# Chapter 18
# Experimental Investigation for Energy-Conscious Welding Based on Artificial Neural Network

**Sudeep Kumar Singh, Suvam Sourav Swain, Amit Kumar, Prashanjeet Patra, Nitesh Kumar, and A. M. Mohanty**

## 1 Introduction

Shielded Metal Arc Welding (SMAW) of Mild Steel (MS) finds wide application in structural frames, pipelines, visually aesthetic designs, and repair due to its high ductility and weldability properties [1–3]. Welding remains the most widely adopted joining process in the industry despite its high energy-intensive property. The selection of proper welding parameters is very important in a multi-input multi-output process like welding [4, 5]. The mechanical properties of welded joints largely depend on process parameters used in the manufacturing process [6]. The welder generally focuses on the quality aspects of the produced joints and pays lesser attention to the process parameters. In practice, the welding process parameters selected imparts a large influence on the resources consumed like joint quality, percentage of rework/rejection, and energy consumed [7]. Power consumption is one among many factors responsible for the negative environmental effects generated from welding operation, raising the need for characterization of the SMAW process considering sustainability aspects [3, 8]. Thus, the present study intends to draw a relationship between the four influential input parameters and the four output parameters adopted for investigation.

S. K. Singh (✉) · S. S. Swain · A. Kumar · P. Patra · N. Kumar · A. M. Mohanty
Centurion University of Technology and Management, Odisha Bhubaneswar, India
e-mail: sudeepuce008@gmail.com



M. Shorif Uddin et al. (eds.), *Intelligent Energy Management Technologies*,
Algorithms for Intelligent Systems,
https://doi.org/10.1007/978-981-15-8820-4_18

## 2 Literature Survey

Adnan et al. [4] carried out Pareto Analysis to find uncontrollable input parameters of the GMAW welding process. They developed three different ANN models for input, output parameter prediction, and classifying products. ANN was also employed for investigating the effects of process parameters in laser welding of AA5754 aluminum alloy [9]. Two parameters welding speed and shielding gas were varied, and the optimization process was implemented using an Excel add-in named Neural Tools. In yet another study, authors developed two different ANN models one for classification of defective products and other for prediction of input parameters [5]. Welding processes have a poor environmental image for which optimization of key welding parameters is very crucial. A hybrid approach involving neural network and fuzzy logic is used for optimizing SMAW process parameters from the sustainability point of view [8]. Current, voltage and welding speed are considered for analysis. Welding of dissimilar metals involving Al alloy and stainless steel has been studied using the laser-arc welding technique [10]. Taguchi is used for studying the effect of various welding parameters to get optimum parameters of angular distortion in SMAW [11]. TIG welding parameter has been optimized using Response Surface Methodology (RSM), central composite design on mild steel [12], and grey wolf optimizer [13] on high strength low alloy 15CDV6 steel. RSM has also been adopted for optimizing GMAW parameters for welding mild steel IS:2062 [14]. Authors [15] have developed model for prediction of mechanical and microstructural properties of copper plate welding using Friction Stir Welding. RPLNN and GA have been used involving three inputs and two response parameters.

Weld quality considering tensile properties and microstructure were analyzed based on power distribution using an arc assisted fiber laser welding of Al–Mg alloy [16]. Tensile and impact properties in multi-pass SMAW have been investigated by Saxena et al. for determining the influence of welding consumables in Armox 500T alloy [17]. Mechanical properties and microstructure of MS welded parts under varying current were analyzed using the E7016 electrode [1]. The highest tensile strength was obtained at 75A with minor welding defects. Sheets of different thicknesses welded using SMAW and GMAW were investigated for finding a new set of welding parameters for structural grade steel welding [6].

The main aim of the current research work is to study the influence of varying input parameters on the output quality of the joint.

The arrangement of the paper is as follows. The experimental methodology is explained in Sect. 3. The next section discusses the outcomes of the experimental and test results. The fifth section discusses the application of ANN for welding parameter selection. The sixth section presents conclusions obtained from the analysis and also provides directions for future scope.

## 3 Methodology

The strategy followed in the current work can be divided into different sections of which, arc welding, testing for obtaining output data, and selection of input parameters to the welding process based on influential responses of welding are important. Arc welding of mild steel considering energy consumption has been considered in the present investigation. The strategy followed in the current investigation is presented pictorially in Fig. 1.

Mild steel plates of different thicknesses 3, 5, and 10 mm (three levels) were utilized in the welding process. The welding parameters, current, joint gap, and face width were also varied during the experiment. The input parameters considered in the investigation include the welding parameters and the plate thicknesses. The output parameters considered are Ultimate Tensile Strength (UTS), impact energy (Izod), Rockwell hardness, and energy consumption. The input parameters (factors) involved in the study are presented in Table 1.

Mild steel procured in flat form was first cut to a rectangular shape with length 200 mm and width 100 mm. One longitudinal edge of each plate was beveled to produce a double V-groove butt joint. The including angle of the V-shaped joint is 60° for all the plates used. The chemical composition of the plates was tested using XRF spectrometer, and the obtained values are tabulated in Table 2.

The data presented in the table displays close conformance in terms of composition for both the workpiece and filler metals. The filler rod used in the welding process is 3.15 mm in diameter Superweld E6013 manufactured by ESAB. The XRF samples for both material types were prepared by grinding on a surface grinder.

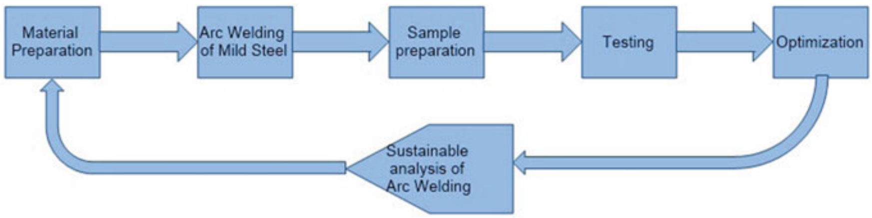


**Fig. 1** Experimental methodology

**Table 1** Different values for the input variables

| Sl. no | Factors | Level 1 | Level 2 | Level 3 |
|---|---|---|---|---|
| 1 | Current | 100A | 110A | 120A |
| 2 | Plate thickness | 3 mm | 5 mm | 10 mm |
| 3 | Root gap | 0 mm | 1 mm | 2 mm |
| 4 | Face width | 0 mm | 1 mm | 2 mm |

**Table 2** Material composition

| Sl. no. | Base material | Si | Mn | S | P | Fe |
|---|---|---|---|---|---|---|
| 1 | Mild steel plate | 0.720 | 0.709 | 0.132 | 0.029 | 96.840 |
| 2 | Electrode E6013 | 1.451 | 0.437 | 0.125 | 0.034 | 96.115 |

**Table 3** Experimental values in the investigation

| Sl. no. | Current (A) | Plate thickness (mm) | Root gap (mm) | Face width (mm) | Power (kW) | UTS (MPa) | Hardness (HRB) | Impact energy (J) |
|---|---|---|---|---|---|---|---|---|
| 1 | 100 | 3 | 0 | 0 | 4.73 | 481 | 76.4 | 60 |
| 2 | 100 | 5 | 1 | 1 | 4.52 | 411 | 77.25 | 62 |
| 3 | 100 | 10 | 2 | 2 | 5.32 | 305 | 83.9 | 74 |
| 4 | 110 | 3 | 1 | 2 | 4.59 | 295 | 78.1 | 50 |
| 5 | 110 | 5 | 2 | 0 | 5.52 | 501 | 78.6 | 52 |
| 6 | 110 | 10 | 0 | 1 | 5.14 | 406 | 85.55 | 160 |
| 7 | 120 | 3 | 2 | 1 | 5.88 | 458 | 80.6 | 52 |
| 8 | 120 | 5 | 0 | 2 | 6.59 | 362 | 84.05 | 112 |
| 9 | 120 | 10 | 1 | 0 | 5.89 | 329 | 82.65 | 110 |

The plates were cleaned properly using solvent to remove all dirt, rust present on the surface of the material to be welded. It is followed by welding the plates using process parameters obtained from TAGUCHI orthogonal array design presented in Table 3.

### 3.1 The Welding Process

Similar to the raw material of three different thickness values, the input current has also been varied into the same number of current values and adopted for the experiments: 100, 110, and 120 amperes. The remaining two input variables adopted are root gap and face width. Three different values were considered for both the variables as 0, 1, and 2 mm. All the varying parameters are taken together, including the plate thickness values, make the total number of factors involved in the experimental design as four. The number of levels for each factor is three. Thus, if the full factorial design of experiments was to be considered, the total number of experiments would become 27. To reduce the number of experiments, Taguchi Design of Experiment (DoE) method was adopted. Using L9 Taguchi orthogonal array design adopting a four-factor and three-level experimental approach, the total number of experimental runs was reduced to 9. The experimental design adopted for the experiments is presented in Table 3.

The welding process was carried out by using RS400 a Thyristorised MMA welding machine manufactured by ESAB India Ltd. The machine is equipped with 50 Hz 3-phase power supply with an input voltage of 415 volts and 27-ampere current. The welding runs were carried out using the AC power supply.

A 3-phase power analyser, model no DPATT-3Bi, manufactured by Uma Electronics Enterprises, Jaipur, India, was used for measuring the instantaneous power consumption values during the arc welding process. A three-phase four-wire connection was used in the process of measurement.

Table 3 presents the four factors and the values of the three levels of process parameters adopted in the experimental runs. It displays the values of different process parameters used in the welding process. Four different parameters welding current, plate thickness, root gap, and face width are used for designing nine number of experiments in total.

The welding speed was considered constant throughout the experiment. The plates of 3 mm thickness were welded using a single pass of welding, but multiple runs were necessary for plates with 5 mm and 10 mm thickness. The former was welded with two passes, and for the latter three number of welding, passes were used. In total, nine numbers of welding joints were produced and processed further for preparing test samples for tensile. Rockwell and Izod impact tests to be conducted further. The details of the test procedure and results have been explained in the next section.

## 4 Post-weld Testing

The welded steel plates were cleaned to remove the slag deposited during welding by using a chipping hammer and wire brush. Tensile, hardness, and Izod test specimens were extracted from the welded plates of different thicknesses with the respective dimensions, presented in Fig. 2.

Welding beads were removed by grinding operation from the welded surface for both the tests.

The tensile test was conducted on a Universal Testing machine manufactured by Blue Star Engineering & Electronics Ltd., having a maximum capacity of 1000 kN. The test specimens were made to undergo the tensile testing procedure, and the Ultimate Tensile Strength values for each test specimen were noted. The average value of HRB was calculated after measuring hardness values at two different points on the weld bead surface. The samples prepared for the Izod test were carried out using Impact test machine, and values of energy absorbed before failure for individual specimen were recorded. The values of UTS, HRB, and energy absorbed have been presented in Table 3 under respective columns.

Figure 3 displays phases of sample preparation for different tests after conducting the tensile, Rockwell, and Izod tests. The Fig. 4a displays the Impact testing machine, and 4 (b) depicts the Rockwell hardness testing machine used for the experimentation.

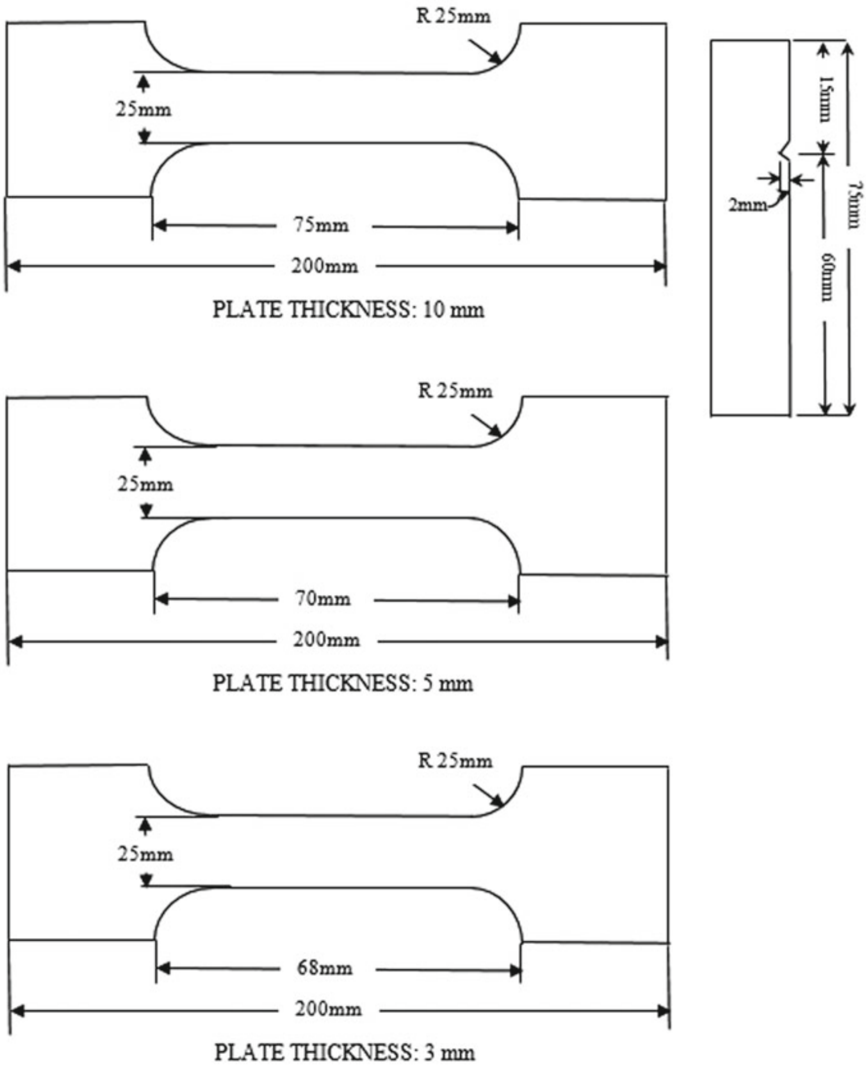


**Fig. 2** Schematic diagrams of **a** Tensile Test specimen; **b** Izod specimen

## 5 Parameter Selection Using ANN

Neural networks find a wide application and recognized as efficient solvers of non-linear problems. Successful applications have been reported in literature containing real-world problems. Thus, ANN has been selected for finding optimum input parameters for SMAW in the present study. The architecture for the employed neural net is presented in Fig. 5.

Fig. 3 Pictorial representations of **a** Tensile Test; **b** Hardness; **c** Izod Specimens

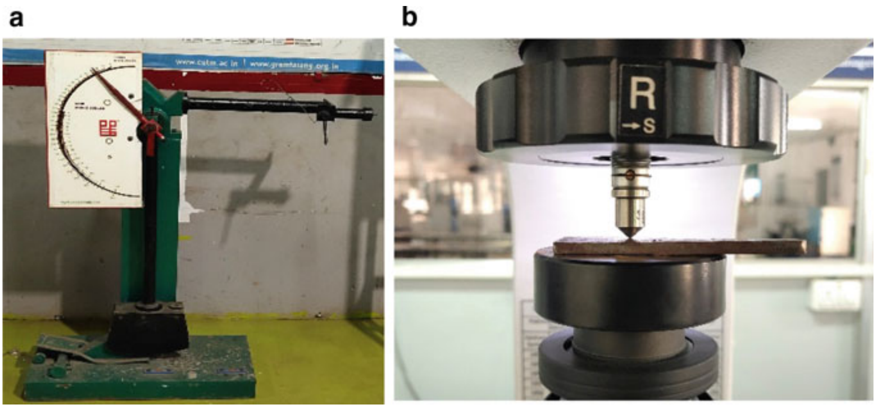


**Fig. 4** **a** Impact testing machine; **b** Rockwell hardness testing machine

An Artificial Neural Network was modeled for training using the data collected from the conducted experiments. The Bayesian Regularization backpropagation method is used for the construction of the network. This method is generally used for difficult, small, and noisy datasets (Fig. 6).

In the current construction, the data set is small and prone to noise in the measured value; thus, the application of Bayesian Regularization fits our requirement. '*trainbr*' learning function is used in the Matlab R2019a platform. The network takes 70% of

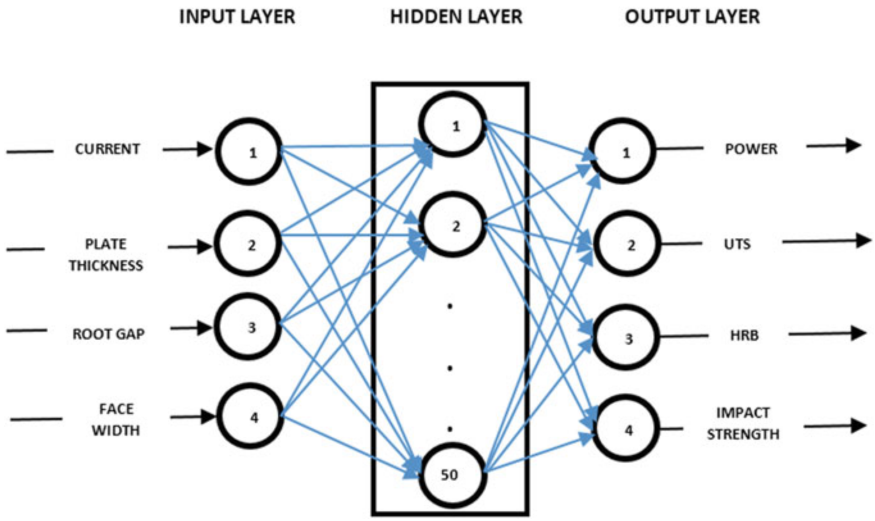


**Fig. 5** ANN architecture

data for training, 15% for validation, and 15% for testing. The ANN model developed in this study involves an input layer, one hidden layer, and one output layer. The input layer consists of four neurons; each neuron corresponding to individual input parameters and the output layer containing four neurons, representing one output parameter each. The hidden layer employs 50 neurons. The most promising network architecture is based on the trial and error method for which many trials have been conducted to arrive at the best combination. The performance of the network has been discussed in detail in the conclusion section.

## 6 Conclusion

The current work involves four input and four output variables for SMAW welding of structural grade mild steel. The quality of the welding has been tested by measuring UTS of the welded joint by applying load in the transverse direction, measuring the impact energy absorbed by the joint before failure, hardness on the bead surface, and also the power consumed for joint preparation. The input and output were fed into an ANN network suitably designed for the purpose. The modeled network is capable of selecting all the four types of input parameters considered in the present work based on desired values of output parameters like energy consumed, UTS hardness, and impact energy. This work can be extended to other welding methods. Other crucial variables not considered in the present work may be considered as future research scope.

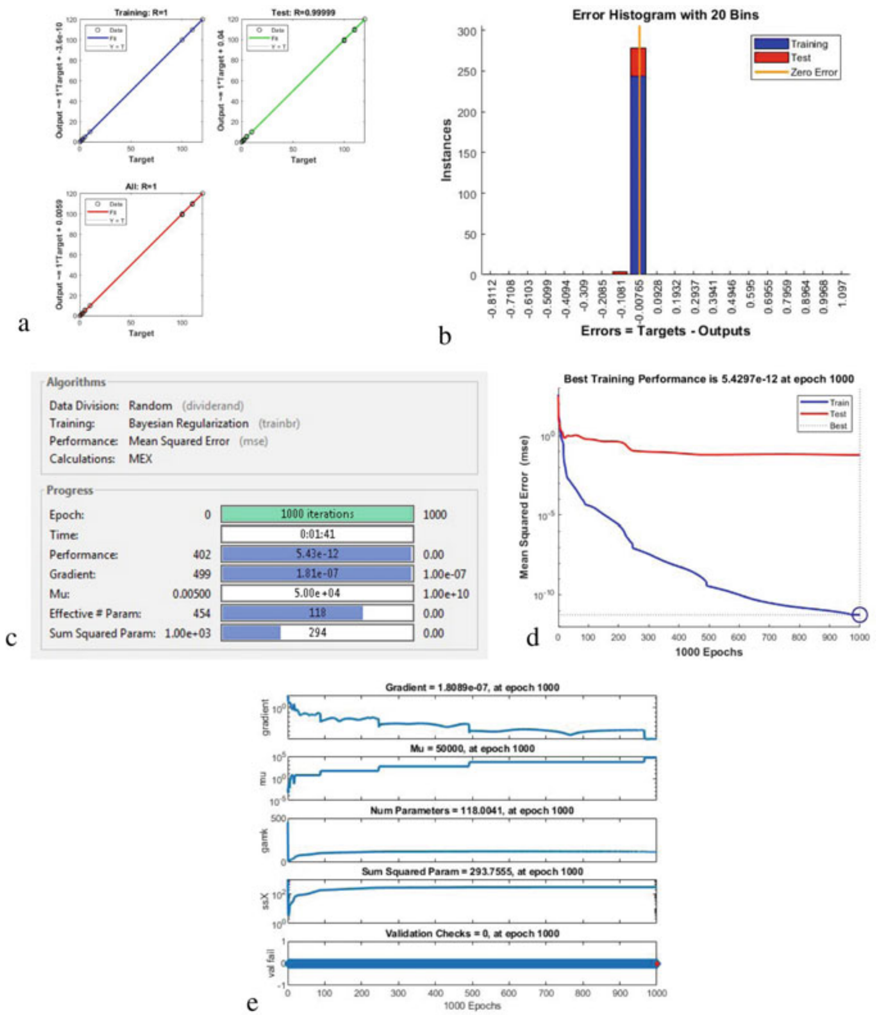


**Fig. 6** **a** Regression; **b** error histogram; **c** performance; **d** training progress; **e** training state

## References

1. Faqih IA, Ma'arif S, Sukarjo H (2019) The effect of current variation on mma welding to mechanical properties and microstructure of mild steel
2. Ahmed AN, Noor CM, Allawi MF, El-Shafie A (2018) RBF-NN-based model for prediction of weld bead geometry in Shielded Metal Arc Welding (SMAW). Neural Comput Appl 29(3):889–899
3. Alkahla I, Pervaiz S (2017) Sustainability assessment of shielded metal arc welding (SMAW) process. In: IOP conference series: materials science and engineering, IOP Publishing, 244(1):012001

4. Aktepe A, Ersöz S, Lüy M (2014) Welding process optimization with artificial neural network applications. Neural Netw World 24(6):655–670
5. Aktepe A, Ersöz S, Lüy M (2012) Backpropagation neural network applications for a welding process control problem. In: International conference on engineering applications of neural networks. Springer, Berlin, Heidelberg, pp 172–182
6. Khamari BK, Dash SS, Karak SK, Biswal BB (2019) Effect of welding parameters on mechanical and microstructural properties of GMAW and SMAW mild steel joints. Ironmaking Steelmaking:1–8
7. Singh SK, Samal BK, Pradhan SR, Ojha SR, Saffin MD, Mohanty AM (2019) Sustainable analysis of TIG parameters for welding aluminum alloy considering joint gap and welding current. In: International conference on application of robotics in industry using advanced mechanisms. Springer, Cham, pp 316–323
8. Vimal KEK, Vinodh S, Raja A (2017) Optimization of process parameters of SMAW process using NN-FGRA from the sustainability view point. J Intell Manuf 28(6):1459–1480
9. Casalino G, Facchini F, Mortello M, Mummolo G (2016) ANN modelling to optimize manufacturing processes: the case of laser welding. IFAC-PapersOnLine 49(12):378–383
10. Gao M, Chen C, Mei S, Wang L, Zeng X (2014) Parameter optimization and mechanism of laser–arc hybrid welding of dissimilar Al alloy and stainless steel. Int J Adv Manuf Technol 74(1–4):199–208
11. Arifin A, Gunawan AM, Yani I, Pratiwi DK, Yanis M, Sani KA (2019) Optimization of Angular Distortion on Weld Joints Using Taguchi Approach. Jurnal Kejuruteraan 31(1):19–23
12. Srivastava S, Kumar S, Garg RK (in press) A multi-objective optimisation of TIG welding parameters using response surface methodology
13. Skariya PD, Satheesh M, Dhas JER (2018) Optimizing parameters of TIG welding process using grey wolf optimization concerning 15CDV6 steel. Evol Intel 11(1–2):89–100
14. Srivastava S, Garg RK (2017) Process parameter optimization of gas metal arc welding on IS: 2062 mild steel using response surface methodology. J Manufact Process 25:296–305
15. Azizi A, Barenji A, Barenji R, Hashemipour M (2016) Modeling mechanical properties of FSW thick pure copper plates and optimizing it utilizing artificial intelligence techniques. Sensor Netw Data Commun 5(142):2
16. Leo P, Renna G, Casalino G, Olabi AG (2015) Effect of power distribution on the weld quality during hybrid laser welding of an Al–Mg alloy. Opt Laser Technol 73:118–126
17. Saxena A, Kumaraswamy A, Reddy GM, Madhu V (2018) Influence of welding consumables on tensile and impact properties of multi-pass SMAW Armox 500T steel joints vis-a-vis base metal. Defence Technol 14(3):188–195