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Reliability-Based Robust Multi-Objective Optimization of Friction Stir Welding Lap Joint AA1100 Plates

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ABSTRACT

The current paper presents a robust optimum design of friction stir welding (FSW) lap joint AA1100 aluminum alloy sheets using Monte Carlo simulation, NSGA-II and neural network. First, to find the relation between the inputs and outputs a perceptron neural network model was obtained. In this way, results of thirty friction stir welding tests are used for training and testing the neural network. Using such obtained neural network model, for the reliability robust design of the FSW, a multi-objective genetic algorithm is employed. In this way, the statistical moments of the forces, temperature, strength, elongation, micro-hardness of welded zone, grain size and welded zone thickness are considered as the conflicting objectives. The optimization process was followed by multi criteria decision making process, NIP and TOPSIS, to propose optimum points for each of the pin profiles. It is represented that some beneficial design principles are involved in FSW, which were discovered by the proposed optimization process.

Keywords: Robust design optimization; Friction stir welding; Multi-objective optimization; Perceptron neural network.

1 INTRODUCTION

FRICTION stir welding (FSW) is a non-melting low cost welding which is introduced first by The Welding Institute (TWI) [1, 2]. This welding method is performed by creating shear stress and plastic deformation below the melting point to reduce the residual stresses. Unlike conventional welding, a rotating pin and a shoulder, traverses along the edges of the joint. Although the common way of FSW are butt and overlap, this method can also be used to other configurations. FSW was basically developed for welding aluminum alloy and many research works have focused on the aluminum alloys [3-7]. Application of the Artificial neural networks (ANN) in the engineering problems is increased during last decades due to their ability in training with the experimental data and predicting the outcomes. Neural networks are employed for modeling FSW in previous research works. In order to model the friction stir welding parameters, Shojaeefard et al. [8] employed the neural networks. With the aim to predict quality of the welded butt joints, Buffa et al. [9] linked the neural network to a 3D finite element model for the FSW. For

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predicting properties of FSW, Okuyucu et al. [10] developed a neural network model as well. Shojaeefard et al. [11] carried out sensitivity analysis of artificial neural network to investigate the effect of inputs on the outputs. Asadi et al. [12] established a correlation between the friction stir processing (FSP) parameters and hardness of nanocomposite and the grain size using neural network. In an optimum design of a friction stir welding test, forces, temperature, strength, elongation, hardness of welded zone, grain size and welded zone thickness are the important objectives to be optimized simultaneously as a complex multi-objective optimization problem (MOP). Many methods have been employed in previous research works for solving MOPs [13]. Non-dominated Sorting Genetic Algorithm (NSGA-II) proposed by Srinivas and Deb [14] generates a set of non-dominated solutions (Pareto solutions). To improve NSGA-II, Nariman-Zadeh proposed modified NSGA-II which employs ε-elimination instead of crowding distance [15]. This method is used successfully in the recent studies [16-18]. After finding out the non-dominated points, it is desired to find some trade-off optimum points. Technique for ordering preferences by similarity to ideal solution (TOPSIS) which is based upon simultaneous minimization of distance from an ideal point and maximization of distance from a nadir point can be used for this purpose [19-21]. Previous studies did not consider the uncertainties associated with the FSW process parameters. In real-world engineering practices, the robust design approach can be adopted to deal with various sources of uncertainties such as model parameter variations or incomplete knowledge of parameters [22, 23]. In fact, optimization without taking into account uncertainty, generally results in non-optimal and potentially high-risk solution [24]. Generally, robust design optimization (RDO) approach is adopted to deal with the stochastic robustness issue [25]. In RDO approach, it is required to make the robust performance less sensitive to the random variation associated with uncertain parameters so that the performance dilapidation from ideal deterministic behavior is minimized [26, 27]. Evolutionary methods have been found to be proper tools for meta-modelling and system identification [28,29].

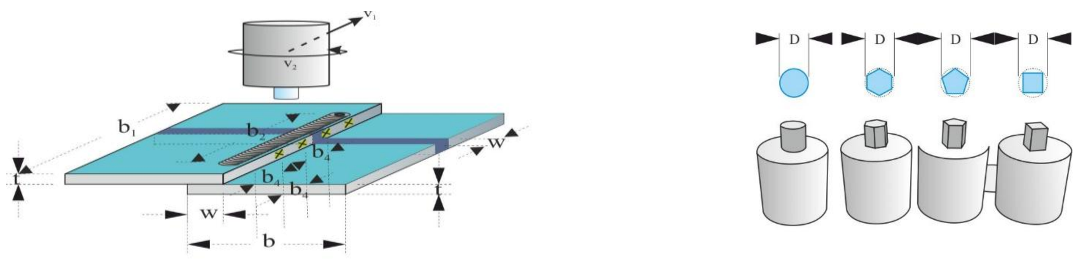
In this paper, first, results of 30 tests, which were designed using Taguchi and carried out experimentally, are represented. Results of such experiments are then used for training and testing of the perceptron neural network. In the next step, the obtained meta-model is used in a robust multi-objective optimization approach to determine the best possible combination of the statistical moments of FSW output parameters.

2 FRICTION STIR WELDING TEST

Using a FP4M milling machine, 30 experiments welding were carried out according to a Taguchi design of experiments. AA1100 aluminum sheets with the dimensions of 80 *mm*× 80 *mm* × 2 *mm* were overlapping welded. To measure the vertical forces applied on the tool during the process, two bending load-cells were used. Horizontal applied force was measured employing an *S* shaped load-cell. Fig. 1 shows the bracing system designed and constructed to measure forces exerted on the tool.

Fig.1
FP4M milling machine and the bracing system for holding the plates as well as *S*-shaped load cell.

The traverse and rotational speed of the tool and the tool tilt angle have been investigated in this paper. The fourth parameter studied in this work is the geometry of the tool pin (Fig. 2). Pin height and shoulder diameter were designed to be 16 and 3 *mm*, respectively, due to the thickness of the sheets. The shoulder angle was considered 10 degrees. The pins fit in a circle of 2.5 *mm* diameter, and all tool pins occupy the equal area when rotating. The tools are shown in Fig. 2(b).



(a) (b)

Fig.2
(a) Configuration of the lap joint AA1100 plates, (b) Pin tool geometries.

3 RELIABILITY-BASED ROBUST DESIGN OPTIMIZATION (RBDO)

In the reliability-based robust multi-objective optimization problem presented in this paper, there are different conflicting reliability-based metrics that should be minimized simultaneously. This methodology can be formulated as:

$$\text{Minimize } \left\{\mu\left[f_i\left(x,d,p\right)\right],\upsilon\left[f_i\left(x,d,p\right)\right]\right\} \qquad \left(i=1,2,3,...,k\right)$$
$$\text{Subject to } P_f^i=P\left[G_i\left(x,d,p\right)\le 0\right]\le\varepsilon_i \qquad \left(j=1,2,3,...,m\right)$$

$$x\ (L)\le x\ \le x\ (U)$$
$$d\ (L)\le d\ \le d\ (U) \qquad (1)$$

where *m* is the number of inequality constraints (i.e. limit state functions) and denotes the probability of failure of the i^{th} reliability measure and ε_i is the highest value of desired admissible probability of failure. There have been many research activities on the sampling techniques to reduce the number of samples, keeping high level of accuracy. Alternatively, the quasi-MCS has now been increasingly accepted as a better sampling technique which is also known as Hammersley Sequence Sampling (HSS) [12]. In this paper, HSS has been used to generate samples for probability estimation of failures.

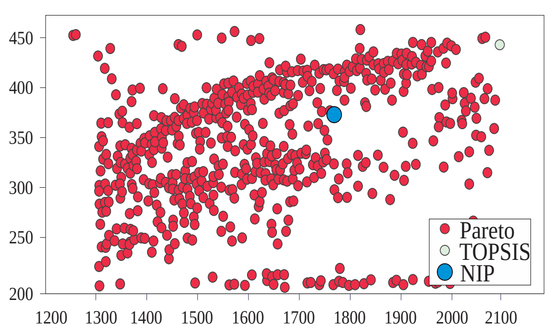
4 RESULTS AND DISCUSSION

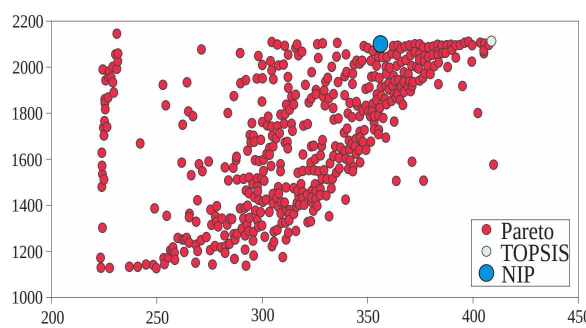
The relationship between the objective functions and the design variables is estimated using the neural network. The details of the neural network model have been represented in the authors previous work [30]. In the optimization process, input parameters of the neural network which are rotational speed, transvers speed, tool tilt angle and tool geometry are considered as design variables. Output parameters of the neural networks including forces, temperature, strength, elongation, micro-hardness of welded zone, grain size and welded zone thickness are also considered as the conflicting objectives. In the robust design approach, the prime aim is to minimize or maximize mean value of the objective functions and minimize their divergence level, simultaneously. To take in the account the uncertainties, different standard deviations are defined for the design variables. On account of the milling device performance, the standard deviation for rotational and translational speeds and also for the tool tilt angle are considered as 2% of their average values. In all the cases, the probability distribution function is considered to be normal probability function.

In the reliability based robust multi-objective optimization, considering the probabilistic uncertainties (i.e. robust design), after producing a solution such as [102.3 (tilt angle), 61.530 (transvers speed), 1238.145 (rotational of rotation)], first, 1000 solution vector samples in the four-dimensional space of the input parameters will be generated using Hammersely sampling method according to the probability distributions and the defined standard deviations. Then, using the neural networks the cost functions are calculated for every 1000 samples. And for each of the eight objective functions, 1000 responses are generated in which for every 1000 responses there is an average and a standard deviation. The output cost function for each solution has eight mean and eight standard deviation values. The mean values, as for the case of multi-objective optimization in a deterministic domain, are being maximized or minimized, and also their corresponding standard deviation values are also being minimized. Consequently, the standard definition of the optimization problem is as follow:

$$\begin{aligned}
&\text{Minimize Mean of Horizontal Force}(n,\ v,\ \alpha,\ \beta)\\
&\text{Minimize Standard Deviation of Horizontal Force}(n,\ v,\ \alpha,\ \beta)\\
&\text{Minimize Vertical Force}(n,\ v,\ \alpha,\ \beta)\\
&\text{Minimize Standard Deviation of Vertical Force}(n,\ v,\ \alpha,\ \beta)\\
&\text{Maximize Temperature}(n,\ v,\ \alpha,\ \beta)\\
&\text{Minimize Standard Deviation of Temperature}(n,\ v,\ \alpha,\ \beta)\\
&\text{Maximize Tensile Strength}(n,\ v,\ \alpha,\ \beta)\\
&\text{Minimize Standard Deviation of Tensile Strength}(n,\ v,\ \alpha,\ \beta)\\
&\text{Maximize Elongation}(n,\ v,\ \alpha,\ \beta)\\
&\text{Minimize Standard Deviation of Elongation}(n,\ v,\ \alpha,\ \beta)\\
&\text{Minimize Grain Size}(n,\ v,\ \alpha,\ \beta)\\
&\text{Minimize Standard Deviation of Grain Size}(n,\ v,\ \alpha,\ \beta)\\
&\text{Maximize Hardness}(n,\ v,\ \alpha,\ \beta)\\
&\text{Minimize Standard Deviation of Hardness}(n,\ v,\ \alpha,\ \beta)\\
&\text{Maximize Thickness }(n,\ v,\ \alpha,\ \beta)\\
&\text{Minimize Standard Deviation of Thickness}(n,\ v,\ \alpha,\ \beta)\\
&\text{Subject to: } 400\leq\ n\leq\ 1600\\
&\qquad\qquad\quad 20\leq\ v\leq\ 1600\\
&\qquad\qquad\quad 1\leq\ \alpha\leq\ 4\\
&\qquad\qquad\quad \beta = 90,\ 108{,}120 \text{ or } 180
\end{aligned} \tag{2}$$

Since the multi-objective optimization in the uncertain domain was discussed thoroughly in the previous section, the results are presented in the following section. There is no method other than the mapping of Pareto on a series of two-dimensional planes after the 16^{th} Pareto was obtained. As an example, Figs. 3 and 4 depict Pareto obtained from optimization on some two-dimensional planes for the tools with square and hexagonal cross-section pins. The proposed optimum points are also identified via the nearest point to the ideal point (NIP) approach and TOPSIS method in these figures.





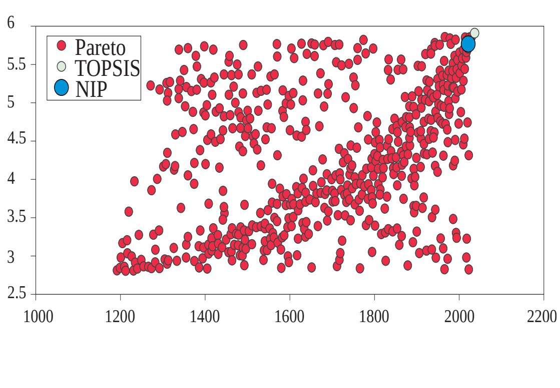
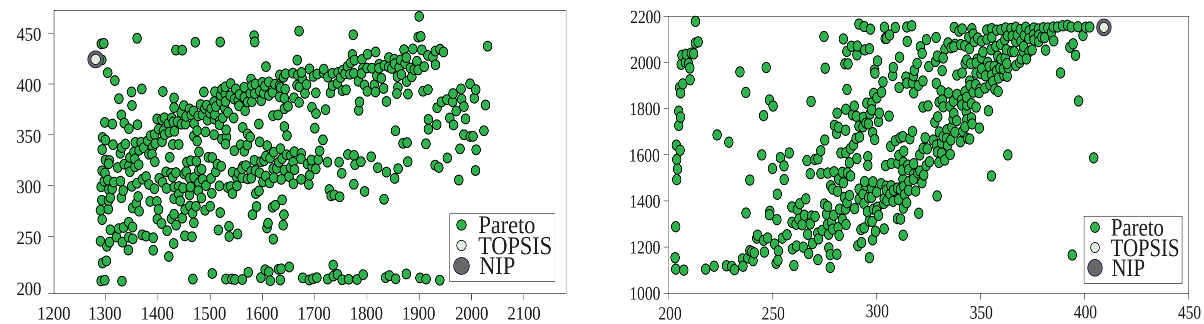


Fig.3
16D Pareto plots on some 2D planes along with the proposed points obtained by NIP and TOPSIS for the case of square pin.



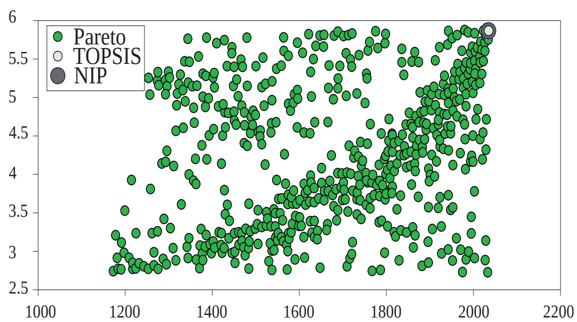


Fig.4
16D Pareto plots on some 2D planes along with the proposed points obtained by NIP and TOPSIS for the case of hexagonal pin.

To investigate the effectiveness of the optimization process represented in the present study, results of this study obtained from reliability based robust optimization process are compared with the results obtained from deterministic optimization represented in the authors previous study [30]. In this way, the optimum design point obtained using NIP method in previous work [30] is compared with the NIP design point obtained in this study, in the Table 1. This table represents an interesting result, which could not be obtained without using the reliability based robust optimization process proposed in this paper. According to this table, it is clear that by implementing uncertainties on the design variables, a design point obtained by deterministic optimization method will result high level of deviations in the objective functions. It means that the deterministic optimization processes can lead to high-risk points instead of reliable optimum ones.

Table1
Comparison between two different optimum points represented in this work and previous work. [30]

Objective function				
	1126.56	Rotational speed	876.34	Rotational speed
	72.77	Transvers speed	21.43	Transvers speed
	2.82	Tool angle	3.41	Tool angle
	Hexagone	Tool	Square	Tool
	This work		Deterministic method [30]	
	Mean	Deviation	Mean	Deviation
Average horizontal force (N)	1722	65.40	1477	83.42
Average vertical force (N)	2937	110.64	3339	700.74
Maximum temperature (ºC)	316	6.58	368	17.72
Tensile strength (N)	2078	39	1977	172.32
Elongation (%)	3.1	0.25	5.0	1.05
Grain size (μm)	2.0	0.03	2.0	2.60
Hardness (μm)	57.2	0.17	57.2	8.32
Thickness (mm)	3.3	0.01	3.1	0.38

Such findings can be concluded also from Fig. 5. In this figure, probability distribution graphs are shown for all eight objective functions for two different points represented in this work and previous work [30]. It is clear from this figure that the point obtained in this study works more robust in comparison with that optimum point obtained in previous work using deterministic approach.

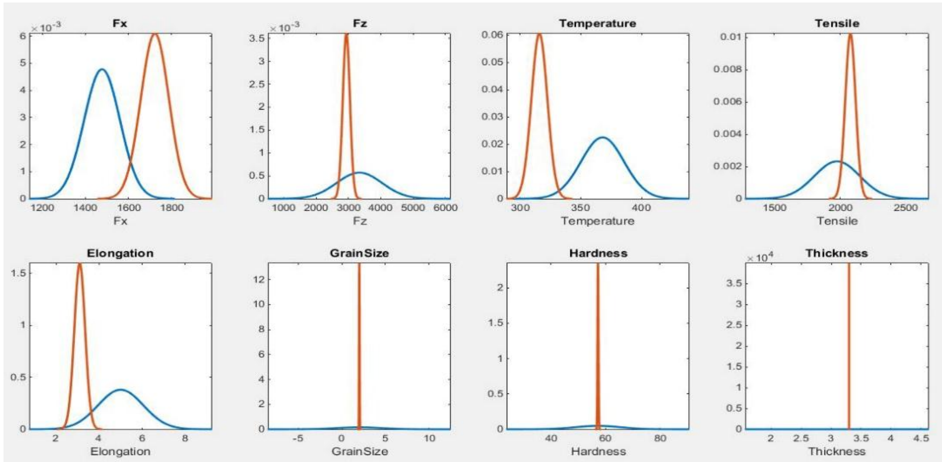


Fig.5
Comparison of the FSW process responses to the solutions obtained from deterministic optimization [30] and robust design.

5 CONCLUSION

In this paper, reliability based design optimization of lap joint AA1100 plates was conducted using artificial neural network and NSGA. The same procedure according to the article of reference [30] was conducted and used in the present study. Firstly, experimental results of mechanical and microstructural tests on 30 FSW samples were obtained. Weld tensile strength and elongation percent are recorded and joint thickness was calculated. Grain size was measured after a metallographic operation by an optical microscope and the micro-hardness is measured. Next, an artificial neural network was designed, trained and tested and the perceptron neural network designed in this research has been able to provide a very good performance. Then, the Pareto front was obtained on two-dimensional planes. Finally, TOPSIS and NIP multi criteria decision-making methods are employed to these optimal points, and for each of the pin profiles some optimum points were proposed. The reliability-based robust optimization procedure was performed with complete success.

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