IOSR Journal of Mechanical and Civil Engineering (IOSR-JMCE)
e-ISSN: 2278-1684, p-ISSN: 2320-334X
PP 72-76
www.iosrjournals.org

Regression Analysis and Optimization of Hardfacing of Inconel for Maximum Strength Using RSM

S.P.Kakade[1], Dr.A.G.Thakur[2]
[1]*Mechanical Engineering, MET,Bhujbal Knowledge City Institute of Engineering,Nashik, India*
[2]*Mechanical Engineering,SRES,College of Engineering,Kopargaon, India*

ABSTRACT: *The optimization of a given hardfacing is important to know how strongly certain processing parameters influence the hardness and surface characteristic such as low distortion, less porosity and crack free surface with optimum value of hardness for a particular material composition, and effect of certain parameters on microstructure and thus the mechanical properties of the hard face matrix. In this regards most influencing parameters for hardfacing of Inconel 825 are identified with their corresponding levels and DOE approach based on response surface methodology(RSM) has been applied to improve the hardness of hardface Inconel by PTA welding, A second order quadratic model is developed to predict the hardness of PTA hard faced .RSM is a good way to describe the process and to find the optimum value of the considered response .It concerns a set of mathematical and statistical tools that can be used to predict the response influenced by the considered input variables, in order to optimize the response. An empirical relationship was developed to predict the Maximum hardness based on regression analysis. Hence, this investigation is an attempt to develop mathematical models based on four-factor, five levels response surface methodology. The result presented here are likely to accept. And this regression equation is used to evaluate the effect of various input parameters at a confidence level of 95%.*

Keywords: *DOE, Optimization, PTA, Response Surface Methodology, Regression.*

I. INTRODUCTION

Welding technology advanced quickly during the early 20th century as World War I and World War II drove the demand for reliable and inexpensive joining methods. Following the wars, several modern welding techniques were developed, including manual methods like shielded metal arc welding, now one of the most popular welding methods, as well as semiautomatic and automatic processes such as gas metal arc welding, submerged arc welding, flux-cored arc welding and electro slag welding. Robot welding is commonplace in industrial settings, and researchers continue to develop new welding methods and gain greater understanding of weld quality and properties. Various optimization methods can be applied to define the desired output variables through developing mathematical models to specify the relationship between the input parameters and output variables. In the last two decades, design of experiment (DoE) techniques have been used to carry out such optimization.[2] Generally, the quality of a weld joint is directly influenced by the welding input parameters during the welding process; therefore, welding can be considered as a multiinput multi-output process. The realization of the economic advantage of increased wear resistance by providing a metal deposit on a relatively low cost substrate has spurred the growth of hardfacing over the last half century. The most common hardface welding technologies implemented are the early oxyacetylene gas welding (OAW), gas tungsten arc welding (GTAW) or tungsten inert-gas welding (TIG), submerged arc welding (SAW), and the present plasma transferred arc welding (PTA).Plasma transferred arc welding (PTAW) is an extension of the GTAW process where both utilize a gas shielded arc produced by a non-consumable tungsten cathode.Imparting wear and corrosion resistance to metal surfaces by providing a hard surface is the basis for hardfacing. In PTA hardfacing, transferred arc melts the powder and the local surface of the treated component so that the whole amount of powder and only a thin film of component surface under the arc will be melted. As a result, a solidified metallurgical bond between the deposit and substrate is obtained with maximum hardness.

II. METHODOLOGY

2.1 Response Surface Methodology (RSM)

Methodology applied for optimization of above parameters is a Response Surface Methodology (RSM) [2]. It is a very useful and modern technique for the prediction and optimization of machining performances. Typically, this involves doing several experiments, using the results of one experiment to provide direction for what to do next. This next action could be to focus the experiment around a different set of conditions, or to collect more data in the current experimental region in order to fit a higher-order model or confirm what we seem to have found. Different levels or values of the operating conditions comprise the factors in each experiment. The fundamental methods for quantitative variables involve fitting first-order (linear) or second-order (quadratic) functions of the predictors to one or more response variables, and then examining the characteristics of the fitted surface to decide what action is appropriate.When there is a curvature in the response surface the first-order model is insufficient.[2] A second-order model is useful in approximating a portion of the true response surface with parabolic curvature. The second-order model includes all the terms in the first-order model, plus all quadratic terms like b1 x12 and all cross product terms like ß13x1x3. It is usually expressed as-

$$y = b_0 + \sum_{i=1}^{n} b_i x_i + \sum_{i=1}^{n} b_{ii} x_i^{\ 2} + \sum_{i=1}^{n} \sum_{i<j} b_{ij} x_i x_j + \varepsilon \qquad (1)$$

The second-order model is flexible, because it can take a variety of functional forms and approximates the response surface locally. Therefore, this model is usually a good estimation of the true response surface. Also, the method of least squares can be applied to estimate the coefficients I, j in a second-order model.

2.2 The basic steps involved in RSM

2.2.1 Coding of data:

An important aspect of response-surface analysis is using an appropriate coding transformation of the data. Using a coding method that makes all coded variables in the experiment vary over the same range is a way of giving each predictor an equal share in potentially determining the steepest-ascent path. Thus, coding is an important step in response-surface analysis.

2.2.2 Generating a design:

This step is the most important as it decides the nature of the response variables. By default, the variable names are x1, x2, . . . and the experiment is randomized. If there are 4 or 5 factors, the design is blocked by default (this is not possible for other numbers of factors), and the blocks are randomized separately. One of the most popular response-surface designs is the central-composite design (CCD) [2,7]. These designs allow for sequential augmentation, so that we may first experiment with just one block suitable for fitting a first-order model, and then add more block(s) if a second-order fit is needed. Typically, we generate the whole design at once, but only actually run the parts that are needed. The blocks in a CCD are of two types—one type, called a "cube" block, contains design points from a two-level factorial or fractional factorial design, plus center points; the other type, called a "star" block, contains axis points plus center points. The levels of the factors are coded, so that the cube blocks contain design points with coordinate values all equal to ±1, and center points at (0, 0, . . . , 0).

2.2.3 Fitting a response-surface model:

A response surface is fitted using the rsm function.Number of softwares are available in which once the parameters are fixed directly gives the response function.

2.2.4 Displaying a response surface:

Once the response function is known, analysis gives a handle on the behavior of a second-order response surface, an effective graph is a lot easier to present and explain. To that end, rsm includes a function for making contour plots of a fitted response surface. While representing a response function, if there are more than one variables, then the others must be fixed in order to get response for only one.

III. EXPERIMENTATION

3.1 Levels and Parameters with their Ranges

With reference of literature levels and most affecting parameters are find out in PTA welding [2, 7]. Table 1 shows Levels and Parameters with their Ranges.

3.2 Design of Experiment (DOE)

RSM is an efficient statistical tool for optimization of multiple variables. In order to describe the response surfaces, a five-level, four-variable central composite design (CCD) was adopted in this study. The four independent variables and their levels for the 32 experiments in the CCD study are shown in Table 3.[2,7]

3.3 Experimental set up and data collection

For conducting the experiment a PTA machine made by Primo automation Pvt. Ltd ,a machine is fully automated by PLC control unit, with touch screen display to control the various parameters. The base material used in this investigation is casting plates of Inconel 825 of UNS No.8825 which is widely used for the fabrication of valves, valve cones, spindles, and pressure vessel parts. Plates of 30 mm in thickness are used as the base material. In this investigation, Deposits were prepared using different combinations of the PTA process parameters as prescribed by the experimental design matrix.. The experiments were conducted by forming layers of stellite grade 6 powder (size 45-125 micron) on the substrate plate with the electrode negative (DCEN) according to the welding process specification (WPS) ASME21 with position of groove 1G. Tungsten electrode size 4 mm diameter (2% Thoriated Tungesten),torch orifice diameter 25mm Industrially, pure argon (99.99%) is used at a constant flow rate of 15 L/min for shielding, 2.5 L/min for centre, and 3 L/min for powder feeding and a constant standoff distance is 4mm The composition of base material Inconel 825 and stellite grade 6B is shown in Table 2

Table 1 Composition of Base Material and Stellite 6B Powder.

Name	Ni%	Fe%	Cr%	Mo%	Cu%	Ti%
Inconel 825 Base Material	38%-46%	22%	19.5%-23.5%	2.5%-3.5%	1.5%-3%	0.6%-1.2%

IV. PREPARATION OF SAMPLES FOR TEST

Samples are prepared for hard facing, is plate of thickness 30 mm as deposition is above 2 mm, according to the WPS EN ISO 11970:2007, the welding joint is G1 as applicable for the casting plate. And the length of the run is taken (3*thickness of the plate up to 9 cm) and width of deposition is 4.5 cm according to EN ISO 11970:2007. Deposit are prepared on each plate using the first combination of parameters as described in the design of experiments matrix , similarly deposition is carried out on the remaining plates according to design matrix. For the discard part of specimen the length of run is increased to 12 cm.After hardfacing the welding coupons (specimens) are grind by using portable grinding machine, now the specimen are ready for hardness testin

4.1 Hardness testing

Vickers hardness testing with a load of HV10 performed on digital Vickers tester available in QC Lab, hardness is measured in the weld cross section, as the main aim to optimize (increase) the hardness of weld cross-section.For the measurement of hardness weld section is divided into two sections on each specimen transverse to the weld travel then hardness is measured and the average value of hardness is marked. In that way hardness is measured and it is found to be 35 HRC to 46 HRC

Table 2 Design of Experiment (DOE) and Measured Hardness

Run	**Coded Value**				**Original value**				**Hardness (HRC)**
No.	**TC**	**TS**	**PF**	**OS**	**TC**	**TS**	**PF**	**OS**	
1	-1	-1	-1	-1	110	80	12	475	35.5
2	1	-1	-1	-1	130	80	12	475	34
3	-1	1	-1	-1	110	120	12	475	36
4	1	1	-1	-1	130	120	12	475	35
5	-1	-1	1	-1	110	80	16	475	40
6	1	-1	1	-1	130	80	16	475	40.5
7	-1	1	1	-1	110	120	16	475	42
8	1	1	1	-1	130	120	16	475	43
9	-1	-1	-1	1	110	80	12	525	36.4
10	1	-1	-1	1	130	80	12	525	38.9
11	-1	1	-1	1	110	120	12	525	36.5
12	1	1	-1	1	130	120	12	525	36.3
13	-1	-1	1	1	110	80	16	525	44.15
14	1	-1	1	1	130	80	16	525	43
15	-1	1	1	1	110	120	16	525	42.1
16	1	1	1	1	130	120	16	525	38.9
17	-2	0	0	0	100	100	14	500	40
18	2	0	0	0	140	100	14	500	38.2
19	0	-2	0	0	120	60	14	500	40
20	0	2	0	0	120	140	14	500	40
21	0	0	-2	0	120	100	10	500	35
22	0	0	2	0	120	100	18	500	46
23	0	0	0	-2	120	100	14	450	38.5
24	0	0	0	2	120	100	14	550	38
25	0	0	0	0	120	100	14	500	41

26	0	0	0	0	120	100	14	500	41
27	0	0	0	0	120	100	14	500	40
28	0	0	0	0	120	100	14	500	39.5
29	0	0	0	0	120	100	14	500	41
30	0	0	0	0	120	100	14	500	40.2
31	0	0	0	0	120	100	14	500	40
32	0	0	0	0	120	100	14	500	39.9

V. Results and discussion

In this experimentation, the response surface model building technique was utilized to predict high hardness in terms of the. process parameters for plasma transferred arc hardfacing. The details of the model building technique are discussed below. In the practical applications of RSM [7], it is necessary to develop a fitting model for the response surface, and it is typically driven by some unknown physical mechanism. For prediction, the RSM is practical, economical, and relatively easy for use. RSM consists of the experimental strategy for exploring the space of the process independent variables, empirical statistical modeling for developing an appropriate relationship between the process variables, and optimization methods for finding the levels or values of the process variables that produce desirable values of the responses'J", In this present investigation, to correlate the process parameters and the hardness of PTA hardfaced joints, a second order quadratic model is developed to predict the hardness of PTA hardfaced Inconel based on the experimentally measured hardness. Representing the hardness of the PTA hardfaced joints"H", the response function H can be expressed as H= f (TC,TS, PF, OS), where, TC is the transferred arc current, TS is the travel speed, PF is the powder feed rate, and OS is the oscillation speed. The model chosen includes the main effects and interaction effect of all factors.

TABLE 4 Estimated Regression Coefficients for Hardness

Term	Constant	TC	TS	PF	OS	TC*TC	TS*TS	PF*PF	OS*OS	TC*TS	TC*PF	TC*OS	TS*PF	TS*OS	PF*OS
Coefficient	40.3250	-0.277083	-0.110417	2.79375	0.385417	-0.401562	-0.176563	-0.0515625	-0.614063	-0.234375	-0.165625	-0.0656250	-0.0406250	-0.915625	-0.309375

S = 1.07991 PRESS = 103.261

R-Sq = 91.89% R-Sq(pred) = 57.75% R-Sq(adj) = 85.21%

In this study, five-factor five-level central composite rotatable design was used. The regression coefficients were calculated with the help of MINITAB 15 statistical software. After determining the significant coefficients (at 95% confidence level), the final model was developed using only these coefficients and the final mathematical model to estimate. Hardness is given below:

H=40.325-0.27708TC-0.110417TS+2.7937PF+0.385417OS-0.401562TC*TC-0.176563TS*TS-0.0515625PF*PF-0.614063OS*OS-0.234375TC*TS-0.165625TC*PF-0.0656250TC*OS-0.040625TS*PF-0.915625TS*OS-0.309375PF*OS.

The determination coefficient (R^2) indicates the goodness of fit for the model. In this case, the value of the determination coefficient (R^2 = 91.89%) indicates that only less than 9%of the total variations are not explained by the model.

VI. CONCLUSION

An empirical relationship was developed to predict the Maximum hardness. The response surface methodology is used to predict the optimal set of input parameters to correlate the process parameters and the hardness of PTA, a second order quadratic model is developed to predict the hardness of Inconel hard faced and the result presented here are likely to accept. And this regression equation is used to evaluate the effect of various input parameters at a confidence level of 95%.

REFERENCES

[1] P.K. Palani a, N. Muruganb "Selection of parameters of Pulsed current gas metal arc welding" Journal of Materials Processing Technology 172 (2006) 1–10

[2] F. Madadi1, F. Ashrafizadeh, M. Shamanian, "Optimization of pulsed TIG cladding process of stellite alloy on carbon steel using RSM", Journal of Alloys and Compounds, 510 (2012) 71– 77

[3] A.K.Lakshminarayanan & V. Balsubramanian, "Process Parameter Optimisation For Friction Stir Welding Of Rde-40 Aluminium Alloy Using Taguchi Method", Trans. nonferrous met.soc.china 18(2008) 548-554

[4] Jeng-Ywan Jeng ,Tzuoh-Fei Mau , "Prediction Of Laser Butt Joint Welding Parameters Using Back Propagation And Learning Vector Quantization Networks", journal of material processing technology 99 (2000) 207-218.

[5] Vidyut Deya, Dilip Kumar Pratihara , M.N. Jhab, T.K. Sahab, A.V. Bapatb , G.L. Dattaa "Optimization Of Bead Geometry In Electron Beam Weldin Using A Genetic Algorithm" , journal of material processing technology 209 (2009)1151-1157

[6] D. S. Nagesh & G. L. Datta , "Genetic Algorithm For Optimization Of Welding Variables For Height To Width Ratio And Application Of Ann For Prediction Of Bead Geometry For Tig Welding Process" ,applied soft computing 10 (2010)897-907

[7] R. Paventhan1, P. R. Lakshminarayanan1, V. Balasubramanian, "Prediction And Optimization Of Friction Welding Parameters For Joining Aluminium Alloy And Stainless Steel" , Trans. nonferrous met.soc.china 21 (2011) 1480-1485

[8] K.Y. Benyounis A.G. Olabi "Optimization of different welding processes using statistical and numerical approaches – A reference guide" Advances in Engineering Software 39 (2008) 483–496.

[9] B. Oraon ,G. Majumdar , B. Ghosh. "Parametric optimization and prediction of electroless Ni–B deposition", Materials and Design 28 (2007) 2138–2147