OPTIMIZATION OF PROCESS PARAMETERS IN REPITITIVE CORRUGATION & STRAIGHTENING (RCS) OF MILD STEEL USING TAGUCHI BASED FUZZY LOGIC

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***Abstract* - Processes of severe plastic deformation (SPD) are defined as metal forming processes in which a very large plastic strain is imposed on a bulk process in order to make an ultra-fine grained metal. The objective of the SPD processes for creating ultra-fine grained metal is to produce light weight parts by using high strength metal for the safety and reliability of micro parts and for eco friendly. Repetitive corrugation and straightening (RCS) is one of the new processes in SPD technique. In this project the strength of mild steel is going to be increased by reducing the grain size to ultrafine grain size by using RCS technique. The taguchi optimization method is used with standard orthogonal array L9. To determine which process parameters are statistically significant on tensile, flexural and hardness a fuzzy logic approach is used. Finally conformation tests were carried out to investigate optimization improvements.**

Keywords: Severe plastic deformation, forming, corrugation process.

I. INTRODUCTION

Bulk nanostructure materials processed by severe plastic deformation (SPD) are of considerable interest in the materials science community because they are porosity free and large enough for mechanical or physical property measurements they have superior mechanical properties including high strength, good ductility, high toughness, and super plasticity [1] at high strain rates and low temperatures. In contrast, the mechanical properties of coarse-grained materials follow a general strength and ductility trade-off, i.e. high strength is almost always accompanied by low ductility. The superior properties of bulk nano-structured materials apparently set them apart from coarse-grained materials and make them very attractive for structural applications.

There are currently several SPD techniques to synthesize bulk nanostructure materials, including equal channel angular pressing (ECAP) and high-pressure torsion (HPT) which are among the most developed and studied. In an ECAP process, a bulk sample is pressed to go through a die with two channels, which are equal in cross section and intersect at an angle, usually 90^0. The sample is subjected to a shear strain as it moves through the intersection of the two channels, which makes it possible to repetitively press the same sample in order to introduce high accumulated strains and refine the grain size significantly. However, ECAP is currently a discontinuous process, and it can process samples only up to certain sizes. In HPT, only disk-shaped samples can be processed under pressure and torsional deformation.

It is suggested the possibility of using a new technique, repetitive corrugation and strengthening (RCS), to process bulk nanostructure materials. In this a prototype discontinuous RCS set up, i.e. a tool-steel die set with teeth is used, to prove the principle.

II. BACKGROUND OF WORK

Equal channel angular pressing (ECAP), high-pressure torsion (HPT), twist extrusion (TE), accumulative roll bonding (ARB), constrained groove pressing (CGP), and repetitive corrugation and straightening (RCS) are a few examples of SPD techniques [2]. Several materials of different geometrical shapes were successfully processed by SPD techniques including solid and hollow rods, sheets, plates, and tubes [3] and the mechanical behavior was found to be improved.

Furthermore, in recent years, materials have been processed by second generation of SPD techniques by providing additional variations to the respective basic method. Among all the SPD techniques, RCS [4] is a simple technique which can be used to develop ultrafine grained (UFG) metallic sheets in bulk. In RCS, a workpiece is repeatedly bent and straightened without a significant change in the cross-sectional dimensions, which impart large amount of strains into the material and results in grain refinement. The objectives of the work were to investigate number of cycles of CRCS on homogeneity mechanical properties hardness and tensile properties and which was justified with micro-structure.

II. METHODS OF SPD TECHNIQUES

Various techniques of SPD [5] are shown in Fig.1, the new technique, Repetitive Corrugation and Straightening (RCS), primarily employs bending as the deformation mode, in contrast to the shear deformation mode in ECA pressing. Similar to the ECA pressing, it introduces large amount of plastic deformation to the work-piece without significantly changing its geometry or cross-sectional area. This allows the work-piece to be processed repeatedly to refine its grain size without reducing the work-piece to the geometry of foil or wire, as do traditional deformation techniques such as rolling, drawing or extrusion.

Pandey et.al [6] designed a new technique called continuous repetitive corrugation and straightening system (CRCS), which produces continues strips without wastage of materials in a single cycle. Few researchers were working on effect of CRCS on materials such as precipitation, strain hardening, and heat treatment processes. They were observed that the ductility of the samples expressed by relative elongation insignificant drop. Micro-hardness of the CRSC samples increased from about 100 to about 150 HV. The similar strength characteristics for the samples increased. However few researchers successfully worked on strengthening CRCS method but no information is available to date on the level of homogeneity achieved in processing by CRSC method.

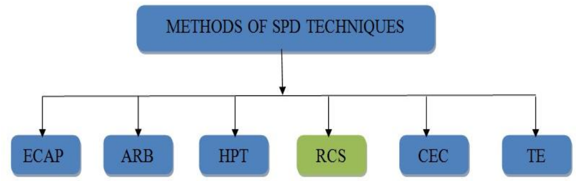

Fig. 1. Methods of SPD Techniques

The technique consists of bending a straight Billet with corrugated tools and then restoring the straight shape of the billet with flat tools. By repeating these processes in a cyclic manner, high strains can be introduced in the work piece as shown in fig 2.

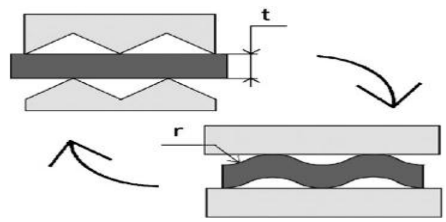

Fig.2. Repetitive Corrugation and Straightening Process

The DOE based studies applied so for mainly focused for the optimization of the single quality characteristics. Only few authors have optimized parameters for multiple quality characteristics. In RCS process precise control of the process parameters are required.

The conventional methods of modeling and optimization require a lot of experiments and pass other substantial challenges. The experimental work is costly and time consuming. To overcome these difficulties, artificial intelligence (AI) based modeling and optimization methods such as fuzzy logic (FL), artificial neural network (ANN) and genetic algorithm (GA) may be used for the modeling and optimization of a process.

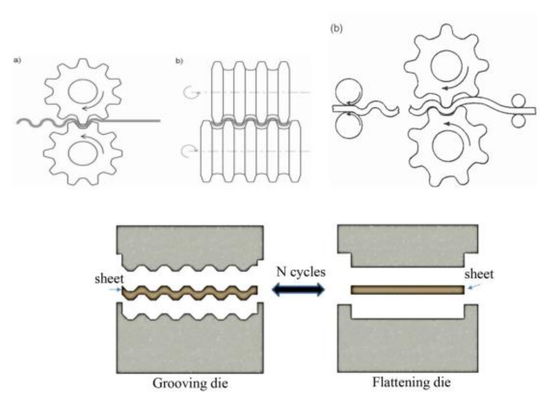

Fig.3. Different types of RCS process

In the present research paper a hybrid approach of Taguchi robust parameter design and Fuzzy logic theory have been used for multi-objective optimization of RCS process. Firstly, Taguchi methodology has been applied to find out the signal to noise(S/N) ratios for different output parameters. Then S/N ratios for individual quality characteristics are used to compute a common performance index using fuzzy logic theory. The input parameters or control factors of Taguchi methodology corresponding to optimum (or maximum) value of this performance index give the optimum parameter level. The experiments have been performed on 1.5,2,2.5 mm thick Mild steel sheet at different number of passes like 1,2,3 and at different strain rates of 1.0,1.5,2.0 mm/min with RCS process .Four input process parameters such as Thickness, Number of passes and Strain rate have been taken. Tensile strength, Flexural strength and Hardness have been considered as output characteristics.

III. DESIGN OF EXPERIMENTS

Taguchi methodology (TM) for robust parameter design is a unique off line statistical design technique that greatly influences the productivity of the manufacturing system. Taguchi has tabulated 18 basic types of designed experimental matrixes known as orthogonal arrays (OA). The selection of OA is based on the number of controllable factors, their levels and interactions, if any. More than one test per trail can be used to conduct the experiments. It increases the sensitivity of the experiments to detect small changes in averages of responses. An economic consideration also can be made for conducting the repeated experiments with same experimental run. If the selected OA is of higher order such as L16, L27 or L32, then the repetition of experiments on the same experimental run has not been found so fruitful from the sensitivity point of view. For example same sensitivity of experiments has been obtained with L16 OA in one repetition per experimental run as with L8 OA with two repetitions per experimental run at 99% of confidence level. Also, an L8 OA with two repetitions or L16 OA with one repetition makes the experimenter 90% sure of detecting the changes of approximately 1.5 standard deviations. In the present study the authors have selected L9 OA run by taking into account of economic considerations as well as sensitivity of the experiments. In present research L9 OA based experiments are performed on the grooving and flattening dies. The chemical composition of the Mild steel sheets used is shown in Table 1. Thickness, Number of passes and Strain rate are selected as variable process parameters (controllable factors). The quality characteristics selected for the analysis are Tensile strength, Flexural strength and Hardness.

Table 1
Processing parameters and their level used in experimentation

Symbol	Processing parameters	Level 1	Level 2	Level 3
A	Thickness (mm)	1.5	2	2.5
B	Number of passes	1	2	3
C	Strain rate (mm/min)	1.0	1.5	2.0

As the larger values of all three quality characteristics tensile strength, flexural; strength and hardness are desired hence larger-the-better type mean square quality characteristics (MSQC) is used to find out the S/N ratios for all quality characteristics.

$$S/N = -10\log_{10}\left(\frac{1}{n}\sum\frac{1}{y^2}\right) \quad (1)$$

Where, y_i is the experimental measured value of the quality characteristics for i^{th} experimental run and n is the total number of experimental trials for same levels of process parameters. The S/N ratios obtained for all three quality characteristics are shown. The S/N ratio is always maximized because larger value of S/N ratio gives minimum scatter. The average value of S/N ratio at a level is used to find out the optimum level of different process parameters at the same level. The maximum value of average S/N ratio at a level, will give the optimum level of a control factor.

IV. TAGUCHI BASED FUZZY LOGIC OPTIMIZATION METHODOLOGY

The theory of fuzzy logic has proven to be useful for dealing with uncertain and vague information. In fact, the definitions of performance characteristics such as lower-the-better, higher-the- better and nominal-the-best contain a certain degree of uncertainty and vagueness. So, fuzzy logic may be applied to convert the S/N ratios of different quality characteristics obtained by Taguchi methodology into a single fuzzy multi-response performance index (MPCI). Fuzzy logic modeling is based on the fuzzy set theory and it deals with the fuzzy sets in place of classical crisp sets. Any fuzzy set A (S/N ratio) in universe of discourse X is a set characterized by a membership function μA(x): X [0, 1], and the value of μA(x): A[0, 1] express the grade of x in fuzzy set A. The fuzzy set can be mathematically expressed as

A = [(X, $\mu_{A(x)}$)]

Or

A = [$\mu_{A(x1)}, \mu_{A(x2)}, \mu_{A(x3)}, \mu_{A(x4)} \ldots \mu_{A(xn)}$]

Where, x€X and n is number of fuzzy variables. Fuzzy modeling basically involves three main processes i.e. fuzzification, fuzzy inference and defuzzification. In this process the linguistic variables are converted into fuzzy variables. After the fuzzification process, fuzzy rule base is formed. The fuzzy rule base consists of a group of ''IF and THEN'' rules with the three inputs x1 (S/N ratio value of Tensile), x2 (S/N ratio value of Flexural) and x3 (S/N ratio value of Hardness), and one output y (MPCI value)i.e.

Rule 1: If x1 is A1 and x2 is B1 and x3 is C1 then y is D1 else,
Rule 2: If x1 is A2 and x2 is B2 and x3 is C2 then y is D2 else,
Rule 3: If x1 is A3 and x2 is B3 and x3 is C3 then y is D3 else

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Rule n: If x1 is An and x2 is Bn and x3 is Cn then y is Dn else where Ai, Bi, Ci and Di are the fuzzy subsets (where A, B and C are S/N ratios fuzzy sets of Tensile, Flexural and Hardness, respectively, and D is fuzzy set of MPCI) defined by the corresponding membership functions μA(i), μB(i), μC(i) and μD(i). X1, x2, x3 and y are the fuzzy values of different fuzzy sets A, B, C and D, respectively. Each rule is evaluated through a process called implication. For fuzzy implication mini operation or Mamdani implication is used. In this operation, the minimum memberships of different fuzzy sets are taken into consideration. This rule may be represented mathematically as follows:

$\mu_{AB(x,y)} = \min [\ \mu_{A(x)},\ \mu_{B(y)}]$

The results of all rules are analyzed through a process known as fuzzy aggregation. For fuzzy aggregation disjunctive system of aggregation rules are used. In this method, the aggregated output is formed by fuzzy union of all individual rules. This may be represented as

$\mu_{A(x)} = \quad \mu_{A(x1)} + \mu_{A(x2)} + \mu_{A(x3)} \ldots\ldots \mu_{A\,(xn)}$

The fuzzy implication and fuzzy aggregation are combined together and are known as fuzzy inference process. By this process the output is obtained as fuzzy variables. In order to convert the fuzzy output into a absolute value, defuzzification is carried out. For defuzzification, the most popular method (Centroid method) is used to find non-fuzzy value y0

$$(Y_0) = \frac{\sum y\, \mu Co(y)}{\sum \mu Co(y)}$$

The defuzzified output (y0) obtained is known as MPCI. This MPCI is used for finding the optimum parameter level of control factors. Average value of MPCI is calculated for different process parameters corresponding to the different level. Maximum

A. Fuzzy modeling of RCS process

The input parameters are the S/N ratios of tensile, flexural and hardness respectively, while MPCI is the output parameter. In fuzzy modeling the input and output variables are also known as linguistic variables. All these three linguistic variables have three linguistic values or memberships namely Low (L) Medium (M) and High (H). For output characteristics nine types of linguistic values or member ships namely Very low (VL), Low (L), Medium (M), High (H), Very High (VH).

Table II

Fuzzy multi performance characteristics index (MPCI)

Exp. No.	Factors			MPCI	RANK
	A	B	C		
1	1.5	1	1.0	0.25	06
2	1.5	2	1.5	0.25	07
3	1.5	3	2.0	0.75	01
4	2.0	1	1.5	0.21	09
5	2.0	2	2.0	0.25	08
6	2.0	3	1.0	0.74	03
7	2.5	1	2.0	0.50	05
8	2.5	2	1.0	0.52	04
9	2.5	3	1.5	0.75	02

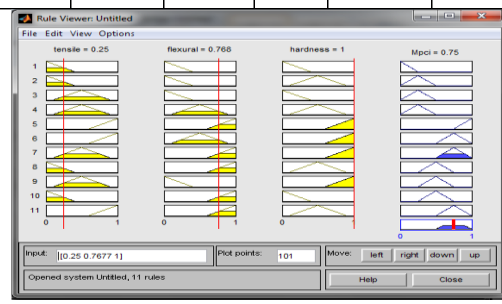

Fig. 4 Rule viewer with 11 rules as a output

Table 2
Response Table

Symbol	Processing parameters	Level 1	Level 2	Level 3
A	Thickness	**1.5***	2	2.5
B	Number of passes	1	2	**3***
C	Strain rate	1.0	1.5	**2.0***

The membership plots for input and output variables are by using triangular shapes. Here, triangular shapes are used because it covers more ranges and smooth as compared to remaining memberships function. Thus, for three input variables and their three membership values number of fuzzy rules formed nine rules.

V. RESULTS AND ANALYSIS

A. Multi-objective optimization

The MPCI at particular level corresponding to a control factor represents the average of all MPCI at that level. The maximum value of MPCI has the highest ranking and the minimum value of MPCI has lowest ranking as shown in Table4. The maximum Tensile, Flexural and Hardness values are obtained at level 1 of thickness (1.5 mm) level 3 of number of passes (3) and strain rate (2.0 mm/min) i.e. the optimum parameter setting for maximum Tensile, flexural strength and Hardness is $A_1 B_3 C_3$.

B. Results of confirmation experiment

The predicted value of FMPI at optimum parameter level may be calculated by using following equation

$$\eta_{mpci} = \eta_m + \sum (\eta_i - \eta_m)$$

Where η_m is the total mean of MPCI, η_i is the mean of MPCI at the optimal level and m is the number of the control factors considered.

The confirmation experiments have also been performed on suggested optimum level of control factors to verify the results. Three experiments have been performed at predicted optimum level and the average values of each quality characteristics obtained from three runs have been indicated as experimental value. The confirmation results show that Tensile, Flexural and hardness have been considerably improved from 10.680 KN/mm^2, 0.320 KN/mm^2 and 185.25 to 11.370 KN/mm^2, 0.42 KN/mm^2 and 426.79 respectively, at predicted optimum level with the negligible change in Strain rate. In other words, it can be said that an overall improvement of multiple quality characteristics have been obtained at suggested optimum level. Further, by computation using fuzzy model, the value of MPCI corresponding to the confirmed experimental values of mechanical properties has been increased.

VI. CONCLUSIONS

A hybrid approach obtained by the integration of robust parameter design with fuzzy logic theory has been used to optimize multiple responses in RCS process of mild steel sheet. The main findings of the paper are given below:

1. It is possible to achieve simultaneous improvement in multiple responses in RCS process by applying the proposed hybrid approach.
2. The mechanical properties (Tensile, Flexural & Hardness) of mild steel sheet has been considerably improved by RCS process.
3. The findings of the research paper indicate that thickness of the sheet is the most significant factor followed by and number of passes of strengthened material like mild steel. The contribution of thickness and number of passes to fuzzy multi-response performance index has been increased.
4. The optimum parameter values for different control factors have been suggested as thickness of 1.5mm, at third pass, strain rate of 2.0mm/min. The predicted optimum results have also been verified by confirmation experiment that shows the increase in mechanical properties like Tensile, Flexural and Hardness.

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