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HYBRID ALGORITHM IN FRICTION WELDING PROCESS

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Abstract: *In friction welding, the joints are formed in the solid state by utilizing the heat generated by friction. The objective of this study an obtaining friction welding of super duplex stainless steel(UNS S32760) joint were investigated considering four process parameters: The process parameters such as friction pressure, upset pressure, burn off length and speed play the major roles in determining the strength of the joints. Optimizing the friction welding parameters in order to establish the weld quality. Similar specimens were joined using the laboratory model friction welding machine. The processed joints were tested for their shrinkage and strength related aspects. Acoustic emission emanated by the joints during tensile testing was acquired to assess the quality of the joints. Also a method to decide near optimal settings of the process parameters using In the present work, a design of experiment (DOE) technique, GENETIC ALGORITHM and artificial neural network (ANN) is proposed minimize shrinkage and maximize tensile strength The optimization procedure resulted in the creation of nondominated optimal points which gave an insight regarding the optimal operating conditions of the process. GA and ANN approach and compare the results obtained.*

Keywords: *Friction welding; Genetic algorithm; Multi objective optimization; Tensile strength; Shrinkage; ANN.*

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HIGHLIGHTS

- Easy to understand, Modular, separate from application, Supports single-objective optimization, Good for noisy environment, We always get an answer and the answer gets better with time, Inherently parallel and easily distributed,
- There are many ways to speed up and improve a GA‟s basic applications as knowledge about the problem domain is general, Easy to exploit for previous or alternate solutions, Flexible in forming building blocks for hybrid applications.
- Tensile strength and shrinkage of friction welded super duplex stainless steel Joints had done by design of experiments.
- The models indicate that burn off length has the highest significance total shrinkage followed by upset force and friction force. And friction force is a strong determinant in changing tensile strength followed by upset force and burn off length.
- The Artificial neural networks from the genetic algorithm based multi objective optimization can aid the process operator to fix the input control variables.
- The selection of a point from the ANN will always be a trade-off between the Tensile strength and total shrinkage of the weld depending on the application.

1. INTRODUCTION

The friction welding is an efficient method of bonding, which has been successfully used in automotive and military industries and also in production of agricultural machinery and part elements [1]. The technical parameters, which determine the effect of technology used include: rotational speed, friction force, friction time, upsetting force and upsetting time. The rotational speed determines the rate of heating in the contact area. The friction force affects the rate of heating in the heat effect zone (SWC). The friction time determines the proper heating in bonding zone area and strength of connection. The force and time of upsetting decide on quality of the obtained metallic connection heated up to a plastic state of contact surfaces of the elements subjected to welding. Many scientists investigated the effect of welding parameters on the quality of spheroidal cast iron connections [2-5]. First of all, the authors optimized the welding parameters using conventional techniques, although the references on the selection and optimization of these parameters have been exceptionally poor. Friction welding is a solid state welding process in which the joining surface of the samples are heated to the desired temperature through frictional heat and then a forging force is introduced to weld the parts [6-7]. Friction welding finds widespread industrial use as a mass production process for the joining of materials.

Sahin et al. [8] carried out an analysis of the friction welding process in relation to the welding of copper and steel bars. The selection of optimum conditions for the friction welding of high speed steel to carbon steel[9]. Ananthapadmanaban et al. [10] have reported the experimental studies of mechanical property variation under different friction welding conditions for mild steel stainless steel joints. Sathiya et al. [11] investigated the effect of friction time on the fully plastically deformed region in the vicinity of the weld. Mumim [12] investigated the hardness variations and microstructure at the interfaces of steel welded joints. Super duplex stainless steels (SDSS) have been found to have a wide spread use in industries, such as oil and gas production, pulp manufacturing, and power plants due to their high corrosion resistance and superior mechanical characteristics, where typical working environments can contain high levels of chloride attack. Duplex stainless steels have higher strength than austenitic stainless steels, higher toughness than ferritic stainless steels, good weldability, and high resistance to different forms of corrosion in different aggressive environments [13-14]. These favorable properties arise from the coexistence of ferrite and austenite phases in equal amounts. Generally super duplex stainless steel has a pitting resistance equivalent number (PREN) greater than 40.

$$PREN = \%Cr + 3.3\,(\%Mo + \%W) + 16\%N \quad (1)$$

But a major concern with fusion welding of super duplex stainless steel is the formation of detrimental inter metallic phases at elevated temperatures. Sigma and chi phases form in super duplex stainless steels at elevated temperature and precipitate preferably in the ferrite. This will considerably affect the toughness of the welded joint [15].The formations of these phases are due to the high chromium and molybdenum content. Topolska et al. [16] have studied the effect of heat treatments and resulting changes in microstructure on mechanical properties, mainly impact toughness, of commercial 2205 duplex stainless steel and higher alloy super duplex 2507 grade. They suggested that high temperature service of duplex stainless steels should be avoided.

Precipitations of secondary phases (mainly σ phase) strongly deteriorate mechanical properties of steels but some amounts of these phases could be acceptable in the microstructure depending upon the application of the steel. The above said problem can be overcome by employing solid state welding process like friction welding. Friction welding process allows welding of several materials that are extremely difficult to fusion weld. Friction welding process parameters play a significant role in making good quality joints [17]. To produce a good quality joint it is important to set up proper welding process parameters. Therefore, identifying the suitable combinations of process input parameters to produce the desired output requires many experiments, making this process time consuming and costly [18]. So to avoid this problem, mathematical models can be built, which can adequately predict the relation between input process parameters and the responses. RSM [19] is widely used for this purpose. The problem becomes more complex when simultaneous optimization of two responses has to be done. This study focuses on simultaneous optimization of shrinkage and tensile strength. There have been many studies on screening experiments, modeling and optimization for weldingprocesses. Yousefieh et al. [20] have used a design of experiment (DOE) technique, the Taguchi method, to optimize the pulsed current gas tungsten arc welding (PCGTAW) parameters for the corrosion resistance of super duplex stainless steel (UNS S32760) welds. Sathiya et al. [21] have done the optimization of friction welding parameters using evolutionary computational techniques. The methods suggested were used to determine the welding process parameters by which the desired tensile strength and minimized metal loss were obtained in friction welding. They described how to obtain near optimal welding conditions over a wide search space by conducting relatively a smaller number of experiments. Paventhan et al. [22] have done the optimization of friction welding process parameters for joining carbon steel and stainless steel. They developed an empirical relationship to predict the tensile strength of friction welded AISI 1040 grade medium carbon steel and AISI 304 austenitic stainless steel, incorporating the process parameters namely friction force, forging force, friction time and forging time, which have great influence on strength of the joints. Abdullah et al. [24] have discussed the different approaches in multi objective optimization using GA. Application of genetic algorithms in optimization of welding parameters is a relatively new idea.[3] used the genetic algorithms in optimization of welding parameters with the Gas Metal Arc Welding method (GMAW) in order to obtain optimal geometry of the welded connections. The main aim of this work was determination of mechanical properties of connections welded by friction. For this purpose the simulated annealing was used as a statistical method for searching of optimal welding parameters to get desirable mechanical properties of the connection. A neural network is a computational structure, consisting of a number of highly interconnected processing elements (or nodes), that produces a dynamic response to external input or stimuli [25].Neural networks were originally developed as approximations of the capabilities exhibited by biological neural systems. Much of the interest in neural networks arises from their ability to learn to recognize patterns in large data sets. This is accomplished by presenting the neural network with a series of examples of the conditions that the network is being trained to represent. The neural network then `learns' the governing relationships in the data set by adjusting the weights between its nodes. In essence, a neural network can be viewed as a function that maps input vectors to output vectors.

Accurate prediction of the values of critical quality parameters of a product during the production process is a key factor in the success of a manufacturing operation. Neural networks have been used successfully to predict parameter values of manufacturing process output. Cook and [26] collected particleboard process data throughout a manufacturing operation, along with the corresponding values of the strength parameters. They developed a radial basis function (RBF) neural-network model to predict the internal bond strength of particleboard, based on current process conditions. The process data included bulk density, temperatures, conveyor speed, blender and press conditions, and bonding treatment. The neural network output was the predicted value of IB. The average prediction error of the RBF neural-network model was 12.5%, which represented a significant improvement over previously developed neural-network models, as well as a statistical regression model. Neural-network technology was also applied to brown stock washer operations in a pulp and paper mill (Patrick, 1991). Forty-four variables were identified as possible parameters to include in the network training. The network was developed to maintain solids in the washing operation at a uniform level. Both the standard deviation and the coefficient of variation of solids uniformity showed an improvement of greater than 20% with the neural-network controller. This improved control implies improved washing efficiency, resulting in quality and economic benefits. [26] developed a radial basis function (RBF) neural-network model of a critical process parameter in a pulping process. The RBF model provided a 30% increase in predictive accuracy over the mathematical model proposed by Masura (1993).

2. EXPERIMENTAL DESIGN BASED ON GA AND ANN

The following independently controllable process parameters were identified to carry out the experiments: friction force (F), upset force (U), burn of length (B). Other parameters like rotational speed were kept as a constant. The working ranges of all selected parameters were fixed by conducting trial runs. This was carried out by varying one of the parameters while keeping the rest of them at constant values. The working range of each process parameter was decided upon by inspecting the weld for a smooth appearance without any visible defects. The upper and lower limits with different levels of the identified process parameters are given in Table 1.

Table 1 Process variables and its bounds

All welding variables at the intermediate level (0) constitute the center points and the combinations of each of the welding variables at either their lowest (-1) level or highest (+1) level with the other two variables at the intermediate levels constitute the star points. Thus the 20 experimental runs allowed the estimation of the linear, quadratic and two way interactive effects of the process parameters.

3. EXPERIMENTAL PROCEDURE

A continuous drive friction welding machine (KUKA, Germany) with a maximum 150kN load was used for welding is shown in the fig1. The friction and forge pressures are in the range of 40-120 MPA and 125–175 MPA respectively. The spindle rotating speed was kept varying at 1000-2000 rpm and the welding was performed under the specified friction upset distance. Super duplex material (UNS S32760) specimens of size 16mm diameters were used as parent materials in this study. The chemical composition of the specimen material is presented in Table2. Similar austenitic stainless steel specimens were joined by friction welding process without any preheat. Friction joints are processed experimentally at randomly chosen parameters sets. For each parameter set, five joints were processed. Strength related properties of the joints were tested and the average data is presented. Theoretical optimization was carried out in order to maximize the tensile strength of the joint and to minimize the shrinkage by non-traditional optimization techniques. The process was considered here as multi-input and multi-output system. The objective function was formulated by design expert software. Multi objective optimization for maximizing the tensile strength and minimizing the total shrinkage was carried out using genetic algorithm (GA).

The welding process is a multi-input and multi-output process in which joints are closely associated with welding parameters. There have been many studies on screening experiments, modeling and optimization for welding processes. However, there are few techniques to move the experimental to region near optimal welding condition. The development of mathematical models for the selection of the process parameters and the prediction of bead geometry (bead width, bead height and penetration). Factorial design was employed as a guide for optimization of process parameters (Kim et al., 2003). Statistical experimental designs were used for optimizing process parameters. Three commonly employed dissimilar metal combinations are used and only fair agreement was obtained between predicted and actual strengths for joints [2].The selection of process parameters for obtaining optimal weld pool geometry in the tungsten inert gas welding of the stainless steel. The modified taguchi method is adopted to analyze the effect of each welding process parameters on the weld pool geometry, and to determine the process parameters with optimal weld pool geometry [27]. These are useful not only for selecting optimum process parameters but also for achieving the desired quality and process optimization [23].

[29] has carried out interesting studies on the use of genetic algorithm & tabu search for the cryptanalysis of mono alphabetic substitution cipher. Applied an attack on transposition cipher using genetic algorithm, tabu Search & simulated annealing. The efficiency of genetic algorithm attack on knapsack cipher can be improved with variation of initial entry parameters.

Table 2 Base material chemical composition (weight in %).

Fig. 1. Friction welding machine.

Fig. 2. Friction welded samples.

The welded samples are shown in Fig. 2.

4. DEVELOPMENT OF MATHEMATICAL MODEL

The response function representing tensile strength or shrinkage can be expressed as

Y = f (F, U, B,N) (2)

where Y is the response or yield, F is the friction force, U is the Upset force and B is the burn off length. The mathematical models to establish the relationships between input and output parameters were developed using Design expert software (Statease Inc., USA) at a confidence level of 95%. Tensile strength(TS) and Shrinkage(S) were expressed as a non linear function of process parameters. Thus the second degree response surface can be expressed as $TS=b_0+\Sigma b_iX_i+\Sigma b_{ii}X_{i2}+\Sigma b_{ij}X_iX_j$ (3)

$TS=b_0+b_1F+b_2U+b_3 B+b_4 N+b_{12} FU+b_{13}FB+ b_{14}FN+b_{23}UB+ b_{24}UN+b_{34}BN+b_{11}F^2+b_{22}U^2+b_{33}B^2+b_{44}N^2$ (4)

where b_0 is the average of responses and b_1, b_2 and b_3, b_{12}, b_{13},... , b_{44} are the response coefficients that depend on respective main and interaction effects of parameters.

The value of the coefficient was calculated using Design expert Software [30]. The significance of each of the model terms was checked using p values. The values of p less than 0.05 indicate that the model terms are significant. The values greater than 0.05 indicate that the model terms are not significant. The final mathematical models were constructed using only significant terms, and the developed final empirical relationship both in coded and actual factors are given below:

Final Equations in Terms of Actual Factors:

Tensile strength, $TS = 892.87-0.68F+1.77U-1.2B-0.23N+ 0.003937FU+0.043FB+0.0002031FN+0.000465UN-0.001938BN-0.002152F^2- 0.009508U_2+0.39B_2+0.00005023N_2$ (7)

Total shrinkage, $S =-11.70-0.008402F+0.067U+1.34B+0.007892N-0.0006163FU-0.004250FB- 0.00004125FN+0.00001180UN+0.0001613BN+0.0008228F^2-0.000001634N^2$ (8)

Analysis of variance (ANOVA) technique [31] was used to check the adequacy of the developed empirical relationship. In this investigation, the desired level of confidence was considered to be95%. The results of basic ANOVA are presented in Table. 4 and 6.

5. SINGLE OBJECTIVE OPTIMIZATION

The traditional methods of optimization and search do not perform well over a broad spectrum of problem domains. Traditional techniques are not efficient when practical search space is too large. These algorithms are not robust. Traditional techniques such as geometric programming, dynamic programming and branch and bound techniques found hard to solve these problem and they are inclined to obtain a local optimal solution. Based on the merits of non-traditional optimization techniques over traditional techniques, this paper has proposed to compare two non-traditional techniques (GA and ANN) in solving welding optimization problem. Simultaneous optimization of corrosion resistance and impact strength of friction welded joints fall into multi objective optimization. There are two different approaches for multi objective optimization [24]. The conventional way is to combine the two objectives into a single objective by weighted sum method or to move all but one objective to the constraint set. But a major concern in the former case is to choose the proper weight for each objective function. Both the methods results in a single solution rather than a set of solutions which can be evaluated for trade-offs. For this reason it is better to prefer a set of good solutions considering the multiple objectives

5.1 Genetic algorithm

The genetic algorithm is a method for solving both constrained and unconstrained optimization problems that is based on natural selection, the process that drives biological evolution [32]. The genetic algorithm repeatedly modifies a population of individual solutions. At each step, the genetic algorithm selects individuals at random from the current population to be parents and uses them to produce the children for the next generation. Over successive generations, the population "evolves" toward an optimal solution. Genetic algorithm can be applied to solve a variety of optimization problems that are not well suited for standard optimization algorithms, including problems in which the objective function is discontinuous, nondifferentiable, stochastic, or highly nonlinear.

The genetic algorithm uses three main types of rules at each step to create the next generation from the current population. Selection rules select the individuals, called parents, which contribute to the population at the next generation. Crossover rules combine two parents to form children for the next generation. Mutation rules apply random changes to individual parents to form children.

[start] Genetic random population of n chromosomes (suitable solutions for the problem)

[Fitness] Evaluate the fitness f(x) of each chromosome x in the population

[New population] Create a new population by repeating following steps until the New population is complete

[Selection] select two parent chromosomes from a population according to their fitness (the better fitness, the bigger chance to get selected).

[Crossover] With a crossover probability, cross over the parents to form new offspring (children). If no crossover was performed, offspring is the exact copy of parents.

[Mutation] With a mutation probability, mutate new offspring at each locus (position in chromosome)

[Accepting] Place new offspring in the new population.

[Replace] Use new generated population for a further sum of the algorithm.

[Test] If the end condition is satisfied, stop, and return the best solution in current population.

[Loop] Go to step2 for fitness evaluation.

5.2 Optimization procedure

Global optimization toolbox in MATLAB (R2010a) was used for generating the Pareto front for corrosion current and impact strength using "gamultiobj‟ function. The MATLAB function "gamultiobj‟ uses a controlled elitist genetic algorithm. An elitist GA always favors individuals with better fitness value (rank) [32]. A controlled elitist GA also favors individuals that can help increase the diversity of the population even if they have a lower fitness value. A MATLAB function was written using the developed GA model. Then this function was called as the input for creating a fitness function for the multi objective optimization problem. The impact strength to be maximized was negated in the fitness function since "gamultiobj‟ minimizes all the objectives. Experimental ranges were placed as bounds on the three input variables which are shown below: Bounds on Friction force $0.8 \leq F \leq 2.4$

- Bounds on Upset force

$2.5 \leq U \leq 3.5$

- Bounds on Burn off length

$2 \leq B \leq 6$

Bounds on Speed $1000 \leq N \leq 2000$

The following algorithm options were set.

The weighted average change in the fitness function value over 100 generations was used as the criteria for stopping the algorithm.

6. RESULTS AND DISCUSSION

Investigations were carried out already to assess the relationship of microstructure/property relationships of similar and dissimilar joints of stainless steel by various welding processes. The mathematical models furnished above have been used to predict the responses: corrosion current and impact strength. The effects of joining process parameters on metallurgical and mechanical properties of friction-welded super duplex material (UNS S32760) joints were investigated, and the correlation between the microstructure and the joint strength was carried out (T.Udaya kumar et al., 2013). Due to the difficulties associated with conventional way of optimization, we used evolutionary computational techniques to get maximized tensile strength and minimized shrinkage. The predicted values are in good agreement with the observed values for both the models. Based on the ANOVA results it is clear that burn off length has high significance on shrinkage followed by upset force and friction force. In the case of tensile strength, friction force has high significance followed by upset force and burn off length. The non-dominated optimal points, resulted from multi objective GA, gave an insight regarding the optimal operating conditions of the process.

6.1 Direct effects of process parameters

Individual effects of process parameters on each of the responses have been found from the developed mathematical models. The variation of the responses with respect to each of the three process parameters: friction force, upset force, burn off length and speed were plotted by keeping two parameters constant at their middle level and varying the third within the upper and lower bounds.

7. CONCLUSION

The following conclusions are achieved from this work. Investigations on the implementation of friction welding of similar super duplex material (UNS S32760) joints is carried out. The relationship between the input parameters such as friction pressure, upset pressure, burn off length and speed with the output parameters like tensile strength and shrinkage is modelled through design expert software. The developed model is suitably integrated with optimization algorithms. To optimize the welding parameters, GA and ANN techniques were employed. Among these two algorithms GA outperforms well for this friction welding process. For the optimized welding parameters of GA, the friction welding joints were processed. Joints exhibit higher quality. The good agreement between the theoretically predicted (GA) and experimentally obtained tensile strength and shrinkage confirms the applicability of these evolutionary computational techniques for optimization of process parameters in the welding process.

In this study, experimentation has been done to simulate the friction welding of SDSS. An effort has been made to model the tensile strength and shrinkage of the friction welded joints using response surface approach. The plots indicate that burn off length has a strong determinant in tensile strength current followed by upset force and friction force. And friction force is the significant parameter in changing tensile strength followed by upset force and burn off length.

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List of Tables

Table 1 Process variables and its bounds

S.NO	INPUT VARIABLE	RANGE
1	Friction pressure	40-120 MPA
2	Upset pressure	125-175 MPA
3	Burn Off Length	2-6 MM
4	Speed	1000-2000 RPM

Table 2 Base material chemical composition (weight in %).

GRADE	UNS NO.	EN NO.	C	Cr	Ni	Mo	N	Mn	Cu	W
2507	S32760	1.4501	0.03	24-26	6-8	3-4	0.2-0.3	1	0.51	0.51

Table 3 Input and output variables for tensile strength

EXP.NO	FRICTION PRESSURE	UPSET PRESSURE	BURN OFF LENGTH	SPEED	TENSILE STRENGTH
1	40	125	2	1000	842
2	120	125	2	1000	821
3	40	175	2	1000	816
4	120	175	2	1000	814
5	40	125	6	1000	846
6	120	125	6	1000	842
7	40	175	6	1000	825
8	120	175	6	1000	835
9	40	125	2	2000	824
10	120	125	2	2000	822
11	40	175	2	2000	825
12	120	175	2	2000	838
13	40	125	6	2000	824
14	120	125	6	2000	835
15	40	175	6	2000	824
16	120	175	6	2000	850
17	40	150	4	1500	821
18	120	150	4	1500	824
19	80	125	4	1500	822
20	80	175	4	1500	818
21	80	150	2	1500	823
22	80	150	6	1500	832
23	80	150	4	1000	839
24	80	150	4	2000	838
25	80	150	4	1500	826
26	80	150	4	1500	824
27	80	150	4	1500	825
28	80	150	4	1500	826
29	80	150	4	1500	827
30	80	150	4	1500	825
31	80	150	4	1500	823

Table 4 ANNOVA table – Tensile strength

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	2395.413762	13	184.2626	139.0864	< 0.0001	significant
A-A	78.68999022	1	78.68999	59.39732	< 0.0001	
B-B	34.61296677	1	34.61297	26.1268	< 0.0001	
C-C	0.820961573	1	0.820962	0.619684	0.4420	
D-D	785.6758095	1	785.6758	593.0492	< 0.0001	
AB	248.0625	1	248.0625	187.2442	< 0.0001	
AC	189.0625	1	189.0625	142.7094	< 0.0001	
AD	264.0625	1	264.0625	199.3215	< 0.0001	
BD	540.5625	1	540.5625	408.0311	< 0.0001	
CD	60.0625	1	60.0625	45.33679	< 0.0001	
A^2	30.75766551	1	30.75767	23.21671	0.0002	
B^2	91.64866897	1	91.64867	69.17887	< 0.0001	
C^2	6.293997693	1	6.293998	4.750878	0.0436	
D^2	409.2213333	1	409.2213	308.8912	< 0.0001	
Residual	22.52172222	17	1.324807			
Lack of Fit	11.66457937	11	1.060416	0.58602	0.7907	not significant
Pure Error	10.85714286	6	1.809524			
Cor Total	2417.935484	30				

Table 5 Input and output variables for shrinkage.

EXP.NO	FRICTION PRESSURE	UPSET PRESSURE	BURN OFF LENGTH	SPEED	SHRINKAGE
1	40	125	2	1000	3.6
2	120	125	2	1000	2.7
3	40	175	2	1000	5.78
4	120	175	2	1000	3.07
5	40	125	6	1000	8.27
6	120	125	6	1000	7
7	40	175	6	1000	11.17
8	120	175	6	1000	7.41
9	40	125	2	2000	6.19
10	120	125	2	2000	3.04
11	40	175	2	2000	9.57
12	120	175	2	2000	3.81
13	40	125	6	2000	12.49
14	120	125	6	2000	7.42
15	40	175	6	2000	15.92
16	120	175	6	2000	8.06
17	40	150	4	1500	9.72
18	120	150	4	1500	5.43
19	120	125	4	1500	5.61
20	80	175	4	1500	7.25
21	80	150	2	1500	3.89
22	80	150	6	1500	8.63
23	80	150	4	1000	5.21
24	80	150	4	2000	6.65
25	80	150	4	1500	6.39
26	80	150	4	1500	6.14
27	80	150	4	1500	6.41
28	80	150	4	1500	6.39
29	80	150	4	1500	6.14
30	80	150	4	1500	6.41

Table 6 ANNOVA table - Shrinkage

Source	**Sum of Squares**	**df**	**Mean Square**	**F Value**	**p-value Prob > F**	
Model	238.9649411	11	21.72408556	339.9910708	<0.0001	significant
A-A	0.014810315	1	0.014810315	0.231787653	0.6360	
B-B	3.185977811	1	3.185977811	49.86189198	<0.0001	
C-C	8.278413356	1	8.278413356	129.5606489	<0.0001	
D-D	1.336198163	1	1.336198163	20.91206292	0.0002	
AB	6.346081585	1	6.346081585	99.3188444	<0.0001	
AC	1.8496	1	1.8496	28.94701748	<0.0001	
AD	10.89	1	10.89	170.4330776	<0.0001	
BD	0.3481	1	0.3481	5.447911325	0.0314	
CD	0.416025	1	0.416025	6.510966127	0.0200	
A^2	6.794516264	1	6.794516264	106.3370356	<0.0001	
D^2	0.679147351	1	0.679147351	10.62894152	0.0043	
Residual	1.150128852	18	0.063896047			
Lack of Fit	1.059595519	13	0.081507348	4.501510362	0.0535	not significant
Pure Error	0.090533333	5	0.018106667			
Cor Total	240.11507	29				

Table 7 Comparison between Theoretical and Experimental Input and Output variable for maximized Tensile Strength

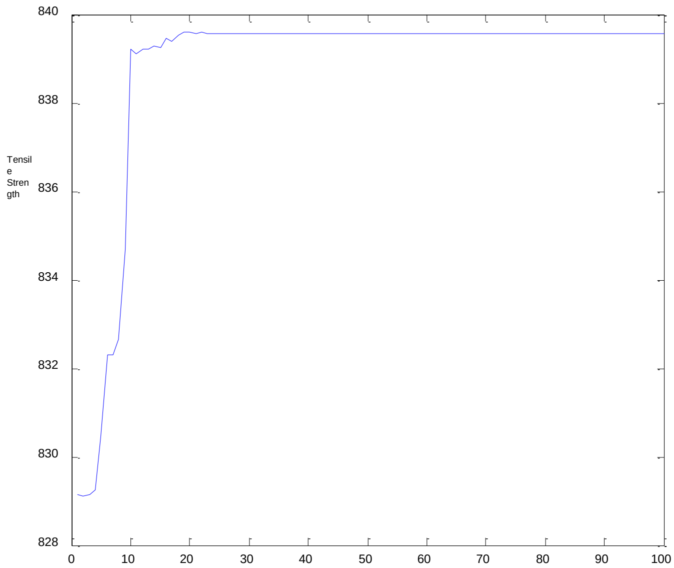
	Input parameters				Output parameter
	Friction Pressure	Upset Pressure	Burn off Length	Speed	Tensile strength
	(MPA)	(MPA)	(MM)	(RPM)	(MPA)
Theoretically optimized parameters by GA	49.4	126.9	5.8	1037.5	847.3048
Experimentally used parameters	40	125	6	1000	846

Table 8 Comparison between Theoretical and Experimental Input and Output variable for minimized Shrinkage

	Input parameters				Output parameter
	Friction Pressure	Upset Pressure	Burn off Length	Speed	Shrinkage
	(MPA)	(MPA)	(MM)	(RPM)	(MM)
Theoretically optimized parameters by GA	118.1	126.3	2.1	1026.5	2.6962
Experimentally used parameters	120	125	2	1000	2.7

Fig. 1. Friction welding machine

Fig. 2. Friction welded samples



Iteration Number

Fig. 3. Graph for maximum value of tensile strength

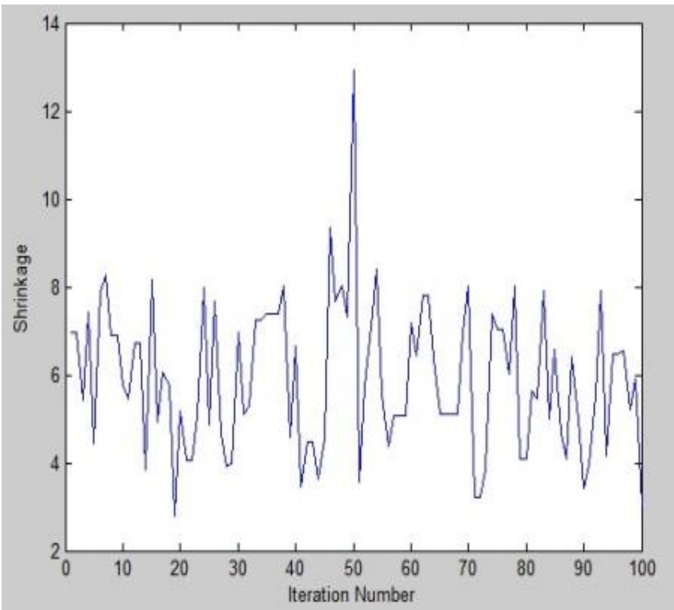


Fig. 4. Graph for minimum value of shrinkage