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Optimization and Prediction of Surface Roughness Profiles of Machined Heat affected Zone of Mild Steel Weld Using Response Surface Methodology and Genetic Algorithms

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ABSTRACT

The service life of a weld fabricated engineering product is dependent on the surface finish of the product. Research has revealed that most of the failures observed in fabricated metal structures is linked to excessive heat input and large heat affect zone. This study is applying response surface methodology and genetic algorithms to optimize and predict the surface roughness of machined heat affected zone of mild steel welds. The design expert software was employed to produce a design matrix using the range and level of the input parameters. The central composite design (CCD) was used. 30 sets of experiment are performed according to the design of experiment; the input parameters are cutting speed, feed rate, nose roughness and chip thickness. 2 analytical methods are employed namely RSM and GA. From the results obtained, the ANOVA showed that the second order polynomials are suggested as the best fit to predict the large response, contour plot and surface plot showed the interaction between the cutting speed, feed rate and the surface roughness. The metals developed have high strength and adequately. Results obtained in this study showed that the interactive combination of nose radius and depth of cut has a very significant influence on surface roughness and chip thickness. The variance inflation factor has a value of 1 for the independent and combined level of the input factors. The model had a coefficient of determination value of 93% for surface roughness.

1. INTRODUCTION

Welding is a fabrication process which involves the joining of materials, usually metals by heating them at elevated temperatures, fusing them together and allowing to cool. The main focus in the welding industry is to manufacture a product with higher quality, lesser weight, lower cost, and more efficiency (Mahmud et al, 2021). In today's competitive business environment, things are entirely diverse. Surface finishing (as the final appearance of

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the product in several areas of modern engineering business, such as aerospace, automotive, construction engineering, environmental technology, industrial maintenance and chemical process engineering) is the last phase of stone processing and it does play a significant role in determining the high-quality of manufacturing components (Mohammad et al, 2016). Steels are among the broadly used structural materials which demand for development and application of effective welding techniques. However, fusion welding of steel highlights major drawbacks such as grain growth, segregation of alloying elements, solidification cracking, porosity, hydrogen embrittlement and development of dendritic structure and result in problems for component integrity (Saman et al, 2016). Gas metal arc weldings are used as automatic and semiautomatic operation modes. Nowadays all commercial metals and alloys such as carbon steels, stainless steels, high strength low alloy steels, alloys of magnesium, copper, aluminum, titanium and nickel can be welded in all positions with this versatile process by choosing appropriate process parameters for the particular joint design and process variables (Shekhar et al, 2017). Mild steels that have less than 0.25% carbon demonstrate good weldability and it possible to join them without special protections. Thus, the existing welding techniques can be applied easily for its welding. For gas turbine applications in which mild steel is used, it is necessary for the weld structure to show satisfactory tensile strength and creep resistance. Thus it is vital to critically study the microstructure as it determines the reliability of the weld parts (Lailesh et al, 2019). Nataliia et al. (2021) showed that slow welding speed results in a soft and irregular surface that is not easy to machine. Also, Hasan et al. (2015) wrote about Friction stir welding (FSW), which is a solid-state joining method in which the relative motion between the welding tool and the material of the work piece produces heat. This heat makes the material soft, thereby enabling it to be joined via plastic deformation and a thermal cycle effect (i.e., dynamic recrystallisation) caused by the rotational welding tool.

Gas metal arc welding (GMAW) is a metal joining process that is commonly used in many industrial sectors. A wide range of materials can be joined by GMAW, although stainless steel and low carbon steel are the materials that typically are welded by this technique. Due to the intense concentration of heat in a reduced area, the areas that are near the weld cord experience severe thermal cycles, which generate residual stresses and changes in mechanical properties (Ruben et al., 2016). Working on a surface is affected by surface roughness. In most of the cases, failure of part starts on the surface. This is due to either incoherence or decline of the surface quality. Surface must be within limits of variations (Bhushan and Sharma, 2020). In the manufacturing industry, the surface must be within certain limits of roughness to improve corrosion resistance and to reduce life cycle cost (Boulahem et al., 2015).

2. METHODOLOGY

2.1 Design of Experiment

Experimentation is a very important aspect of scientific study, which can be developed using computer soft wares like design expert and Minitab. For proper polynomial approximation an experimental design is used to collect the data. There are different types of experimental designs which includes central composite design, taguchi, D-optimal design, factorial design and latin hyper cube designs.

2.2 Identification of Range of Input Parameters

The key parameters considered in this work are cutting speed feed rate depth of cut and nose radius . The range of the process parameters obtained from literature is shown in the Table 1.

2.3 Method of Data Analysis

In this study two expert systems were employed in the modeling, optimization and prediction which are Response surface methodology (RSM) genetic algorithm (GA) The desirability method is recommended due to its simplicity, availability in the software and it also provides flexibility in weighting and giving importance to individual responses. Solving such multiple response optimization problems using this technique consists of using a technique for combining multiple responses into a dimensionless measure of performance called the overall desirability function.

2.3.1 Response Surface Methodology

(RSM) Engineers often search for the conditions that would optimize the process of interest. In other words, they want to determine the values of the process input parameters at which the responses reach their optimum. The optimum could be either a minimum or a maximum of a particular function in terms of the process input parameters. Response Surface Methods (RSM) are used to develop empirical model, commonly called response surface, for the response of a process in terms of the relevant controllable factors. RSM determines the operating conditions that produce the optimum response. Response Surface Methodology allows you to specify and fit a model up to the second order, RSM fits a model and provides the ANOVA and the 'Lack of Fit' test separately when there is more than one response. Contour and Surface plots of each response for pairs of factors are also produced. The aim of the response surface is to help understand the topography of the surface plot using simple maximum or minimum, saddles and ridges 3D diagrams and to find the region with the optimum response using contour plots.

2.3.2 Genetic Algorithm

Genetic Algorithm (GA) is a search-based optimization technique based on the principles of Genetics and Natural Selection. Genetic algorithm is a search heuristic that is inspired by Charles Darwin theory of natural evolution. This algorithm reflects the process of natural selection where the fittest individuals are selected for reproduction in order to produce offspring for the next generation. It is frequently used to find optimal or near-optimal solutions to difficult problems which otherwise would take a lifetime to solve. It is frequently used to solve optimization problems, in research, and in machine learning. Nature has always been a great source of inspiration to all mankind. Genetic Algorithms (GAs) are search based algorithms based on the concepts of natural selection and genetics. In GAs, we have a pool or a population of possible solutions to the given problem. These solutions then undergo recombination and mutation (like in natural genetics), producing new children, and the process is repeated over various generations. Each individual (or candidate solution) is assigned a fitness value (based on its objective function value) and the fitter individuals are given a higher chance to mate and yield more “fitter” individuals. This is in line with the Darwinian Theory of “Survival of the Fittest”. In this way we keep “evolving” better individuals or solutions over generations, till we reach a stopping criterion. Genetic Algorithms are sufficiently randomized in nature, but they perform much better than random local search (in which we just try various random solutions, keeping track of the best so far), as they exploit historical information as well.

3. RESULTS

3.1 Response Surface methodology (RSM)

To validate the suitability of the quadratic model in analysing the experimental data, the sequential model sum of squares was calculated for the surface roughness response as presented in Table 2.

Table 1: Process parameters and their levels

Parameters	**Unit**	**Coded value**	**Coded value**
		Low (-1)	High (+1)
Cutting speed	m/min	100	150
Feed rate	Mm/rev	0.1	0.15
Nose radius	mm	0.3	0.6
Depth of cut	mm	0.1	1.0

To test how well the quadratic model can explain the underlying variation associated with the experimental data, the lack of fit test was estimated for each of the responses. Model with significant lack of fit cannot be employed for prediction. Results of the computed lack of fit for the surface roughness is presented in Table 3.

The model summary statistics computed for surface roughness response based on the model sources is presented in Table 4.

Table 2: Sequential sum of square for surface roughness

Source	**Sum of Squares**	**Df**	**Mean Square**	**F Value**	**p-value Prob > F**	Remark
Mean vs Total	3.15	1	3.15			
Linear vs Mean	0.12	4	0.030	1.73	0.1753	
2FI vs Linear	0.25	6	0.041	4.27	0.0069	
Quadratic vs 2FI	0.15	4	0.037	15.41	< 0.0001	Suggested
Cubic vs Quadratic	0.013	8	1.675E-003	0.53	0.8059	Aliased
Residual	0.022	7	3.180E-003			
Total	3.70	30	0.12			

Table 3: Lack of fit test for surface roughness

Source	Sum of Squares	Df	Mean Square	F Value	p-value Prob > F	Remark
Linear	0.41	20	0.020	5.61	0.0324	
2FI	0.16	14	0.012	3.21	0.1023	
Quadratic	0.017	10	1.740E-003	0.48	0.8508	Suggested
Cubic	4.005E-003	2	2.003E-003	0.55	0.6090	Aliased
Pure Error	0.018	5	3.651E-003			

Table 4: Model summary statistics surface roughness

Source	Std. Dev.	R-Squared	Adjusted R-Squared	Predicted R-Squared	PRESS	Remark
Linear	0.13	0.2166	0.0913	-0.1506	0.63	
2FI	0.098	0.6663	0.4906	0.3722	0.34	
Quadratic	0.049	0.9347	0.8737	0.7682	0.13	Suggested
Cubic	0.056	0.9592	0.8311	-0.1047	0.60	Aliased

The summary statistics of model fit shows the standard deviation, the r-squared, adjusted r-squared, predicted r-squared and predicted error sum of square (PRESS) statistic for each complete model. Low standard deviation, R-Squared near one and relatively low PRESS is the optimum criteria for defining the best model source. To validate the adequacy of the quadratic model the surface roughness goodness of fit statistics is presented in Table 5.

Table 5: Goodness of fit statistics for surface roughness

Std. Dev.	0.049	R-Squared	0.9347
Mean	0.32	Adj R-Squared	0.8737
C.V. %	15.05	Pred R-Squared	0.7682
PRESS	0.13	Adeq Precision	16.089

To obtain the optimal solution, we first consider the coefficient statistics and the corresponding standard errors. The computed standard error measures the difference between the experimental terms and the corresponding predicted terms. In order to detect a value or group of values that are not easily detected by the model, the predicted values are plated against the actual values, for surface roughness which is shown in the Figure 1. To determine the presence of a possible outlier in the experimental data, the cook’s distance plot was generated for the different responses. The cook’s distance is a measure of how much the regression would change if the outlier is omitted from the analysis. A point that has a very high distance value relative to the other points may be an outlier and should be investigated. The generated cook’s distance for the surface roughness is presented in Figures 2.

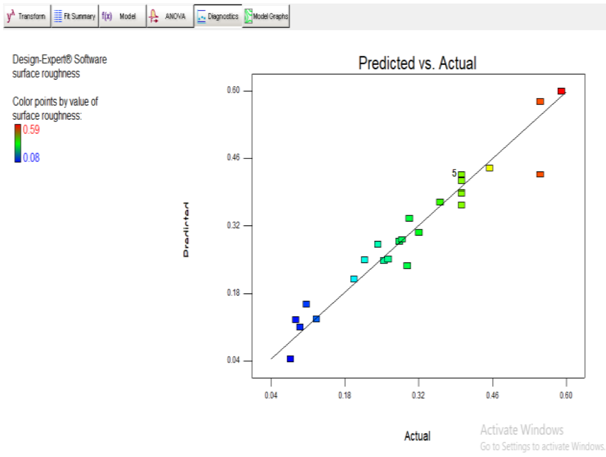

Figure 1: Plot of Predicted Vs Actual for surface roughness

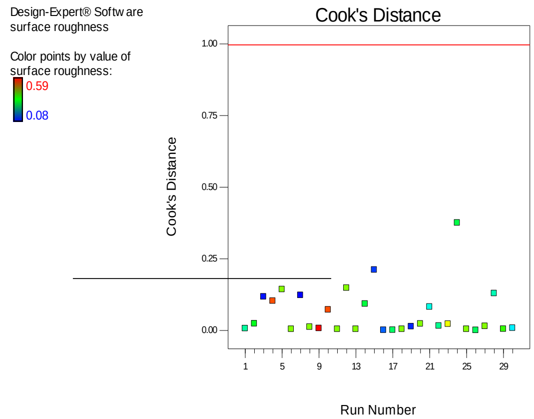

Figure 2: Generated cook's distance for surface roughness

To study the effects of combine input variables on the surface roughness, 3D surface plots presented in Figure 3and Figure 4 generated.

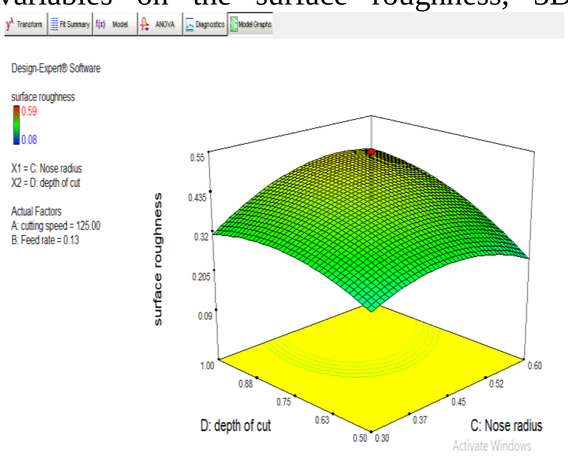

Figure 3: 3D surface plots showing Nose radius and depths of cut

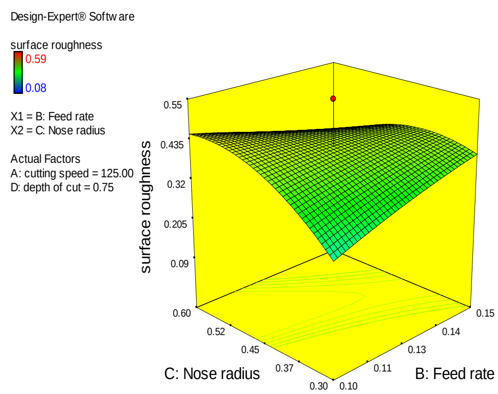

Figure 4: 3D surface plots showing feed rate and Nose radius

3.2 Genetic Algorithms Analysis

Multi-objective genetic algorithm problem, during the simulation to attain optimality, GA would work through different generations keeping the fittest or best parameters and mutating if necessary, so that optimality can be achieved. The optimization goal is to minimize surface roughness using genetic algorithm.

The procedure of solving Genetic algorithm using Matlab can be summarized thus,

(a) Write the fitness function
(b) Select the genetic algorithm optimization toolbox
(c) Input all the necessary parameters and configurations to run the program

(d) Run the optimization algorithm to obtain the optimal result.

The time series plot as shown in Figure 5 is used to show how the responses are affected at different factor settings with time while the Distance versus generation plot used to indicate how many generations attained before optimality and the average distance between individual generation is shown in Figure 6.

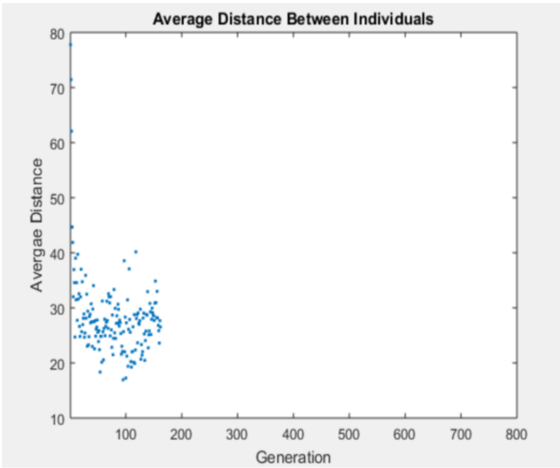

Figure 5: The time series plot

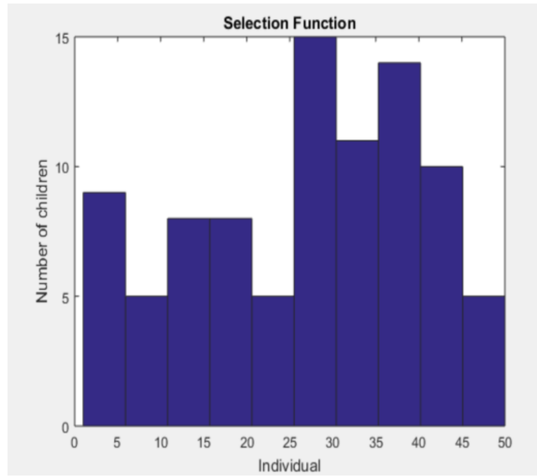

Figure 6: Distance versus generation plot

The plot of Individual selection plot shown in Figure 7, while the Average Pareto distance plot in Figure 8 is used to show the average distance measure.

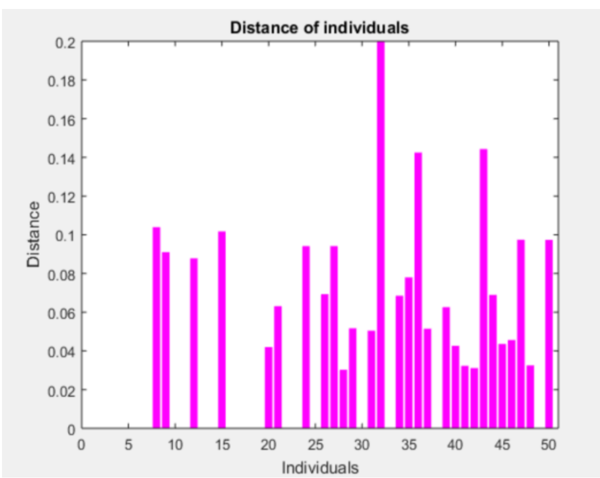

Figure 7: The plot of Individual

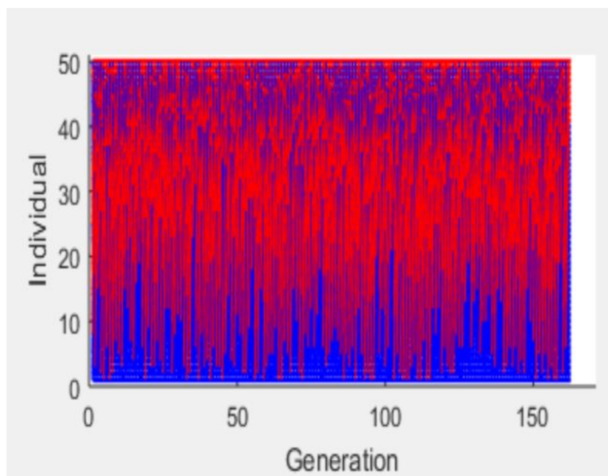

Figure 5: Average Pareto distance plot

When optimality is achieved, iteration would be forced to terminate at the optimum generation. For this simulation, optimality was achieved before 20% of the stopping criteria. The Individual vs generation plot shown in Figure 6 is obtained after the completion of the simulation. This generation plot terminated at the 177th generation. The Rank histogram plot shown in figure 7 shows the fraction of individuals in each Pareto tier. Rank 1 individuals are best, followed by rank 2, etc

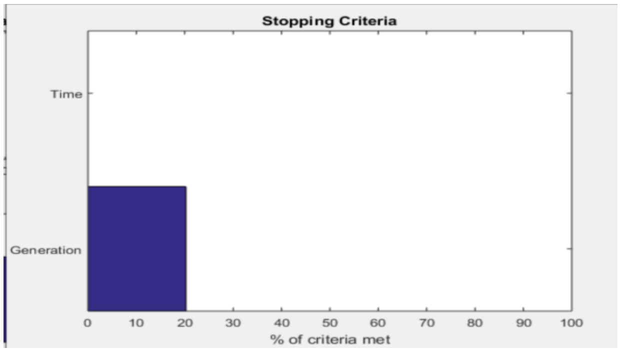

Figure 6: The Individual vs generation plot

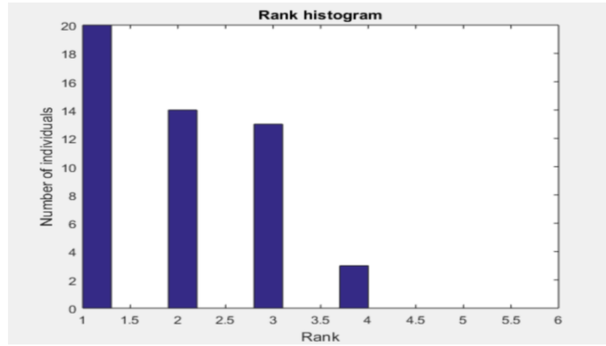

Figure 7: Rank histogram plot

Pareto front plot in Figure 8 shows the objective function values for all non-inferior solutions. The behaviour of objective 1 surface roughness and objective 2 (chip thickness) is best described with a polynomial relationship. As the aim is to minimize surface roughness and minimize chip thickness responses. While the Average

Pareto spread in Figure 9 is the plot showing the change in distance measure of individuals with respect to the previous generation. Kindly refer to the iteration table for successive generation for more information on the average spread values per generation.

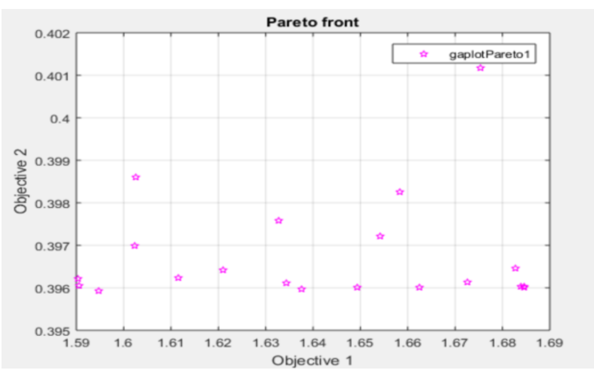

Figure 8: Pareto front plot

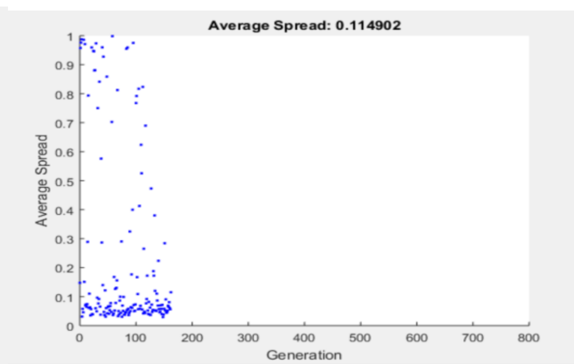

Figure 9: Average Pareto spread

3.2 Discussion

In this study, the Response Surface methodology and the genetic algorithm methods were used to optimize and predict surface roughness. The input parameters are cutting speed, feed rate, nose radius, depth of cut, while the response is surface roughness. The relationship between the nose radius, depth of cut parameters and the surface roughness shows a strong correlation having a P-value of 0.00001 and 93% coefficient of determination. The variance inflation factor (VIF) was 1.00 which indicates that the model is significant because a (VIF) greater than 10.00 is a cause for alarm. The ANOVA table shows that the model is significant and possess a very good fit with a P -value of < 0.0001. the goodness of fit statistics gave a Coefficient of determination R^2 indicating how well the model can predict the values of the selected variables. The models have a noise to signal ratio of 47 and 16, which is greater than 4 is desirable and indicates an adequate signal. .Finally, numerical optimization was performed to ascertain the desirability of the overall model. In the numerical optimization phase, the design expert was used to minimize surface roughness.From the results of table it was seen that a cutting speed(133.93) feed rate (0.10) nose radius (0.30)depth of cut 0.50.will produce a machined product with surface roughness 0.0796222.This solution was selected by design expert as the optimal solution having a desirability value of 0.911.In this study a second model known as the genetic algorithm was also used to optimize the properties of machined metal products for tungsten inert gas welding of mild steel plates. The data was populated, objective function evaluated before mutation. The generation plot indicates the start and termination point after the completion of the simulation which terminated at the 177th generation. The Pareto front plot shows objective function values for all non-inferior solutions. The behavior of objective 1 (surface roughness) and objective 2 (chp thickness) is best described with a polynomial relationship.

4. CONCLUSION

The study has successfully developed a genetic algorithm and response surface model by using the design expert software to produce optimal sets of welding and machining experiments. optimal solutions were obtained for the chip thickness and surface roughness responses. Result of the study have shown that the nose radius and depth of cut has significant effect on the output responses. The RSM model possess satisfactory statistical indices making it a highly effective tool to optimize and predict the target responses.

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