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Parametric Study & Development of Surrogate Models of Friction Stir Welding Process of Copper Plate

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Abstract**:** ***Friction stir welding is a pretty a new solid-state amalgamation process. This amalgamation method is energy proficient, environment friendly, and handy. In unambiguous, it can be used to yoke high strength aerospace aluminum alloys and other metallic alloys that are hard to weld by orthodox fusion welding. FSW is deliberated to be the most significant growth in metal joining in a era. In latest times, friction stir processing (FSP) was established for microstructural modification of metallic materials. In this research paper, optimization of friction stir welding of copper plate is talked. Exact accent has been given to: (i) mechanisms responsible for the formation of welds and microstructural improvement, and (ii) effects of friction stir welding parameters on resultant microstructure and concluding mechanical properties. The technology diffusion has gloomily overtaken the fundamental accepting of microstructural evolution and microstructure– goods relationships.***
Keywords: ***Friction stir welding, friction stir processing, thermo-mechanical modeling, DataFit, Minitab, regression analysis, linear and nonlinear, residual stress.***

I. INTRODUCTION

In order to conduct parametric study of FSW process, experiment methodology's design is implemented in this study. Design of experiment (DOE) technique is used to optimize the number of experiments required to determine the effects of various factors affecting the response of the system. It eliminates the need for extensive experimental analysis and reduces the computational time and cost. The described sections depict the details of DOE and development of surrogate models for FSW process.

II. DESIGN OF EXPERIMENTS

Thermal and mechanical models developed in the [1] are used as base models for carrying out parametric studies. The very first step is to identify important independent input factors & response variables. Response variables selected are: (a) Maximum temperature T, (b) residual stress R. Input variables affecting T are: (a) Heat input H, (b) welding speed (S) and variables affecting are: H, S and clamping location (C). Identification of the range and the specific levels at which selected factors have to be varied. Table I lists the process parameters, their range and selected levels used in this study for maximum temperature T and residual stress R.

TABLE I
THE PROCESS PARAMETERS, THEIR RANGE AND DESIGN LEVEL USED

response	process parameters	units	range	level 1	level 2	level 3	level 4	level 5
Temperature (T)	Weld Speed (S)	mm/s	0.5-2.54	0.5	0.85	1.00	1.69	2.54
	Heat Input (H)	watt	500-970	500	600	760	970	-
Residual stress (R)	Clamping location (C)	mm/s	0.5-2.54	0.5	0.85	1	1.69	2.54
	Heat Input (H)	watt	500-970	500	600	760	970	-
	Clamping location (C)	mm	50.2-76.2	50.2	76.2	-	-	-

After that experimental runs are to be done and the significant factor effects are analyzed. Total number of factors and the number of levels selected helps to decide the total number of experimental runs to be conducted. Table 2 depicts the design matrix for response variable T used in screening design for parametric study.

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TABLE III

DESIGN MATRIX WITH FACTORS, SELECTED LEVELS AND RECORDED RESPONSE TEMPERATURE (T) FOR PARAMETRIC STUDY

Heat input (watt) H	Weld speed (mm/s) S	Temperature (°C) T
500	0.50	1117.721
500	0.85	1012.28
500	1.00	967.505
500	1.69	795.271
500	2.54	643.857
600	0.50	1313.42
600	0.85	1188.72
600	1.00	1135.30
600	1.69	928.272
600	2.54	753.712
760	0.50	1455
760	0.85	1424.85
760	1.00	1407.68
760	1.69	1146.799
760	2.54	903.794
970	0.50	160
970	0.85	1480
970	1.00	1490
970	1.69	1396.29
970	2.54	1155.04

III. SURROGATE MODELS OF FRICTION STIR WELDING

A surrogate models can be used for optimization studies. It can be used to model the design objectives or to model the constraints. They are constructed to establish the relationship between the output responses and process parameters. For any given set of data linear or nonlinear regression, neural networks, response surface approximations, support vector regression, etc. can be used to model a surrogate model. In this study we have used Linear and nonlinear regression methods are used to construct surrogate models. At last their performance was analyzed and evaluated.

IV. DEVELOPMENT OF MODEL FOR RESPONSE – TEMPERATURE T

To establish relationship between the selected input process parameters and the thermal response variable the multiple regression analysis was used. As stated above heat input (H) and welding speed (S) are the selected input process parameters for the response temperature (T). The simulated data obtained in table B.1 in appendix B, is used for setting up surrogate models. To compute the regression constants for multi-linear regression model, Minitab 17, data analysis statistical software was used. Temperature's fitted linear regression model is given by equation (1).

$$T = 741.2 + 1.0329 \times H - 238.0 \times S \quad \ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Table III includes the results of multiple linear regression analysis.

TABLE IIIII

REGRESSION MODEL FOR RESPONSE TEMPERATURE USING MINITAB 17

Predictor	Coefficient	Standard Error	t-ratio	Prob (t)
Constant	741.2	67.8	10.93	0.00
Heat Input	1.0329	0.0850	12.15	0.00
Weld Speed	-238	20.9	-11.41	0.00

In addition to that table I's simulated data in table II is used to setup a nonlinear regression models. DataFit version 9.0 (statistical software capable of curve fitting and nonlinear regression analysis) was used to carry out the nonlinear regression analysis. The fitted nonlinear regression model for temperature obtained from DataFit is given by equation (2).

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$$T = -3408.6 + 747.34 \times \ln (H) - 238.0 \times S \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Table IV includes the complete nonlinear regression analysis using model definition $Y = a + b * \ln (x1) + c * x_2$

TABLE IVV

REGRESSION MODEL FOR RESPONSE TEMPERATURE USING DATAFIT 9.0

Variable	Value	Standard Error	t-ratio	Prob(t)
a	-3408.568455	342.150087	-9.962202	0.0
b	747.3398705	52.2288802	14.308939	0.0
c	-238.0038116	17.9793487	-13.237621	0.0

V. DEVELOPMENT OF MODEL FOR RESPONSE – RESIDUAL STRESS R

To set relationship between the selected input process parameters and the thermomechanical response variable R, multiple regression analysis was used. Input process parameters for the response residual stress (R) are welding speed (S), heat input (H) and clamping location (C). The simulated data summarized in Table V was used to set surrogate models for residual stress R. The regression constants for multi-linear regression model were calculated using Minitab 17. The fitted linear regression model for residual stress is given by equation (3).

$$R = 110.8 + 0.1182 \times H + 4.97 \times S + 1.956 \times C \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

TABLE V

DESIGN MATRIX WITH FACTORS, SELECTED LEVELS AND RECORDED RESPONSE RESIDUAL STRESS (R) FOR PARAMETRIC STUDY

eat input (watt) H	Weld speed (mm/s) S	Clamping location (mm) C	Residual Stress (MPa) R
500	0.50	50.2	267.36
500	0.50	76.2	293.34
500	0.85	50.2	282.85
500	0.85	76.2	329.84
500	1.00	50.2	288.48
500	1.00	76.2	341.73
500	1.69	50.2	277.23
500	1.69	76.2	332.59
500	2.54	50.2	266.07
500	2.54	76.2	326.83
600	0.50	50.2	282.93
600	0.50	76.2	305.37
600	0.85	50.2	286.44
600	0.85	76.2	332.33
600	1.00	50.2	293.76
600	1.00	76.2	346.61
600	1.69	50.2	300.69
600	1.69	76.2	355.41
600	2.54	50.2	277.70
600	2.54	76.2	335.49

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760	0.85	50.2	292.53
760	0.85	76.2	342.09
760	1.00	50.2	297.64
760	1.00	76.2	354.28
760	1.69	50.2	317.78
760	1.69	76.2	374.83
760	2.54	50.2	309.39
760	2.54	76.2	363.14
970	1.69	50.2	329.09
970	1.69	76.2	389.26
970	2.54	50.2	332.43
970	2.54	76.2	388.92

Table VI includes the results of multiple linear regression.

TABLE VI
REGRESSION VARIABLE RESULTS

Predictor	Coefficient	Standard Error	t-ratio	Prob (t)
Constant	110.8	14.5	7.65	0.000
Heat Input	0.1182	0.0152	7.78	0.000
Weld Speed	4.97	3.21	1.55	0.132
Clamping Location	1.956	0.169	11.54	0.000

In addition to that table V's simulated data was used to setup a, nonlinear regression. DataFit version 9.0 was used to carry out the nonlinear regression analysis. The fitted nonlinear regression model for residual stress obtained from DataFit is given by equation (4).R = exp (3.60 × H + 1.64 × S + 6.15 × C + 5.11) ……………………. (4)

TABLE VII
REGRESSION VARIABLE RESULTS

Variable	Value	Standard Error	t-ratio	Prob(t)
a	3.5942 E-4	4.4813 E-5	8.02064	0.0
b	1.6423 E-2	9.88634 E-3	1.66118	
c	-6.154407 E-3	5.25229 E-4	11.71756	
d	5.111902	4.51192 E-2	113.29757	

VI. ESTIMATING THE PERFORMANCE OF DEVELOPED SURROGATE MODELS

To estimate the temperature of the workpiece at the selected location, linear and one nonlinear model were fitted and to estimate the residual stress at the selected location another linear and one nonlinear model were fitted additionally. The surrogate models were judged based on the following statistics:

1) The coefficient of determination R^2

R^2 is a statistical measure which indicates how well a regression model describes the given data set. A model with higher values of R^2 is selected as it indicates a better fit using this criterion.

2) The residual sum of squares RSS

It measures the discrepancy between the given dataset and the estimated model. A model with lower values of residual sum of squares is always preferred.

3) It is used to compare the relative goodness-of-fit of the predicted models. It is parameter independent AIC is estimated by the following equation (5):

$$AIC = 2k + n \times \ln 2\pi (RSS) / n + 1 \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

where n is the number of observations, and k is the number of parameters in the model.
The model with the highest AIC is selected as the best fit model from the models ranked based on their AIC.

4) The adjusted coefficient of determination R^2_{adj}

The adjusted coefficient of determination is used as a measure to find the optimal regression model. It is also a parameter independent and a higher value of R^2_{ad} indicates better fit.

The perfectness of the surrogate models was determined by the values of R^2, RSS, AIC and R^2_{adj}. The regression statistics of linear and nonlinear surrogate models developed for estimating temperature and residual stress is shown in table 4.2. The values of R^2 and R^2_{ad} are higher for surrogate models of temperature whereas the values of AIC and RSS are higher and lower respectively for nonlinear model which can be seen in table VIII. This indicates that the nonlinear model given by equation (2) fits the data better than the linear model given by equation (1).

TABLE VIII
REGRESSION STATISTICS OF LINEAR AND NONLINEAR SURROGATE MODELS

Response Variable	Regression Model	Equation No.	k	R^2	RSS	AIC	R^2_{adj}
Temperature	Linear	(1)	3	0.9423	77607	187.19	0.9355
	Nonlinear	(2)	3	0.9571	57611.69	222.07	0.9521
Residual Stress	Linear	(3)	4	0.8837	4347.01	112.76	0.8713
	Nonlinear	(4)	4	0.8879	4188.05	254.78	0.8759

A similar trend was observed for the surrogate models of residual stress. The nonlinear regression model had higher R^2_{adj} and R^2 values and higher AIC and lower RSS values compared to the linear model, indicating nonlinear linear model given by equation (4) has better fit than linear model given by equation (3). Hence nonlinear regression models were the best models for estimating the responses, work piece temperature and residual stress.

VII. CONCLUSION

From above analysis we can conclude that the nonlinear regression models are the best for estimating and calculating the responses like temperature of work piece and residual stress developed.
In future Improved Harmony Search Algorithm can be used to optimize the friction stir welding of copper plates.

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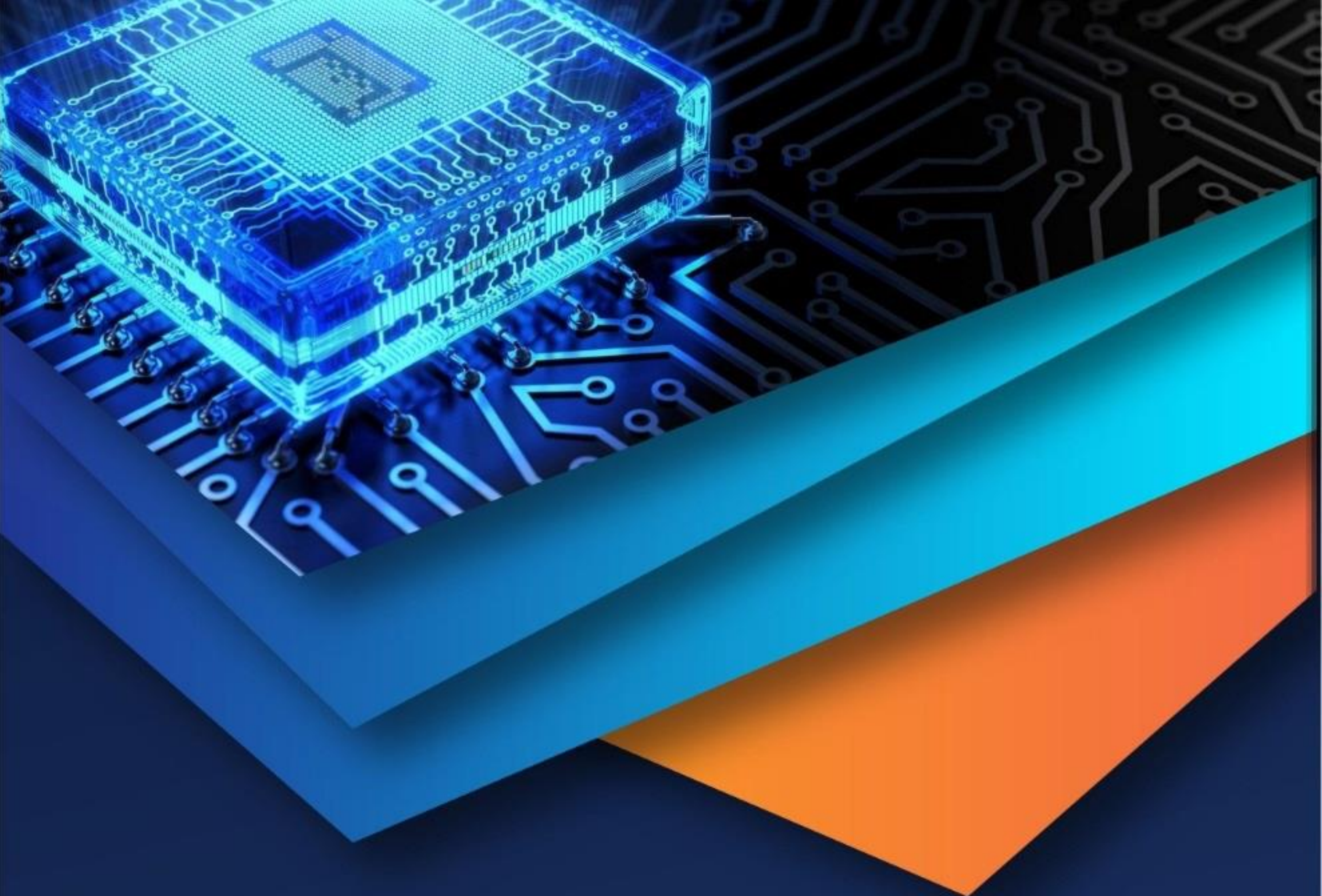

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