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Parametric optimization for the production of nanostructure in high carbon steel chips via machining

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Abstract Nano crystalline materials are an area of interest for the researchers all over the world due to its superior mechanical properties such as high strength and high hardness. But the cost of nano-crystals is high because of the complexity and cost incurred during its production. This paper focuses on the application of Taguchi method with Fuzzy logic for optimizing the machining parameters of nano-crystalline structured chips production in High Carbon Steel (HCS) through machining. An orthogonal array, multi-response performance index, signals to noise ratio and analysis of variance are used to study the machining process with multi-response performance characteristics. The machining parameters namely rake angle, depth of cut, heat treatment, feed and cutting velocity are optimized with considerations of the multi-response performance characteristics. Using the Taguchi and Fuzzy logic method optimum cutting conditions are identified in order to obtain the smallest nanocrystalline structure via machining.

1. Introduction

Nanocrystalline material stands out in the material science domain due to its superior mechanical properties like higher strength, hardness, ductility, etc. For synthesizing the nanocrystalline material bottom-up approach and top-down approach are used. Severe Plastic Deformation (SPD) is one of the top down approach for synthesizing the materials. The SPD breaks down the microstructure into finer and finer grains. The use of the SPD for the processing of bulk ultra fine-grained materials is now widespread [1]. The interest in ultra-fine grained materials which exhibit significantly enhanced mechanical properties has been developed and the attention has been focussed on the application of SPD in the view of achieving microstructure refinement in metals and alloys. A commonly used approach for refinement of microstructure in metals and alloys is the SPD [2]. The SPD generally refers to a class of processes wherein a material is deformed to large plastic strains through the use of multiple

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passes of deformation. The SPD has become a preferred methodology for producing bulk nanostructured material. The Equal Channel Angular Pressing/Extrusion (ECAE), drawing, rolling, or HPT, High Energy Ball Milling (HEBM) and machining are some of typical SPD approaches existing today to produce bulk nanocrystalline materials.

Top-down approach starts with materials that have conventional crystalline microstructures. Typically in metals and alloys, defects such as dislocations and point defects introduced during SPD such as Mechanical Alloying (MA), Equal Channel Pressing (ECAP), Equal Channel Angular Extrusion (ECAE) and High-Pressure Torsional straining (HPT) result in nanocrystalline structures [3,4]. In bottom-up approach, materials are built up with atom by atom, molecule by molecule or cluster by cluster from bottom such as Physical Vapor Deposition (PVD) and Chemical vapors Deposition (CVD). This method requires a highly complex and controlled environment and hence it is very costly whereas top-down approach requires no controlled environment and so its processing cost is less. This research focuses on the SPD approach for the production of nanocrystalline materials.

Brown et al. [5] demonstrated that the chips produced form plain strain machining of a material exhibit nanocrystalline structures and high hardness. Swaminathan et al. [3] have produced nanocrystalline metals and alloy chips by plain strain machining. Swaminathan et al. [6] demonstrated that the chips produced in the machining of a material experience very large shear strains and so plane strain machining (2-D) can be an attractive route for creating very large plastic strains in a single stage of deformation thus overcoming the limitations of the SPD process. Iglesias et al. [7] have defined that the chip formation approach is a top-down approach and it is applicable essentially to any metal or alloy, including high-strength materials such as Ni-based alloys, stainless steels and Ti alloys. Suryanarayana [8] has defined that nanocrystalline metals and alloys of high strength can be formed through a normal machining process. Ravi Shankar et al. [9] have identified that the machining parameters such as rake angle, depth of cut, speed influences the strain rate imposed by the cutting tools. These studies suggest that machining is an attractive process for producing nanocrystalline materials. Most of the existing researchers have worked on plain strain machining. This research work focuses on production of nanocrystalline materials through normal oblique machining route. In this experiment the machining parameters to be considered are rake angle, depth of cut, feed, nose radius and cutting velocity. However a great in-depth knowledge and experience is required to find the optimal parameters and adding to that numerous experiments are also need to be conducted. Therefore to conduct the experiment, Taguchi method is adopted which is a powerful tool for design of experiments method using orthogonal arrays. It provides a simple, efficient and systematic approach to optimize the parameters. However, most published Taguchi applications have been dealing with the optimization of a single performance characteristic. But the problem still remaining is that of multiple performance characteristics [10,11]. The theory of fuzzy logics, initiated by Zadeh [12] proven to be useful for dealing with uncertain and unclear information. In fact, the definition of performance characteristics such as lower-the-better, higher-the-better, and nominal-the-better contains a certain degree of uncertainty and vagueness. So an optimization of the multiple characteristics is done by fuzzy. In this study, a fuzzy reasoning of the multiple performance characteristics has been developed based on fuzzy logic and using that complicated characteristics can be transformed into the optimization of a single multi-response performance index (MRPI). In short, the research work focuses on production of nanocrystalline chips through oblique machining and optimizing the machining parameters.

2. Proposed multi-response performance index (MRPI) model

The experimental design methods were developed by Fisher [13] to select and set the ranges of the control variables. The classic experimental design requires conducting of numerous experiments which further increases the overall cost, complexity and time. The orthogonal arrays enable the study of entire parameter space with less number of experiments. The experimental results are then transformed into signal-to-noise ratio that can be used to measure performance characteristics deviating from the desired values. Usually there are three categories of signal-to-noise ratio: the lower-the-better, higher-the-better and nominal-the-better. In this experiment microhardness has higher-the-better characteristics and crystalline size has lower-the-better characteristics. As a result improving one performance characteristics may affect the other's performance. Hence, optimization of such multiple performance characteristics is much more complex than optimization of a single performance characteristic [14]. So Taguchi method with fuzzy logic is used to investigate the multiple performance characteristics in the machining process.

Firstly, the process parameters namely rake angle, depth of cut, feed, nose radius and cutting velocity are selected and then Taguchi's L16 orthogonal array is created. Using the array machining process is carried out and the outputs are taken. Microhardness of the machined chips is measured using microhardness tester and the values are converted to S/N ratio. Crystalline sizes of the chips are analyzed using XRD method and then converted to S/N ratio. In the Fuzzy logic system, the calculated S/N ratios of both crystalline size and microstructure are converted into MRPI. From the MRPI response, the optimum value for the machining parameters is found out and finally image characterization of the chips is carried out using Scanning Electron Microscope (SEM). The research procedure methodology is shown in Fig. 1.

3. Methods

3.1. Experimental procedure

Foremost step is the machining process which is done with CNC Fanuc lathe. Tungsten carbide coated tool is used for this machining process with a negative rake angle [3].

High resolution FEG–SEM is used for characterization of chips. For this analysis, the mounted specimens are etched. The etchant is prepared as per the ASM (American Society of Metals) standards i.e. 45 ml of Hydrochloric acid, 15 ml of Nitric acid and 20 ml of methanol. The etching time is 10–30s.

The following procedures are adopted to characterize the samples

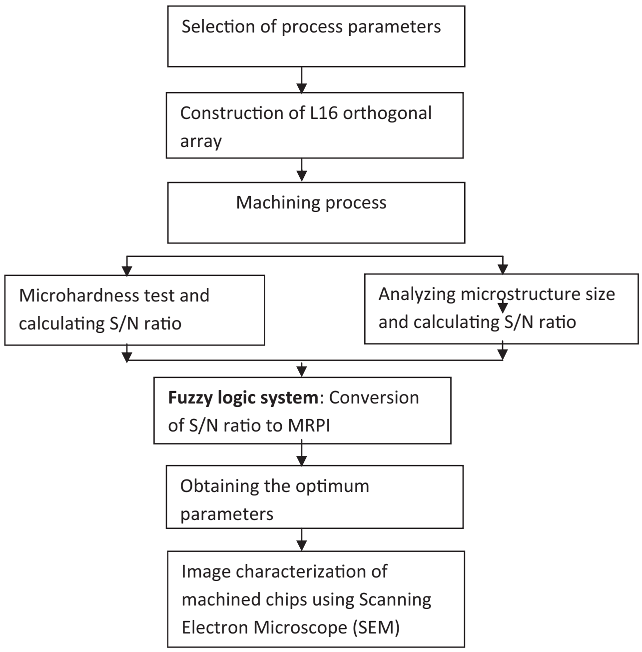

Figure 1 Research procedure methodology of MRP.

- The polished mounted chips are etched as per the ASM standards.
- The etched specimen is coated with platinum with the help of platinum coater in order to make the surface conductive.
- Then the coated specimen is placed in the specimen holder of the FEG–SEM and vacuum is created.
- The images of the specimen are captured at different magnifications.
- From the captured image the average crystalline size is estimated based on the scale. Fig. 2 shows the flow diagram of the image capturing procedure.

The machined chips are then mounted on a Rigaku Ultima X-ray diffractometer to measure the crystalline size. Then the microhardness of the polished samples was measured by indentation with a Vickers indenter with a 200 g load and 30 s dwell time on a Mitutoyo micro hardness tester. The mounted chips were analyzed using XRD and SEM. X-ray diffraction patterns were recorded using Rigaku Ultima III XRD, in the 2θ range from 30° to 80°. Scherer equation has been applied to estimate the size of crystallites [15].

$$T = \frac{k\lambda}{B\ \cos\theta} \tag{1}$$

where T is the crystalline size, k is a constant that varies with the method of taking the breath, λ is the wavelength of incident X-rays ($\lambda = 1.5406$ Å), B is the width of the peak at half maximum intensity of a specific phase (hkl in radians), θ is a Bragg angle.

3.2. Orthogonal array experiments

In order to follow the Taguchi method, it is important to fix the parameters that influence the machining output to a greater extent. From the literatures and previous work [9], the important machining parameters considered are (1) rake angle, (2) depth of cut, (3) heat treatment, (4) feed, (5) cutting velocity for which the output response used to measure the machinability is crystalline size and micro hardness. Different levels of machining parameters are chosen to determine the optimal machining parameters to get the desired output response (i.e.) higher hardness and lower crystalline size. All the machining parameters and their corresponding levels are shown in Table 1.

The appropriate orthogonal array for this experiment depends upon the degrees of freedom. The degrees of freedom is defined as the number of comparisons between process parameters that must be made to determine which level is

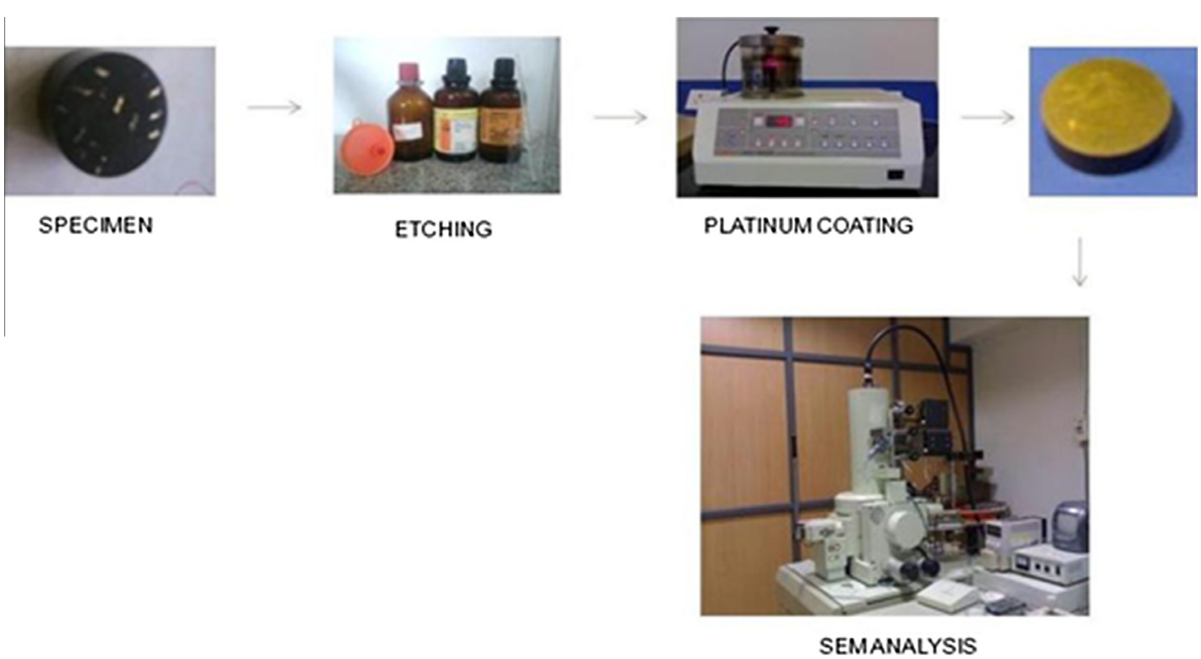

Figure 2 FEG–SEM – flow diagram.

Table 1 Machining parameters and their levels for HCS.

Symbol	Parameter	Levels			
		Level 1	Level 2	Level 3	Level 4
A	Rake angle (degree)	−6	−10	−14	−18
B	Depth of cut (mm)	0.2	0.4	0.6	0.8
C	Heat treatment	Annealed	–	–	–
D	Feed (mm/rev)	0.1	0.15	0.20	0.25
E	Cutting velocity (m/min)	20	40	60	80

better and specifically how much better it is. In this experiment there are fifteen degrees of freedom. After determining the degrees of freedom, the next step is to fix the orthogonal array. An L_{16} orthogonal array is considered with five columns and sixteen rows and it is shown in Table 2. The array deals with a three level process parameters. Every machining parameter is assigned to a column and every row indicates the parametric combination.

3.3. Signals-to-noise (s/n) ratio

In Taguchi method, Taguchi recommends the use of loss function to measure the deviation between the experimental value and the desired value which is further transformed into signal-to noise ratio (S/N). There are three different categories of the performance characteristics in evaluation of the S/N ratios to obtain the optimum parameters setting. i.e., the lower-the better, the higher-the better and the nominal-the better. To obtain optimal machining performance, the minimum crystalline size and the maximum micro hardness are desired. Therefore, the lower-the-better crystalline size and the higher-the-better micro hardness should be selected.

(1) Loss function L_{ij} of the lower the better performance characteristic can be expressed as

Table 2 Experimental layout using L_{16} orthogonal array.

Experiment number	Rake angle (degree)	Depth of cut (mm)	Heat treatment (mm)	Feed (mm/rev)	Cutting velocity (mm/min)
1	1	1	1	1	1
2	1	2	1	2	2
3	1	3	2	3	3
4	1	4	2	4	4
5	2	1	1	4	3
6	2	2	1	3	4
7	2	3	2	2	2
8	2	4	2	1	1
9	3	1	2	2	4
10	3	2	2	1	3
11	3	3	1	4	2
12	3	4	1	3	1
13	4	1	2	3	2
14	4	2	2	4	1
15	4	3	1	1	4
16	4	4	1	2	3

$$L_{ij} = \left[\frac{1}{n}\sum_{i=1}^{n} y_i^2\right] \tag{2}$$

Loss function L_{ij} of the higher the better performance characteristic can be expressed as

$$L_{ij} = \left[\frac{1}{n}\sum_{i=1}^{n} \frac{1}{y_i^2}\right] \tag{3}$$

where n represents the number of repeated experiments, L_{ij} is the loss function of the ith performance characteristic in the jth experiment, and $y_{ij}k$ is the experimental value of the ith performance characteristic in the jth experiment at the kth test.

(2) The loss function is further transferred into an s/n ratio. The S/N ratio Z_{ij} for the ith performance characteristic in the jth experiment can be expressed as

$$Z_{ij} = -10\log_{10}(L_{ij}) \tag{4}$$

3.4. Fuzzy logic unit

Fuzzy logic was developed by Prof. Zadeh [12] to deal with vagueness, uncertainty and imprecision in decision making process for real world applications. A fuzzy system is a system of variables and there are input and output linguistic variables. The fuzzy logic approach is based on the definition of a fuzzy sets, linguistic variables and fuzzy If-then rules. It consists of three basic elements: fuzzification, inferencing, defuzzification and are described as follows.

3.4.1. Fuzzification

Fuzzification is a process which converts input data to degrees of membership by a lookup in one or several membership functions [16]. Membership functions are numerical functions corresponding to linguistic terms. Triangular, Trapezoidal and bell shaped membership functions are commonly used for engineering applications. Among which triangular membership functions is chosen for this research work. Triangular membership functions require less computational process, most economical one and well suited for real time applications [17]. The triangular membership function can be represented as follows,

$$\mu(x) = \begin{cases} 0 \text{ for } x < a \\ \frac{x-a}{b-a} \text{ for } a < x < b \\ \frac{c-x}{c-b} \text{ for } b < x < c \\ 0 \text{ for } c > 0 \end{cases}$$

where a, b, and c indexes show the crisp values of triangular membership functions.

3.4.2. Fuzzy inferencing

Fuzzy inferencing is the process of formulating the relationship between given input and output variables based on their linguistics terms. Membership functions, If-Then rules and logical operations are involved in the process of fuzzy inferencing. The rules are created by analyzing experimental data along with membership functions of each linguistic variable.

Table 3 Experimental results and S/N ratio.

Trail no.	Micro hardness (VHN)		S/N ratio (dB)	Crystalline size (nm)		S/N ratio (dB)
	Reading 1	Reading 2		Reading 1	Reading 2	
1	546.5	650.5	55.44	28.53	32.64	29.73
2	630.5	662.5	56.20	28.52	32.10	29.65
3	672.5	655.5	56.44	42.85	42.76	32.63
4	683	635.5	56.36	34.97	28.53	30.08
5	509	545.5	54.42	64.20	51.32	35.29
6	488	462	53.052	73.39	53.32	36.14
7	738.5	747.5	57.42	45.28	42.81	32.88
8	877	751.5	58.14	36.67	64.20	34.37
9	750.5	774.5	57.64	32.09	42.87	31.56
10	804	834.5	58.26	51.35	36.67	32.99
11	614.5	695	56.27	32.10	51.33	32.63
12	777.5	771.5	57.78	42.87	61.38	34.48
13	703	694.5	56.89	54.38	64.19	35.49
14	819.5	779.5	58.05	30.73	32.10	29.94
15	559	502.5	54.46	42.78	42.85	32.63
16	779	768	57.77	32.11	32.09	30.13

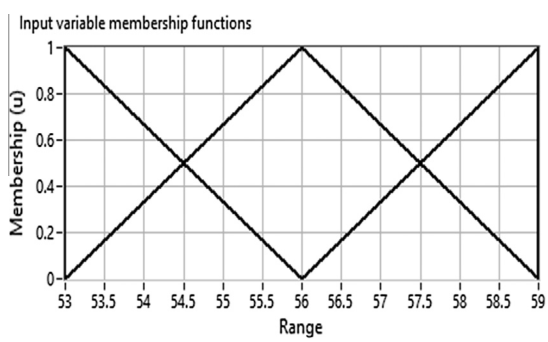

Figure 3 Membership function for the micro hardness.

3.4.3. Defuzzification

The output values which are obtained on analyzing are in the form of linguistic or symbolic value. Conversion of this value into crisp data is called defuzzification. In literatures, there are many types of defuzzification methods are described such as center of gravity/area, center of mass, center of largest area, first of maxima, middle of maxima, and height [17]. The defuzzification method derives a crisp output value that best represents the linguistic result obtained from the fuzzy inference process.

3.5. Analysis of variance (ANOVA)

The technique of ANOVA is used to establish the relative significance of the individual processing factors and the interaction between them. The ANOVA is based on the variance (V), the degree of freedom (DOF), the sum of the squares (SS), and the percentage of contribution to the total variation (C) [18].

4. Analysis of experimental results

The experimental results based on the experimental scheme are tabulated in second and fourth column of Table 3. The microhardness and crystalline size S/N ratio are calculated using Eqs. 2–4 and the obtained values are tabulated in third and fifth column of Table 3.

4.1. Construction of fuzzy logic model

4.1.1. Fuzzification

The proposed model was developed using the FIS Editor graphical user interface in the Fuzzy Logic Toolbox within the framework of LABVIEW® V10.0. S/N ratios are converted

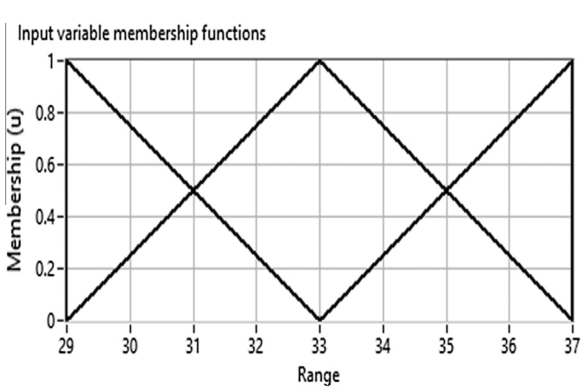

Figure 4 Membership function for the crystalline size.

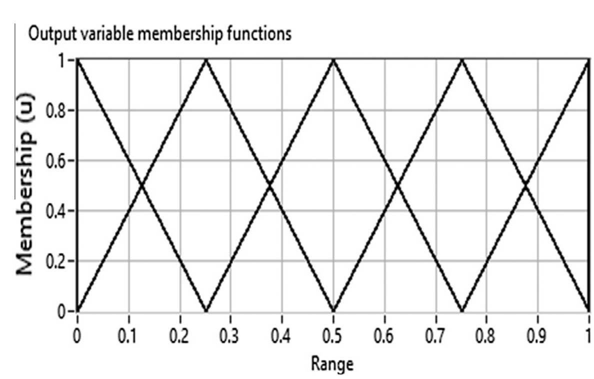

Figure 5 Membership function for the MRPI.

Table 4 Results of MRPI.

Trail no.	MRPI	Trail no.	MRPI
1	0.4430	9	0.6508
2	0.5244	10	0.6781
3	0.5481	11	0.5319
4	0.5541	12	0.5146
5	0.3343	13	0.4327
6	0.2549	14	0.6912
7	0.6199	15	0.3724
8	0.5408	16	0.6646

Table 5 Response table for MRPI.

Machining parameter	Level 1	Level 2	Level 3	Level 4
Rake angle	0.5149	0.4374	0.5938	0.5402
Depth of cut (mm)	0.4295	0.5371	0.4128	0.5660
Heat treatment	0.4550	0.5703	–	–
Feed (mm/rev)	0.5085	0.6149	0.4375	0.525
Cutting velocity (m/min)	0.5671	0.5074	0.5562	0.4555
			Mean	0.6592

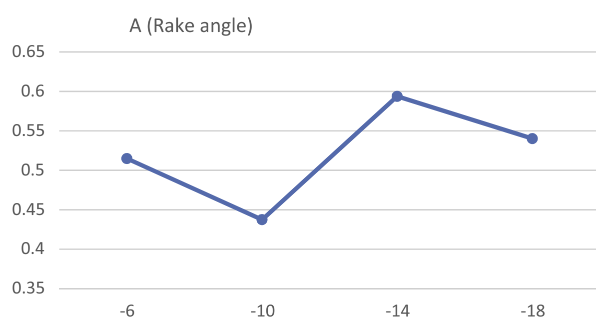

Figure 6 MRPI response graph for Rake angle.

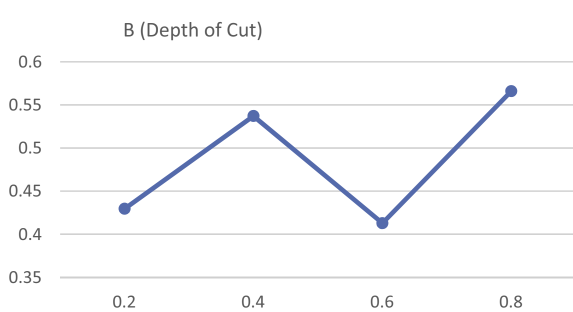

Figure 7 MRPI response graph for depth of cut.

to MRPI and are shown in Figs. 3–5. Here S/N ratios of crystalline size and microhardness are considered as inputs and MRPI is considered as output. The input and output variables are quantified by using linguistic terms. For this model input variables are expressed into three fuzzy sets, namely low, medium, and high. The output variable is expressed into five fuzzy sets namely very low, low, medium, large and very large. In

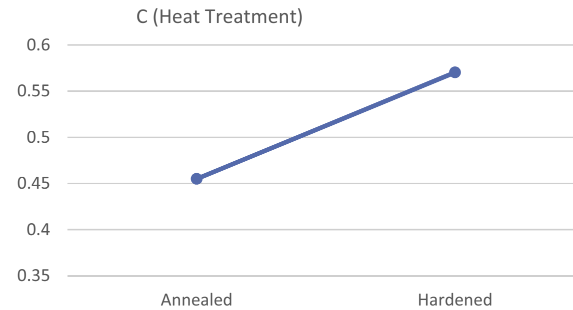

Figure 8 MRPI response graph for heat treatment.

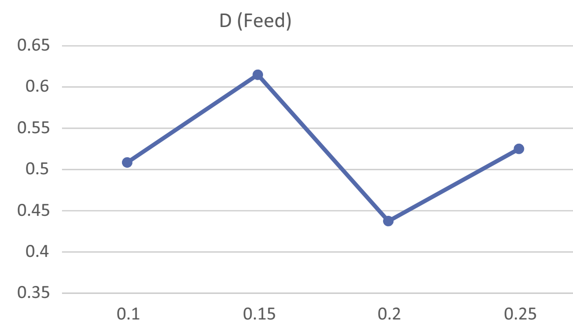

Figure 9 MRPI response graph for feed.

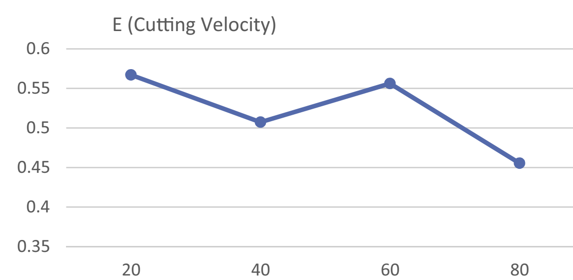

Figure 10 MRPI response graph for cutting velocity.

this model triangular membership function is used for describing the inputs and outputs variables. The graphical representation of input and output variables membership functions is depicted in Figs. 3–5.

4.1.2. Fuzzy inferencing

The next stage of the fuzzy logic is to construct the IF-THEN rules to represent the relationship between input and output variables based on the linguistic terms. In this model, nine rules are written by using rule editor for the best fit of the model.

4.1.3. Defuzzification

The last stage of fuzzy model is Defuzzification process. In this model, center of area method is used for Defuzzification. The developed fuzzy model provides the values of MRPI when proper input data are fed into the model. The final values for MRPI are shown in Table 4.

Table 6 ANOVA of HCS chip for crystalline size.

Factors	Sum of squares	DOF	Variance	Pure sum	*F*-ratio	Percentage contribution
Rake angle (degree)	35.96	3	11.99	32.17	9.51	44.40
Depth of cut (mm)	1.83	3	0.61	1.96	0.48	2.71
Heat treatment	0.03	1	0.03	1.23	0.02	1.70
Feed (mm/rev)	28.48	3	9.49	24.69	7.53	34.08
Cutting velocity	3.63	3	1.21	0.96	0.96	0.22

Table 7 ANOVA of HCS chip for micro hardness.

Factors	Sum of squares	DOF	Variance	Pure sum	*F*-ratio	Percentage contribution
Rake angle (degree)	6.34	3	2.11	6.00	19.18	18.59
Depth of cut (mm)	5.17	3	1.72	4.83	15.63	14.97
Heat treatment	11.10	1	11.10	10.98	100.90	34.05
Feed (mm/rev)	0.97	3	0.97	2.58	8.81	7.99
Cutting velocity (m/min)	2.17	3	2.17	6.18	19.72	19.16
Other factors	0.23	2	0.11	–	–	5.24
Total	32.18	15	18.18	–	–	100

Table 8 ANOVA of HCS chip for simultaneous optimization.

Factors	Sum of squares	DOF	Variance	Pure sum	*F*-ratio	Percentage contribution
Rake angle (degree)	215.157	3	71.719	199.77	14.0	32.550
Depth of cut (mm)	55.466	3	18.488	40.079	3.6	6.5330
Heat treatment	84.464	1	84.464	79.335	16.49	12.926
Feed (mm/rev)	149.693	3	49.897	134.307	9.74	21.884
Cutting velocity (m/min)	98.682	3	32.894	83.296	6.42	13.572
Other factors	10.257	2	5.128	–	–	12.538
Total	623.722	15	262.58	–	–	100

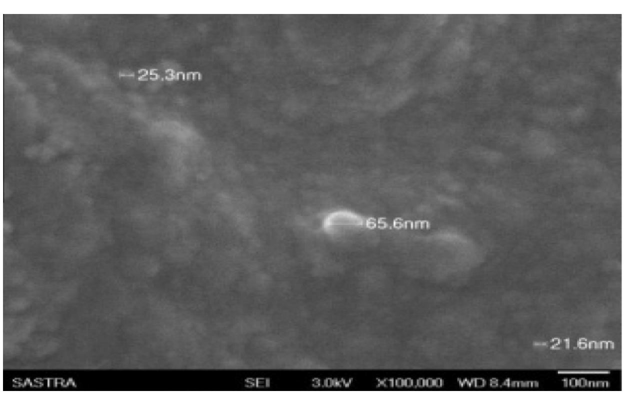

Figure 11 HCS chip SEM image of experiment trial 1.

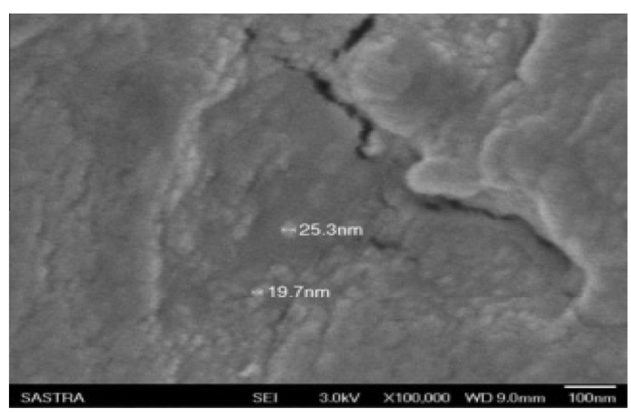

Figure 12 HCS chip SEM image of experiment trial 2.

Since we are using Taguchi's orthogonal array for this experiment, it is possible to separate the effect of each machining parameter on the MRPI at different levels. For example, the mean of MRPI for rake angle at levels 1, 2, 3 and 4 can be found out by averaging MRPI values from 1 to 4, 5 to 8, 9 to 12 and 13 to 16 respectively. For other parameters also the same method of finding the average of each level can be implemented. Then the mean MRPI at each level for the different parameters is presented in Table 5 which is called as response table, which also contains the mean of the MRPI.

The influence of each machining parameter can be more clearly presented by means of MRPI response graph shown in Figs. 6–10. Figs. 6–10 show the change in response when a given factor moves from level 1 to level 4. Based on the response graph and response table, the optimal machining

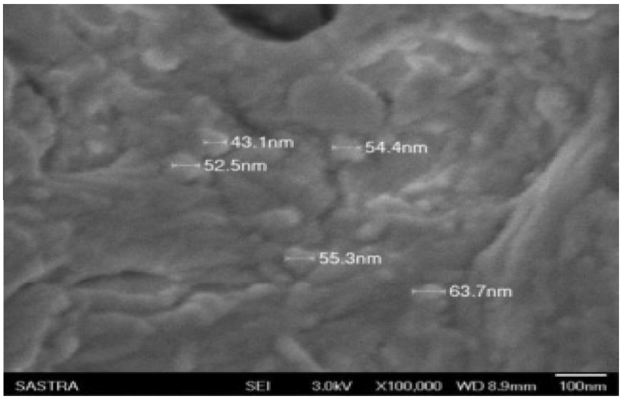

Figure 13 HCS chip SEM image of experiment trial 13.

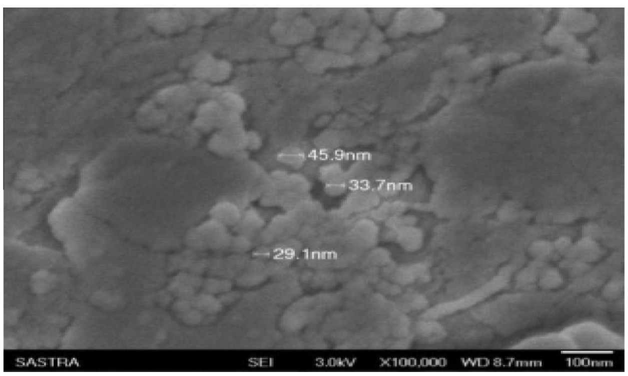

Figure 14 HCS chip SEM image of experiment trial 14.

parameters for the production of nanocrystalline structure in HCS chips can be obtained. Basically larger MRPI value is preferred and it was found that for experiment number 14 had the highest MRPI value. Therefore, experiment 14 machining parameter settings are optimal for attaining desired multiple performances simultaneously among 16 experiments. However the relative importance among the machining parameters for the multiple performance characteristics still needs to be analyzed, so that the optimal combinations of the machining parameter levels can be determined more clearly. The relative importance among the factors can be analyzed through an analysis of variance (ANOVA).

4.2. ANOVA

Analysis of variance (ANOVA) is a collection of statistical methods to analyze the difference between group means and their associated procedures. The purpose of ANOVA is to investigate which process parameters significantly affect the performance characteristics. In Table 6, last column shows the percent contribution (P) of each factor as the total variation, indicating its influence on the result. From the ANOVA result, the depth of cut is the most significant factor affecting the crystalline size. Rake angle, nose radius, feed and cutting velocity are the least significant factors affecting the crystalline size. In Table 7, the last column shows the percent contribution (P) of each factor as the total variation, indicating its influence on the result. From the ANOVA results, rake angle, feed and nose radius are the most significant factors affecting the micro hardness. Depth of cut and cutting velocity are least significant factors affecting the micro hardness. From Table 8, rake angle, feed and cutting velocity are most significant factors affecting both the micro hardness and crystalline size whereas other factors are least significant factors affecting both the micro hardness and crystalline size.

5. Image characterization of chips

FE-SEM image shows that the microstructure of the machined HCS chips that are refined to sub-micron level due to large strain deformation imposed by cutting tool at the cutting conditions. In Equal Channel Pressing, Equal Channel Angular Extrusion (ECAE) and High-Pressure Torsional straining (HPT) processing methods materials microstructure is non equiaxed structure whereas in this machining methods SEM images show equiaxed nanocrystalline structure which improves the mechanical properties of the materials. Some sample XRD is shown in Fig. 15. From the XRD graph, peak widths are measured. The measured peak width is substituted in the Scherer equation and found the crystalline size. The crystalline size of the chips which calculated from Scherer

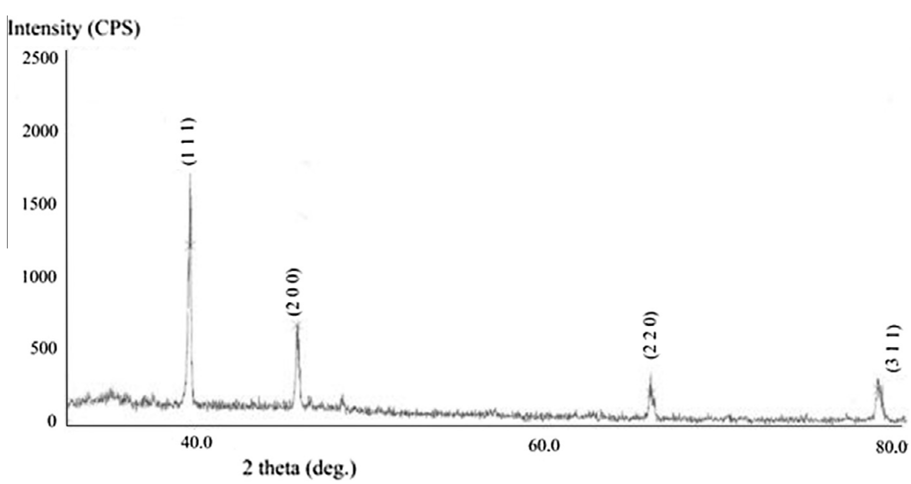

Figure 15 HCS chip XRD image of experiment 12.

equation is in submicron range. The crystalline size which is calculated from XRD peak is validated by comparing the approximate values estimated from the FE-SEM image using the micron scale obtained. The FE-SEM and XRD images of the samples for selected trials are shown in Figs. 11–15.

6. Conclusion

This paper has presented an application of fuzzy logic in the Taguchi method for the optimization of machining parameter for producing the nanostructure in HCS chips. The fuzzy logic is used to eliminate the vagueness in the information and produces the best machining conditions. The proposed fuzzy Taguchi model is used to convert the complicated multiple performance characteristics into the optimization of single multi response performance index. As a result, the optimization methodology developed in this research is useful for enhancing the multiple performances characterizing in the production of nanostructure in HCS chips. From the experience and knowledge gained through this study, the work can be further extended to the low cost production of nano powders by high energy ball milling of the nano structured HCS chips.

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