J Intell Manuf (2013) 24:35–44
DOI 10.1007/s10845-011-0535-3

Optimization of bead geometry of submerged arc weld using fuzzy based desirability function approach

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Received: 23 February 2011 / Accepted: 6 April 2011 / Published online: 21 April 2011

Abstract The present study highlights application of Taguchi's robust design coupled with fuzzy based desirability function approach for optimizing multiple bead geometry parameters of submerged arc weldment. Fuzzy inference system has been adapted to avoid uncertainly, imprecision and vagueness in experimentation as well as in data analysis by traditional Taguchi based optimization approach. Detailed methodology and unique features of the proposed method has been highlighted through a case study. The said approach can efficiently be used in off-line quality control of any production process as well as automation of the process.

Keywords Taguchi's robust design · Fuzzy logic · Desirability function · SAW

Introduction

The Submerged Arc Welding (SAW) process finds wide industrial application due to its easy applicability, high current density and ability to deposit a large amount of weld metal using more than one wire at the same time (Patnaik et al. 2007). The process is mainly characterized by multiple process parameters influencing multiple performance outputs such as deposition rate, percent dilution, features of bead geometry, and mechanical-metallurgical characteristics of weldment as well as the heat affected zone (HAZ). Proper selection and precise control of process parameters can achieve satisfactory weld quality. However, SAW optimization is difficult due to existence of multiple quality indices which may be contradicting in nature depending on the requirements. Moreover, direct and interactive effects of process parameters also influence the extent of weld quality. It is, therefore, indeed required to select the best suited process environment i.e. optimal parametric combination to produce desired quality weld.

Toyofumi et al. (1986) investigated on optimization of welding materials and welding conditions for high speed submerged arc welding of spiral pipes. Tsai et al. (1996) optimized submerged arc welding process parameters in hardfacing. Tarng and Yang (1998) applied Taguchi method to the optimization of the submerged arc welding process. Gunaraj and Murugan (1999) applied Response Surface Methodology (RSM) for prediction and optimization of weld bead quality in submerged arc welding of pipes by establishing mathematical models. Tarng et al. (2002) applied grey based Taguchi method for optimization submerged arc welding process parameters in hardfacing. Datta et al. (2008a) applied Taguchi philosophy for parametric optimization of bead geometry and HAZ width in submerged arc weld. In another paper, Datta et al. (2008b) used grey relational analysis in combination with Taguchi method to optimize multiple features of bead geometry of submerged arc weld. Murugananth Kumar et al. (2000) used Non-dominated Sorting Genetic Algorithms (NSGA) to optimize the contradicting combination of strength and toughness of steel welds.

Literature highlights that Taguchi method is very popular in product/process optimization as it requires a well balanced experimental design (limited number of experiments) which

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saves time as well as cost. In addition, Taguchi approach finds optimal setting at discrete levels of the process parameters that can easily be adjusted in the machine/setup. But the method fails to solve multi-objective optimization problems. In order to overcome this limitation, utility theory (Walia et al. 2006; Datta et al. 2006), grey relation theory (Datta et al. 2008b), and desirability function approach (Kumar et al. 2000) have been applied by previous investigators in combination with Taguchi method. The purpose is to aggregate multiple responses (objective functions) into an equivalent quality index (single objective function) which can easily be optimized using Taguchi method.

In such aggregation procedure, individual priority weights are required to be assigned to different responses. In practice, these responses may not be of equally importance. Degree of importance/priority of various responses depends on application area and functional requirements of the product. For example, a weldment should have high degree of penetration depth in order to increase joint strength. To reduce weld metal consumption, it is desired that the weld should have less bead height and bead width. In general, weld strength is of vital importance. Therefore, priority weight of penetration depth is to be set more compared to bead width and bead reinforcement. Assignment of response priority weights basically depends on the judgement of the decision maker. Change in value of the priority weights yields change in the value of aggregated quality index.

Moreover, aforesaid approaches are based on the assumption that responses are uncorrelated. Interdependence of the responses has been assumed negligible while in practice any change in one response remarkably affects another response. Thus, judgement of priority weights in conjunction with assumption of negligible response correlation may lead to imprecision, uncertainty as well as vagueness in the solution. It is, therefore, indeed required to develop a model which can efficiently avoid those limitations. In this context, fuzzy expert system has been proposed.

Desirability function approach

In this approach, individual responses are transformed into corresponding desirability values. Desirability value depends of acceptable tolerance range as well as target of the response. If the response reaches its target value, which is the most desired situation, its desirability is assigned as unity. If the value of the response falls beyond the prescribed tolerance rage, which is not desired, its desirability value is assumed as zero. Therefore, desirability value may vary with zero to unity. In this section, individual desirability values for each bead geometry parameters have been calculated using the formulae proposed by Derringer and Suich (1980). For bead width, reinforcement, area of reinforcement and bead volume, Lower-the-better (LB) and for depth of penetration, area of penetration and dilution percentage Higher-the-better (HB) criterion has been selected.

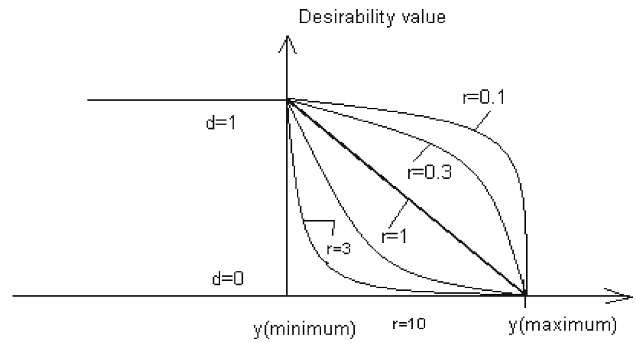

Fig. 1 Desirability function (lower-the-better)

Individual desirability value using Lower-the-better (LB) criterion is shown in Fig. 1. The value of $\hat{y}$ is expected to be the lower the better. When $\hat{y}$ is less than a particular criteria value, the desirability value d_i equals to 1; if $\hat{y}$ exceeds a particular criteria value, the desirability value equals to 0. d_i varies within the range (0, 1). The desirability function of the Lower-the-better (LB) criterion can be written as below in Eqs. (1–3). Here, $y_{\min}$ denotes the lower tolerance limit of $\hat{y}$, the $y_{\max}$ represents the upper tolerance limit of $\hat{y}$ and r represents the desirability function index, which is to be assigned previously according to the consideration of the optimization solver. If the corresponding response is expected to be closer to the target, the index can be set to the larger value, otherwise a smaller value.

$$\text{If} \quad \hat{y} \leq y_{\min}, \quad d_i = 1 \tag{1}$$

$$\text{If} \quad y_{\min} \leq \hat{y} \leq y_{\max}, \quad d_i = \left(\frac{\hat{y} - y_{\max}}{y_{\min} - y_{\max}}\right)^r \tag{2}$$

$$\text{If} \quad \hat{y} \geq y_{\max}, \quad d_i = 0 \tag{3}$$

Individual desirability value using Higher-the-better (HB) criterion is shown in Fig. 2. The value of $\hat{y}$ is expected to be

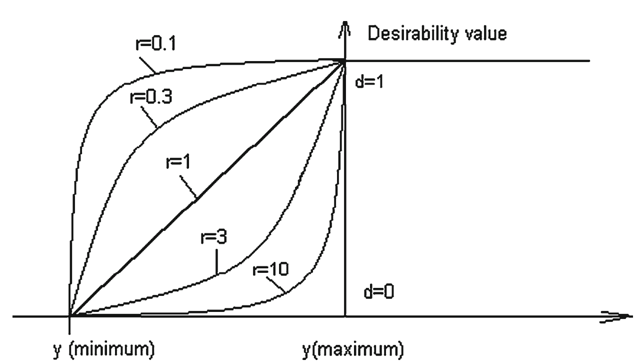

Fig. 2 Desirability function (higher-the-better)

the higher the better. When $\hat{y}$ exceeds a particular criteria value, according to the requirement, the desirability value d_i equals to 1; if $\hat{y}$ is less than a particular criteria value, i.e. less than the acceptable limit, the desirability value equals to 0. The desirability function of the Higher-the-better (HB) criterion can be written in the form as given in Eqs. (4–6). Here, $y_{\min}$ denotes the lower tolerance limit of $\hat{y}$, the $y_{\max}$ represents the upper tolerance limit of $\hat{y}$ and r represents the desirability function index, which is to be assigned previously according to the consideration of the optimization solver. If the corresponding response is expected to be closer to the target, the index can be set to the larger value, otherwise a smaller value.

$$\text{If} \quad \hat{y} \leq y_{\min}, \quad d_i = 0 \tag{4}$$

$$\text{If} \quad y_{\min} \leq \hat{y} \leq y_{\max}, \quad d_i = \left(\frac{\hat{y} - y_{\min}}{y_{\max} - y_{\min}}\right)^r \tag{5}$$

$$\text{If} \quad \hat{y} \geq y_{\max}, \quad d_i = 1 \tag{6}$$

The individual desirability values have been accumulated to calculate the overall desirability using the following Eq. (7). Here D_O is the overall desirability value, d_i is the individual desirability value of ith quality characteristic and n is the total number of responses. Wi is the weight for ith attribute. Sum of all attribute weights should be equal to 1.

$$D_0 = \left(d_1^{w1} d_2^{w2} \cdots d_n^{Wn}\right)^{1/\sum Wi} \tag{7}$$

However, overall desirability D_0 can be treated as equivalent aggregated quality index but the problem arises in assigning priority weights of various responses. Literature showed that previous investigators determined optimal setting of process parameters (Datta et al. 2006) by maximizing D_O in the experimental domain. The results obtained thereof, may be erroneous because the exact value of priority weight to be assigned to each and individual responses is difficult to predict. Therefore, slight change in priority weight may shift the optimal setting if these weights are found sensitive to predict the optima.

To avoid this uncertainty, the present study proposes fuzzy approach to be discussed in later sections.

Fuzzy inference system

A fuzzy rule based system consists of four parts: *knowledge base*, *fuzzifier*, *inference engine* and *defuzzifier*. Detailed analysis on fuzzy can be found in numerous literature (Zadeh 1976; Mendel 1992; Cox 1992). The four parts are described below.

Fuzzifier

The real world input to the fuzzy system is applied to the fuzzifier. In fuzzy literature, this input is called crisp input since it contains precise information about the specific information about the parameter. The fuzzifier convert this precise quantity to the form of imprecise quantity like 'large', 'medium', 'high' etc. with a degree of belongingness to it. Typically the value ranges from 0 to 1.

Knowledge base

The main part of the fuzzy system is the knowledge base in which both rule base and database are jointly referred. The database defines the membership functions of the fuzzy sets used in the fuzzy rules where as the rule base contains a number of fuzzy IF–THEN rules.

Inference engine

The inference system or the decision making input perform the inference operations on the rules. It handles the way in which the rules are combined.

Defuzzifier

The output generated by the inference block is always fuzzy in nature. A real world system will always require the output of the fuzzy system to the crisp or in the form of real world input. The job of the defuzzifier is to receive the fuzzy input and provide real world output. In operation, it works opposite to the input block.

In general, two most popular fuzzy inference systems are available: Mamdani fuzzy model and Sugeno fuzzy model. The selection depends on the fuzzy reasoning and formulation of fuzzy IF-THEN rules. Mamdani fuzzy model (Mamdani and Assilia 1975) is based on the collection of IF-THEN rules with both fuzzy antecedent and consequent predicts. The benefit of this model is that the rule base is generally provided by an expert and hence to a certain degree it is translucent to explanation and study. Because of easeness, Mamdani model is still most commonly used technique for solving many real world problems.

The first step in system modeling was the identification of input and output variables called the system variables. In the selection procedure, the inputs and the outputs are taken in the form of linguistic format. A linguistic variable is a variable whose values are words or sentences in natural or man-made languages. Linguistic values are expressed in the form of fuzzy sets. A fuzzy set is usually defined by its membership functions. In general, triangular or trapezoidal membership functions are used to the crisp inputs because of their simplicity and high computational efficiency (Yager and Filev 1999; Chang et al. 2005; Güngör and Arıkan 2007; Sapkota and Ohmi 2009; Castillo and Melin 2008; Li et al. 2009; Wang et al. 2010).

In the present study, a fuzzy set $\tilde{A}$ is represented by triangular fuzzy number which is defined by the triplet (a, b, c). Membership function $\mu_{\tilde{A}}(x)$ is defined as:

$$\forall x, a, b, c \in R$$

$$\mu_{\tilde{A}}(x) = 0, \quad \text{if } x < a \text{ else } \left(\frac{x-a}{b-a}\right), \text{ if } a \le x \le b \text{ else } \left(\frac{c-x}{c-b}\right), \text{ if } b \le x \le c \text{ else } 0, \text{ if } x > c$$

The Mamdani implication method is employed for the rules definition. For a rule,

$$R_i: \text{ If } x_1 \text{ is } A_{ti} \text{ and } x_2 \text{ is } A_{ti\ldots x_s} \text{ is } A_{si} \text{ then } y_i \text{ is } C_i, \quad i = 1, 2, \ldots, M$$

Here, M is the total number of fuzzy rule, $x_j (j = 1, 2, \ldots, s)$ is the input variable, y_i is the output variable and A_{ij} and C_i are the fuzzy sets modeled by membership functions $\mu_{Aij}(x_j)$ and $\mu_{ci}(y_i)$ respectively. The aggregated output for the M rules is:

$$\mu_{ci}(y_i) = \max\left[\min_j \left\{\mu_{A_{1i}}(x_1), \mu_{A_{2i}}(x_2), \ldots, \mu_{A_{si}}(x_s)\right\}\right], \quad i = 1, 2, \ldots, M \tag{8}$$

Using a defuzzification method, fuzzy values can be obtained into one single crisp output value. The centre of gravity, one of the most popular methods for defuzzifying fuzzy output functions, is employed in the study. The formula to find the centroid of the combined outputs:

$$\widehat{y}_i = \frac{\int y_i \mu_{ci}(y_i)\, dy}{\int \mu_{ci}(y_i)\, dy} \tag{9}$$

In this work, the non-fuzzy value $\widehat{y}_i$ is called a MPCI (Multi-Performance Characteristic Index). Based on the above discussion, the larger is the MPCI, the better is the performance characteristic.

Experimentation

Experiments of submerged arc welding on mild steel (MS) plates of thickness 15.50 mm (SAIL Steel, IS 2062, Grade A) have been carried out as per Taguchi's L_{25} Orthogonal Array (OA) design with twenty five combinations of voltage (OCV), wire feed rate, traverse speed and electrode stick-out. The selected process control parameters and corresponding parametric values at different levels have been furnished in Table 1. Based on the parameter settings available in the machine and knowledge acquired from literature; the domain of parameters and levels of variation have been chosen. Design of experiment has been given in Table 2. In order to form bead-on-plate submerged arc welds on the samples [$100 \times 50 \times 15.50$], copper coated electrode wire of 3.15 mm diameter has been used with type AUTOMELT EL8 (AWS A 5.17/5.23 EL8, IS 7280: AS-1) of ADOR WELDING LIMITED, INDIA. Chemical composition of the wire: C-0.04%, Mn-0.4%, Si-0.05%. AUTOMELT A55 flux (Make: ADOR WELDING LIMITED, INDIA) has been used with the following compositions.

$SiO_2 + TiO_2 = 30\%$
$CaO + MgO = 10\%$
$Al_2O_3 + MnO = 45\%$
$CaF_2 = 15\%$
Grain Size $= 0.25 - 2.00$mm
Basicity Index $= 0.6$

Welding has been performed on the SAW setup (Make: ADOR WELDING LIMITED, INDIA; Model—MAESTRO 1200(F)). After removing the solidified slag, the weld samples have been cooled in the room atmospheric condition. Cross section of the welded samples of about 15–20 mm of thickness has been cut by hydraulic power saw with normal water as coolant. The section faces of each sample have been machined by shaper to get parallel plane as well as semi-finished surface. Then the samples (sections) have been filed with smooth flat file followed by finishing with emery papers of grade 150, 600, and 2,000 consecutively to get almost mirror finish. The faces of the samples have been polished by self-fabricated polisher using leather buffer to achieve the mirror finished surface. The finished surfaces

Table 1 Domain of experiment

Parameters	Units	Notation	Level values				
			Level 1	Level 2	Level 3	Level 4	Level 5
Voltage (OCV)	V	V	32.5	35	37	39	41
Wire feed	Knob setting	F	2	3	4	5	6
Traverse speed	m/min	S	0.30	0.45	0.60	0.75	0.90
Stick-out	Mm	N	25	27	29	31	33

Table 2 Taguchi's L_{25} orthogonal array and collected experimental data

Sl. no.	Design of experiment (coded)				Experimental data (mm)		
	V	F	S	N	Penetration	Reinforcement	Bead width
1	1	1	1	1	1.61	2.14	15.41
2	1	2	2	2	3.27	2.19	15.25
3	1	3	3	3	4.93	3.38	12.68
4	1	4	4	4	5.30	3.69	9.80
5	1	5	5	5	5.17	3.71	9.73
6	2	1	2	3	1.39	1.81	13.99
7	2	2	3	4	2.27	2.16	12.65
8	2	3	4	5	4.17	2.43	13.20
9	2	4	5	1	4.99	3.16	12.19
10	2	5	1	2	8.76	5.77	18.13
11	3	1	3	5	1.51	1.59	11.15
12	3	2	4	1	2.47	2.07	13.35
13	3	3	5	2	4.78	2.64	10.01
14	3	4	1	3	7.34	5.58	17.00
15	3	5	2	4	8.21	4.85	11.59
16	4	1	4	2	1.70	1.45	10.01
17	4	2	5	3	2.76	1.63	11.97
18	4	3	1	4	6.82	3.92	20.53
19	4	4	2	5	6.99	4.35	16.06
20	4	5	3	1	8.62	3.94	13.89
21	5	1	5	4	1.45	1.53	8.57
22	5	2	1	5	3.35	2.74	21.37
23	5	3	2	1	6.30	3.09	18.14
24	5	4	3	2	8.81	2.54	15.77
25	5	5	4	3	7.26	4.57	13.16

have been etched with natal solution i.e. 10% nitric acid solution in distilled water in room atmospheric condition. The weld bead geometry features namely percentage dilution and HAZ width has been observed (Table 2) under Optical Trinocular Metallurgical Microscope (Make: Leica, GERMANY, Model No. DMLM, S6D & DFC320 and Q win Software).

Proposed methodology

Table 3 shows calculated individual desirability values corresponding to each parameters of weld bead geometry. In this computation, linear desirability function has been chosen (desirability function index unity). While calculating various desirability values; a Higher-the-better (HB) criterion has been chosen for penetration depth, whereas a Lower-the-better (LB) criterion has been selected for reinforcement and bead width. These selections have been based on functional requirements of the weldment when subjected to application filed. Weld strength is directly proportional to the penetration depth. Therefore, it is necessary that the produced weld should confirm deeper penetration. To reduce weld metal consumption it is desired that bead width and reinforcement should be as small as possible. The aim of the analysis is to simultaneously maximize penetration depth and minimize reinforcement as well as bead width. Keeping in view; the traditional Taguchi method deals with single response. Therefore, prior to exploration of Taguchi method, it is necessary to convert three objectives into single performance index. Therefore, desirability values have been computed for the selected bead geometry parameters. Irrespective of the criteria chosen; computed desirability value should always be maximized. Instead of computing overall desirability; a fuzzy inference system has been proposed to receive individual response desirability values as inputs with MPCI as output. Therefore, desirability values of aforesaid three bead

Table 3 Individual desirability values of bead geometry parameters and MPCI

Sl. no.	Individual desirability values of bead geometry parameters			MPCI	S/N ratio
	Penetration	Reinforcement	Bead width		
1	0.0296	0.8403	0.4656	0.634	−3.95821
2	0.2534	0.8287	0.4781	0.627	−4.05465
3	0.4771	0.5532	0.6789	0.734	−2.68608
4	0.5269	0.4815	0.9039	0.737	−2.65065
5	0.5094	0.4769	0.9094	0.733	−2.69792
6	0.0000	0.9167	0.5766	0.698	−3.12289
7	0.1186	0.8356	0.6812	0.667	−3.51748
8	0.3747	0.7731	0.6383	0.680	−3.34982
9	0.4852	0.6042	0.7172	0.744	−2.56854
10	0.9933	0.0000	0.2531	0.494	−6.12546
11	0.0162	0.9676	0.7984	0.724	−2.80523
12	0.1456	0.8565	0.6266	0.679	−3.36260
13	0.4569	0.7245	0.8875	0.742	−2.59192
14	0.8019	0.0439	0.3414	0.44	−7.13095
15	0.9191	0.2129	0.7641	0.655	−3.67517
16	0.0418	1.0000	0.8875	0.751	−2.48720
17	0.1846	0.9583	0.7344	0.736	−2.66244
18	0.7318	0.4282	0.0656	0.496	−6.09037
19	0.7547	0.3287	0.4148	0.580	−4.73144
20	0.9744	0.4236	0.5844	0.706	−3.02391
21	0.0081	0.9815	1.0000	0.750	−2.49877
22	0.2642	0.7014	0.0000	0.489	−6.21382
23	0.6617	0.6204	0.2523	0.635	−3.94453
24	1.0000	0.7477	0.4375	0.733	−2.69792
25	0.7911	0.2778	0.6414	0.648	−3.76850

geometry parameters have been treated as three inputs to the fuzzy inference system. The single output (crisp value) of the fuzzy system is defined as MPCI which has been treated as multi-performance characteristic index. By this way three bead geometry parameters have been aggregated to compute MCPI. Therefore, optimal process environment may be evaluated by maximizing this MPCI. In this technique it is not required to check interdependence (correlation) of the responses. Individual priority weights need not to be assigned. Fuzzy inference system takes care of that.

In this procedure, the quality characteristics evaluation strategy for the welding process that has been designed as membership function using the fuzzy model as illustrated in Fig. 3. As shown in Fig. 3, there are three fuzzy sets for each of the parameters of bead geometry: small (S), medium (M) and Large (L). Five fuzzy sets have been assigned for MPCI (Fig. 4): very small (VS), small (S), medium (M), large (L) and very large (VL). The fuzzy rules (Tzeng and Chen 2007; Lu and Antony 2002) in a matrix form used for the fuzzy logic controller have been shown in Table 4. The possible numbers of fuzzy rules used for this experimental controller have been shown (Fig. 5). After the input parameters are fuzzified into the appropriate linguistic values, applying the logic rules in Table 4 along with Mamdani inference, the fuzzy linguistic values and their membership values for the output MPCI can be obtained. Then, defuzzification method by the centre of gravity in (Eq. 9) has been used to calculate the crisp value as the final MPCI's outputs (Table 3).

To determine the optimal process environment, it is required to find out the highest MPCI value among all possible combinations $\left(5^4\right)$ of the process parameters. Optimization (maximization) of MPCI has been carried out using Taguchi method. Taguchi method converts response value into corresponding S/N ratio. The Signal-to-Noise (S/N) ratio is the ratio of mean to deviation of the response from targeted value. Target can closely be reached by maximizing S/N ratio. Therefore, in Taguchi analysis the optimal parametric combination is determined by incorporating Higher-the-better criteria of the response S/N ratio. Optimal parametric combination has been valuated from the plot in Fig. 6. Optimal setting becomes: $V_1F_1S_5N_1$. Predicted value (S/N Ratio) of MPCI becomes −1.06947 (highest among all entries of

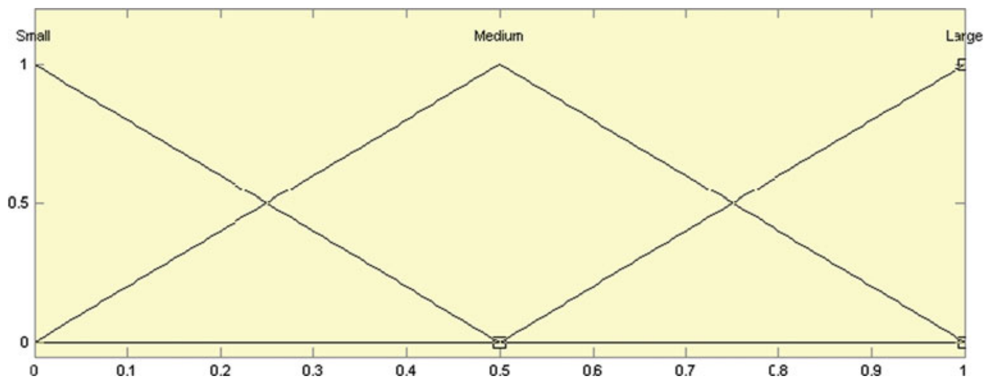

Fig. 3 Membership functions for desirability of individual responses

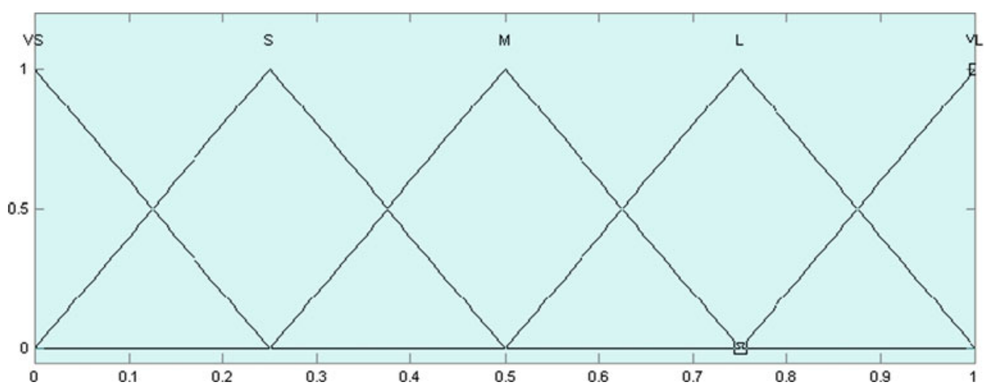

Fig. 4 Membership functions for MPCI

MPCI values in Table 3) whereas in confirmatory test it has been computed as −1.0589. So quality has improved by using this optimal setting (increment of S/N ratio).

The mean value of MPCIs for each level of control factors have been computed and summarized in Table 5. The term ‘delta’ in Table 5 represents maximum change of MPCI due to factorial variation. If change in factors greatly affects delta value; it can be concluded that the response is significant with respect to the factors under consideration. In other words, the factors are highly significant in affecting the response. According to various values of delta for each and every factor level; the degree of importance of the factors

Table 4 Fuzzy rule matrix

MPCI		Bead width		
		Small	Medium	Large
Penetration	*Small*			
Reinforcement	Small	VS	S	M
	Medium	S	M	L
	Large	M	L	L
Penetration	*Medium*	Small	Medium	Large
Reinforcement	Small	S	M	L
	Medium	M	L	L
	Large	L	L	VL
Penetration	*Large*	Small	Medium	Large
Reinforcement	Small	M	M	L
	Medium	M	L	VL
	Large	VL	VL	VL

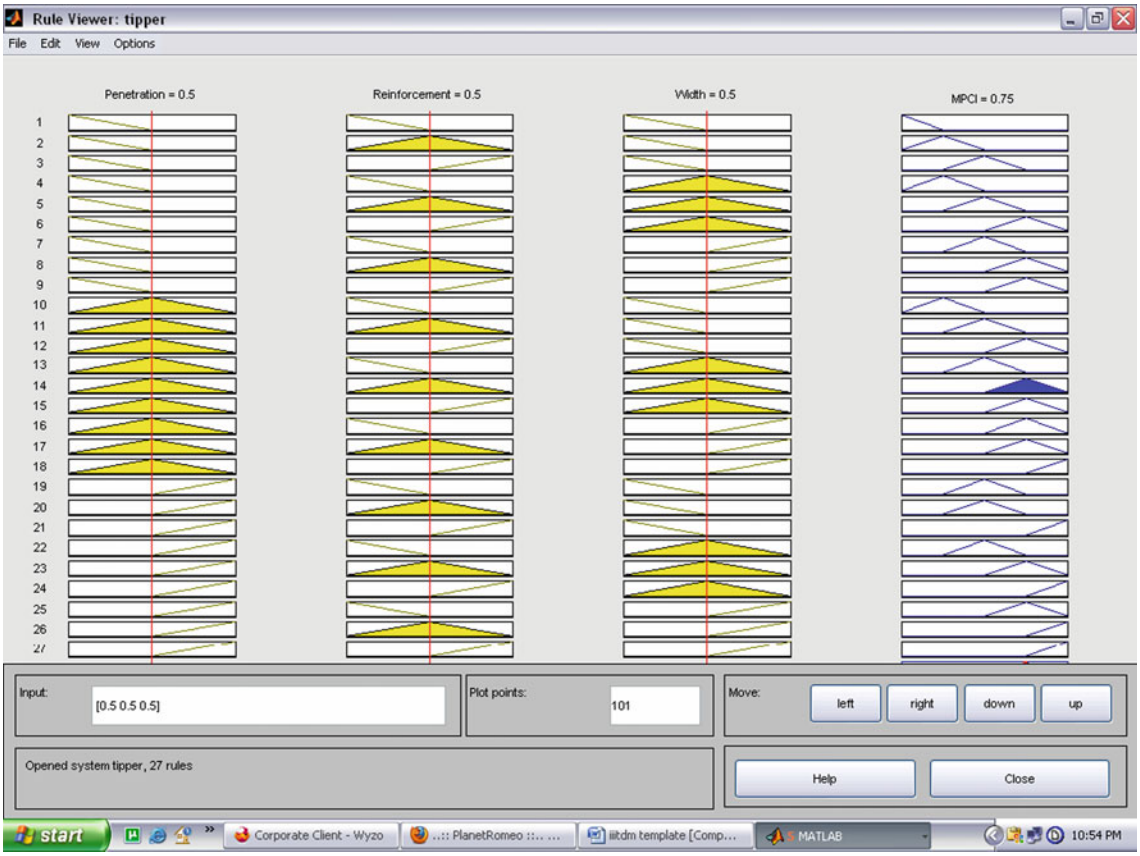

Fig. 5 Membership functions for MPCI

Fig. 6 S/N ratio plot of MPCI (evaluation of optimal setting)

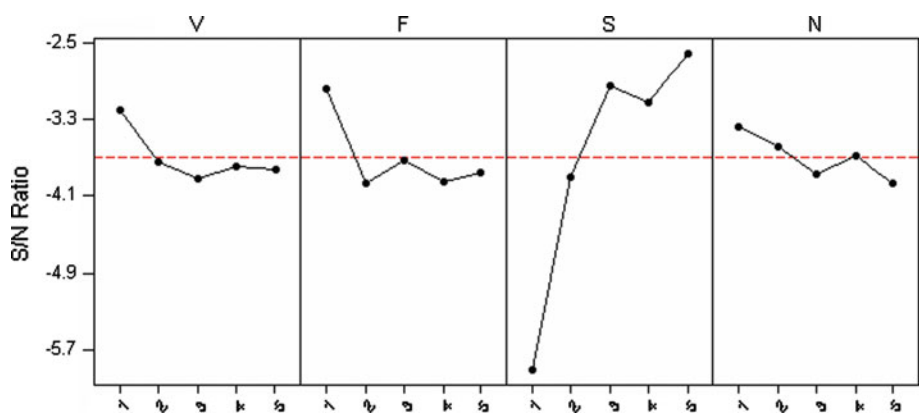

Table 5 Mean value table of MPCI

Level	*V*	*F*	*S*	*N*
1	0.6930	0.7114	0.5106	0.6796
2	0.6566	0.6396	0.6390	0.6694
3	0.6480	0.6574	0.7128	0.6512
4	0.6538	0.6468	0.6990	0.6610
5	0.6510	0.6472	0.7410	0.6412
Delta	0.0450	0.0718	0.2304	0.0384
Rank	3	2	1	4

Delta = (maximum value − minimum value)

on the response variable (factor ranking) can be made. Factors corresponding to negligible delta value may be assumed insignificant. From Table 5 it has been inferred that welding speed is the most important factor influencing MPCI; next significant factor is wire feed, then voltage. Electrode stick-out shows negligible influence.

Conclusions

In the foregoing study, the fuzzy rule based model has been developed using three input variables (corresponding to three process responses to be optimized) and one output variable i.e. MPCI. By this way, a multi-response optimization problem has been converted into an equivalent single objective optimization problem which has been solved by Taguchi philosophy. The proposed procedure is simple and effective in developing a robust, versatile and flexible welding process. Optimization of MPCIs of the process can easily be achieved through proper system model simulation in order to fulfill customers demand. Degree of influence of various process control factors can be investigated easily. Accuracy in prediction of the model analysis can be subsequently increased by increasing number of membership function in the fuzzy system.

The unique features of the proposed approach are:

1. Exploration of desirability function approach can take care contradicting requirements of response features such as Higher-the-better, Lower-the-better, and Target-the-Best.
2. Desirability function approach can convert various response values into a non-dimensional index (ranging from zero to unity).
3. In the proposed desirability function based fuzzy approach, individual response priority weights need not to be assigned.
4. The proposed approach converts numerical response into linguistic so that issue of response correlation can be avoided.

Acknowledgments The authors gratefully recall the contributions rendered by Mr. A Biswas, Workshop Superintendent, Department of Mechanical Engineering, National Institute of Technology, Agartala, Tripura (West), India. Special thanks to Prof. Andrew Kusiak, Editor-in-Chief (JIM) as well as anonymous reviewers whose valuable suggestions and recommendations made the paper a good contributor.

References

Castillo, O., & Melin, P. (2008). Intelligent systems with interval type-2 fuzzy logic. *International Journal of Innovative Computing, Information and Control, 4*(4), 771–784.

Chang, P. C., Hsieh, J. C., & Liao, T. W. (2005). Evolving fuzzy rules for due date assignment problem in semiconductor manufacturing factory. *Journal of Intelligent Manufacturing, 16*(4–5), 549–557.

Cox, E. A. (1992). Fuzzy fundamentals. *IEEE Spectrum, 29*, 58–61.

Datta, S., Bandyopadhyay, A., & Pal, P. K. (2006). Desirability function approach for solving multi-objective optimization problem in submerged arc welding. *International Journal for Manufacturing Science and Production, 7*(2), 127–135.

Datta, S., Bandyopadhyay, A., & Pal, P. K. (2008a). Application of Taguchi philosophy for parametric optimization of bead geometry and HAZ width in submerged arc welding using mixture of fresh flux and fused slag. *International Journal of Advanced Manufacturing Technology, 36*, 689–698.

Datta, S., Bandyopadhyay, A., & Pal, P. K. (2008b). Grey based Taguchi method for optimization of bead geometry in submerged arc bead-on-plate welding. *International Journal of Advanced Manufacturing Technology, 39*, 1136–1143.

Derringer, G., & Suich, R. (1980). Simultaneous optimization of several response variables. *Journal of Quality Technology, 12*(4), 214–219.

Gunaraj, V., & Murugan, N. (1999). Application of Response Surface Methodology for predicting weld bead quality in submerged arc welding of pipes. *Journal of Materials Processing Technology, 88*, 266–275.

Güngör, Z., & Arıkan, F. (2007). Using fuzzy decision making system to improve quality-based investment. *Journal of Intelligent Manufacturing, 18*(2), 197–207.

Kumar, P., Barua, P. B., & Gaindhar, J. L. (2000). Quality optimization (multi-characteristics) through Taguchi's technique and utility concept. *Quality and Reliability Engineering International, 16*, 475–485.

Li, C., Yi, J., & Zhao, D. (2009). Design of interval type-2 fuzzy logic system using sampled data and prior knowledge. *ICIC Express Letters, 3*(3B), 695–700.

Lu, D., & Antony, J. (2002). Optimization of multiple responses using a fuzzy-rule based inference system. *International Journal of Production Research, 40*(7), 1613–1625.

Mamdani, E. H., & Assilia, S. (1975). An experiment in linguistic synthesis with a fuzzy logic controller. *International Journal of Man-Machines Studies, 7*, 1–13.

Mendel, J. M. (1992). Fuzzy logic systems for engineering: A tutorial. *Proceedings of the IEEE, 83*, 345–377.

Patnaik, A., Biswas, S., & Mahapatra, S. S. (2007). An evolutionary approach to parameter optimizationof submerged arc welding in the hardfacing process. *International Journal of Manufacturing Research, 2*(4), 462–483.

Sapkota, A., & Ohmi, K. (2009). Error detection and performance analysis scheme for particle tracking velocimetry results using fuzzy logic. *International Journal of Innovative Computing, Information and Control, 5*(12B), 4927–4934.

Tarng, Y. S., & Yang, W. H. (1998). Application of the Taguchi method to the optimization of the submerged arc welding process. *Materials and Manufacturing Processes, 13*(3), 455–467.

Tarng, Y. S., Juang, S. C., & Chang, C. H. (2002). The use of grey-based Taguchi methods to determine submerged arc welding process parameters in hardfacing. *Journal of Materials Processing Technology, 128*, 1–6.

Toyofumi, K., Hirotaka, N. W., Yukio, N., & Katsuyuki, S. (1986). Optimization of welding materials and conditions for high speed submerged arc welding of spiral pipe. *Transactions of the Iron and Steel Institute of Japan, 26*(5), 439–444.

Tsai, H. L., Tarng, Y. S., & Tseng, C. M. (1996). Optimization of submerged arc welding process parameters in hardfacing. *International Journal of Advanced Manufacturing Technology, 12*, 402–406.

Tzeng, Y.-F., & Chen, F.-C. (2007). Multi-objective optimization of high-speed electrical discharge machining process using a Taguchi fuzzy-based approach. *Materials and Design, 28*, 1159–1168.

Walia, R. S., Shan, H. S., & Kumar, P. (2006). Multi-response optimization of CFAAFM process through Taguchi method and utility concept. *Materials and Manufacturing Processes, 21*, 907–914.

Wang, T., Li, L., & Tong, S. (2010). Application of type-2 fuzzy logic system in indoor temperature control. *ICIC Express Letters, 4*(5B), 1919–1924.

Yager, R. R., & Filev, D. P. (1999). *Essential of fuzzy modeling and control*. New York: Willey.

Zadeh, L. A. (1976). Fuzzy-algorithm approach to the definition of complex or imprecise concept. *International Journal of Man-Machines Studies, 8*, 249–291.