.3
21	1	100	7	10	37	3.2	15.2
22	1.5	70	4	24	37	1.7	6.92
23	1.5	70	5.5	10	27	4	7.63
24	1.5	70	7	17	32	3.3	7.38
25	1.5	85	4	17	37	2.05	8.4
26	1.5	85	5.5	24	27	2.8	4.85
27	1.5	85	7	10	32	4.15	11.12
28	1	70	4	10	27	3.5	7.13
29	1	70	5.5	17	32	2.3	8.48
30	1	70	7	24	37	2	9.87
31	1	85	4	10	32	3	9.34
32	1	85	5.5	17	37	2.2	11.36
33	1	85	7	24	27	3.1	5.36
34	1	100	4	17	27	2.65	5.4
35	1	100	5.5	24	32	2.05	7.2
36	1	100	7	10	37	3.05	15.05
37	1.5	85	4	17	37	2.05	8.94
38	1.5	85	5.5	24	27	2.85	4.57

Table 6.4 Training Dataset for BH and BW

Training Dataset for Bead Penetration

S.No	x1	x2	x3	x4	x5	BP
1	1	85	5.5	17	37	1.95
2	1	85	7	24	27	1.6
3	1	100	4	17	27	1.05
4	1	100	5.5	24	32	1.8
5	1	100	7	10	37	1.55
6	1.5	70	4	24	37	1.5
7	1.5	70	5.5	10	27	0.45
8	1.5	70	7	17	32	1.35
9	1.5	85	4	17	37	1.5
10	1.5	85	5.5	24	27	0.95
11	1.5	85	7	10	32	0.9
12	1.5	100	4	24	32	1.1
13	1.5	100	5.5	10	37	1.3
14	1.5	100	7	17	27	0.5
15	1	70	4	10	27	0.75
16	1	70	5.5	17	32	1.3
17	1	70	7	24	37	2.4
18	1.5	70	4	24	37	1.1
19	1.5	70	5.5	10	27	0.5
20	1.5	70	7	17	32	1.35
21	1.5	85	4	17	37	1.65
22	1.5	85	5.5	24	27	1.1
23	1.5	85	7	10	32	1
24	1.5	100	4	24	32	1.3
25	1.5	100	5.5	10	37	1.2
26	1.5	100	7	17	27	0.6
27	1	70	4	10	27	0.6
28	1	70	5.5	17	32	1.35
29	1	70	7	24	37	2.2
30	1	85	4	10	32	1.05
31	1	85	5.5	17	37	1.85
32	1	85	7	24	27	1.25
33	1	100	4	17	27	0.8
34	1	100	5.5	24	32	1.5

Table 6.5 Training Dataset for BP

6.4.2 Testing Dataset

Testing Data for Training Dataset for Bead Height and Bead Width

S.No	x1	x2	x3	x4	x5	BH	BW
1	1.5	70	4	24	37	1.6	7.37
2	1.5	70	5.5	10	27	4.25	7.57
3	1.5	70	7	17	32	3.2	8.42
4	1	85	4	10	32	2.55	10.25
5	1	85	5.5	17	37	2.15	11.47
6	1	85	7	24	27	2.95	5.55
7	1.5	100	4	24	32	2	5.77
8	1.5	100	5.5	10	37	3.1	12.8
9	1.5	100	7	17	27	3.8	5.47
10	1.5	70	4	24	37	1.9	7.25
11	1.5	70	5.5	10	27	4.1	7.41
12	1.5	70	7	17	32	3.4	7.77

Table 6.6 Testing Dataset for BH and BW

Testing Data for Training Dataset for Bead Penetration

S.No	x1	x2	x3	x4	x5	BP
1	1	70	4	10	27	0.85
2	1	70	5.5	17	32	1.45
3	1	70	7	24	37	2.6
4	1	85	4	10	32	1.1
5	1	85	4	10	32	0.8
6	1	85	5.5	17	37	1.55
7	1	85	7	24	27	1.3
8	1	100	4	17	27	0.9
9	1	100	5.5	24	32	1.6
10	1	100	7	10	37	1.7
11	1	100	5.5	24	32	1.5
12	1	100	7	10	37	2
13	1.5	70	4	24	37	1.15
14	1.5	70	5.5	10	27	0.45
15	1.5	70	7	17	32	1.35
16	1.5	85	4	17	37	1.8

Table 6.7 Testing Dataset for BP

6.5 MGGP Matlab Implementation

GP Control Parameters:

- Population Size: 100
- Number of Generations: 100
- Terminal set: {x1, x2, x3,x4,x5}
- Function set: {+, −, ×}
- Selection Method: Tournament Selection
- Crossover probability (%): 85
- Mutation probability (%): 5
- Reproduction probability (%): 10
- Fitness Measure: Root Mean square Error(R^2 value)
- Maximum Tree Depth: 4
- Maximum Genes: 12
- Constant Range: [-10 10]

6.5.1 MGGP Matlab Code (Configuration File)

```
function gp=Y1_config(gp)
%Bead Height- Y1
gp.runcontrol.pop_size=100;
gp.runcontrol.num_gen=100;
gp.runcontrol.verbose=20;
gp.fitness.fitfun=@regressmulti_fitfun;
gp.fitness.minimisation=true;
gp.runcontrol.showBestInputs = true;
gp.runcontrol.runs = 1;

gp.selection.method='tour';
gp.selection.tournament.size=15;
```

```
gp.selection.elite_fraction = 0.3;

%Load the variables xtrain, ytrain, xtest and ytest and assign to gp structure
load mydataY1;
gp.userdata.xtrain=xtrain;
gp.userdata.ytrain=ytrain;
gp.userdata.xtest=xtest;
gp.userdata.ytest=ytest;

%Define the number of inputs
gp.nodes.inputs.num_inp = size(gp.userdata.xtrain,2);

%Enable multiple gene mode and set max number of genes per individual.
gp.genes.multigene=true;
gp.genes.max_genes=12;
gp.genes.max_depth=6;

%Define function nodes
gp.nodes.functions.name={'times','minus','plus'};
End
```

Note: Here we are not using Fitness Function (R^2 value) as a Termination Criteria but we are using Number of Generations as Termination Criteria.

6.5.2 MGGP Matlab Code (Run File)

```
%run MGGP on Experiment data for Surface Roughness
clear;
clc;
disp('>>gp=rungp(@Y1_config);');
disp('Press a key to continue');
disp(' ');
pause;
gp = rungp(@Y1_config);
disp(' ');
disp('Evaluate the best individual of');
disp('the runs on the fitness function using:');
disp('>>runtree(gp,"best");');
disp('Press a key to continue');
disp(' ');
pause;
runtree(gp,'best');
if gp.info.toolbox.symbolic

    disp(' ');
    disp('Next, use the the GPPRETTY command on the best individual: ');
    disp('>>gppretty(gp,"best")');
    disp('Press a key to continue');
    disp(' ');
    pause;
    gppretty(gp,'best');
     disp(' ');
end
disp('Next, use the the DRAWTREE command: ');
disp('>>drawtrees(gp,"best")');
```

```
disp('Press a key to continue');
disp(' ');
pause;
drawtrees(gp,'best');
disp(' ');
   pause;
if gp.info.toolbox.symbolic
  disp('Finally, an HTML report listing the models on the Pareto optimal front');
  disp('of model expressional complexity and performance can be generated using');
  disp('the PARETOREPORT function.');
   disp('>>paretoreport(gp)');
   disp(' ');
   disp('Press a key to continue');
   disp(' ');
   pause;
   paretoreport(gp);
   disp('end');
end
```

Above Run file was executed for several times and for 100 Generations which resulted in following Multigene Regression expression for Bead Height, found to have the largest fitness value.

6.5.3 Regression Equation for Bead Height

0.1128*x(1)+0.09485*x(2)-0.02602*x(3) - 0.209*x(4) - 0.2718*x(5) + 0.000006581*x(3)^2*x(5)^2 - 0.01413*x(1)*x(4) - 0.0001016*x(2)*x(3) + 0.0009025*x(2)*x(5) - 0.0007613*x(3)*x(4) - 0.01704*x(3)*x(5) +0.006804*x(4)*x(5) - 0.0001016*x(2)*x(3)^2 - 0.000006581*x(3)*x(5)^2 + 0.000006581*x(3)*x(5)^3 + 0.000006581*x(4)*x(5)^2 - 0.06228*x(1)^2 -0.0008008*x(2)^2 + 0.06228*x(3)^2 + 0.00006209*x(5)^2 -0.000006581*x(5)^3 - 0.000006581 *x(3)*x(4)*x(5)^2 - 0.000006581*x(3)^2*x(4)*x(5) + 0.001951*x(1)*x(2)*x(3) -0.001951*x(1)*x(3)*x(4) + 0.000006581*x(3)*x(4)*x(5) + 6.988

Similarly Regression Equation for Bead Width and Bead Penetration was obtained by making certain modifications in above Configuration file and Run file by changing Training Data and Testing Data for Bead Width and Bead Penetration.

6.5.3 Regression Equation for Bead Width

2.009*x(1) + 0.03323*x(2) + 0.7483*x(3) - 0.2624*x(4) - 0.8165*x(5) - 0.004934*x(1)*x(2) + 0.1478*x(1)*x(3)+0.01017*x(2)*x(3) - 0.1654*x(1)*x(5) + 0.007701*x(2)*x(4) - 0.004934*x(2)*x(5) + 0.004979*x(3)*x(4) +0.0008902*x(3)*x(5) - 0.02423*x(4)*x(5) - 0.0009996*x(2)*x(3)^2 +0.00004368*x(3)*x(4)^2-0.00001491*x(3)*x(4)^3- 0.0000448*x(4)^2- 0.00004368*x(4)^3+ 0.036095*x(5)^2 +0.00001491*x(4)^4 +0.001528*x(1)*x(2)*x(3) - 0.0004023*x(2)*x(3)*x(4) + 10.8

6.5.4 Regression Equation for Bead Penetration

0.3521*x(1) - 0.03335*x(2) - 0.8992*x(3) - 0.4097*x(4) + 0.03605*x(5) - 0.00001482*x(1)*(x(2) + x(3))+ 0.03516*x(4)*(x(2) + x(3)) - 0.01764*(x(1) - 1.0*x(3))*(x(3) - 1.0*x(4)) - 0.07032*x(3)*(x(1) - 1.0*x(5)) - 0.02633*x(2)*x(4) - 0.04817*x(3)*x(5) - 0.00002977*x(4)*(x(2) + x(3))*(2.0*x(1)+x(2)) -0.00001482*x(1)*x(2)*x(4)^2 - 0.00003858*x(4)*(x(2) + x(3))*(x(3) + x(5)) + 2.578

A comparison of the predicted models and the experimental values for the Training and Testing datasets of BH, BW and BP are shown in Figs 23, 24 and 25 respectively.

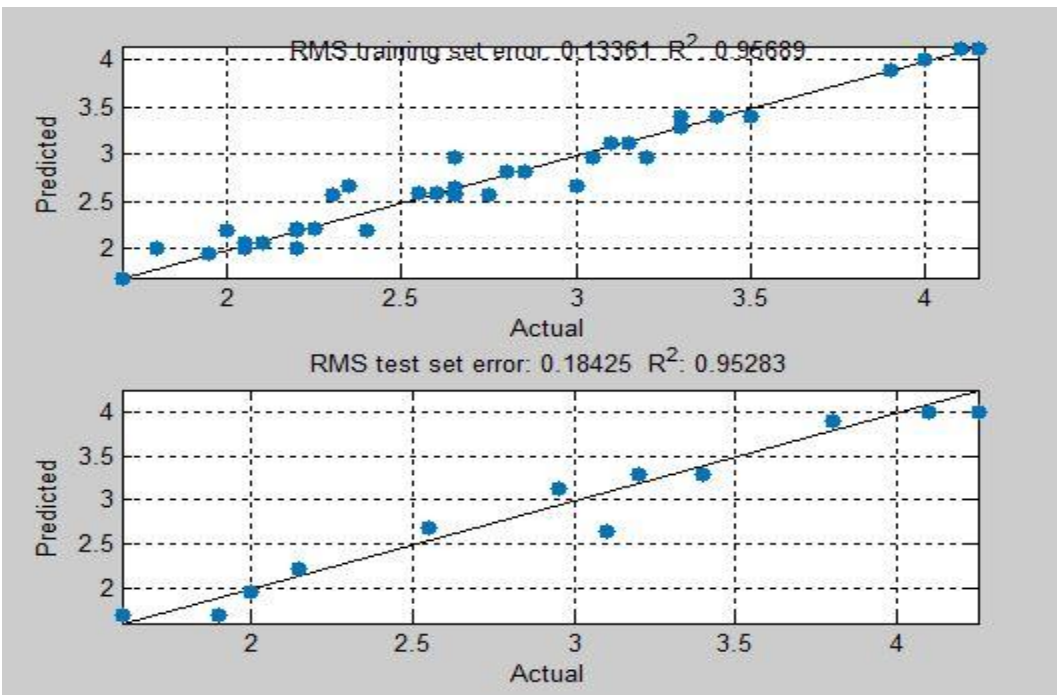


Fig. 23 Scatter Plot for Bead Height

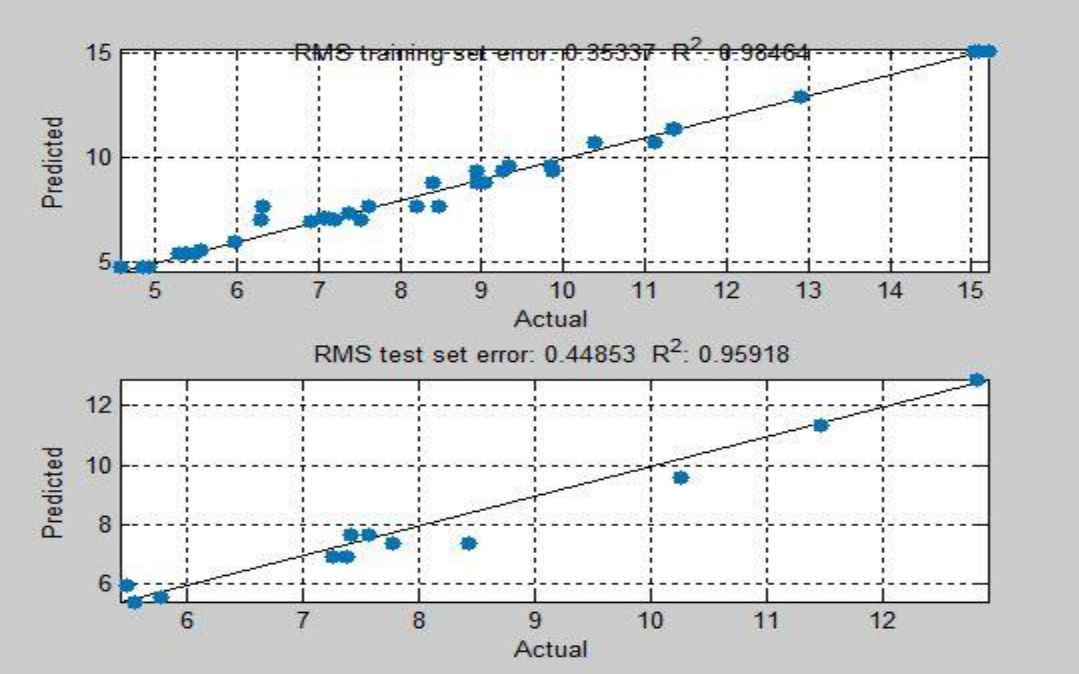


Fig. 24 Scatter Plot for Bead Width

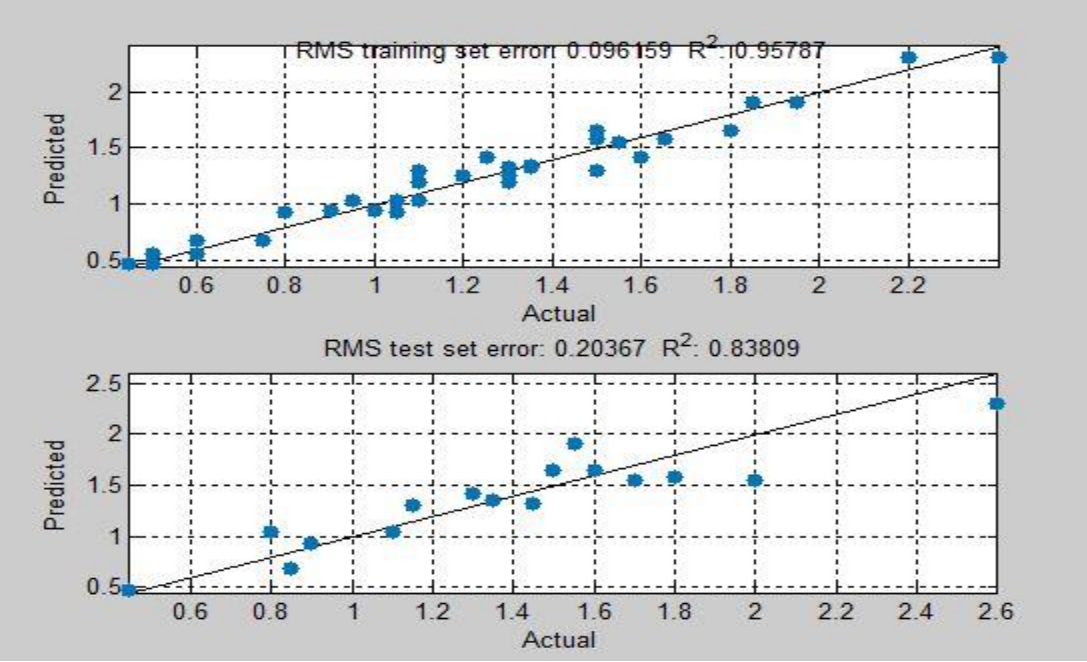


Fig. 25 Scatter Plot for Bead Penetration

While developing the above models, the correlation coefficient R^2 was taken as the fitness measure. GP was continued until a value as close as possible to the maximum value of R^2 was obtained. R^2 was used as the fitness measure in order to check whether the fitted models actually describe the experimental data. Below figures show the convergence graphs of the models predicted by the proposed algorithm. The fitness measures for BH, BW and BP have gradually improved with the number of generations and finally converged to 0.95689, 0.98464 and 0.95787 respectively. This shows that the models can explain the variation in the BH, BW and BP up to the extents of 95.68%, 98.46% and 95.78 % respectively. On the basis of the high values of R^2 it can be said that the models are adequate in representing the process.

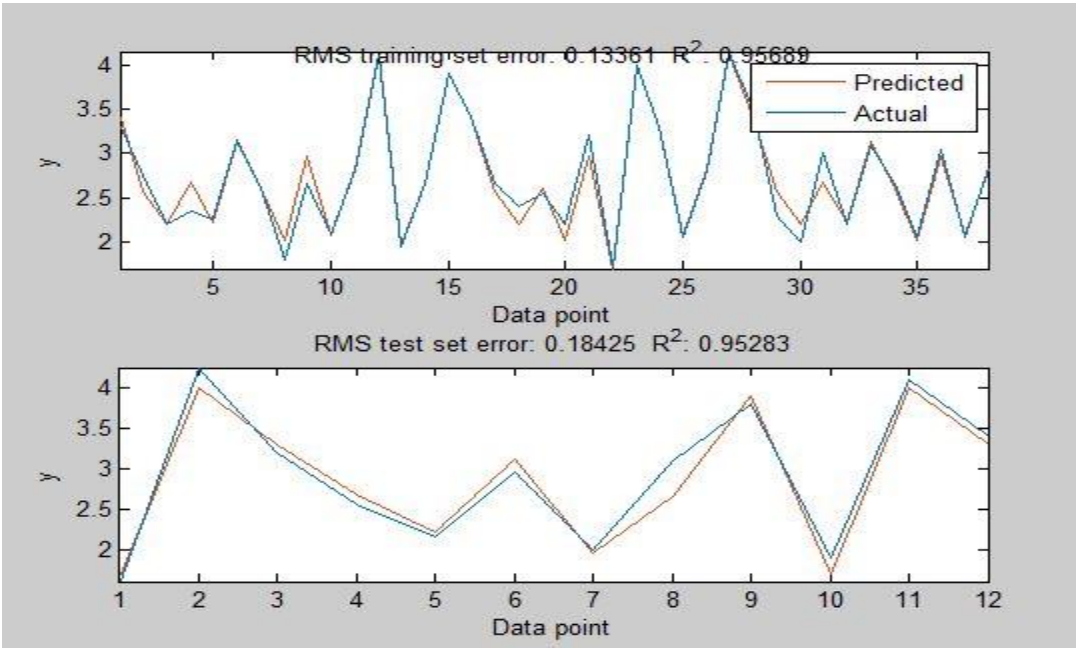


Fig. 26 Comparison Graph for Bead Height

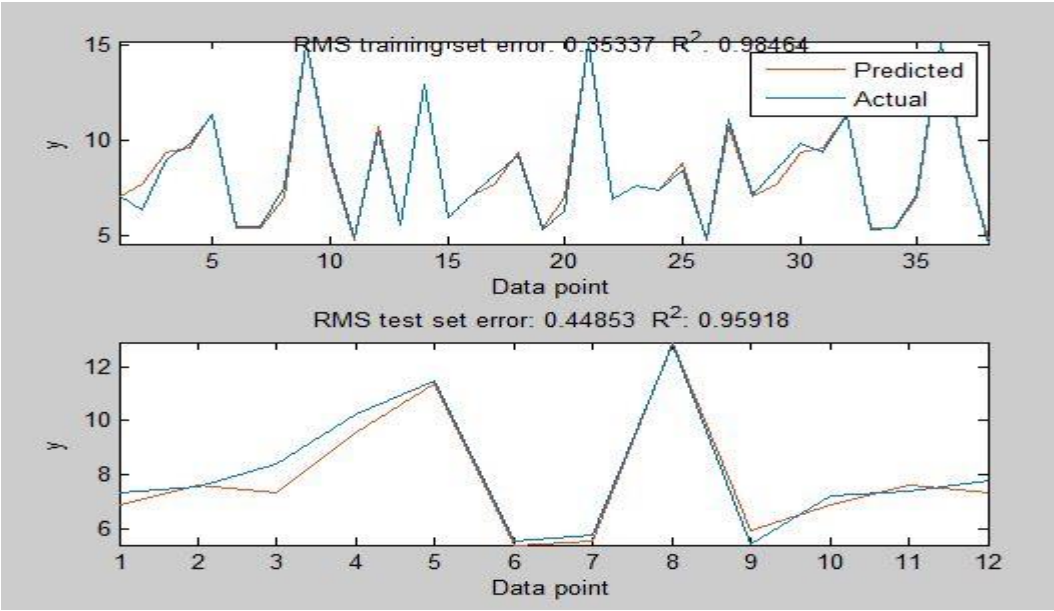


Fig. 27 Comparison Graph for Bead Width

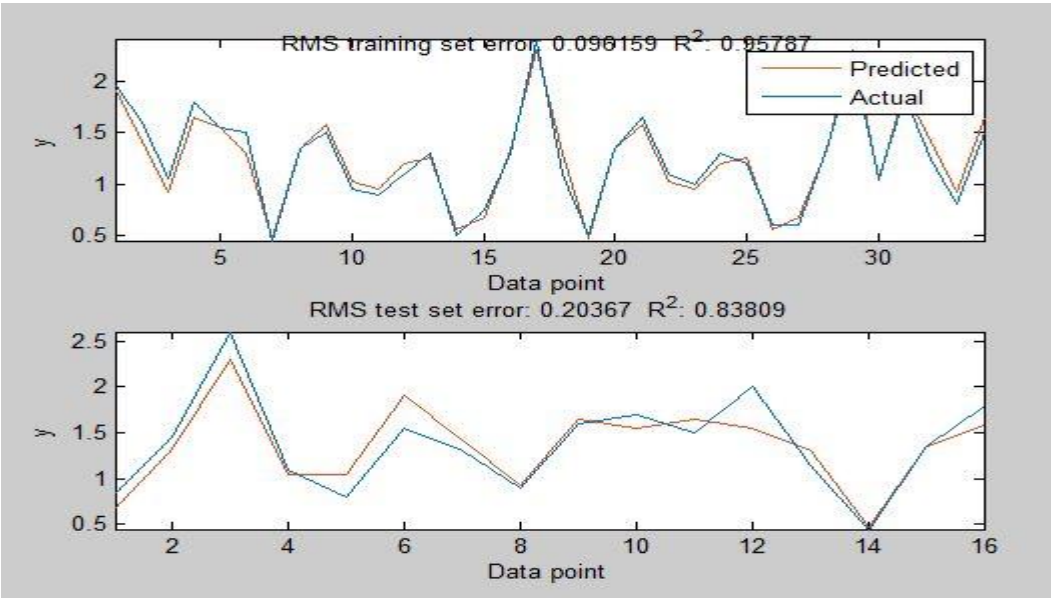


Fig. 28 Comparison Graph for Bead Penetration

6.6 Optimization using Multi Objective Genetic Algorithm

MOGA Control Parameters:

- Population Size:100
- Selection Function: Tournament selection
- Tournament Size: 2
- Crossover fraction: 0.8
- Crossover function: 1
- Mutation: Constraint Independent
- Stopping Criteria: Generations(200*no. of variables)

6.6.1 Multi Objective Genetic Algorithm Settings in Matlab

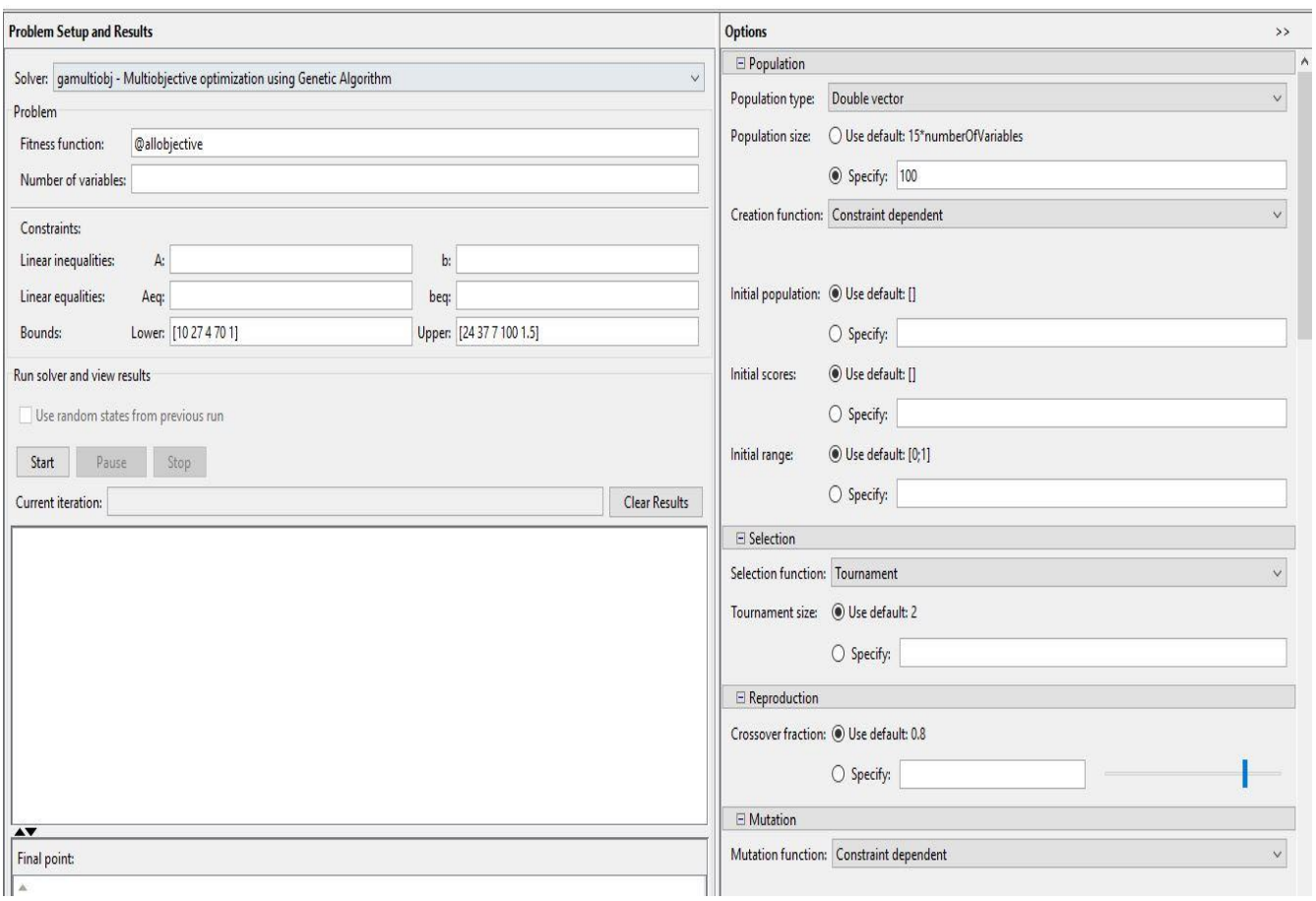


Fig. 29 MOGA Settings Matlab

6.6.2 Optimal Solutions through MOGA

After running MOGA with desired settings we got Optimal Solutions which are all good Solutions and we can select any combination of Optimal Solutions depending upon a particular Manufacturing Process.

S.No	x1	x2	x3	x4	x5	BH	BW	BP
1	10	27	4	70	1.015701	-23.2308	355.0771	19.31211
2	23.90948	29.59492	6.813159	95.21426	1.218325	-94.3605	1179.35	76.14842
3	23.97789	29.43092	6.825296	96.94628	1.20179	-96.2985	1264.012	78.86614
4	10.05817	29.03444	6.751716	70.09944	1.187404	-23.8912	349.8717	21.5988
5	23.92246	28.88116	6.772906	93.20593	1.207527	-92.8619	1087.022	70.8734
6	15.70024	27.5784	5.826338	70.69887	1.138632	-41.0683	378.9757	27.12669
7	16.69314	27.38771	4.060752	72.82757	1.126228	-44.0631	427.7858	27.78377
8	23.71512	28.70758	6.368888	81.85216	1.195346	-81.4533	670.2948	52.48107
9	23.57217	28.70929	6.530703	85.49057	1.205849	-84.1318	785.4121	57.56139
10	23.88041	28.53747	6.776162	88.77264	1.160352	-88.9816	903.9376	63.01623
11	23.69081	28.37885	5.53173	77.87167	1.197076	-76.7069	561.607	45.1725
12	23.25972	28.6056	6.321685	75.46972	1.058259	-74.0704	501.2338	43.26694
13	19.96195	27.96443	4.269491	71.79801	1.049224	-55.2013	414.8835	31.04537
14	23.48721	28.56642	5.550186	73.80615	1.194853	-72.5566	464.4822	40.18913
15	20.85588	28.35866	4.868334	73.34349	1.158775	-60.3779	448.3454	35.00349
16	23.86904	29.13495	6.530836	90.36778	1.20067	-89.5353	968.1729	66.50404
17	17.18921	27.18125	4.637895	71.86456	1.080071	-45.8544	408.0829	27.95783
18	23.87155	28.86209	6.084849	79.01389	1.212644	-79.257	591.1227	48.74119
19	10	27.03223	4.000244	70	1.048828	-23.2218	354.9524	19.32114
20	23.38741	28.50905	6.118812	81.60407	1.158474	-79.3515	662.9056	50.78482
21	23.99443	29.43085	6.815063	95.85867	1.217915	-95.4139	1210.392	77.02712
22	23.89835	28.99204	6.782296	92.69183	1.19365	-92.2835	1064.396	70.28852
23	23.20702	28.0041	4.401196	72.37379	1.098134	-68.6483	434.5033	35.33832
24	14.66659	27.0299	4.369023	73.70186	1.046102	-38.3439	441.1922	26.43111
25	23.96264	28.99287	6.450265	94.62551	1.204193	-93.4685	1154.299	73.12361
26	23.98623	29.29031	6.608927	98.10109	1.215834	-96.8337	1324.819	80.17961
27	20.38078	27.31997	5.375588	71.44069	1.176202	-58.0943	406.5124	32.00794
28	23.9297	28.75821	6.603456	87.04982	1.208507	-87.2965	840.8066	60.79013
29	23.89256	29.54007	6.788524	94.67368	1.208725	-93.7728	1154.086	75.00228
30	23.08544	27.86506	5.722515	74.09525	1.141549	-71.5252	469.4989	39.24363
31	23.97021	29.51035	6.827781	89.90784	1.199679	-90.1529	948.5053	67.38868
32	22.95918	27.51115	4.426195	74.03082	1.186993	-68.9676	468.739	36.2866
33	23.33831	28.36487	5.807143	76.89542	1.159602	-74.8346	535.6855	43.86975
34	23.91297	29.33519	6.736198	91.85779	1.204619	-91.4093	1028.941	69.79436
35	23.99981	29.13081	6.829598	99.81879	1.216052	-99.0126	1414.59	83.07396

Table 6.6.1 Optimal Solutions

6.6.3 Results and Discussions

- The source code of the proposed optimization algorithm was run on a Core i5 processor using C++ programming language on a Windows 10 platform. The control parameters required for implementation of the algorithm are listed in Table 6.6.1. The predicted values of thrust force and torque of MGGP model closely matched with the experimental values which signified the accuracy of the developed model. The algorithm found the Pareto optimal front of the conflicting objective functions with good diversity of the solutions, as shown in Fig.28. The optimal input variables and their corresponding objective function values are presented in Table 6.6.1. By analyzing the Pareto front, some decisions could be taken, depending upon specific requirements of the process. As can be observed from the graph, no solution in the front is better than any other as they are non-dominated solutions. The choice of a solution has to be made purely based on production requirements so that Bead Width, Bead Height is minimum and Bead Penetration is maximum. We can have combination of intermediate values from Table 6.6.1 for optimum production requirements.

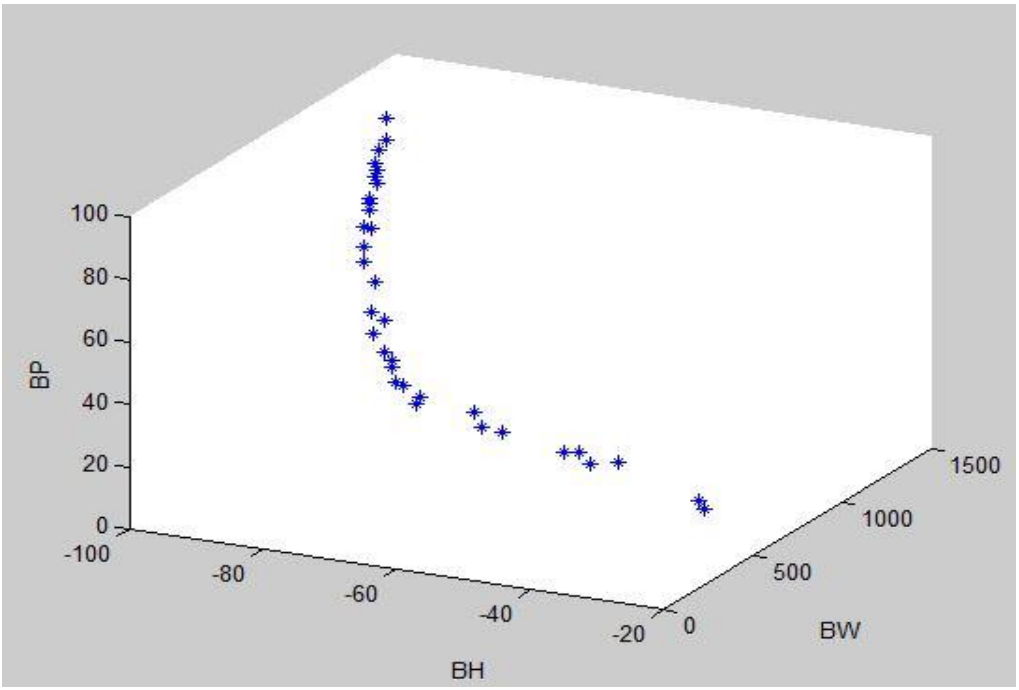


Fig. 30 Pareto Optimal Front for BH, BW and BP

- Here in this Journal they got predicted R^2 value through RSM as 94.1%, 94.7% and 83.9% for BH, BW and BP respectively. Predicted R^2 value through MGGP is 95.68% for BH, 98.46% for BW and 95.78% for BP. So the predicted values of BH, BW and BP of MGGP model closely matched with the experimental values which signified the accuracy of the developed model as compared through RSM method. In the actual journal they got R^2 value for BH, BW and BP through RA in Minitab as 94.1%, 94.7% and 83.9% respectively but through MGGP we are getting R^2 as 95.68%, 98.46% and 95.78% for BH, BW and BP respectively which proves that MGGP is more effective in Multiple Symbolic Regression as compared to RA in Minitab.

6.7 Validation

Validation was performed from outside in MS Excel by finding out the percentage error between MGGP value and Experimental value w.r.t Experimental value. MGGP value was calculated by using the Regression Equation which was obtained by performing Multi Gene Genetic Programming symbolic Regression.

$$\text{Relative Error (\%)} = \frac{MGGP\ VALUE - EXPERIMENTAL\ VALUE}{EXPERIMENTAL\ VALUE} \times 100$$

s.no.	D	A°	F	S	V	Y1 EXP	Y1 MGGP	%error	Y1 RSM	% error
1	1.5	85	7	10	32	3.8	3.712448	2.3	3.9077	2.83
2	1.5	100	4	24	32	2.05	2.07995	1.46	1.9629	4.24
3	1.5	100	5.5	10	37	3.35	3.164489	5.53	2.961	11.61
4	1.5	100	7	17	27	3.55	3.469447	2.26	3.7632	6

Table 6.7.1 Validation based on BH

s.no.	D	A°	F	S	V	Y2 EXP	Y2 MGGP	%error	Y2 RSM	% error
1	1.5	85	7	10	32	10.36	10.47378	1.06	10.761	3.87
2	1.5	100	4	24	32	6.23	6.711189	7.72	5.592	10.24
3	1.5	100	5.5	10	37	13.7	13.52697	1.26	12.7875	6.66
4	1.5	100	7	17	27	6.2	6.225078	3.952	6.861	10.66

Table 6.7.2 Validation based on BW

s.no.	D	A°	F	S	V	Y3 Exp	Y3 MGGP	%error	Y1 RSM	% error
1	1.5	85	7	10	32	1.35	1.30705	3.18	0.8379	37.93
2	1.5	100	4	24	32	0.9	0.908762	0.973	0.9158	1.75
3	1.5	100	5.5	10	37	0.9	0.76889	14.56	1.0426	15.84
4	1.5	100	7	17	27	0.8	0.690978	13.62	0.6222	22.25

Table 6.7.3 Validation based on BP

Here we can see that % error in MGGP value for BH, BW and BP is less as compared to % error in RSM value which confirms that MGGP is more efficient in conforming the actual Experimental conditions.

6.8 Conclusion

Many manufacturing industries machine intricate shapes of electrically conductive materials irrespective of their hardness. However, the selection of the right combination of input variables for optimal performance is not possible by the trial-and-error method. The present work proposes a novel approach based on the integration of two evolutionary approaches, namely, MGGP and MOGA. MGGP is such powerful tool that it can extract any complex quantitative relationship between input variables and output parameters effectively, whereas MOGA is a widely used potential tool for multi-objective optimization.

In this work, the most important machining, drilling and welding performances are considered. Initially, MGGP was used to model the mathematical relations for the chosen manufacturing process. Then, the models developed by GP were tested for their suitability using statistical methods. Later, the validated mathematical models of GP were used by MOGA to find the multiple sets of optimal solutions so as to enable a manufacturing engineer to choose a particular optimal set of input.

CHAPTER 7

FUTURE SCOPE

This analysis explained the framework for various operations of Genetic Algorithm and additionally the hybridization of multi objective GA optimization techniques. This analysis can be groundwork for more analysis in future. A number of the attainable directions for future analysis area unit highlighted here:

- Implementation of analysis work can be extended to alternative Benchmark functions.
- This analysis can be extended to other optimization problems such as Traveling Salesman problem like Knapsack problem, Bin Packing, Circuit designing problem, Vehicle Routing problem etc.
- The analysis work is confined to Tournament Selection process whereas examination the performance of planned alpha cut choice with numerous crossover operators. The

selection criterion can be extended to alternative choice mechanisms like roulette wheel selection, rank selection mechanisms etc.

- This study can be extended more complex real word problems which are using Evolutionary Computational Techniques since after a survey we can see that 42% application papers fall in the category of simple Genetic Algorithm and 32% papers fall in the category of Genetic Algorithm with advance operators. Multi Objective Genetic Algorithm shares 18% to application papers.

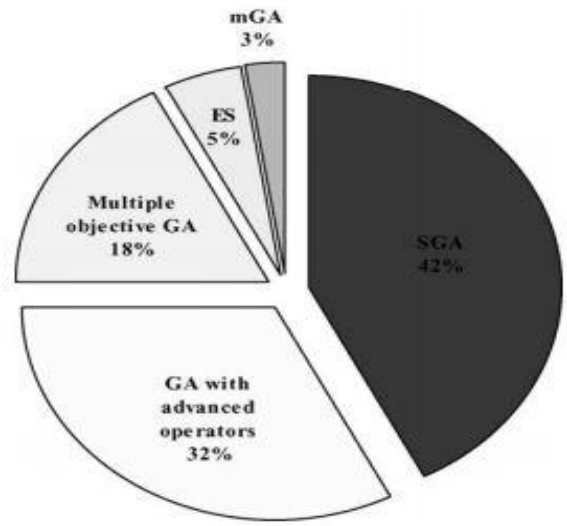


Fig. 31 Proportion of Evolutionary Computation in publications

So almost 50% publications based on real world complex problems are using GA but very few papers are based on MGGP and multi objective Genetic Algorithm Computational Technique. So this analysis can be extended to more real world problems since they are multi objective in nature. Some real world problems to which this study can be extended are metal forming industry, paper industry, chemical industry, scheduling and process planning, engineering design optimization etc.

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