A Fuzzy-Based Modeling for Nanostructured W-20 wt% Cu Composite Synthesized by Mechanical Alloying

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Abstract— In this research work, synthesis of W-20 wt% Cu nanocomposite by mechanical alloying and subsequent sintering has been modeled using fuzzy inference system. Experiments are conducted with elemental W and Cu powder. Several mechanical alloying times and sintering temperatures are investigated to produce a range of densities and sintering parameters. The characteristics of nanocomposite powder are analyzed by different methods including X-ray powder diffraction (XRD), scanning electron microscopy (SEM) and the relative density and hardness of the sintered samples are measured. Milling time and sintering temperature are selected as input process parameters and the relative density and hardness are chosen as the output process parameters for development of fuzzy inference system. It has been observed that W-20 wt% Cu exhibits different densification behavior and electrical conductivity with processing conditions. The predicted performance characteristics viz. hardness and relative density by fuzzy inference system are in good agreement with the experimental values.

Keywords- Fuzzy Inference System; Membership Function; W-20 wt% Cu nanocomposite; Mechanical Alloying; Sintering

I. INTRODUCTION

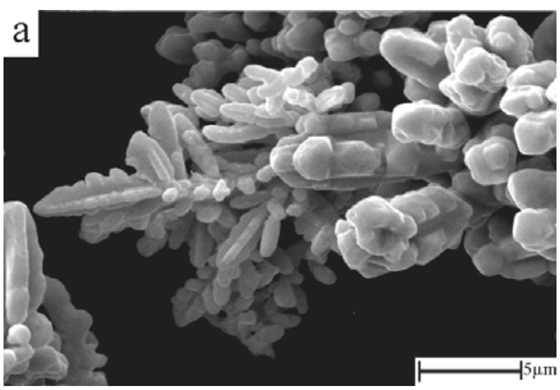
All In recent years, the use of W-Cu composite heavy alloys has increased in both commercial and military applications. W-Cu composite materials have been applied in various industrial fields such as ultrahigh-voltage electric contact materials, blocking materials for microwave packages of microelectronic devices and heat sink materials for high density integrated circuits due to the good thermal and electrical properties of Cu, and the high melting point (3410 °C), low vapor pressure (1.3×10^{-7} Pa at T_{melt}), good erosion resistance of W [1]. Kecskes, et al. [2] describes the mechanical alloying of 80W-20Cu by ball milling in air, followed by liquid-phase sintering above the melting temperature of Copper. Near full densification has been achieved after 480 minutes of milling. Kang [3] describes the production of a hybrid W/Cu composite plate by a modified powder-in-tube method. Grain growth was observed after hot rolling the pressed powder-in-tube construct with the mixture. The measured electrical conductivities of the composite were relatively similar to those of the predictive model. Kang and Kang [4] discussed the production of W/Cu composite deposits using cold spray. Most pores resulting from the spraying were found in the vicinity of Tungsten rich region of the final product. Processing routes include infiltration of a W skeleton with Cu or liquid phase sintering of milled powder, co-reduction and mechanical alloying of powders. Sintered properties can display a wide variation for a given composition depending on the processing method. The sintering of well mixed ultrafine or nanostructured W/Cu powders made by mechanical alloying (MA) has been studied by many researchers [5, 6]. Kim, et al. [7] investigates the sintering behavior of W-15wt%Cu nanocomposite powder and explains the microstructure characteristics dependency.

Accurate characterization of the microstructure and physical properties of sintered ball milled compacts as a function of milling time and sintering conditions is a necessary step in understanding the synthesis of W-20 wt% Cu nanocomposite [8]. A fuzzy-based model of the liquid phase sintering and solid state sintering of W-20 wt% Cu nanocomposite has been carried out to complement the previous experimental work. The materials behavior is significantly influenced by the milling time and thermal activation from sintering.

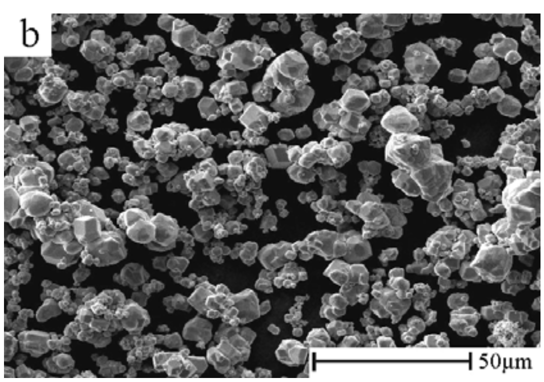
Modeling of process and system identification using input–output data has always attracted many research efforts. The system identification techniques are applied in many fields in order to model and predict the behaviors of unknown and complex systems based on input–output data [9]. Theoretically, in order to model a system it is required to understand the explicit mathematical input–output relationship precisely. Such explicit mathematical modeling is difficult and also not readily tractable in poorly understood system. The soft computing methods [10] that concern computation in imprecise environment have gained significant attention. A number of soft computing methods namely fuzzy logic, neural network, and genetic algorithm have shown high ability in solving complex non-linear system identification and control problems. Several research efforts have been expended to use evolutionary methods as effective tools for system identification [11]. Fuzzy-based methodologies have been an active research field for its unique ability to build models based on experimental data. The concept of fuzzy sets that deal with uncertain or vague information may be applied to model real and complex tasks. The fuzzy logic coupled with rule-based systems has the ability to model the approximate and imprecise reasoning processes that is common in human thinking or human problem solving. The theory of fuzzy logics has been useful in dealing uncertainties and vague information. Analysis of the performance characteristics of nanostructured W-20wt% Cu composite with fuzzy logics has been considered for this study.

II. EXPERIMENTAL PROCEDURE

The morphology and the physicochemical characteristics of the two powders are given in **Fig. 1** and **Table 1**. Elemental Cu powder was produced by the electrolysis process. The Cu particles are denderitic shape with a mean diameter of 32.8 µm. Elemental W-powders are produced by reduction route with polygonal shape and the average particle size of W powder is 14.7 µm. **Fig. 2** shows Equilibrium phase diagram of W-Cu system at 1 atmosphere. **Table 2** shows the characteristics of starting powders of Tungsten and Copper.



(a)



(b)

Fig. 1: Morphology of (a) pure Copper and (b) Tungsten powder

Table 1: Physicomechanical Properties of Tungsten and Copper

Property	linear thermal expansion coefficient $(^{\circ}C)^{-1}\times10^{-6}$	Thermal cond. W/m.K	Electrical Resistivity $\Omega.m\times10^{-8}$	Mod. of Elasticity GPa	Yield Strength MPa	Elong. %
W	4.5	155	5.3	400	760	2
Cu	17	388	1.72	115	69	50

Table 2: Characteristic of Raw Materials

Material	Average particle size (µm)	Particle shape	Purity
W	14.718	polygonal	>99.7%
Cu	32.788	denderitic	>99.5%

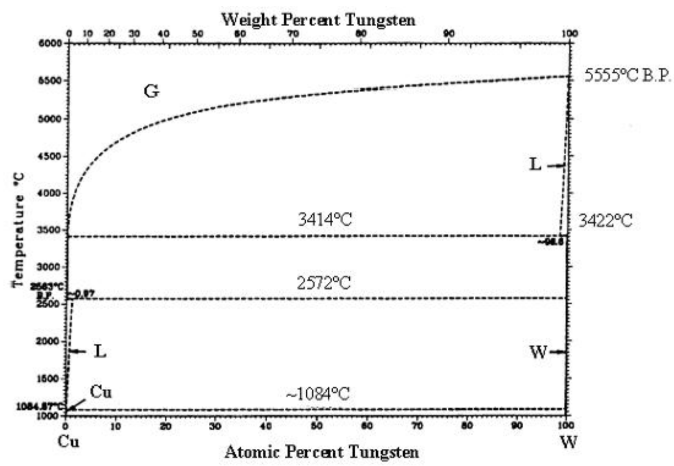


Fig. 2: Equilibrium Phase Diagram of the W-Cu System at 1 atm.

Elemental powders of W and Cu were mixed in the mass ratio of 4:1 in a Turbula T2C mixer (Basel, Switzerland) for 30 min. A process control agent, 1.5 wt % of stearic acid was added to prevent extra welding during mechanical alloying (MA). The ball milling was performed in an Attritor ball mill (Union Process Co, Akron, Ohio, USA) with a rotational speed of 250 rpm. The WC-3wt% Co balls were used with the ball to powder weight ratio (BPR) of 20:1 for milling. The mechanical alloying of W-20wt%Cu was done under Argon gas atmosphere up to 100 hours with varying mechanical alloying time (5, 10, 15, 20, 40, 60, 80 and 100hr). A small amount of powders was taken out from the ball mill and the mixed powders were compacted in a cylindrical die (10 mm in diameter at 1:1 ratio of diameter to height).

Sintering was performed at six different temperatures viz. 900, 950, 1000, 1050, 1100, and 1200˚C, from liquid phase sintering to solid state sintering in a combined Argon and Hydrogen gas atmospheres with heating rates of 10˚C / minute for 90 minute in a hydrogen atmosphere controlled furnace (Exciton, Tehran, Iran). The green density (d_g) of compacted unmilled and milled W-20 wt% Cu nanocomposite was 55±1% of theoretically calculated pore-free density (d_{th}). The excessive green density for W/Cu composite causes decreasing in transmission of Cu into capillary opening. The green density (d_g) and the sintered density (d_s) were measured by Archimedes method to recognize the sintering behavior.

For micro structural observation of sintered samples by Optical Microscopy (OM), the samples were grounded by silicon carbide emery paper in sequence of #320, # 400, # 600, #1200, #2500 and 0.3 and 0.05 μm alumina slurries were used for mechanical polishing. Image analysis system was used for the measurement of pore size of W-Cu power. Hardness was measured with the help of Vickers tester (Instron Wolpert, Norwood, MA, USA) using a 20kg load. Differential Thermal Analysis (DTA NETZSCH STA 409 PC/PG, Burlington, MA, USA) was performed to determine melting point temperature of W and Cu powder.

Atomic absorption spectrophotometer method (Varian Techtron AA6, Mulgrave, Victoria, Australia) was used to measure the Fe content of 100 hours milled W-20wt%Cu composite. Co content may present due to WC-3wt% Co balls, was measured by ICP method (Jobin Yvon Emission, JY 138, Edison, New Jersey, USA). Transmission Electron Microscopy (TEM) was used (Philips, FEGCM200, Amsterdam, The Netherlands) to measure MA particles size and to observe particles.

III. Fuzzy Model

In this paper, the fuzzy model has been designed for selecting the process parameters for synthesizing and solid state sintering of W/Cu nanocomposite. There are three main stages during the development of the model: formation of membership functions (fuzzification), selecting the proper shape, definition of the expert rules and selecting defuzzification method. Milling time, sintering temperature and sintering time are chosen as input parameters while relative density and hardness are chosen as output parameters in the system. Fuzzy expressions for Milling time, sintering temperature, sintering time, relative density and hardness are shown in **Table 3**.

A. Membership Functions for Input and Output Variables

Many things in nature cannot be characterized with simple or convenient shapes or distributions. Membership functions characterize the fuzziness in a fuzzy set whether the elements in the set are discrete or continuous in graphical form. Since the membership function essentially embodies all fuzziness for a particular fuzzy set, its description is the essence of a fuzzy property or operation. Because of the importance of the shape of the membership function, a great deal of attention has been focused on development of these functions. Triangular, trapezoidal, Gaussian and z-shaped are some types of membership function shapes.

In selecting the membership functions for fuzzification, the events and type of membership functions are mainly dependent upon the relevant event. In this model, each input and output parameter has five membership functions. Triangular shape is selected as the main membership functions. But a few trapezoidal membership functions are also used at the marginal ranges. Triangular membership function has gradually increasing and decreasing characteristics and only one definite value has been used. Membership functions and their ranges of the input and output parameters are shown in **Fig. 3**.

Table 3: The Abbreviation and Expressions of Input and Output Parameters

Input Parameters	
Input 1: Milling Time (Hours)	Input 2: Sintering Temperature
VSMT : very short milling time	VLT : very low temperature
SMT : short milling time	LT : low temperature
MMT : medium milling time	MT : medium temperature
LMT : large milling time	HT : high temperature
VLMT : very long milling time	VHT : very high temperature
Input 3: Sintering Time (Hours): 1.5 hours (Constant)	
Output Parameters	
Output 1: Relative Density	Output 2: Hardness
VLD : very low density	VLH : very low hardness
LD : low density	LH : low hardness
MD : medium density	MH : medium hardness
HD : high density	HH : high hardness
VHD : very high density	VHH : very high hardness

B. Fuzzy-expert Rules

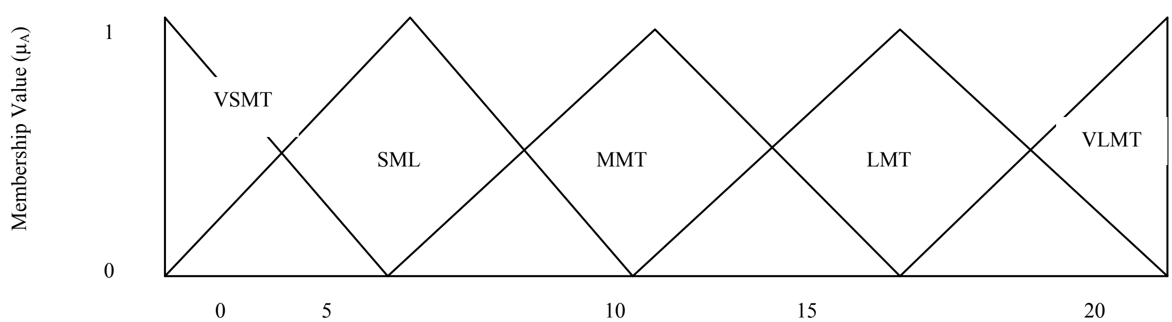
The inputs and the outputs relationship in a fuzzy model is characterized by a set of linguistic statements known as fuzzy rules. They are defined based on experimental work, expert opinion and engineering knowledge. The number of fuzzy rules in a fuzzy system depends on the number of fuzzy sets for each input variable. In this research work, the two input variables are classified into five fuzzy sets and one is kept as constant value. The maximum number of rules for this model is set to 25. Conditional statements, such as IF–THEN rules make fuzzy logic useful. All rules are evaluated in parallel, and the order of the rules is unimportant. The rules themselves are useful because they refer to variables and adjectives that describe these variables [12]. In this research work, knowledge is interpreted with IF–THEN rules and multiple statements are joined by AND connective. A part of the fuzzy rules in linguistic form are shown in **Table 4**.

Table 4: Fuzzy-expert Rules in Linguistic Form

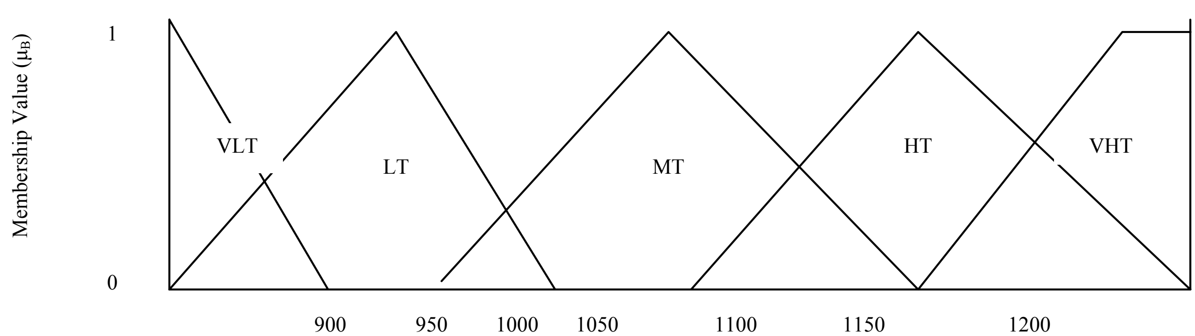
	Antecedent	Consequent
1.	IF (milling time is VSMT) AND (sintering temperature is VLT)	THEN (relative density is VLD)(hardness is VLH)
2.	IF (milling time is SMT) AND (sintering temperature is VLT)	THEN (relative density is LD)(hardness is VLH)
3	IF (milling time is MMT) AND (sintering temperature is VLT)	THEN (relative density is LD)(hardness is LH)
.	.	.
.	.	.
.	.	.
25	IF (milling time is VLMT) AND (sintering temperature is VHT)	THEN (relative density is VHD)(hardness is VHH)

C. *Defuzzification*

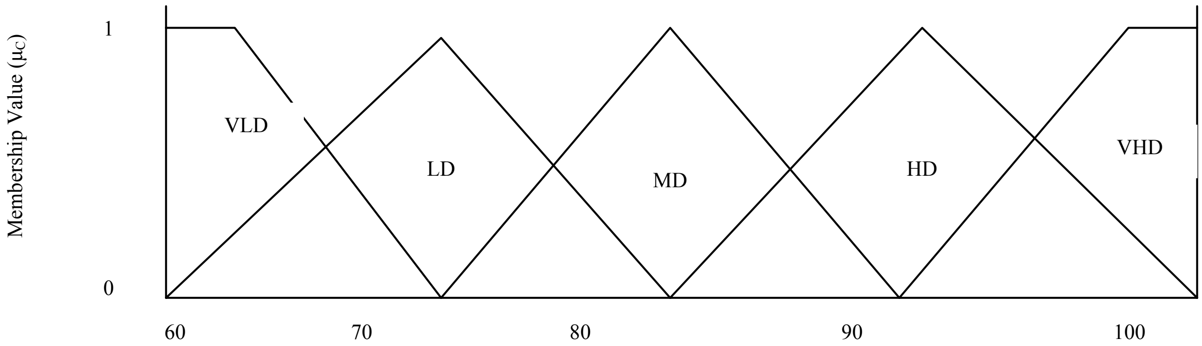
Defuzzification is the conversion of a fuzzy quantity to a precise quantity, as fuzzification is the conversion of a precise quantity to a fuzzy quantity [13]. In recent years, a number of defuzzyfication methods are proposed by researchers. Some of the proposed methods are: centroid method, weight average method, mean of max.-membership method, center of sums method, center of largest area method, first (or last) of maxima method. The selection of a suitable defuzzification method is critical and has a significant effect on the speed and accuracy of the fuzzy system. In this research work, centroid of area defuzzification method is used as it gives more reliable and accurate results compared to other methods [12, 14]. Furthermore, the center of area defuzzification method is suitable for a multidimensional fuzzy output. In this method, the resultant membership functions are developed by considering the union of the output of each rule, i.e. the overlapping area of fuzzy output sets is counted only once to provide the final result.



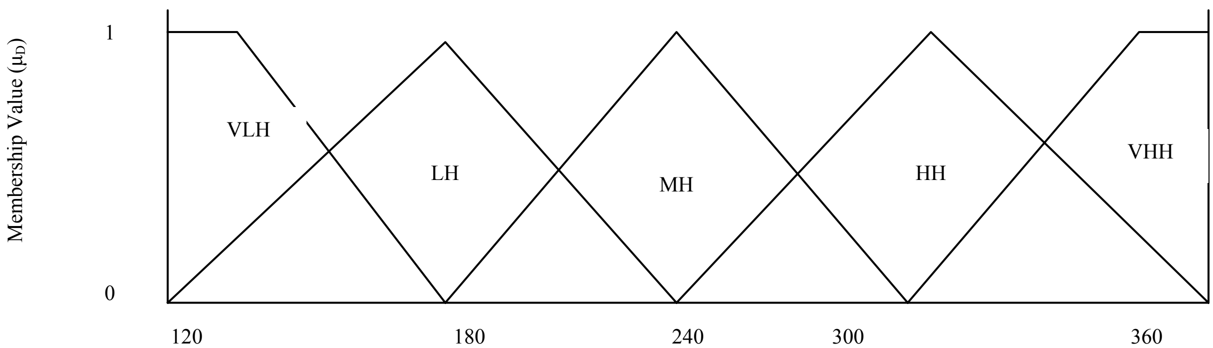
(a) Milling Time (MT) in Hours



(b) Sintering Temperature in ^{0}C



(c) Relative Density in g/cm^2



(d) Hardness in BHN

Fig. 3: Membership functions of Input and Output Parameters

IV. General Structure of the Fuzzy Inference System

After The developed fuzzy-based system runs interaction of five fuzzy editors: fuzzy inference system (FIS) editor, membership function editor, rule editor, rule viewer editor and fuzzy inference system. FIS editor handles the high level issues for the system. Number of inputs and outputs, their names and marginal ranges are edited in this editor. Also, type of defuzzification method and inference type, such as Mamdani or Sugeno, can be defined. In this system, Mamdani inference method is used. It is the most commonly used fuzzy methodology [15]. Mamdani based inference system gives the output membership functions as fuzzy sets. After the aggregation process, each output variable has a corresponding fuzzy set that needs defuzzification. A single spike output membership functions are more efficient than a distributed fuzzy set. It enhances the efficiency of the defuzzification process because of the simplified computation in finding the centroid of a two-dimensional shape. The centroid can be obtained by weighted average of data points. Sugeno systems [16] support this kind of behavior. It is similar to the Mamdani method in many respects. The first two parts of the fuzzy inference process, fuzzifying the inputs and applying the fuzzy operator are the same for both methods.

Another useful editor is membership function editor and it is used to define the shapes of all the membership functions associated with each variable. As well as selecting the shapes, range, type and number, the name of each membership function can be defined. Rule editor is for editing the list of rules that defines the behavior of the system and for editing the AND or OR connectives that logically changes the results of the IF–THEN rules. The rule viewer is a result display of the fuzzy inference diagram. It is used as diagnostic and shows which rules are active, or how individual membership function shapes are influencing the results. It displays a guideline of the whole fuzzy inference process. As a result, rule viewer editor facilitates the end-user in entering the inputs easily and seeing the outputs on the window. For instance, end-user would be able to enter milling time and sintering temperature and then relative density and hardness are seen on the rule viewer editor window. FIS editor, the membership function editor and rule editor are all able to read and modify the FIS data, but the rule viewer does not modify the FIS domain in anyway.

The structure of the developed fuzzy-based inference system is shown in **Fig. 4**. Expert rule database contains new generated modern expert rules that can be easily modified, added and subtracted. System outputs are always scalar quantity. An end-user uses them to determine the synthesizing and solid state sintering parameters of W-Cu nanocomposite.

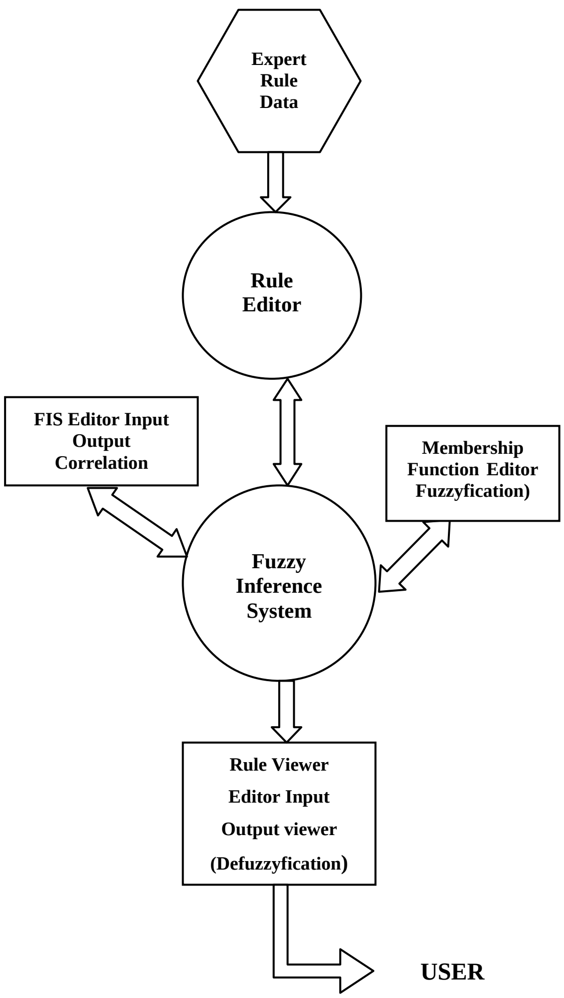


Fig. 4: Structure of the developed Fuzzy Inference System

V. RESULTS AND DISCUSSION

Text The rule viewer generated by the developed fuzzy inference system is shown in **Fig. 5.** It predicts the output performance characteristics, namely relative density and hardness of nanostructured W-20 wt% Cu Composite. The rule viewer plots every part of each rule and shows the influence of the membership functions on the overall output performance characteristics. In the rule viewer, a set of input process parameters are given. The rule viewer fires the rules corresponding to the input values and gives the defuzzified output performance characteristics. Similarly, the output performance characteristics namely relative density and hardness for other input values could also be predicted with the rule viewer. In this Figure the input process parameters selected are 15 and 1100 corresponding to milling time and sintering temperature respectively. The corresponding output values are 90 and 262 for relative density and hardness respectively.

Fig. 6 and **Fig. 7** illustrate the output performance characteristic surfaces generated by the developed fuzzy inference system. These surface plots are helpful in analyzing nanostructured W-20 wt% Cu composite in terms of input process parameters, milling time and sintering temperature and corresponding output performance characteristics; relative density and hardness. The two input process parameters, namely milling time and sintering temperature, vary between 0 to 20 Hours, and 900 to 1200^0C, respectively. The 3-D output performance characteristics plots as shown in **Fig. 6 and 7** are helpful in evaluating the combined effect of two input process parameters on output namely, relative density and hardness of nanostructured W-20 wt% Cu composite. Once the knowledge base is prepared and stored in the FIS in the form of rule base, it become easier to predict the outputs for any combination of input process parameters.

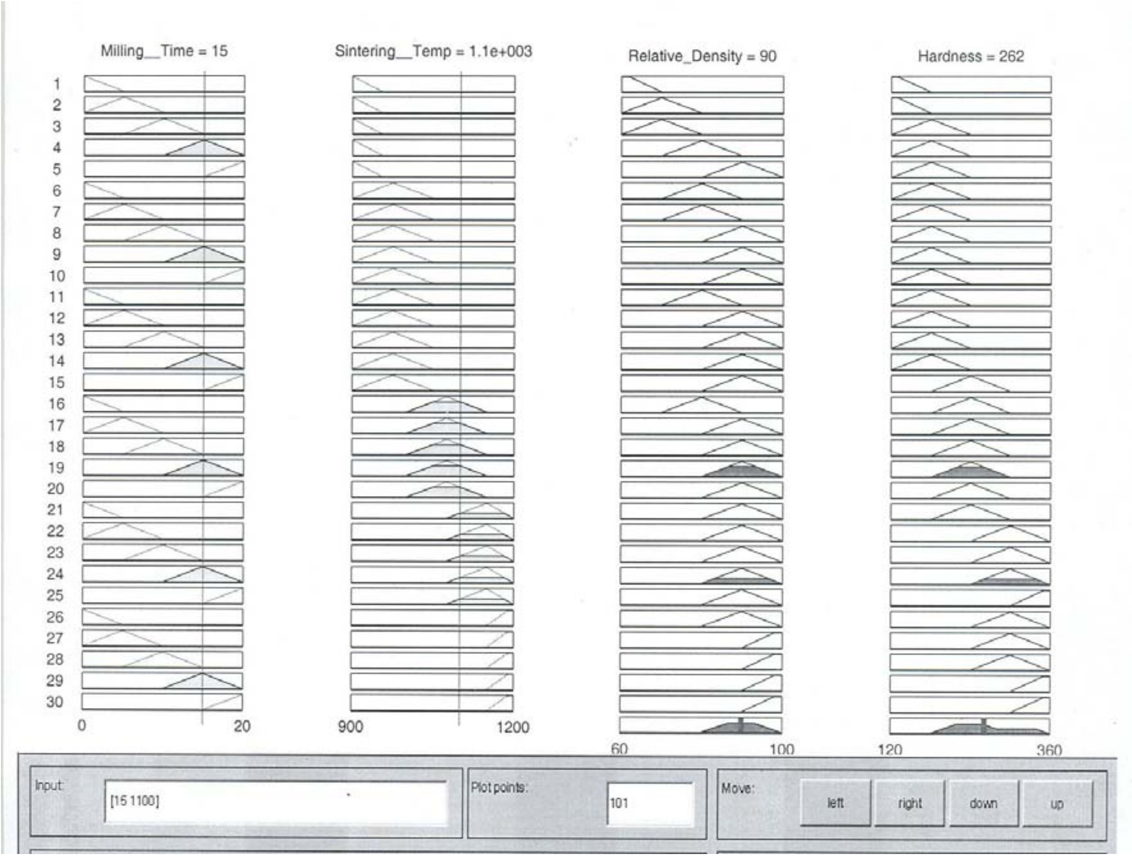


Fig. 5: Rule viewer of developed Fuzzy Inference

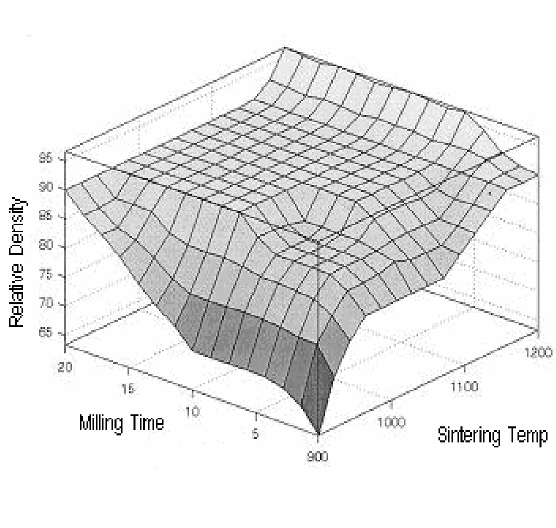


Fig. 6: Output surface of developed Fuzzy Inference System (Relative Density)

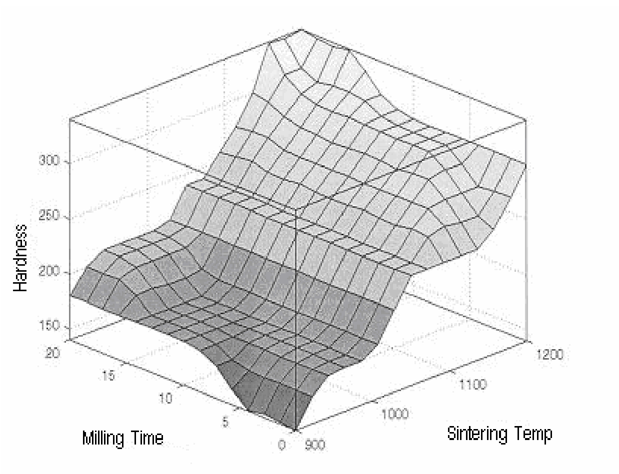


Fig. 7: Output surface of developed Fuzzy Inference System (Hardness)

The plot of Experimental value versus the predicted value by the developed fuzzy-based inference model as well as the equation of the regression model is shown in the **Fig. 8**. The coefficient of correlation R^2 value is 0.955.

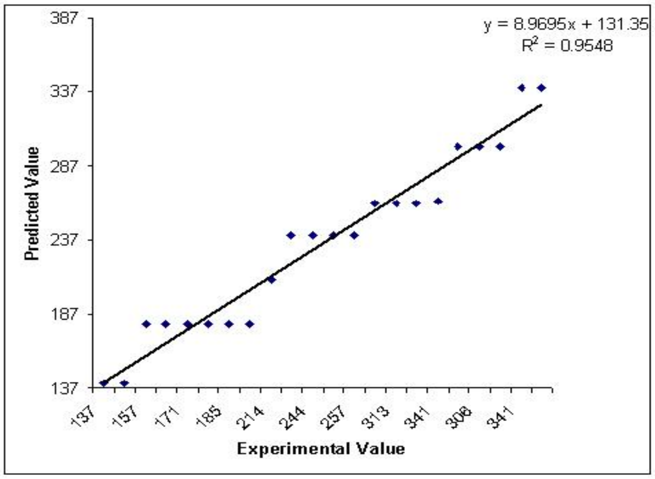


Fig. 8: Plot of Predicted value versus Experimental value (Hardness)

VI. Conclusion

In this paper, a fuzzy-based expert system for the selection of nanostructured W-20 wt% Cu composite input process parameters has been introduced. Hardness increases with the increase in milling time and sintering temperature. The rate of increase in high sintering temperature is slightly more than in low sintering temperature. On the other hand, relative density has sharp changes in low sintering temperature and short milling time. The linear regression analysis has been carried out between the actual hardness values and the predicted hardness values to evaluate the performance of the developed fuzzy-based expert system. The coefficient of correlation (R^2) between the experimental and predicted values obtained is 0.955 as shown in **Fig. 8**. It may be inferred from the Fig. that fuzzy-based expert system can be utilized to predict the output performance characteristics of nanostructured W-20 wt% Cu composite much accurately because of a good learning precision and generalization.

VII. Acknowledgment

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