International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 07 Issue: 09 | Sep 2020 www.irjet.net p-ISSN: 2395-0072

Optimization of Advance Machining Process Parameters by Advance Optimization Techniques

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ABSTRACT- *Ultrasonic metal welding has been used in manufacturing industries. It takes very short time to weld the material (less than one second), thus it can be used for mass production. But many times, the problems faced by industries due to this process are the poor weld quality and strength of the joints. In fact, the quality and success of the welding depend upon its control parameters. In this study the control parameters like vibration amplitude, weld pressure and weld time are considered for the welding of dissimilar metals like Aluminum (AA1100) and brass (UNS C27000) sheet of 0.3 mm thickness. As the quality is an important issue in these manufacturing industries, the optimal combinations of these process parameters are found out by using teaching learning-based algorithm (TLBO) and JAYA algorithm. From the test, it has been observed that, the teaching learning-based algorithm (TLBO) and JAYA algorithm better output results than fuzzy logic yields and GA. A variety of weld quality levels, such as "under weld", "good weld" and "over weld" have also been defined by performing micro structural analysis.*

1. INTRODUCTION

Various sectors such as Automotive, aircraft, railway transportation, medical, microelectronics etc. have the main objective to reduce the weight and energy consumption. To attain these goals, lightweight and high strength materials such as aluminum, titanium, magnesium, copper alloys are necessary. But major barriers of using this material are its high thermal conductivity, joining and its machining cost. So, it is important to pursue for lower cost joining methods. Ultrasonic metal welding (USMW) is one such promising method for joining this type of softer metal. The basic applications for USMW include wire bonding in the electronics industry, tube sealing in thermal reactors and thin foil joining. This technique is also appropriate to join dissimilar materials [5].

In USMW, two metal surfaces are joined due to the friction like relative motion between them with a clamping pressure. During this motion, the local surface roughness, contaminants and oxides present over it, deform and disappear and make metal-to- metal contact possible. As this process is a solid-state welding process, it occurs without melting of base metal. Generally, the ultrasonic vibration is generated in the transducer and transmitted through booster to the sonotrode. The sonotrode is one of the parts of a system that directly touches with the upper part of the specimen and vibrates parallel to the plane of the weld interface and perpendicular to the axis of clamping force application [5].

Thus, the vibratory energy is transmitted to the weld spot. These spot welds are elliptical in shape at the weld zone and when they are overlapped, they form a continuous weld joint.

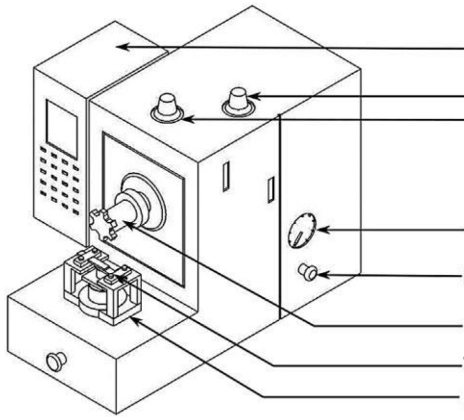


Fig. 1. Schematic diagram of lateral drive ultrasonic welding system.

In friction stir welding technique, whenever brass was tried to weld with aluminium, hard and brittle intermetallic compounds were formed giving poor weld strength. So, USMW has been believed to be one of the solid-state welding processes to overcome this difficulty. These paper not only explore the interdependence among the input parameters, but also predict the weld strength of welded joints made by USMW [5]. Mantra Prasad Satpathy et al. used fuzzy logic approach and genetic algorithm (GA) approach design and conducted experimental trials using similar metals like copper. The teaching learning-based algorithm and jaya algorithm also become very popular in optimization of

Manufacturing processes. It was observed that application of this optimization technique significantly improved multiple responses. The same technique was also used to predict the material removal rate (MRR), tool wear rate (TWR) and surface roughness (SR) in ultrasonic-assisted EDM (US/EDM) process [5]. Different other manufacturing processes were also optimized using a similar type of optimization technique. Now-a-days, as the quality is a vital matter in every manufacturing industry, these should be designed in such a way that it should take less time, less cost and less manpower to produce a high-quality product with great accuracy and this can be achieved through process optimization. It is also observed that significant challenges emerge in the welding of aluminum with brass by fusion welding as well as friction stir welding process. Thus, the weldability of brass mostly relies upon the percentage of zinc present in brass. As the zinc has a low boiling temperature, lethal vapours may produce during these kinds of welding processes.

In the current study, an effort has been taken to investigate the effects of individual input parameters like amplitude, weld pressure and weld time through USMW on different output parameters such as tensile shear stress, T-peel stress and weld area. Two nonconventional optimization techniques i.e. teaching learning-based algorithm (TLBO) and JAYA algorithm. Have been applied to determine the optimal process parameter conditions at which the outputs are maximized.

2. EXPERIMENTAL WORK

A. Equipment and materials

The spot-welding experiments were performed with Telsonic lateral drive welding machine which provides a maximum power of 3 kW and a vibration frequency of 20 kHz. The ultrasonic horn with a knurled and flat welding tip of 11 mm x 9 mm has been employed for this study. It is made up of D2 steel because it offers high wear resistance and low acoustic losses, thus it acts as a tool for offering a good overall performance. The maximum peak-to peak amplitude of the tip was 68 mm without any load. This is called as the maximum working amplitude. The two materials were clamped between this tip and a jig and one support is provided with it to fix both base metals [5]. The schematic diagram is given in Fig. 1. The tensile shear stress (TS), T-peel stress (TP) and weld area (WA) have been deliberated for the evaluation of welding performance. All these performance characteristics were correlated with input parameters. So, proper selection of input factors with its range is highly needed for getting desired outputs.

In microelectronics industry as well as in small scale industries, aluminum and brass are the most commonly used material for fabrication work and also to produce solder free joints. For these reasons, these two materials have been chosen for this study [5]. The welding experiments were carried out on

0.3 mm thick dissimilar materials like AA1100 aluminum sheet of grade H16 and UNS C27000 brass sheet of grade H04. For each weld trial, two coupon configurations were involved in the static tests: lap shear and T-peel [5].

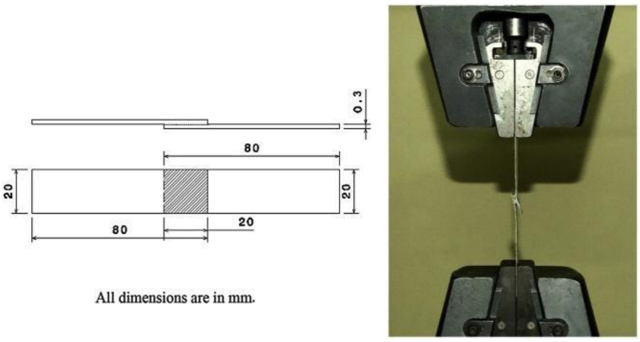


Fig. 2. Lap-shear coupon design and test fixture.

The specimen design with dimensions and fixture design are shown in Figs. 2 and 3. Just before welding, the surfaces of the base metals were degreased and oxide free by the help of swabbing with acetone. This process is necessary in order to get a satisfactory weld.

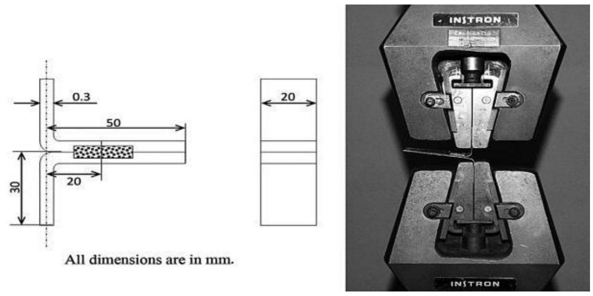


Fig. 3. T-peel coupon design and test fixture

B. Identification of control factor

The ultrasonic welding involves a number of process parameters which can influence the welding performance characteristics. From numerous literature studies and experimental trials, three important parameters as weld pressure (P), weld time (T) and vibrational amplitude (A) have been selected [5].

Table 1: Input parameter and search ranges.

Input parameters	**Search Range**
Amplitude(A)	54-68
Weld pressure(P)	0.2-0.4
Weld Time(T)	0.2-1.0

The working range of each one has been selected in such a way that, the good welding can be obtained in that range and it has been found from trial experiments. In this current analysis, weld pressure and weld time have been divided into three levels each and the vibration amplitude has been varied in five levels. These factors with their level values are shown in Table 1[5].

3. OPTIMIZATION OF USMW PROCESS PARAMETERS USING TLBO AND JAYA

A. *Teaching-Learning-Based Optimization*

Teaching-learning-based optimization is based on teaching- learning process in which every learner tries to learn something from other individuals to improve themselves. This algorithm simulates the traditional teaching-learning phenomenon of a class room. Here, two different teachers, T1 and T2 are assumed teaching same subject to the same merit level students in two different classes. The distribution of marks obtained by the learners of two different classes as shown in the Figure 4 is evaluated by the teachers [1].

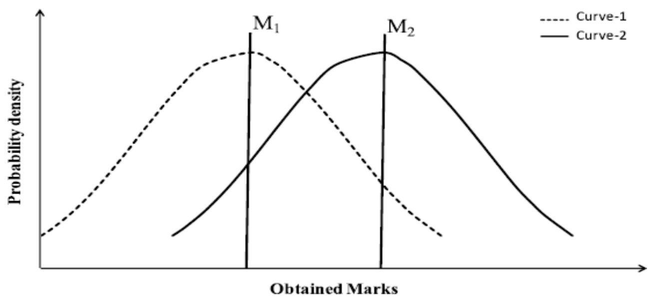


Figure 4: Distribution of marks obtained by learners taught by two different teachers

Curves 1 and 2 shown in Figure 4 represent the marks obtained by the learners taught by teacher T1 and T2 respectively. Generally, a normal distribution is assumed for the obtained marks [1]. As represented in the Figure 4, let us assume that the teacher T2 is better than teacher T1 in terms of teaching. The main difference between both the results is their mean (M2 for Curve-2 and M1 for Curve-1), i.e. a good teacher produces a better mean for the results of the learners. Learners also learn from the interaction among themselves, which helps in the in the improvement of their results.

This algorithm is divided into two levels of learning phase i.e. through the teacher (known as the teacher phase) and interacting with other learners (known as the learner phase).

Teacher Phase

In this phase the learning is through the teacher. During the learning process the teacher spread knowledge among the learners and tries to increase the mean results of the class. At any iteration

„i", let, there are „m" number of subjects (i.e design variables) offered to „n" number of students (i.e. population of solutions i.e. k = 1, 2,…, n) and $M_{j,i}$ is the mean results of the students in a particular subject (j = 1, 2,…., m) As the teacher is considered as the most knowledgeable person in each subject, the best learner in the whole population is considered a teacher in the algorithm. The best overall result is X_{total}-$k_{best,i,}$ obtained in the whole population of learners considering all the subjects together can be considered as a the result of best learner $K_{best.}$ However, as the teacher is usually considered as a highly learned person who trains learners so that they can have better results, the best learner identified is considered as the teacher. The difference between the existing mean result of each subject and the corresponding result Difference_Mean$_{j,k,i}$ = r_i ($K_{j,k\ best,i}$ - TF $M_{j,i}$) [2]

where $X_{j,kbest,i}$ is the result of the best learner (i.e., teacher) in subject j, TF is the teaching factor which decides the value of mean to be changed, and r_i is the random number in the range [0,1]. The value of TF is decided randomly with equal probability as:

$$TF = round\ [1+rand\ (0, 1)\ \{2-1\}]$$

TF is not a parameter of the TLBO algorithm. The value of TF is not given as an input to the algorithm and its value is randomly decided by the algorithm using Equation. Rao et al. have conducted a number of experiments on many benchmark functions and it is concluded that the algorithm performs better if the value is between 1 and 2. However, the algorithm is found to perform much better if the value of TF is either 1 or 2 and hence to simplify the algorithm, the teaching factor is suggested to take either 1 or 2 depending on the rounding up criteria given by Equation. However, one can take any value of TF in between 1 and 2.

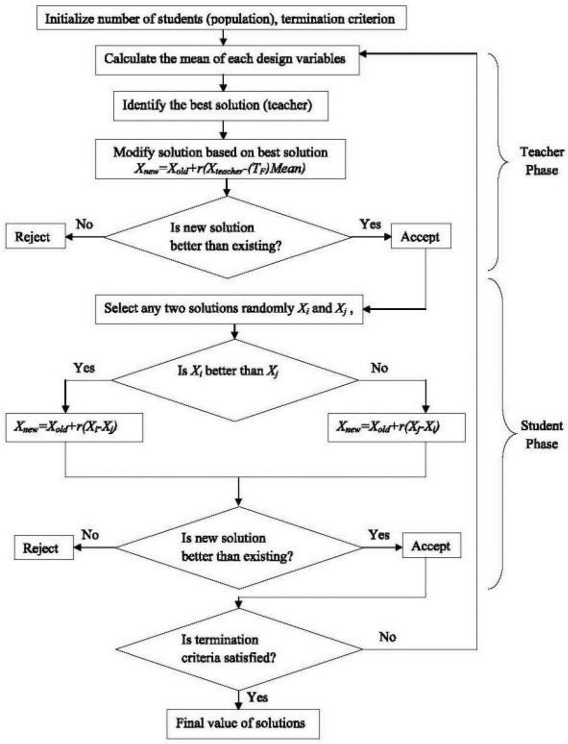


Figure 5: Flow chart for Teaching–Learning-Based Optimization (TLBO)

Based on the Difference_Mean$_{j,k,i}$ the existing solution is updated in the teacher phase according to the following expression.

$$X'_{j,k,i} = X_{j,k,i} + \text{Difference\_Mean}_{j,k,i}$$

where $X'_{j,k,i}$ is the updated value of $X_{j,k,i}$. $X'_{j,k,i}$ is accepted if it gives a better function value. At the end of teacher phase all the accepted values are maintained and these values become the input to the learner phase.

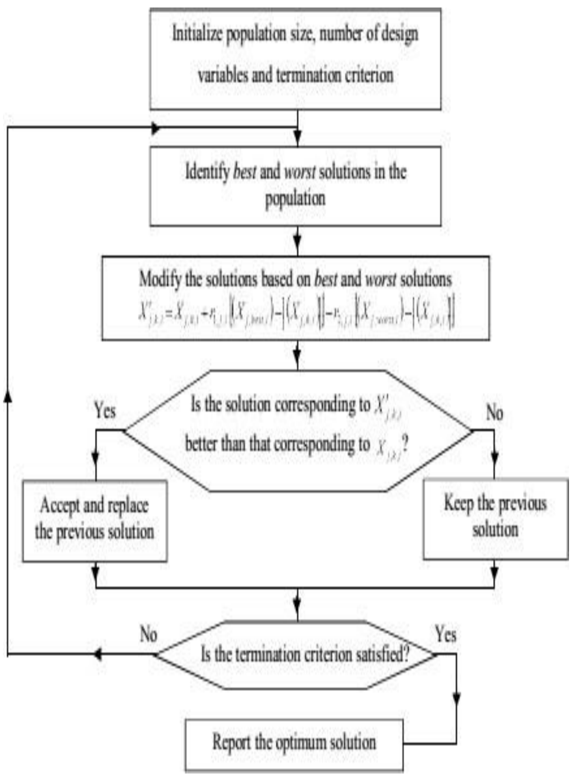
Learner Phase

Learners increase their knowledge by interacting themselves in this second section of this algorithm. A learner interacts randomly with other learners for enhancing their knowledge and experience. A learner learns new things or ideas if the other learner has more knowledge than him or her. Considering a population size of „n", the learning phenomenon of this phase is expressed below. Two learners P and Q are randomly selected such that

X′total-P,i ≠ X′total-Q,i (where, X′total-P,i and X′total-Q,i are the updated values of Xtotal-P,i and Xtotal-Q,i respectively at the end of teacher phase). X′′j,P,I = X'j,P,I + ri(X'j,P,i−X'j,Q,i), if X'total−P,i < X'total−Q,i

X′′j,P,i=X'j,P,i+ri(X'j,Q,i−X'j,P,i), if X'total−Q,i<X'total−P,I Accept X′′j,P,i , if it gives a better function value. All the accepted function values at the end of the learner phase are maintained and these values become the input to the teacher phase of the next iteration. The values of ri used in above equations can be different. Repeat the procedure of teacher phase and learner phase till the termination criterion is met.

Figure 6: Flow chart for Jaya algorithm



B. Optimization by JAYA algorithm

Let f(x) is the objective function to be minimized (or maximized). At any iteration i, assume that there are „m" number of design variables (i.e. j=1, 2…, m), „n" number of candidate solutions (i.e. population size, k=1, 2,…,n). Let the best candidate best obtains the best value of f(x) (i.e. $f(x)_{best}$) in the entire candidate solutions and the worst candidate worst obtains the worst value of f(x) (i.e. $f(x)_{worst}$) in the entire candidate solutions. If $X_{j,k,I}$ is the value of the j^{th} variable for the k^{th} candidate during the i^{th} iteration, then this value is modified as per the following Eq[4].

$$X'_{j,k,i}= X_{j,k,i}+ r_{1,j,i} (X_{j,best,i}- |X_{j,k,i}|) - r_{2,j,i} (X_{j,worst,i}- |X_{j,k,i}|)$$

where, $X_{j,best,i}$ is the value of the variable j for the best candidate and $X_{j,worst,i}$ is the value of the variable j for the worst candidate. Fig. shows the flowchart of the proposed algorithm. The algorithm always tries to get closer to success

(i.e. reaching the best solution) and tries to avoid failure (i.e. moving away from the worst solution). The algorithm strives to become victorious by reaching the best solution and hence it is named as Jaya (a Sanskrit word meaning victory). The proposed method is illustrated by means of an unconstrained benchmark function known as Sphere function in the next section.

C. Development of mathematical model

Mathematical model developed to predict the FMPI for the ultrasonic welding is given below [5].

$$FMPI= -2.54 + 0.015 * A + 13.361 * P + 1.492 * T - 0.875 * P * T$$

$$-19.966 * P^2 - 0.83 * T^2$$

4. RESULTS AND DISCUSSION

Figure 7 and Figure 8 shows the weld time with respect to weld strength. From these figures, it clearly signifies that, the maximum weld strength can be achieved at a moderate amount of weld time (0.618 Sec) by JAYA algorithm and by TLBO algorithm weld time is (0.8 Sec). For the lower clamping pressure X'j,k,I is the updated value of X tj,k,I and r 1,j,I and r 2,j,I are the two like 0.2 MPa, it takes a slightly longer time period to reach its optimum value. The possible reason behind this is that, the oxide random numbers for the j variable during the ith iteration in the range [0, 1]. The term "$r_{1,j,i}$ (($X_{j,best,i}$- $|X_{j,k,i}|$)" indicates the tendency of the solution to move closer to the best solution and the term "-$r_{2,j,i}$ ($X_{j,worst,i}$- $|X_{j,k,i}|$)" indicates the tendency of the solution to avoid the worst solution. $X'_{j,k,i}$ is accepted if it gives better function value. All the accepted function values at the end of iteration are maintained and these values become the input to the next iteration [4].

Layer may not be broken at short welding period of time and thus the formation of micro bonds may not happen.

For high clamping force like 0.4 MPa, the strength decreases even if the welding time is high. This is because, at a higher pressure, the relative motions between the sheets are ceased. Thus, the dissipation of energy and formation of

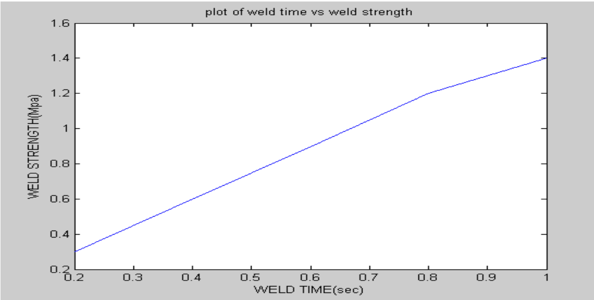


Figure 7: plot of weld time vs weld strength by JAYA algorithm

micro bonds could not happen. The other reason for this behavior is the occurring of the interfacial lock at the weld interface and the heat which is generated due to it, breaks the bonds.

Table 2: Comparison between Fuzzy Based Genetic Algorithm and of Optimized Process parameters by JAYA and TLBO algorithm.

Process parameters	Fuzzy Based Genetic Algorithm	TLBO	JAYA
Amplitude(A)	67.00	68.0000	99.051148
WeldPressure (P)	0.20	0.3196	0.272601
Weld time(T)	0.611	0.8	0.618964
FMPI	0.81	0.8357	1.245476

5. CONCLUSIONS

In this study, the following points are gathered.

- Based on its main effects results, the most influencing parameter on the response is the vibration amplitude as it occupies rank 1 followed by weld time and weld pressure. An amplitude of 68 mm, weld pressure of 0.3196 MPa and weld time of 0.8 Sec are the optimum inputs to get excellent weld using TLBO method.
- An amplitude of 68 mm, weld pressure of 0.272601 MPa and weld time of 0.611894 Sec are the optimum inputs to get excellent weld using JAYA method.
- Lastly, a comparison between fuzzy logic and TLBO and JAYA algorithm techniques is done in this work to show which technique accurately optimizes the process parameters to get the maximum FMPI value. Observations indicate that the tlbo and jaya results a high FMPI value than modeling fuzzy. So, techniques could be an economical and better methods for prediction of quality characteristics with respect to the process variables.

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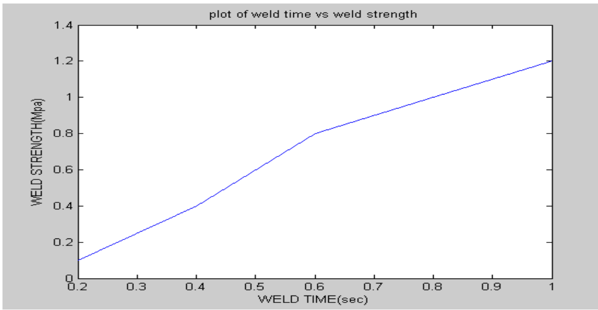

Figure 8: plot of weld time vs weld strength by TLBO algorithm

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