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Optimization of process parameters of SMAW process using NN-FGRA from the sustainability view point

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Abstract Welding process does not possess a good environmental image due to fumes, noise and other health hazards. But, it has been widely applied and is irreplaceable as far as structural industries are concerned. In welding process, many factors are responsible for environmental burdens, of which this study investigates and optimizes process parameters. Based on the pilot study, operating levels for parameters like current, voltage and welding speed, and various responses were identified. Further, the responses considered in the study include spatter, slag, fume generation rate, particulates and power consumption. A full factorial design of three factors at five levels requires 125 experiments for a complete analysis; however the conduct of a full factorial design experiment is expensive and consumes much time. Hence, L_{27} orthogonal design was adopted for three inputs and five levels and 27 experiments were conducted. Further, five back propagation neural network model with network structure of 3-12-1 was individually developed to predict responses. R^2 values obtained for back propagation neural network model pertaining to slag, spatter, power consumption, fume generation rate and particulate formation are 0.99, 0.99, 0.989, 0.965 and 0.97 respectively. The responses for full factorial interaction were simulated. Fuzzy based grey relational analysis was used to optimize process parameters. Finally, life cycle assessment methodology outlined by ISO 14040 and 14044 was adopted to quantify the improvement in environmental performance due to parameter optimization. Thus, the proposed methodology helps to improve environmental performance of the manufacturing process with the experiments conducted using partial factorial design. Apart from environmental benefits, economic benefits and man hours saving are attained without compromising accuracy.

Keywords Sustainability practices · Process parameters optimization · Neural network · Grey fuzzy methods · Life cycle assessment

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Abbreviations

SMAW	Submerged metal arc welding
BPNN	Back propagation neural network
FGRA	Fuzzy based grey relational analysis
LCA	Life cycle assessment
FGR	Fume generation rate
ANOVA	Analysis of variance
EIA	Environment impact analysis

Introduction

The view of economic growth as a competitive advantage to sustain in a dynamic market (Tybout and Westbrook 1995) changed in last two decades, due to external pressure, uncompromising government regulations (Ageron et al. 2012), foreign investment and increased awareness of customers towards environmental issues (Gunasekaran and Spalanzani 2012; Vimal and Vinodh 2013). Thus, many organizations shift their focus towards implementing environmental practices in manufacturing operations. Manufacturing organizations in developing countries cope with these changes by taking research initiatives to implement sustainable practices. On the other hand, Kaebernick and Kara (2006) emphasized that factors such as economic benefits, long term survival in the market, environmental responsibility, green competitive advantage and green image are the major reasons for implementing environmental practices apart from external pressure and government legislation. Due to globalization and foreign investment, green competitive pressure and government legislations are no more indifferent in developing and developed countries. Thus, many organizations focus on implementing sustainable practices in their manufacturing operations.

Sustainable development can be viewed in three orientations namely: product, material and process. Many studies in material and product orientations in the past have improved sustainable performance. The brief insights from the reported studies are discussed as: Kaebernick and Kara (2006) proposed a sustainable product development methodology widely accepted by researchers and practitioners. With reference to traditional product development and manufacturing, a sustainable product development strategy was developed. Among the major phases of product development, a sustainable way of converting requirements, design and end of life options were discussed. The discussion and importance of the manufacturing process with respect to sustainability were not highlighted. Ljungberg (2007) studied the importance of material selection to enable product sustainability. Apart from design, Ljungberg (2007) mentioned material selection and proper end of life strategy as other factors which improve sustainable performance of products. In this study, an attempt is made to study the importance and improvement of process orientations with respect to sustainability. Process parameters and environmental issues are studied in this research to analyze sustainability of the manufacturing process.

Among manufacturing processes, welding is an important process used for metal fabrication in construction, shipbuilding and other metal structure industries. Welding has the ability to join similar and dissimilar metals. Popularly used automatic and semi-automatic welding processes include: Shielded Metal Arc Welding (SMAW), flux cored arc welding, gas metal arc welding and submerged arc welding. In India, SMAW process has a 65–70 % share in the metal fabrication organizations (Raja et al. 2012). In SMAW process, an arc developed in the air gap between electrode and base metal forms the main source of heat that melts the electrode which deposits over the base metal. The electrode consists of a metal core (mostly mild steel), surrounded by flux and (minerals and organic components) coating (Goel et al. 1993). The process parameters of SMAW process with the objective of improving mechanical properties were researched in the past (Vimal et al. 2015). Singh et al. (2013) analyzed the effect of process parameters like current, voltage and electrode position on the depth of penetration of the SMAW process. Kumar and Vijayakumar (2012) analyzed the effect of SMAW process parameters in the welding of pipes. Based on these two studies, current and voltage (arc length) are found to be the important process parameters and from welding expert opinion, the importance of welding speed has been understood. For the 7018 electrode of 3.15 mm diameter, current value of 110–150 A and voltage of 16–24 volts are widely used. Apart from current and voltage, another influential parameter is welding speed. From the experiment, average speed by an operator is found to be 200 mm/min. A wide range of studies were conducted in the SMAW process considering the mechanical properties; still environmental aspects of welding with reference to process parameters optimization were not addressed.

The process flow diagram (Fig. 1) depicts the interaction of the SMAW process with techno sphere (Stub) and Eco-sphere (Heat, fumes, etc.). Thus fumes, solid wastes, energy consumption and stub are the major reasons for environmental vulnerability. On the other hand, due to economic constraints and man hour limitations, a complete interaction analysis of the process parameter level is not feasible. This forces the adaptation of a suitable Taguchi design layout. Thus, objectives formulated in this study are:

- To develop a methodology to predict responses for all levels of interactions with the aid of conducting experiments
- To optimize process parameters (current, voltage and welding speed) to improve environmental performance of the SMAW process
- To analyze the improvement in environmental performance through the conduct of environmental impact analysis (EIA) using LCA methodology

Experimental details and procedure

The experimental details and procedure are presented in the following subsections.

Material

Seven thousand and eighteen electrode is used for welding Mild steel using the SMAW process. The material composition of the electrode used is shown in Table 1. Mild steel base metal of 240 mm × 100 mm × 10 mm is used. KemppiMastertig MLS 4000 welding setup is used with direct current electrode positive (DCEP). DCEP has already been proven with better penetration depth (Tandon et al. 1984).

Experimental setup

The various factors responsible for environmental burden in the SMAW process are: current, voltage, welding

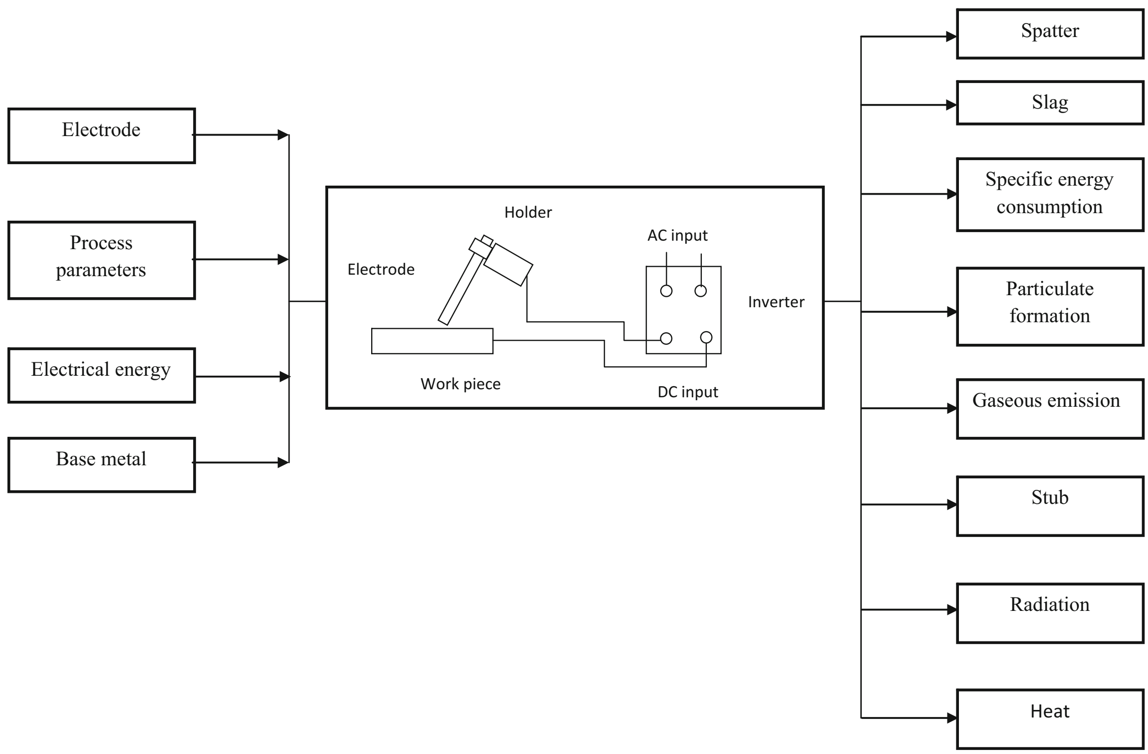


Fig. 1 Process flow diagram of SMAW process

Table 1 % Weight composition of electrode core

Mild steel core	%Fe	%Mn	%Cr	%Ni	%Cu	%Si
Typical	98–99	<0.6	<0.1	<0.1	<0.1	<0.2

speed, operator performance, room temperature and humidity. These factors can be classified (Phadke 1989) into controllable and uncontrollable factors (noise). A pilot experiment was conducted to identify various control factors, their corresponding levels and responses. Based on the pilot experiment, three factors and five responses were measured for optimization with an environmental objective. Three factors are current, voltage and welding speed; responses are fume generation rate (FGR), particulate formation, slag, spatter and power consumption. The levels are current (in A) at 110, 120, 130, 140 and 150; voltage (in V) at 16, 17.5, 19, 20.5 and 23 and welding speed (in mm/s) at 140, 160, 180, 200 and 220. For these levels, the responses are measured for welding the base metal of 200 mm length (reference unit).The methods adopted to measure the three factors and five responses are discussed below.

Current, voltage and power consumption

The average efficiency of KemppiMasterTig MLS 4000 inventor is 75–80 %. Using 'Powerlite' power analyzer, voltage, current and power consumption are measured. The power consumption for the reference unit is computed using Eq. 1.

$$\text{Power consumption, E} = \frac{\text{p}}{\text{t}} \tag{1}$$

P = measured power consumption in kW, t—time taken to weld reference unit length in hour, E—power consumption in kW/h.

Slag

The electrode contains alloying elements, deoxidizers, scavenger elements that remove extra dissolved gases, stabilizers, slag forming elements and flux materials. The slag forming elements and flux materials, forms the slag which floats over the molten metal because of density difference. American Welding Society (AWS) defined slag as '*A non-metallic product resulting from the mutual dissolution of flux and nonmetallic impurities in some welding and brazing processes*' (AWS A3.0:2001). Slag acts as a protective cover against atmospheric contamination. After the completion of the weld bead, slag is collected and weighed using a weighing machine.

Spatter

Spatter is defined as '*The metal particles expelled during fusion welding that do not form the part of the weld*' (AWS A3.0:2001). Spatter is largely accounted for quality issues in the welding process. Spatter rate is highly influenced by the waveform used. Praveen et al. (2005) stated that, waveform and area under waveform are responsible, allowing heat transfer in an effective way without spatter. However, arc length is another significant factor influencing the spatter. Chu and Tung (2005) identified that the stability of arc has huge influence in spatter generation rate. Usually, arc length is maintained to the diameter of electrode core; but Ueguri et al. (1985) proved that maintaining the arc length of half the diameter eliminates spatter and also avoids the possibility of electrode touching the base metal.

Particulate formation

Solid particulate matters generated by welding process are Airborne. They tend to remain airborne and drift with the air current (AWS A3.0:2001). Metal fumes are generated from an arc welding process directly from volatilization of metal vapor at superheated state, and indirectly from spatter particles ejected during the welding process. Thus, arc stability plays an important role in particulate generation. The submicron level particles may not settle and have an adverse effect on human health (Zimmer et al. 2002). Using the guidelines for particulate measurement in ANSI/AWS F1.2. (1992), a fume chamber is built over a working table. The fumes generated are extracted using the blower at 800 l/min. The fumes are passed through filter paper (refer Fig. 2), where the metal particles are above 2 µm size. The filter paper used for experimental purpose is GF/A glass fiber paper (Manufacturer—WHATMAN Limited). The filter papers are weighed before and after the conduct of experiments through which particulates deposited are measured (Eq. 2). Further, using SEM/EDX, the chemical composition of the collected particulates is found.

$$\text{Particulate formation} = (w_f - w_i) \tag{2}$$

w_f—initial weight of filter paper, w_i—final weight of filter paper.

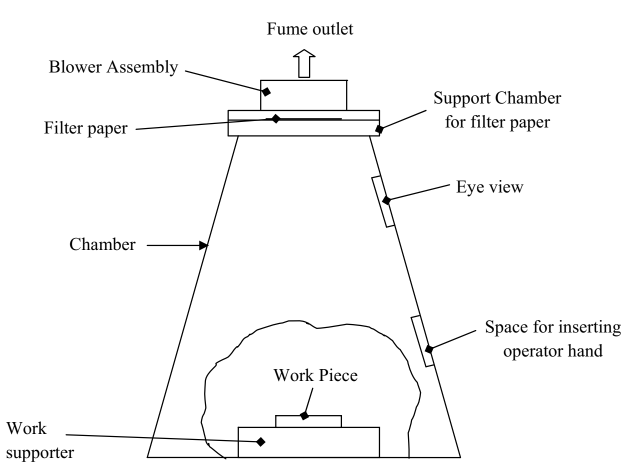


Fig. 2 Fume chamber for experiments ANSI/AWS F1.2. (1992)

Fume generation rate (FGR)

FGR is mostly influenced by base metal composition, flux composition, current and voltage. Voltage has a huge influence in arc stability, which controls spatter generation. Micro-spatter contributes to the amount of fume generated. However, the volume of fume generated cannot be measured exactly, thus linguistic terms, namely: very low, low, medium, high and very high which corresponds to values 1, 3, 5, 7 and 9 respectively are used.

Greenhouse gases

Green House Gases (GHGs) is another important environmental burden as far as the welding process is concerned. GHGs are measured using detector tubes. The method of measuring gases using detector tubes is approved by AWS (ANSI/AWS F1.5-87)). This method applies to air sampling, which contains O_3, NO_X and CO. There are two types of tubes: stain and color comparison tubes. In this study, color comparison tubes are used.

Experimental design

Experiments are conducted with three parameters for each of five levels. The parameters, their corresponding levels and measurement units are shown in Table 2. For the selected parameters, L_{27} orthogonal array was selected. The design of L_{27} array and collected responses are shown in Table 2.

Research methods

Three parameters and five levels are considered for this research. To completely analyze the interaction of parameters and the influence of various levels, level$^{\text{factors}}$ experiments need to be conducted. Thus, the number of experiments to be conducted to completely analyze the interactions is 125 (5^3). However, conducting 125 trials is not economically viable and also, the results of these experiments may not contribute directly to the organizational bottom line. Thus, organizations do not show interest to conduct many experiments. For this purpose, full factorial interaction can be predicted with the conduct of experiments for L_{27} design layout. The linear

Table 2 Experimental observation based on L_{27} orthogonal array

S. no	A	B	C	Current (A)	Voltage (v)	Speed (mm/min)	Power consumption (kWh)	Spatter (g)	Slag (g)	Particulate formation (g)	FGR, linguistic variable
1	1	1	1	110	16	140	0.055	1.54	12.08	0.112	1
2	1	2	2	110	17.5	160	0.055429	1.35	11.5	0.109	1
3	1	3	3	110	19	180	0.059507	1.83	11.05	0.121	2
4	1	4	4	110	20.5	200	0.065144	1.98	10.32	0.125	3
5	1	5	5	110	23	220	0.065885	2.07	12.2	0.126	4
6	2	1	2	120	16	160	0.055285	1.653	11.02	0.1	1
7	2	2	3	120	17.5	180	0.061325	1.78	12.82	0.11	2
8	2	3	4	120	19	200	0.060244	1.94	10.3	0.13	3
9	2	4	5	120	20.5	220	0.064063	2.4	10.4	0.131	4
10	2	5	1	120	23	140	0.0736	2.3	12.91	0.144	5
11	3	1	3	130	16	180	0.057778	1.546	11.82	0.11	2
12	3	2	4	130	17.5	200	0.070778	1.9	10.3	0.14	3
13	3	3	5	130	19	220	0.065181	2.45	9.9	0.14	4
14	3	4	1	130	20.5	140	0.066806	2.34	12.23	0.15	5
15	3	5	2	130	23	160	0.072674	2.53	11.99	0.153	6
16	4	1	4	140	16	200	0.056911	1.723	10.9	0.123	2
17	4	2	5	140	17.5	220	0.062101	1.98	10.4	0.132	3
18	4	3	1	140	19	140	0.068963	2.3	12.21	0.132	5
19	4	4	2	140	20.5	160	0.07474	2.6	11.32	0.14	6
20	4	5	3	140	23	180	0.070901	2.8	9.85	0.153	7
21	5	1	5	150	16	220	0.064103	1.965	9.6	0.142	4
22	5	2	1	150	17.5	140	0.064024	2.04	12.5	0.142	4
23	5	3	2	150	19	160	0.069271	2.6	11.4	0.153	8
24	5	4	3	150	20.5	180	0.069401	2.69	9.9	0.145	8
25	5	5	4	150	23	200	0.070122	2.75	9.4	0.165	9

regression model fails in prediction because of the existence of nonlinear properties. This demands the adaptation of an artificial intelligence technique to model, simulate and predict the interactions. As far as the manufacturing process is considered, Neural Network (NN) is widely used to predict various parameters (Xiong et al. 2014) like surface roughness, weld bead geometry, mechanical strength, etc. Also, NN has already proved its acceptability in real world conditions (Yu et al. 2014). However, the prediction of sustainability characteristics of welding processes like spatter, slag, fume generation, particulates and power consumption was not attempted in the past. Thus, based on past research acceptability, a NN model has been adopted for this purpose. From 125 predicted trials, best process parameters need to be identified. Multi criteria decision making (MCDM) techniques, namely TOPSIS and GRA were used in the past. However, compared to TOPSIS, GRA proposed by Deng (1982) is widely used to deal with poor, incomplete and uncertain data. Also, GRA is successful in solving complicated interrelationships between contradicting objectives in manufacturing (Yang et al. 2014). GRA uses grey relational generation through which Grey Relational Coefficient (GRC) can be computed. This helps to handle problems with partial known information. Other benefits of GRA include: the merit of point set topology so, global comparison between two sets of data is considered instead of local comparison by measuring the distance between two points which avoids subjectivity; also, multi objective nature of the problem can be converted into a single objective function using GRA. Few researchers used the principles of fuzzy sets in the GRA. Liu et al. (2009) claimed the GRC for each sequence contains subjectivity because of manual definition of performance characteristics. Thus, the application of fuzzy sets for the computation of GRC may fetch results with a better confidence level (Pang and Bai 2013; Kumru and Kumru 2014). To overcome the above constraints, Singh et al. (2013), Kovac et al. (2013) and Hou (2010) successfully implemented fuzzy concepts like inference mechanism and min-max approach. Pandey and Panda (2014) pointed out the uncertainty associated with GRA and mentioned the use of fuzzy inference system (FIS) along with GRA. Apart from performance characteristics, in this study, for FGR experts' opinion is obtained which is subjective and time varying in nature. In line with Zadeh (1965), Ahilan et al. (2013) highlighted the usefulness of Fuzzy systems in uncertain, nonlinear as well as dynamic in time varying process control systems like a manufacturing process. Thus, Fuzzy based Grey Relational Analysis (FGRA) system was adopted to select the optimum process parameters to enable sustainability of SMAW process. The proposed methodology for experimenting, predicting and optimizing process parameters is shown in Fig. 1. Also, the principles of Taguchi factorial design, NN, FGRA and various steps in the proposed methodology are detailed in the following subsections.

NN prediction for full factorial design

NN is an approach inspired by the brain's structure and attempts at simulating its processing capabilities. Neural network resembles the human brain in two aspects: Learning process and Inter neuron connection weights storage. The neurons are integral part of an NN model. The application of NN is very much appreciated in a dynamic environment. The advantage of NN includes: dynamic systems that connect inputs and output using neurons weighted connections, generalized learning and parallel processing. The significant functions of NN are tackling non-linearity and mapping input–output information. NN finds wide range of applications in process parameters optimization and various responses of the manufacturing process (Asiltürk and ÇUnkaş 2011), time series forecasting (Khashei and Bijari 2010), ground water level prediction (Taormina et al. 2012), supplier selection (Kuo et al. 2010) and stock market index prediction (Guresen et al. 2011). It also finds application in combination with other non-traditional methods like Genetic Algorithm (Ahilan et al. 2013) and Particle Swarm Optimization (Zhou et al. 2006).

Mostly, trial and error is used the adoption of learning algorithm, transfer function, training function, learning function and performance function. Different types of neural network algorithms which are in practice include back propagation neural network (BPNN), counter propagation neural network and radial basis function neural network. Among these methods, BPNN finds varied applications because of its feedback phenomenon (Kuo et al. 2014; Tsai and Luo 2014; Tsai and Lee 1999).

Notations used in NN prediction

x_{ik} = Normalized value of response k of trial i
max $y_i(k)$ = Maximum value of $y_i(k)$ where I = Number of experimental trials
$y_i(k)$ = Response k of trial i
I_j = Input data set, where I_j = [curent$_i$voltage$_i$, welding speed$_i$]
min $y_i(k)$ = Minimum value value of $y_i(k)$ (i = 1, 2, 3 … n) where i = Number of experiment trials
net_h = Net output of hidden layer
W_{jk} = Weight between input layer (jth node) and hidden layer (kth node)
b_k—Bias to kth node in hidden layer
C_{jk} = Weight between hidden layer (jth node) and output layer (kth node)
net_i = Net output of output layer
h_k = Output value set of hidden layer
b_i—Bias to ith node in output layer
d_{tk} = Desired output of tth trial of kth node
o_{tk} = Calculated output of tth trial of kth node
E_t = Performance evaluation
η = Learning rate
α = Momentum parameter
w_{jk}^{new} = New weight between input layer (jth node) and hidden layer (kth node)
Δw_{jk} = Weight difference between ith and (i − 1)th epoch

Learning algorithm—back propagation neural network (BPNN)

Back propagation neural network (BPNN) model is a multi-layer model consisting of input layer, output layer and 'n' hidden layers (Zain et al. 2011; Çaydaş and Hasçalık 2008). In BPNN, the output of each neuron in a layer is connected to neurons of the next layer. The important factor influencing training and learning efficiencies is the network structure. Figure 3 shows the basic structure of a BPNN. There are two major steps in the BPNN algorithm. The first step is also known as forward pass where, the input vector is applied to the network and it propagates through network layer by layer. In forward pass, weights are maintained constant throughout. The second step is also known as back pass where, weights are updated based on the error (the difference between predicted and desired output) in the forward pass. This cycle is repeated till the model satisfies the performance criteria.

The normalized input data set is fed into the structure to initiate a forward pass. First, the responses are to be normalized between [0,1], [−1,1], and [0.1, 0.9]. In this study, responses are normalized between [0.1, 0.9] because, logically current, voltage and welding speed cannot be 0 or negative. If there are 'k' responses and 'I' trials in an experiment, then the normalized value corresponds to lower the better performance characteristics as given in Eq. (3). With reference to Fig. 3, net output of a hidden layer (input to hidden) net_h can be calculated using Eq. (4). Then, using Eq. (5), the net output (hidden layer to output layer) of the model is computed. In this step, results for the hidden and output are computed as:

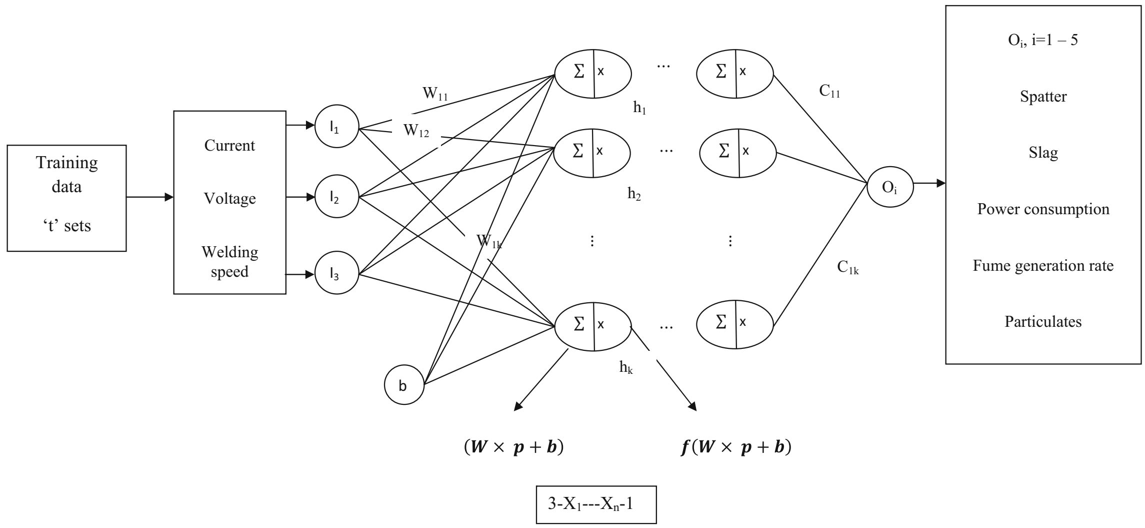


Fig. 3 Back propagation neural network structure (BPNN)

$$x_{ik} = \left(0.8 \times \frac{\max\ y_i(k) - y_i(k)}{\max\ y_i(k) - \min\ y_i(k)}\right) + 0.1 \tag{3}$$

$$net_h = \sum \left(W_{jk} \times I_j + b_k\right) \tag{4}$$

$$net_i = \sum (C_{ki} \times h_k + b_i) \tag{5}$$

Transfer function

The widely applied transfer functions are log-sigmoid transfer function (logsig), linear transfer function (purelin), hyperbolic tangent sigmoid transfer function (tansig), and hard limit transfer function (hardlim). The influence of transfer function on the performance of the model was not available. However, the advantage of the sigmoid function over other functions is that the output cannot grow infinitely large or small. Also, Zain et al. (2011) compared the results of log-sigmoid transfer function and tansigmoid transfer function and found the prediction to be similar. Still, based on existing patterns of application, log-sigmoid (for input to hidden layer) and pure linear (hidden layer to output layer) transfer functions are used (Ramadhas et al. 2006). Equations 6 and 7 denote the general representation of functions. Then, using suitable transfer function, the outputs are computed. Equation (8) demonstrates the application of log-sigmoid transfer function and Eq. (9) demonstrates the application of the pure linear transfer function.

$$h_k = f(net_h) \tag{6}$$

$$O_i = f(net_i) = \text{Spatter, Slag, Power consumption, Fume generation rate \& Particulates} \tag{7}$$

where 'f' is the transfer function.

$$\text{f(x)} = \frac{1}{1 + e^{-net_h}} = h_k = \frac{1}{1 + e^{W_{jk} \times I_j + b_k}} \tag{8}$$

$$\text{f(x)} = \text{x} = o_i = C_{jk} \times h_k + b_i = \{\text{Spatter, Slag, Power consumption, Fume generation rate \& Particulates}\} \tag{9}$$

Performance evaluation

The performance of iteration is checked with Mean Square Error using Eq. (10). The goal is to minimize the performance criteria, based on which the best network structure is selected.

$$E_t = \frac{1}{2} \sum_{t=1}^{t} \sum_{k=1}^{k} (d_{tk} - o_{tk})^2 \tag{10}$$

Learning function

The learning rate should be as small as possible for true approximation. However, this may increase with the iteration time. The learning and weight updation are done using Eqs. 11 and 12. In this, η is learning rate and α is the momentum parameter used to converge to the objective during a back pass. Thus, α helps reduce oscillations during convergence.

$$w_{jk}^{new} = w_{jk} + \Delta w_{jk} \tag{11}$$

$$\Delta w_{jk} = -\eta \frac{E_t}{w_{jk}} + \alpha \Delta w_{jk} \tag{12}$$

FGRA

For ranking trials, fuzzy inference based GRA was adopted. The following subsection details the basics of FIS and GRA. The integration algorithm is detailed in the proposed methodology section.

Notations used in FGRA

ζ—distinguishing coefficients, usually 0.5 (Deng 1982)
$\chi\ (x_{ok}, x_{ik})$—Grey relation coefficient
x_{ok}—Reference value for kth response
x_{ik}—Measured value for kth response for i^{th} trial
$\phi\ (\boldsymbol{x_o}, \boldsymbol{x_i})$—GRG score for i^{th} trial
ω_k—Weight of k^{th} response
r_{ij}—represent the comparison values of response i and response j
λ_{max}—Maximum Eigen value
n—Size of the matrix
μ—Membership function
$\emptyset\ (A)$—Fuzzy subsets of parameter A
$\emptyset\ (B)$—Fuzzy subsets of parameter B
$\emptyset\ (B)$—Fuzzy subsets of Response R

GRA

GRA is an impact evaluation model that measures the degree of similarity of difference between two sequences based on the grade of relation. GRA proved to be effective when dealing with incomplete and uncertain information (Lin and Lin 2002; Tseng 2010). Also, GRA finds many applications in the manufacturing field as the responses are in different units, thus a few responses may be neglected. Also, in manufacturing applications, direction of goal for different responses may vary. GRA is the most appropriate in these applications. Thus, the responses need to be normalized. In this study, the responses are normalized between [0.1, 0.9]. Using Eq. (1), normalization is done. If, $x_i(k)$ is 0.9 for response k and trial I, then the performance of trial I, is superior to other trials with respect to response k. However, for other responses, it may not be the same, thus, a reference sequence x_o is generated as $X_{ok} = \{X_{o1}, X_{o2}, X_{o3}, X_{o4...}X_{ok}\} = \{0.9, 0.9, 0.9, 0.9\ldots 0.9\}$. By comparing X_{ik} with reference sequence, a trial closer to the reference sequence is identified as the best trial.

The computation of GRC helps to determine trial X_{ik} closer to the reference sequence X_{ok}. Larger the GRC implies closeness to the reference sequence. GRC is computed using Eq. (13).

$$\chi\ (x_{ok}, x_{ik}) = \frac{\Delta_{\min} + \zeta\Delta_{\max}}{\Delta_{ik} + \zeta\Delta_{\max}}$$
$$\Delta_{ik} = |x_{0k} - x_{ik}|$$
$$\Delta_{\min} = \mathrm{Min}\{\Delta_{ik}, i = 1, 2, \ldots, m; j = 1, 2, \ldots, n\}$$
$$\Delta_{\max} = \mathrm{Max}\{\Delta_{ik}, i = 1, 2, \ldots, m; j = 1, 2, \ldots, n\} \quad (13)$$

Grey relational grade

After calculating GRC ($\chi\ (x_{ok}, x_{ik})$) for all responses and trials, GRG is computed using Eq. (14) (Tseng 2010)

$$\phi\ (x_o, x_i) = \sum\nolimits_{k=1}^{k} (\omega_k \times \chi\ (x_{ok}, x_{ik})) \quad (14)$$

'$\boldsymbol{\omega}$' is computed using a pairwise comparison matrix based on the principle of AHP (Saaty 1988). If 'k' responses are compared, then the pairwise comparison matrix is constructed using Eq. (15). Using Eq. (16), the weights of responses are computed.

$$R = \begin{bmatrix} r_{11} & \cdots & r_{1k} \\ \vdots & \ldots & \vdots \\ r_{k1} & \cdots & r_{kk} \end{bmatrix} \quad (15)$$

$$W_k = \frac{\sum_{j=1}^{k} r_{ij} / \sum_{i=1}^{k} r_{ij}}{n}$$
$$\text{where i,j} = 1, 2, 3 \ldots k \quad (16)$$

Using consistency test, the consistency of the responses collected from experts were verified. Saaty (1980) stated that, a consistent response should satisfy the condition $\lambda_{max} = n$, where n is the size of matrix. The deviation of inconsistency is measured as Consistency Index using Eq. (17).

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (17)$$

However, the weight (ω) computation using AHP is associated with subjectivity and also, from the Eq. (14), it is evident that, weight plays a major role in the computation of the GRG score. Thus, to eliminate subjectivity, FIS was used to infer GRG score through which, ranking can be done.

Fuzzy inference system

The model proposed by Zadeh (1965) is based on linguistic synthesis which is a widely accepted inference model. The model is based on conditional statements consisting of antecedents (IF) and consequent (THEN) statements. The algorithm generates fuzzy relationship using linguistic variables. For two parameters (A and B) and one response (R), the linguistic terms are $A_1, A_2 \ldots A_n$, $B_1, B_2, \ldots B_n$ and $R_1, R_2 \ldots R_n$ respectively. Zadeh (1965) defined a fuzzy set for parameter and responses as shown in Eqs. (18–20).

$$\emptyset\ (A) = \{A_i \parallel \mu \to [0, 1]\}, \quad (18)$$
$$\emptyset\ (B) = \{B_i \parallel \mu \to [0, 1]\}, \quad (19)$$
$$\emptyset\ (R) = \{R_i \parallel \mu \to [0, 1]\}, \quad (20)$$

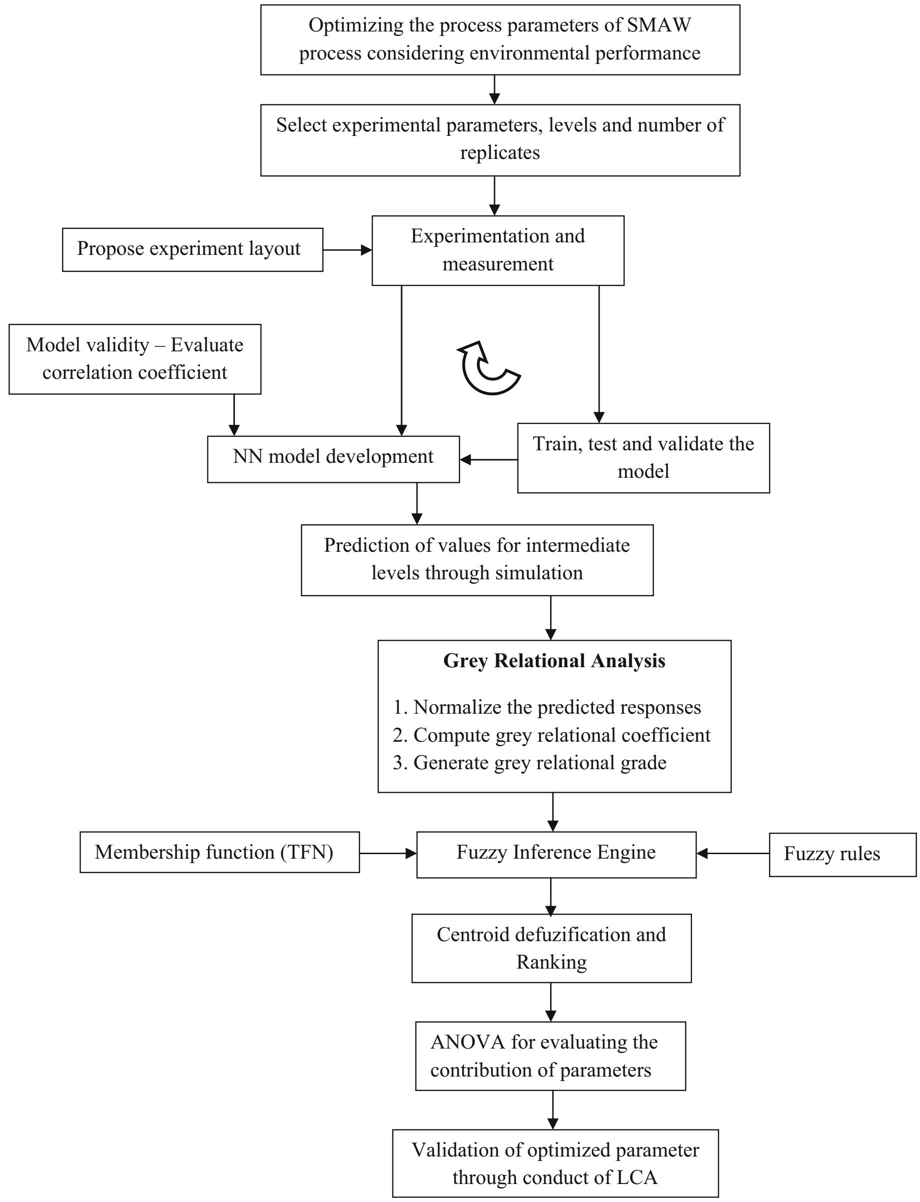
With fuzzy sets, the fuzzy conditional statement is formulated as:

IF A is A_1 and B is B_1 then R is R_1

IF A is A_2 and B is B_1 then R is R_2.

Based on the relation, fuzzy relationship matrix is obtained using the implication operators. The widely used implication operator (Vimal and Vinodh 2012) is shown in Eq. (21).

Fig. 4 Proposed methodology



$$\mu\,(A, B, R) = \cup[\mu_A(A_1) \cap \mu_B(B_1), \mu_R(R)], \tag{21}$$

Using the implication operator, GRG for all responses and trials are computed. FIS toolbox in MATLAB is used for this purpose.

Gate to gate (GtG) LCA

ISO 14040 (2006) and ISO 14044 (2006) outlined LCA methodology which is widely accepted for assessing the environmental performance of a manufacturing process. This methodology is also called GtG LCA methodology. Many researchers explored GtG LCA methodology to assess a manufacturing process. The application of GtG is well demonstrated by Rubin et al. (2014), Kasah (2014) and Foolmaun and Ramjeawon (2008). This methodology has four major steps.

1. Goal and Scope definition
   a. System definition
   b. Functional unit
2. Inventory analysis
3. Impact assessment (European Commission 2010)
   a. Selection of impact category model
   b. Classification
   c. Characterization
4. Interpretation

Table 3 R^2 values pertaining to BPNN models

	BPNN models				
	Slag	Spatter	Power consumption	FGR	Particulate formation
Training	1	1	1	.99	0.99
Testing	0.99	0.99	0.989	0.965	0.97

Gabi 5.0 LCA package follows the LCA methodology outlined by ISO 14044 for analyzing and comparing the environmental performance of products, processes and services. GaBi has its own database created by PE INTERNATIONAL. Apart from the GaBi database, it utilizes data from Ecoinvent which was created by the Ecoinvent Centre. Once the inventory data are collected, the inventory results are assigned to impact categories. Characterization factor is used to assign the impact category score. The characterization models available in GaBi are: Eco-invent 95 & 99, ReCiPe, ILCD recommendation and a few others. The commonly used impact categories are: depletion of resources, land use, acidification, Ecotoxicity, Climate change, ozone layer depletion, respiratory effects and ionizing radiation. These impact categories are grouped under three damage categories, namely: human health, ecosystem quality and resources.

Steps in the proposed methodology

NN-FGRA based methodology was proposed to predict the full factorial design and optimize process parameters of the SMAW process from a sustainability viewpoint. An expert group was formulated for opinions and validation of the methodology. The expert group consists of a welding expert—Assistant General Manager, WRI-BHEL (case organization), and sustainability expert from our research group. Then, the steps followed are listed below (Fig. 4).

1. *Identification of process parameters, levels and responses for the selected objective* Various influential process parameters and responses are identified. The objective of the study is to improve sustainability of the SMAW process without compromising its mechanical properties; thus based on literature, number of levels, upper and lower limits are fixed. Then, after analyzing Input-Output diagram (Fig. 1), the responses influenced by selecting para-

Fig. 5 R^2 values pertaining to model developed for spatter

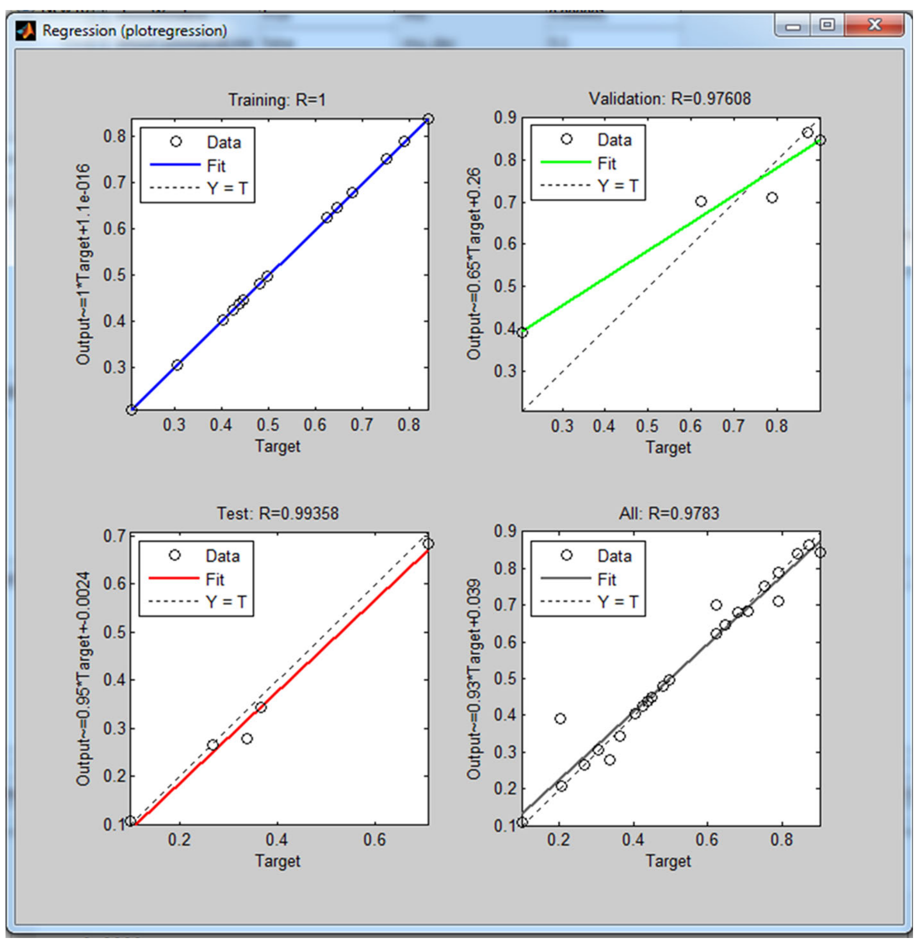


Table 4 Weights computed using AHP methodology

	Power consumption (kWh)	Spatter (g)	Slag (g)	Particulate formation (g)	FGR	Eigen vector	Normalized Eigen vector (ω)
Power consumption (kWh)	1	5	5	1	1	0.638	0.314
Spatter (g)	0.2	1	7	0.33	0.33	0.27	0.133
Slag (g)	0.2	0.142	1	0.33	0.33	0.11	0.054
Particulate formation (g)	1	3	3	1	1	0.504	0.248
FGR	1	3	3	1	1	0.504	0.248

Table 5 GRG score for L_{27} orthogonal array

S. no	Process parameters			GRG score					GRG score
	Current	Voltage	Speed	Power consumption	Spatter	Slag	Particulate formation	FGR	
				Weights (ω)					
				0.314906	0.133268	0.054294	0.248766	0.248766	
1	0.9	0.9	0.9	1	1	0.188056	0.686815	1	0.774974
2	0.9	0.728571	0.7	0.956622	0.758987	0.237236	0.745158	1	0.739601
3	0.9	0.557143	0.5	0.677329	0.544317	0.283588	0.556176	0.764089	0.5651
4	0.9	0.385714	0.3	0.482575	0.440493	0.415184	0.512823	0.61824	0.493863
5	0.9	0.1	0.1	0.465	0.395258	0.189145	0.50302	0.519146	0.414314
6	0.7	0.9	0.7	0.970757	0.812386	0.287331	1	1	0.814095
7	0.7	0.728571	0.5	0.599323	0.590728	0.160354	0.724639	0.764089	0.567827
8	0.7	0.557143	0.3	0.643381	0.464099	0.42053	0.467292	0.61824	0.522709
9	0.7	0.385714	0.1	0.510737	0.287139	0.395092	0.459139	0.519146	0.434251
10	0.7	0.1	0.9	0.337153	0.313092	0.156887	0.374254	0.447429	0.325763
11	0.5	0.9	0.5	0.773017	0.982974	0.212533	0.724639	0.764089	0.691451
12	0.5	0.728571	0.3	0.374851	0.490379	0.42053	0.396827	0.61824	0.460165
13	0.5	0.557143	0.1	0.481666	0.275712	0.566403	0.396827	0.519146	0.447951
14	0.5	0.385714	0.9	0.444862	0.302167	0.187516	0.34483	0.447429	0.345361
15	0.5	0.1	0.7	0.348659	0.259208	0.201392	0.331787	0.393122	0.306834
16	0.3	0.9	0.3	0.831952	0.65433	0.303344	0.53362	0.764089	0.617467
17	0.3	0.728571	0.1	0.571242	0.440493	0.395092	0.451266	0.61824	0.495267
18	0.3	0.557143	0.9	0.403896	0.313092	0.188599	0.451266	0.447429	0.360856
19	0.3	0.385714	0.7	0.323991	0.246306	0.253831	0.396827	0.393122	0.322816
20	0.3	0.1	0.5	0.373033	0.215641	0.592075	0.331787	0.350572	0.372621
21	0.1	0.9	0.1	0.509637	0.449058	0.765573	0.38521	0.519146	0.525725
22	0.1	0.728571	0.9	0.511815	0.409267	0.174026	0.38521	0.519146	0.399893
23	0.1	0.557143	0.7	0.398654	0.246306	0.246177	0.331787	0.316332	0.307851
24	0.1	0.385714	0.5	0.396483	0.231492	0.566403	0.369006	0.316332	0.375943
25	0.1	0.1	0.3	0.384854	0.222568	1	0.288186	0.288186	0.436759

meters are identified. Finally, the method of measurement for parameters and responses is decided.

2. *Design matrix and conduct of the experiments* For the selected process parameters and number of levels, suitable Taguchi design layout is selected. Based on the selected layout, the experiments are conducted and responses are measured and recorded.
3. *Development of NN model to predict full factorial design* To eliminate the influence of units and to avoid the omission of responses, it is normalized using Eq. (3). With

Table 6 Rules formed based on L_{27} orthogonal results

	IF SLAG is	IF SLAG is	IF SLAG is	IF SLAG is	IF SLAG is	Then GRG score is
1	HST	H	LST	M	HST	VH
2	HST	HST	LST	H	HST	HST
3	M	M	LST	M	H	M
4	L	M	L	M	M	M
5	L	L	LST	M	M	L
6	HST	M	LST	HST	HST	HST
7	L	M	L	H	H	M
8	M	M	L	L	M	M
9	L	L	L	L	L	L
10	LST	L	LST	L	L	L
11	M	H	LST	H	H	H
12	LST	M	L	L	M	L
13	L	LST	M	L	L	L
14	L	L	LST	LST	L	L
15	LST	LST	LST	LST	LST	L
16	H	M	LST	M	H	H
17	M	M	L	L	M	M
18	LST	L	LST	L	L	L
19	LST	LST	LST	L	LST	L
20	LST	LST	M	LST	LST	L
21	L	M	H	L	L	M
22	L	L	LST	L	L	L
23	LST	LST	LST	LST	LST	L
24	LST	LST	M	L	LST	L
25	LST	LST	HST	LST	LST	M
26	HST	H	LST	M	HST	VH
27	HST	HST	LST	H	HST	HST

the experimented data and using BPNN algorithm, a NN model is developed. Then, transfer function, learning function and performance evaluation are defined for BPNN algorithm. Based on the performance evaluation criteria and R^2 value, best structure (Number of neurons in input layer—Number of neurons in hidden layer—Number of neurons in output layer) is adopted. Using the developed neural network structure, the response for a full factorial design is predicted.

4. *Optimizing the parameters using FGRA* For all responses, reference sequences are derived. The closeness to reference sequence indicates better performance of a particular trial. Then, GRC is computed for all responses and trials ($\chi\ (x_{ok}, x_{ik})$) using Eq. (13). GRG is computed using FIS. Based on the conducted experiments, IF-THEN rules were developed in a fuzzy logic toolbox (MATLAB). Finally, using rule viewer, the GRG score for all 125 experiments were simulated. Based on the GRG score, the experimental trials were ranked and optimized parameters were selected. A high GRG score implies better performance of the responses for a particular trial.
5. *Conduct of LCA* LCA is conducted to validate the environmental performance improvement. For this, GtG LCA was conducted and environmental score was computed for the current practice and optimized parameters.

Results

The following subsection details the results obtained from the development of the ANN model and application of FGRA

Prediction of full factorial design

For three input parameters and five responses, a NN model of 3-X-1 was developed. The transfer function used is logsigmoid between input and hidden layers, and purelin between the hidden layer to the output layer. The learning function and rate is assumed in the NN toolbox

Table 7 Membership function defined for GRC and GRG scores

Fuzzy scale	Linguistic variable
(0.1, 0.2, 0.35)	Lowest (LST)
(0.2, 0.35, 0.45)	Low (L)
(0.35, 0. 5, 0.65)	Medium (M)
(0.5, 0.65, 0.75)	High (h)
(0.65, 0.75, 0.85)	Very high (VH)
(0.75, 0.85, 0.9)	Highest (HST)

of MATLAB package. For performance evaluation, MSE of 1E-10 is used. The number of neurons in the hidden layer is varied from 1 to 15. Of the 27 values, 17, 5 and 5 datasets are used for training, testing and validation. Based on the performance evaluation and R^2value, network structure 3-12-1 is found to be effective. Then, five models for five responses are developed. R^2 values pertaining to training and testing of the five models are shown in Table 3. Figure 5 depicts R^2 values pertaining to BPNN model developed for spatter. Finally, a full factorial design layout is designed for three parameters and five levels (125 trials), and the parameters are normalized using Eq. (3). By providing the input parameters, the response values for 125 trials are simulated and presented in "Appendix".

Optimization of parameters using FGRA

For the conducted 27 experiments, GRC score is computed using Eq. (13). Then, based on expert opinion, $\boldsymbol{\omega}$ value (refer Table 4) is computed based on AHP principle using Eq. (16). Based on the weight computed, GRG score is computed using Eq. (14). With the computed GRC and GRG scores (Table 5), 27 rules were defined in the FIS tool box (Table 6). For this, triangular fuzzy membership function was defined for GRC and GRG scores, and are shown in Table 7. For responses shown in Appendix I, the GRC scores are computed using Eq. (11). Then, FIS computes GRG score for the predicted 125 experiments (sample prediction is shown in Fig. 6). Based on the predicted GRG score, ANOVA is conducted to find the most influential parameters (Table 8).

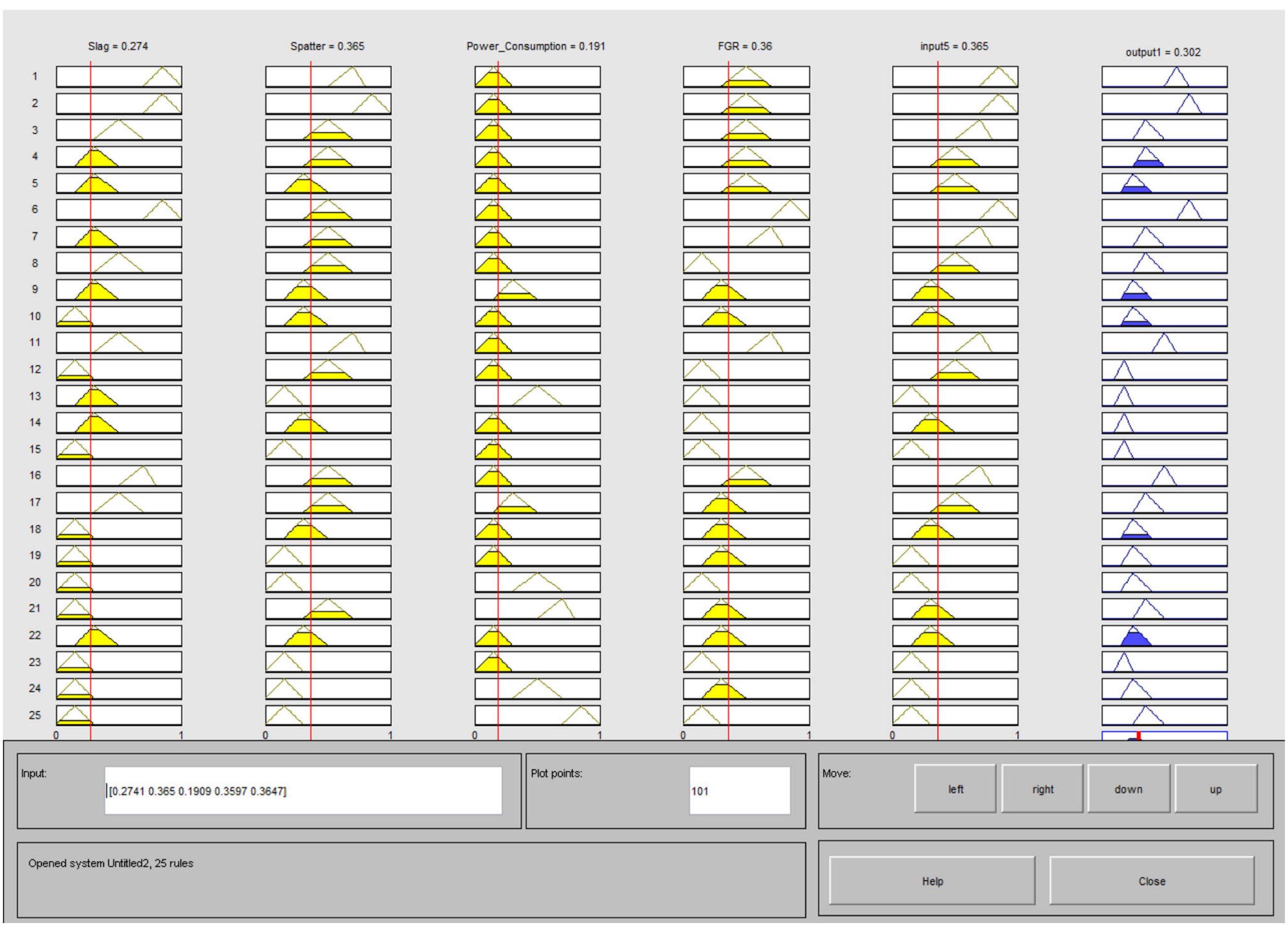


Fig. 6 FIS rule viewer

Table 8 ANOVA results

Source	DF	Seq SS	Adj SS	Adj MS	F	% of contribution
Current (A)	4	0.570973	0.570973	0.142743	28.19	29.3
Voltage (B)	4	1.239317	1.239317	0.309829	61.19	63.78
Welding speed (C)	4	0.031966	0.031966	0.007991	1.58	1.64
Current * Voltage	16	0.179344	0.179344	0.011209	2.21	2.3
Current * Welding speed	16	0.080542	0.080542	0.005034	0.99	1.03
Voltage * Welding Speed	16	0.061990	0.061990	0.003874	0.77	0.79
Error	64	0.324063	0.324063	0.005063		1.04
Total	124	2.488194				

Table 9 Mean responses for various levels

Level	A	B	C
1	0.4509	0.5190	0.3211
2	0.3724	0.3526	0.3522
3	0.3360	0.3267	0.3628
4	0.2725	0.2799	0.3241
5	0.2698	0.2234	0.3412

Using the contribution percentage, the most influential parameters are identified. The contribution percentage is computed using mean square values. The result implies that, the voltage (63.7 %) and current (29.3 %) are the influential parameters as compared to the welding speed (1.5 %). Then, the mean GRC was computed by taking the average of various level cumulative (Table 9). Using the mean GRC, an interaction plot was made (Fig. 7). The interaction plot suggests that, current at level 1 (110 A), voltage at level 1 (16 V) and speed at level 3 (180 mm/min) are the optimized input parameters (higher the GRC better the environmental performance). The optimized values and existing values of process parameters (refer "Experimental setup" section) are shown in Table 10. Using these values, improvement in environmental performance was evaluated using LCA. Also, Normal probability plot of residuals for GRG (Fig. 8) reveals that, variation in the residuals is minimal and almost fits as a straight line (distributed normally). The non existence of unusual structure and random pattern show minimal error in the computed GRG score. Thus, the FIS model is validated.

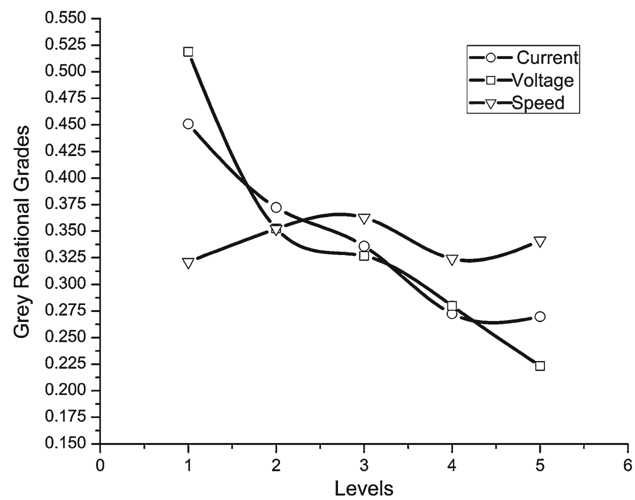


Fig. 7 Interaction of process parameters

Table 10 Inventory data

	Optimized process parameter	Existing process parameter
Current (A)	110	130
Voltage (V)	16	18
Welding speed (mm/s)	180	200

Environmental impact analysis

EIA is done using GtG LCA methodology and the major steps are discussed below.

Goal of the study Comparing the optimized process parameters with existing parameters

Inventory data Reference flow unit is collected for the functional unit of 200 mm. Inventory data such as, electrode consumption, energy consumption and other responses namely: slag, spatter, particulates, fumes, etc. are collected. The inventory data are listed in Table 6.

Life cycle impact assessment For the collected inventory data, environmental impact scores are characterized using Eco-Indicator'99 model. The results are shown in Figs. 9 and 10. Figure 9 depicts the comparison of input and Fig. 10

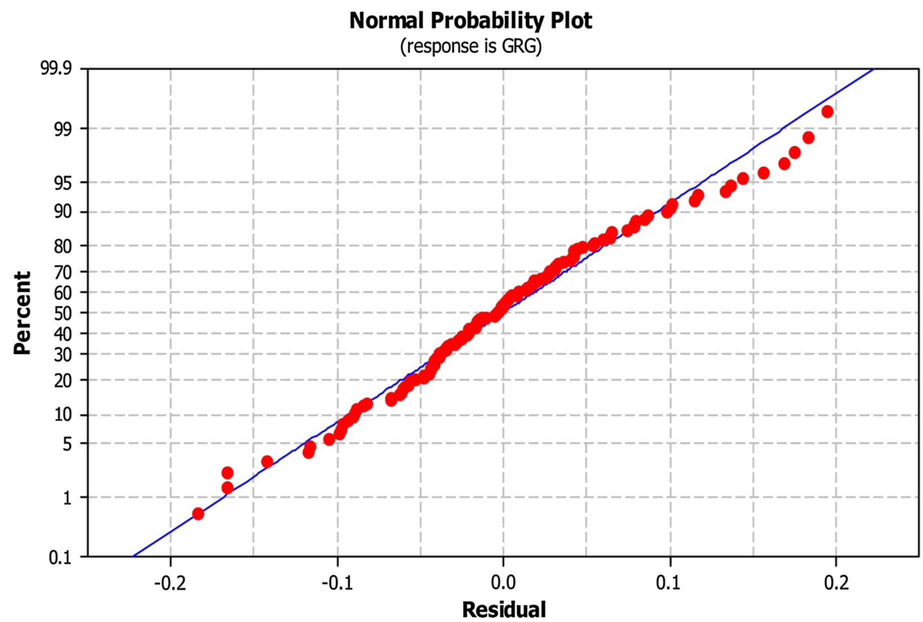


Fig. 8 Normal probability plot

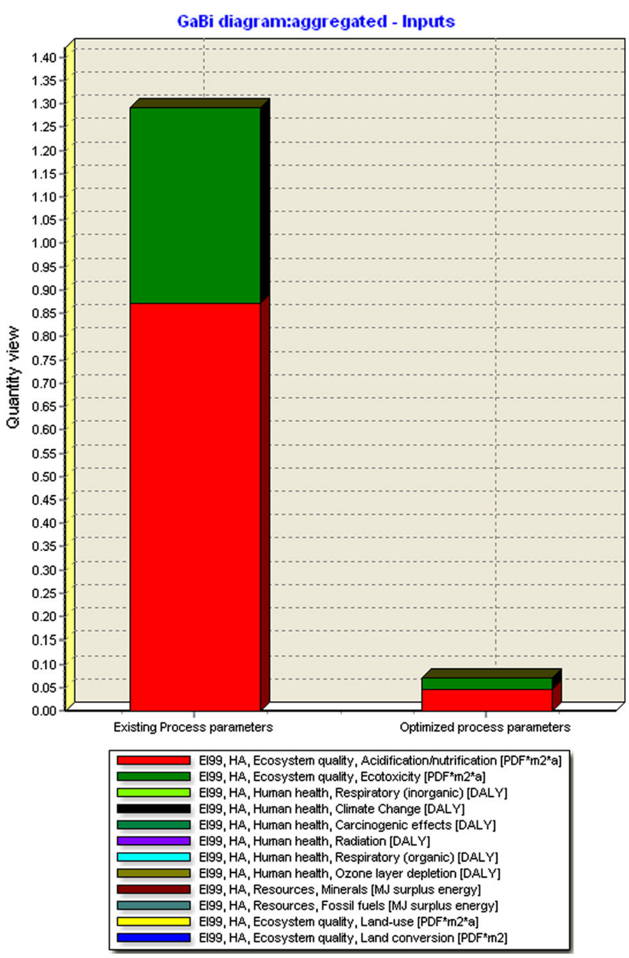


Fig. 9 Comparison of LCA scores computed for inputs

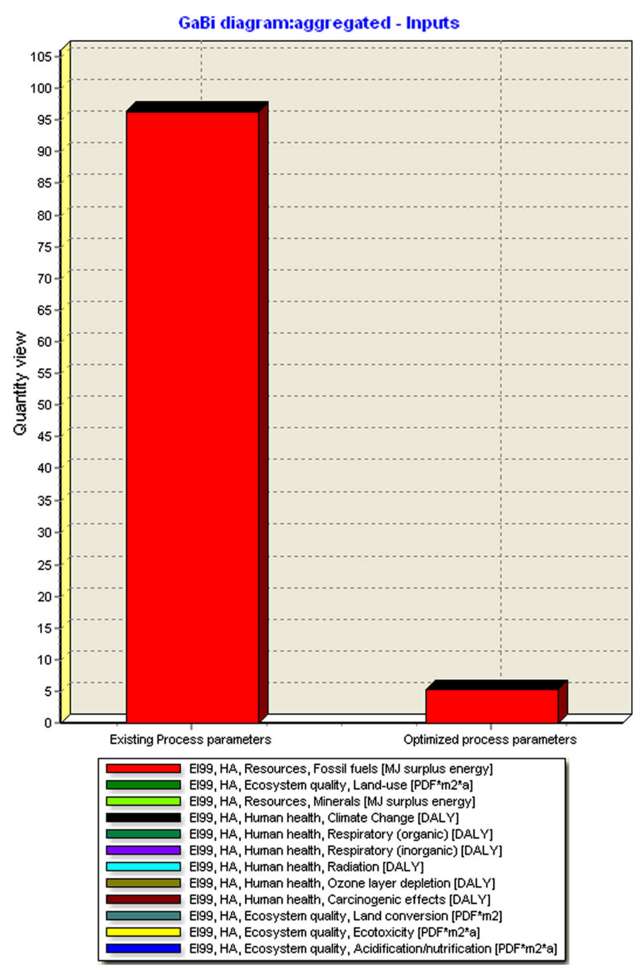


Fig. 10 Comparison of LCA scores computed for outputs

depicts the comparison of the output of existing and optimized process parameters.

Interpretation Based on the results, it is evident that, the adaptation of optimized parameters results in improvement from a sustainability viewpoint. The main reasons interpreted are: reduction in power consumption per millimeter of welding, reduction in spatter due to reduced arc length and improved stability. The optimized parameters are demonstrated to industry personnel and efforts are currently being undertaken for further deployment.

Conclusions

In an attempt at improving environmental performance of a manufacturing process, the SMAW process was studied. In the past, the environmental performance was studied in two ways: process control and end-of-pipe improvement. However, the process control method is widely recognized for its long term sustainability and economic viability. Thus, improvement in environmental performance is attempted through optimization of process parameters.

The main contribution of this study is to improve the environmental performance of the SMAW process through process parameters optimization not attempted in the past. Based on the pilot study and the SMAW process flow analysis, three inputs (current, voltage and welding speed) and five responses (slag, spatter, particulate formation, fume generation rate, and power consumption) are found to be critical to the environment. Taguchi's design of experiments is the widely accepted method to analyze the influence of parameters and its optimization. However, conclusion on influence of parameter with the conduct of selected trials may support detailed analysis. Thus, a methodology using the principles of design of experiments, neural network, and grey and fuzzy logic was developed which forms the other contribution of this study. Based on the conduct of study, current at level 1 (110 A), voltage at level 1 (16 V) and welding speed at level 3 (180 mm/s) are selected as optimized process parameters for ensuring a sustainable SMAW process.

The salient findings of the study include:

- Based on the process flow diagram, GhGs are found to be an important environmental burden. However, Linke (2013) suggested the omission of an input or output, if it does not influence the result significantly. Thus, GhG generation is omitted in the present study.
- BPNN algorithm with logsigmoid training function (input layer to hidden layer)—purelin (hidden layer to output layer) was used to simulate the responses. For the developed BPNN model, R^2 values of 0.99, 0.99, 0.989, 0.965 and 0.97 for slag, spatter, power consumption, FGR and particulate formation models respectively.
- Based on ANOVA results, the most significant parameter is voltage followed by current, whereas welding speed is found to be insignificant. But, welding speed influences the power consumption for the defined functional unit.
- Based on the conduct of EIA, environmental performance of the SMAW process attains 10 % improvement. Thus, the influence of welding process parameters on environmental performance was justified.

Based on these findings, it can be concluded that the proposed methodology is effective for complete analysis of influential process parameters and responses without compromising economical benefits and analysis quality.

Conflict of interest The authors declare that they have no conflict of interest.

Appendix

See Table 11.

Table 11 Simulated full factorial design using BPNN model

S. no	Current	Voltage	Speed	Slag	Spatter	Power	Part	FGR	Slag	Spatter	KW	Particulate	FGR	GRS
1.	0.1	0.9	0.1	0.9	0.80576	0.59351	0.31138	0.30209	0.166667	0.217648	0.139492	0.486169	0.441879	0.290371
2.	0.9	0.614	0.5	0.21406	0.83755	0.68334	0.65644	0.79193	0.583814	0.209267	0.120602	0.264396	0.187809	0.273178
3.	0.3	0.271	0.9	0.24348	0.58859	0.43437	0.22489	0.41798	0.527218	0.29963	0.193064	0.615593	0.334742	0.394049
4.	0.7	0.9	0.5	0.9	0.83122	0.74442	0.59181	0.81855	0.166667	0.210884	0.110433	0.289097	0.182118	0.19184
5.	0.7	0.1	0.3	0.60934	0.50015	0.21868	0.72376	0.14666	0.239041	0.353919	0.402658	0.242789	0.774219	0.402525
6.	0.5	0.442	0.9	0.65966	0.70003	0.51178	0.55941	0.37564	0.222327	0.251096	0.162674	0.303301	0.367276	0.261335
7.	0.7	0.442	0.1	0.74718	0.6335	0.66541	0.47608	0.47568	0.198221	0.277977	0.123952	0.347174	0.298686	0.249202
8.	0.3	0.442	0.3	0.79395	0.57537	0.39328	0.18436	0.23902	0.187365	0.306662	0.214316	0.703334	0.535081	0.389352
9.	0.9	0.1	0.5	0.50694	0.51407	0.2912	0.71476	0.38598	0.282217	0.344106	0.294985	0.245471	0.35876	0.305108
10.	0.7	0.1	0.1	0.9	0.66604	0.34723	0.49325	0.19579	0.166667	0.264147	0.244476	0.337126	0.625513	0.327586
11.	0.1	0.614	0.5	0.29958	0.68345	0.44359	0.4989	0.34123	0.444964	0.257297	0.188862	0.333946	0.398774	0.324768
12.	0.7	0.1	0.5	0.59622	0.32905	0.19519	0.46733	0.20471	0.243821	0.544939	0.456647	0.352529	0.604435	0.440474
13.	0.3	0.442	0.5	0.40013	0.53693	0.62435	0.38183	0.27986	0.347728	0.32912	0.132374	0.415084	0.470782	0.339017
14.	0.7	0.271	0.3	0.67353	0.56965	0.64494	0.6168	0.22238	0.218123	0.309807	0.128012	0.279018	0.566612	0.300315
15.	0.5	0.1	0.7	0.24142	0.23661	0.43292	0.22527	0.19625	0.530821	0.76925	0.193742	0.614874	0.62439	0.546615
16.	0.7	0.614	0.7	0.79099	0.84709	0.74322	0.82495	0.5726	0.188016	0.206876	0.110616	0.216228	0.252924	0.194932
17.	0.3	0.614	0.5	0.18321	0.6808	0.64212	0.6106	0.54445	0.657868	0.258317	0.128593	0.281452	0.264703	0.318187
18.	0.7	0.1	0.7	0.2075	0.32278	0.37357	0.4224	0.31504	0.598131	0.555935	0.226264	0.382848	0.426621	0.43796
19.	0.7	0.442	0.7	0.35645	0.7641	0.67408	0.71214	0.29999	0.3842	0.229705	0.122309	0.246263	0.444457	0.285387
20.	0.3	0.9	0.9	0.9	0.69821	0.44811	0.4863	0.9	0.166667	0.251762	0.186868	0.341122	0.166667	0.222617
21.	0.1	0.9	0.5	0.33025	0.83516	0.49173	0.68891	0.27632	0.409994	0.209875	0.169589	0.253514	0.475737	0.303742
22.	0.1	0.9	0.7	0.35609	0.69992	0.40582	0.53732	0.39409	0.384532	0.251137	0.207351	0.313814	0.352353	0.301837
23.	0.7	0.1	0.9	0.1	0.33411	0.4788	0.23789	0.39132	1	0.536378	0.174368	0.591909	0.354516	0.531434
24.	0.5	0.1	0.3	0.61593	0.47192	0.25696	0.1	0.10686	0.236711	0.375645	0.33761	1	0.958888	0.581771
25.	0.1	0.1	0.1	0.7117	0.20465	0.1	0.23161	0.17951	0.207334	0.896891	1	0.603118	0.668031	0.675075
26.	0.5	0.614	0.5	0.17041	0.78764	0.72312	0.59102	0.50739	0.694414	0.222733	0.113779	0.289427	0.281993	0.320469
27.	0.9	0.1	0.1	0.7793	0.60932	0.21742	0.84706	0.22202	0.190635	0.289231	0.405227	0.21118	0.567336	0.332722
28.	0.5	0.1	0.5	0.65133	0.25063	0.21258	0.23119	0.12298	0.224931	0.724048	0.415412	0.603883	0.874413	0.568537
29.	0.5	0.9	0.1	0.9	0.82351	0.82937	0.65505	0.77062	0.166667	0.212888	0.098842	0.264883	0.192627	0.187181
30.	0.1	0.9	0.9	0.83557	0.49853	0.36445	0.43627	0.40556	0.178657	0.355098	0.232254	0.372946	0.343672	0.296526
31.	0.5	0.442	0.7	0.43602	0.76741	0.7354	0.70464	0.25142	0.322568	0.228698	0.111826	0.248558	0.513776	0.285085
32.	0.1	0.1	0.7	0.58702	0.34727	0.1	0.1	0.343	0.247288	0.515321	1	1	0.397022	0.631926
33.	0.3	0.1	0.3	0.46929	0.26632	0.15113	0.1	0.11992	0.302292	0.679372	0.610082	1	0.889284	0.696206
34.	0.7	0.271	0.7	0.17338	0.55189	0.53314	0.5952	0.33862	0.685577	0.319999	0.155903	0.287687	0.401385	0.37011
35.	0.5	0.271	0.9	0.15598	0.40582	0.45887	0.10845	0.40582	0.740809	0.4387	0.182286	0.959463	0.34348	0.532948

Table 11 continued

S. no	Current	Voltage	Speed	Slag	Spatter	Power	Part	FGR	Slag	Spatter	KW	Particulate	FGR	GRS
36.	0.7	0.614	0.3	0.54116	0.78817	0.9	0.58833	0.58476	0.266152	0.222581	0.090909	0.290558	0.248154	0.223671
37.	0.9	0.614	0.3	0.55152	0.81918	0.85293	0.42876	0.80969	0.261643	0.21403	0.096046	0.378243	0.183974	0.226787
38.	0.3	0.614	0.1	0.1	0.71698	0.35977	0.54859	0.55784	1	0.245059	0.235453	0.308361	0.258967	0.409568
39.	0.7	0.9	0.3	0.79632	0.75222	0.76644	0.48371	0.78193	0.186846	0.233392	0.107175	0.342636	0.19004	0.212018
40.	0.3	0.614	0.9	0.9	0.67051	0.46709	0.50666	0.40112	0.166667	0.262353	0.178935	0.329674	0.346981	0.256922
41.	0.5	0.9	0.7	0.9	0.78257	0.82016	0.84064	0.9	0.166667	0.224199	0.09998	0.212621	0.166667	0.174027
42.	0.9	0.9	0.1	0.9	0.77747	0.9	0.13823	0.78722	0.166667	0.225693	0.090909	0.839525	0.188853	0.302329
43.	0.9	0.442	0.3	0.55438	0.67457	0.72862	0.76331	0.7728	0.260425	0.260746	0.112895	0.231666	0.192123	0.211571
44.	0.1	0.1	0.9	0.18186	0.49282	0.1	0.51213	0.39392	0.66154	0.359315	1	0.326728	0.352485	0.540014
45.	0.5	0.271	0.3	0.70509	0.6255	0.48894	0.12937	0.14788	0.209126	0.281602	0.170598	0.871954	0.769675	0.460591
46.	0.1	0.1	0.5	0.50499	0.21313	0.1	0.1	0.25188	0.283191	0.85907	1	1	0.513018	0.731056
47.	0.9	0.271	0.1	0.80596	0.59745	0.46518	0.61975	0.43245	0.184766	0.295095	0.179703	0.277874	0.324906	0.252469
48.	0.3	0.1	0.1	0.64565	0.25398	0.23271	0.20635	0.24076	0.226741	0.714023	0.376099	0.652848	0.531986	0.500339
49.	0.9	0.9	0.3	0.9	0.85605	0.88479	0.24156	0.75177	0.166667	0.20468	0.092508	0.585549	0.1971	0.249301
50.	0.1	0.9	0.3	0.75827	0.84572	0.56856	0.50402	0.25268	0.195534	0.207216	0.145836	0.331115	0.511705	0.278281
51.	0.3	0.9	0.7	0.51864	0.67476	0.47094	0.87167	0.88043	0.27651	0.260671	0.177407	0.205831	0.170135	0.218111
52.	0.3	0.271	0.3	0.73429	0.32539	0.21353	0.15264	0.13872	0.201438	0.551304	0.413373	0.79164	0.805153	0.552582
53.	0.9	0.1	0.7	0.19702	0.56009	0.44553	0.44711	0.41683	0.62252	0.315212	0.188001	0.365557	0.335549	0.365368
54.	0.3	0.1	0.5	0.49226	0.21313	0.10387	0.1	0.1558	0.289719	0.85907	0.953857	1	0.741427	0.768815
55.	0.3	0.1	0.9	0.1	0.35994	0.33379	0.20288	0.43785	1	0.496554	0.254948	0.660328	0.321382	0.546642
56.	0.3	0.442	0.7	0.30418	0.60575	0.60456	0.4745	0.34775	0.439343	0.29097	0.136855	0.348129	0.392397	0.321539
57.	0.3	0.271	0.5	0.49125	0.34246	0.35545	0.19627	0.21529	0.290249	0.522823	0.238486	0.67506	0.581205	0.461565
58.	0.1	0.442	0.9	0.57483	0.51011	0.44005	0.1	0.16751	0.252036	0.346842	0.190454	1	0.703266	0.498519
59.0.	0.5	0.614	0.7	0.65288	0.83797	0.70336	0.71735	0.48302	0.224442	0.209161	0.117069	0.244693	0.294648	0.218003
60.	0.3	0.9	0.5	0.39278	0.73787	0.70159	0.9	0.56317	0.353372	0.238006	0.117373	0.2	0.256752	0.233101
61.	0.9	0.614	0.7	0.9	0.83158	0.61441	0.71809	0.71551	0.166667	0.210791	0.134587	0.244472	0.206316	0.192567
62.	0.1	0.271	0.5	0.55626	0.27493	0.1	0.19372	0.22939	0.259631	0.657122	1	0.680921	0.552887	0.630112
63.	0.9	0.9	0.9	0.9	0.8758	0.59445	0.9	0.9	0.166667	0.2	0.139264	0.2	0.166667	0.174519
64.	0.7	0.9	0.7	0.9	0.85949	0.9	0.78535	0.9	0.166667	0.203849	0.090909	0.225899	0.166667	0.170798
65.	0.9	0.1	0.9	0.14546	0.44154	0.46892	0.61585	0.37504	0.77874	0.402215	0.178205	0.279388	0.367782	0.401266
66.	0.9	0.442	0.5	0.1	0.75005	0.56527	0.82052	0.63193	1	0.234078	0.146716	0.217269	0.231237	0.36586
67.	0.5	0.271	0.7	0.32429	0.40345	0.7392	0.56845	0.24094	0.416352	0.441357	0.111235	0.2992	0.531667	0.359962
68.	0.5	0.9	0.3	0.69273	0.75452	0.85542	0.75168	0.6094	0.21256	0.232669	0.09576	0.23483	0.23902	0.202968
69.	0.1	0.271429	0.9	0.62813	0.79513	0.33798	0.31812	0.67107	0.232514	0.220603	0.251588	0.478332	0.218857	0.280379
70.	0.7	0.614	0.9	0.9	0.84533	0.61007	0.74003	0.44495	0.166667	0.207313	0.135577	0.238087	0.316863	0.212901

Table 11 continued

S. no	Current	Voltage	Speed	Slag	Spatter	Power	Part	FGR	Slag	Spatter	KW	Particulate	FGR	GRS
71.	0.1	0.614	0.3	0.9	0.713	0.37991	0.27084	0.39413	0.166667	0.24645	0.222278	0.539316	0.352322	0.305407
72.	0.1	0.271429	0.3	0.75305	0.84545	0.1	0.9	0.51032	0.19679	0.207283	1	0.2	0.280544	0.376923
73.	0.1	0.442	0.5	0.47706	0.40686	0.28185	0.35355	0.2059	0.297918	0.437545	0.305518	0.440966	0.60173	0.416735
74.	0.9	0.271429	0.5	0.75872	0.7869	0.53934	0.89801	0.9	0.195427	0.222946	0.154042	0.200399	0.166667	0.187896
75.	0.9	0.614	0.1	0.86499	0.72514	0.85267	0.38345	0.9	0.172975	0.242255	0.096076	0.413693	0.166667	0.218333
76.	0.7	0.442	0.9	0.50641	0.7201	0.42615	0.67885	0.2458	0.282481	0.243979	0.196972	0.256789	0.523218	0.300688
77.	0.5	0.614	0.1	0.74544	0.64602	0.57534	0.67053	0.50376	0.198649	0.272488	0.144056	0.259562	0.283809	0.231713
78.	0.3	0.271429	0.7	0.65654	0.79511	0.54343	0.9	0.67784	0.223295	0.220609	0.152838	0.2	0.216849	0.202718
79.	0.3	0.614	0.3	0.66821	0.70189	0.5082	0.27472	0.51221	0.219717	0.250419	0.163867	0.533732	0.279618	0.289471
80.	0.5	0.1	0.9	0.1	0.30081	0.43727	0.1	0.38078	1	0.59823	0.191722	1	0.362993	0.630589
81.	0.7	0.271429	0.5	0.68768	0.79417	0.77115	0.72416	0.86354	0.213995	0.220874	0.106503	0.242671	0.173246	0.191458
82.	0.1	0.271429	0.7	0.57393	0.79569	0.10257	0.6531	0.65657	0.252394	0.220445	0.968875	0.265569	0.223286	0.386114
83.	0.7	0.271429	0.1	0.64108	0.78571	0.56255	0.76513	0.73049	0.228219	0.223289	0.147452	0.231179	0.202406	0.206509
84.	0.7	0.271429	0.9	0.9	0.76358	0.38778	0.9	0.9	0.166667	0.229864	0.217521	0.2	0.166667	0.196144
85.	0.5	0.614	0.9	0.9	0.8268	0.69502	0.9	0.51712	0.166667	0.212028	0.118515	0.2	0.277239	0.19489
86.	0.3	0.442	0.9	0.71737	0.68147	0.36079	0.35235	0.32207	0.205822	0.258058	0.234749	0.442136	0.418771	0.311907
87.	0.7	0.442	0.3	0.66152	0.66834	0.9	0.543	0.49945	0.221754	0.263221	0.090909	0.311042	0.285995	0.234584
88.	0.5	0.442	0.5	0.33189	0.75628	0.88175	0.32123	0.24494	0.408278	0.232119	0.092834	0.4748	0.524693	0.346545
89.	0.3	0.271429	0.1	0.57773	0.85095	0.20404	0.82015	0.477	0.25089	0.205924	0.434688	0.217356	0.297952	0.281362
90.	0.9	0.9	0.7	0.9	0.87321	0.81288	0.83389	0.9	0.166667	0.200602	0.100898	0.214158	0.166667	0.169798
91.	0.9	0.442	0.1	0.89171	0.65524	0.66566	0.47304	0.77403	0.168118	0.268582	0.123904	0.349016	0.19184	0.220292
92.	0.5	0.271	0.1	0.87207	0.54257	0.42517	0.44825	0.21794	0.171661	0.325621	0.197448	0.364797	0.575664	0.327038
93.	0.5	0.442	0.1	0.8286	0.49394	0.48326	0.60451	0.44466	0.180059	0.35848	0.172689	0.283885	0.317045	0.262432
94.	0.5	0.9	0.9	0.9	0.8467	0.86937	0.68166	0.9	0.166667	0.206973	0.094187	0.255866	0.166667	0.178072
95.	0.5	0.1	0.1	0.79166	0.57181	0.34521	0.33991	0.22025	0.187868	0.308612	0.245995	0.454638	0.570919	0.353607
96.	0.9	0.271	0.9	0.26112	0.62179	0.49535	0.70397	0.2377	0.498256	0.283316	0.168297	0.248766	0.537454	0.347218
97.	0.7	0.614	0.1	0.64315	0.62243	0.79425	0.54882	0.65064	0.227547	0.283019	0.103326	0.308252	0.225149	0.229459
98.	0.5	0.9	0.5	0.59393	0.69435	0.8248	0.89082	0.72839	0.244675	0.253187	0.099404	0.201853	0.202945	0.200413
99.	0.1	0.1	0.3	0.53611	0.18479	0.1	0.15487	0.18819	0.268407	1	1	0.784714	0.644667	0.739558
100.	0.1	0.614	0.9	0.9	0.37347	0.44991	0.1	0.1	0.166667	0.477966	0.186085	1	1	0.566144
101.	0.1	0.442	0.7	0.27809	0.4426	0.38925	0.35507	0.22816	0.473247	0.401225	0.216655	0.439493	0.555247	0.417173
102.	0.9	0.1	0.3	0.42365	0.50603	0.17689	0.9	0.29791	0.330818	0.349707	0.509911	0.2	0.44704	0.367495
103.	0.9	0.614	0.9	0.9	0.82226	0.58934	0.71558	0.53716	0.166667	0.213216	0.140514	0.245224	0.267935	0.206711
104.	0.7	0.442	0.5	0.31993	0.76183	0.9	0.71012	0.45559	0.42113	0.2304	0.090909	0.246877	0.310324	0.259928
105.	0.3	0.1	0.7	0.45067	0.26243	0.25397	0.1	0.32849	0.313314	0.689927	0.341924	1	0.411851	0.551403

Table 11 continued

S. no	Current	Voltage	Speed	Slag	Spatter	Power	Part	FGR	Slag	Spatter	KW	Particulate	FGR	GRS
106.	0.9	0.271	0.7	0.17806	0.69736	0.49472	0.70027	0.35755	0.672099	0.252075	0.16852	0.249916	0.383188	0.34516
107.	0.5	0.271	0.5	0.62291	0.46649	0.73747	0.18117	0.15599	0.234291	0.380133	0.111503	0.711313	0.740775	0.435603
108.	0.3	0.9	0.1	0.89954	0.82619	0.68577	0.54415	0.47808	0.166747	0.212187	0.120162	0.310487	0.297354	0.221387
109.	0.3	0.442	0.1	0.9	0.6029	0.20673	0.44843	0.37312	0.166667	0.292373	0.428426	0.364677	0.369413	0.324311
110.	0.9	0.271	0.3	0.37589	0.53307	0.53072	0.9	0.44917	0.367065	0.331558	0.156642	0.2	0.314237	0.2739
111.	0.1	0.614	0.1	0.9	0.73352	0.31723	0.10592	0.40631	0.166667	0.239441	0.269152	0.971251	0.343119	0.397926
112.	0.1	0.442	0.3	0.8793	0.48699	0.28113	0.27977	0.12074	0.17034	0.363726	0.306361	0.526635	0.88525	0.450462
113.	0.5	0.442	0.3	0.55597	0.62206	0.71187	0.39633	0.32436	0.259753	0.28319	0.115629	0.402958	0.416276	0.295561
114.	0.1	0.271	0.1	0.86972	0.35249	0.9	0.27297	0.1	0.172095	0.50742	0.090909	0.536236	1	0.461332
115.	0.7	0.9	0.9	0.9	0.86854	0.9	0.9	0.9	0.166667	0.201695	0.090909	0.2	0.166667	0.165188
116.	0.9	0.442	0.9	0.66128	0.71437	0.6107	0.6976	0.22379	0.221828	0.24597	0.135433	0.250752	0.563797	0.283556
117.	0.1	0.442	0.1	0.9	0.65739	0.12139	0.26336	0.1	0.166667	0.267687	0.789032	0.550418	1	0.554761
118.	0.7	0.9	0.1	0.9	0.75184	0.84124	0.43883	0.80039	0.166667	0.233512	0.097414	0.371175	0.185962	0.210946
119.	0.9	0.9	0.5	0.9	0.87398	0.88092	0.57305	0.7807	0.166667	0.200422	0.092924	0.297155	0.190318	0.189497
120.	0.5	0.614	0.3	0.53558	0.69037	0.73487	0.62459	0.46156	0.268646	0.254672	0.111908	0.276018	0.306772	0.243603
121.	0.7	0.614	0.5	0.22021	0.84874	0.84114	0.74819	0.65382	0.571	0.206468	0.097426	0.235796	0.224146	0.266967
122.	0.3	0.9	0.3	0.7339	0.83069	0.81672	0.63315	0.32685	0.201537	0.211021	0.100412	0.272795	0.413597	0.239872
123.	0.1	0.614	0.7	0.31023	0.44998	0.51121	0.40557	0.16861	0.432164	0.394464	0.162863	0.395593	0.699882	0.416993
124.	0.3	0.614	0.7	0.48525	0.65266	0.5533	0.71264	0.42513	0.293443	0.269663	0.150009	0.246111	0.329809	0.257807
125.	0.9	0.442	0.7	0.32115	0.74709	0.54667	0.80045	0.35864	0.419782	0.235021	0.151898	0.222111	0.38219	0.2822

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