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Grain Size Estimation of Superalloy Inconel 718 After Upset Forging by a Fuzzy Inference System

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A fuzzy logic inference system was designed to predict the grain size of Inconel 718 alloy after upset forging. The system takes as input the original grain size, temperature, and reduction rate at forging and predicts the final grain size at room temperature. It is assumed that the system takes into account the effects that the heterogeneity of deformation and grain growth exerts in this particular material. Experimental trials were conducted in a factory that relies on upset forging to produce preforms for ring rolling. The grain size was reported as ASTM number, as this value is used on site. A first attempt was carried out using a series of 15 empirically based set of rules; the estimation error with these was above two ASTM numbers; which is considered to be very high. The system was modified and expanded to take into account 28 rules; the estimation error of this new system resulted to be close to one ASTM number, which is considered to be adequate for the prediction.

Keywords fuzzy logic modeling, grain size estimation, superalloy upset forging

1. Introduction

Process modeling has become one of the most important tools for industry during the past few decades as it brings the powerful advantage of predicting process behavior. This capability improves efficiency by variable estimation and setup in product development, process control, machinery adjustments and calibration, etc. Process modeling may also assist engineers in troubleshooting and thus, reducing failure recovery time and defect diagnosis.

Several engineering components rely on metallic rings made from wrought alloys. Ring geometries are used, among others, in oil-drilling operations, high-pressure boilers, and turbines. Jet turbines require rings made from nickel and titanium-based superalloys to withstand the temperatures and stresses developed within the engine. Forging superalloys is not an easy task as most of these alloys are stronger at temperatures within the hot working regime than at lower temperatures; therefore, the pieces acquire their final shape through a series of passes, with intermediate reheating (Ref 1, 2).

The steps involved in ring forming are the initial upsetting of an ingot or bar of the adequate shape. The piece is then reheated within the 1000 to 1300 °C range and reduced in height in either mechanical or hydraulic presses; this upsetting stage may require more than one intermediate reheating stage. The upset piece is reheated again to pierce its center and it is taken to another furnace to carry out the proper ring forging. This process involves the reduction in thickness of the wall while increasing the diameter of the ring; up to four or six tools get in touch with the ring to produce the final shape (Ref 3, 4).

Various metallurgical phenomena are involved while the material is deformed at high temperature; some alloys may undergo an allotropic phase transformation or dissolution or homogenization during reheating. The material will undergo deformation and will be susceptible to either dynamic or static restoration and, once the structure has fully recrystallized, the material will exhibit grain growth, sometimes called secondary recrystallization. Some alloys are designed to promote precipitation during heating or deformation to avoid grain growth (Ref 5-9).

The mechanism of grain growth is particularly critical during hot forming of superalloys that do not form precipitates, as forming is carried out in various stages that include intermediate heating. These conditions are most favorable to promote a mixed structure of various grain sizes within the piece. The low amount of deformation imposed at each pass does not allow a sufficient number of recrystallization nuclei to regenerate a homogeneous structure, but will promote a small number of nuclei that will be able to grow at a very fast rate. Moreover, the heterogeneous nature of deformation by upsetting and rolling will promote a varied range of nuclei able to grow in different regions, increasing the tendency for the development of mixed grain sizes (Ref 5-9).

Fuzzy logic (FL) inference has been widely used to solve engineering problems given its capability to approximate nonlinear functions and incorporate human knowledge (Ref 10, 11). FL is simple to use and it does not require a deep physical knowledge of the process to be modeled. On the other hand, its simplicity to incorporate new variable inputs to the system makes it suitable as an initial approach to model highly complex and unknown systems. Fuzzy inference system (FIS) modeling has been applied to industrial processes, such as hot rolling of steel (Ref 12-17). FIS has been used to correct the setup force error (Ref 12), to predict the mechanical properties

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of hot-rolled bars (Ref 13-15), and to estimate the entry temperature at descaling stations (Ref 16, 17).

Mechanical properties and other characteristics have been modeled by FL and FIS (Ref 18-24). Such examples are a neuro-fuzzy friction stress model used within a hybrid model scheme in modeling thermomechanical processing of an aluminum-magnesium alloy (Ref 18). Fuzzy models have been developed to improve sawing of granite by selecting optimum machining parameters and suitable tooling (Ref 19) and to predict the impact properties of structural steel used for ship construction from the composition and microstructure of the steel (Ref 20). The characteristics of superalloys have been modeled by FL (Ref 21-24). The advantages of predicting the fatigue threshold of a Ni-base superalloy by neuro-fuzzy modeling are presented and compared with results from modeling by neural networks (Ref 21). FIS has been used to predict grain size in hot-forged Ti-6Al-4V and TC6 superalloys (Ref 22, 23), and to obtain the grain size distribution in an IN718 disk forged at temperatures within the 960 to 1020 °C range as a function of temperature, strain, and strain rate (Ref 24).

An empirical rule-based FIS designed to estimate changes in the grain size of a superalloy IN718 after upset forging is presented in this work. The aim of this model is to provide for an accurate approximation of the grain size within the preform used in ring forging of aerospace components. The inputs to the FIS model are the temperature, initial grain size, and amount of deformation. The temperature range considered in this work was from 1020 to 1120 °C. The rules were based on expert empirical knowledge. It is shown that the error in the prediction of the grain size is restringed to a narrow range by using simple rules.

2. Experimental Procedure

A series of trials were conducted on the forging press of a local company that produces rings for the aeronautic industry. The process starts by reheating a billet of the alloy to be forged

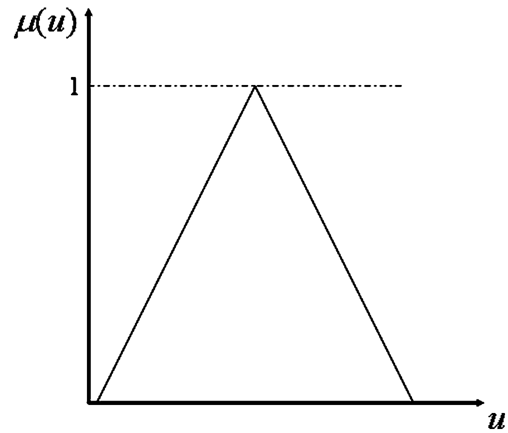

Fig. 2 Triangular membership function

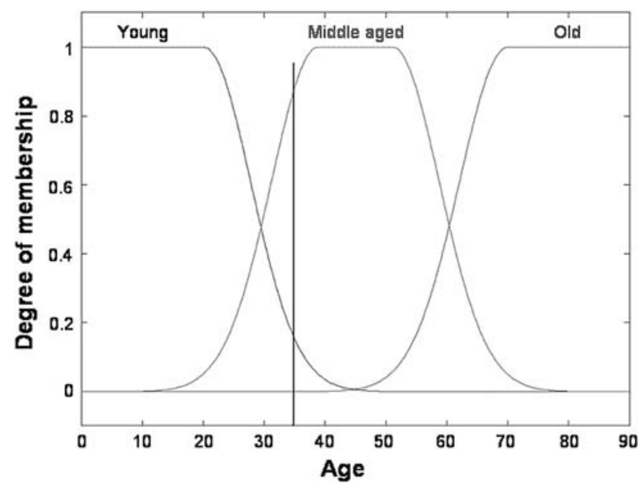

Fig. 3 Human age as modeled by fuzzy sets

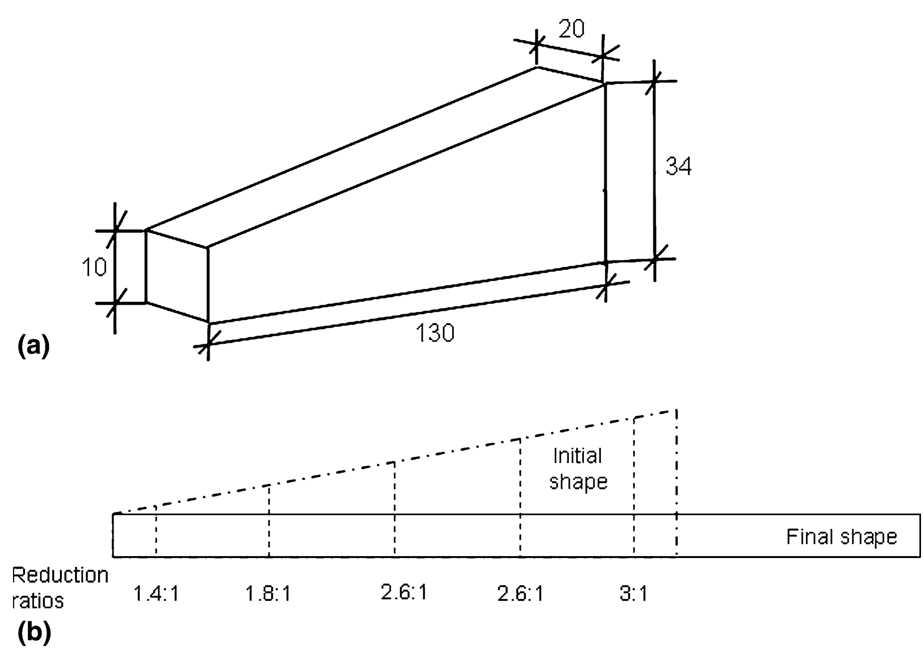

Fig. 1 Schematic diagram of the wedge-shaped sample (a) and the positions at which the grain size measurements were carried out (b)

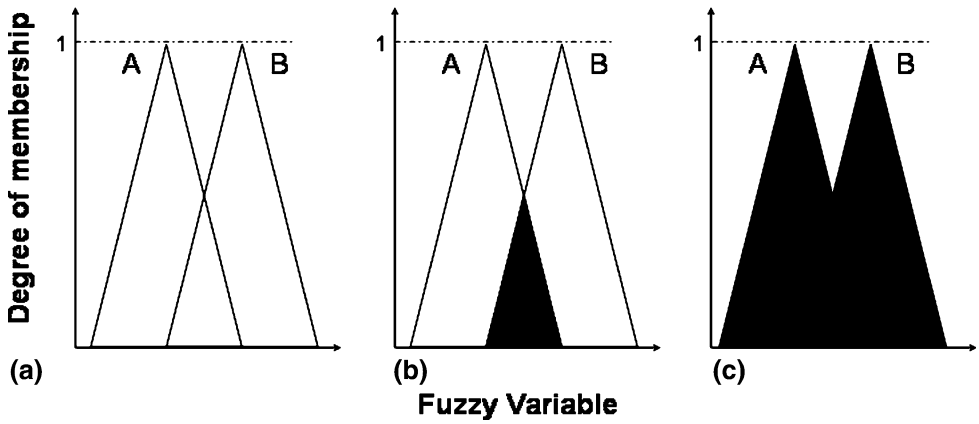

Fig. 4 Fuzzy set operations, fuzzy sets (a), fuzzy intersection C = A∩B = A AND B (b), and fuzzy union C = A∪B = A OR B (c)

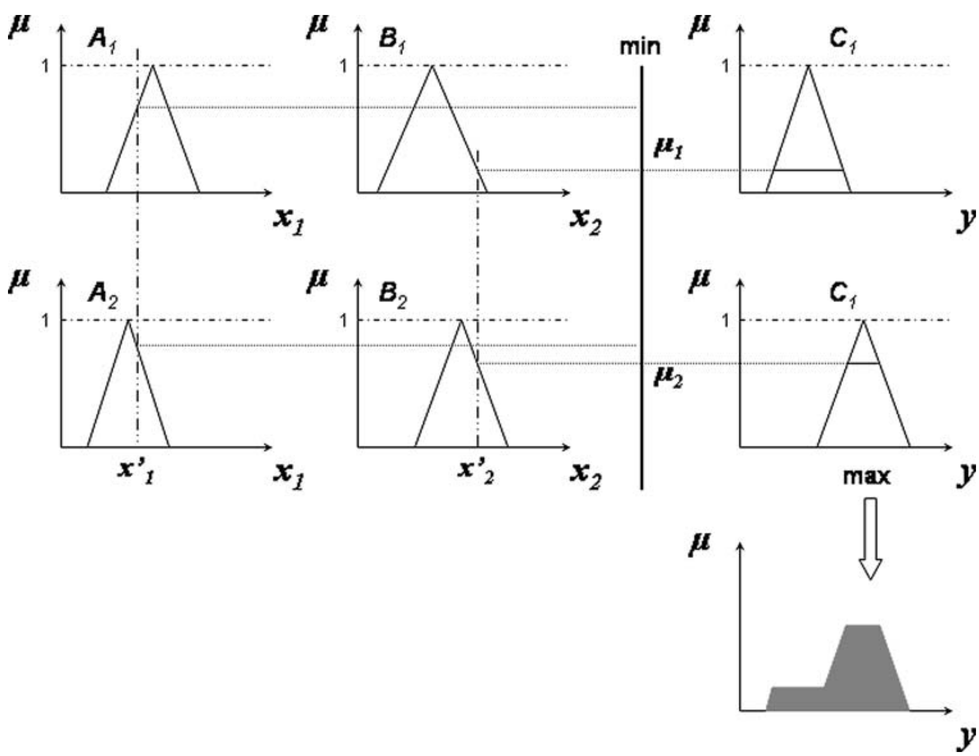

Fig. 5 Two-rule fuzzy inference mechanism using t-norm for the antecedent and t-conorm for the consequent

for the time required to achieve a homogeneous temperature. The billet is upset to obtain the shape required to make the ring to be rolled. This upsetting operation can be given in one pass or can be carried out in a series of passes. Once the shape of the disk is achieved, it is pierced to make it into a ring, which is then heated again before proceeding to form the final ring (Ref 2-6). The repeated thermomechanical cycle promotes variation in grain size (Ref 7-9).

The IN718 alloy (0.02 C, 0.05 Mn, 0.10 Co, 0.11 Si, 0.55 Al, 1.01 Ti, 5.32 Nb, 17.8 Fe, 17.9 Cr, Ni bal., wt.%) used in the present study was machined into wedge-shaped specimens, Fig. 1(a), to be compressed in a hydraulic press to obtain a 10 mm thick strip. These samples were reheated within the temperature range of 1020 to 1120 °C, in heating steps of 20 °C; the reheating time was 2 h. Compression promoted a strain gradient within the samples, which were cut into pieces to analyze the portions of material that were subjected to five different reduction ratios (1.4:1, 1.8:1, 2.2:1, 2.6:1, and 3.0:1, which correspond to reduction of heights around 29, 44, 55, 62, and 67%), Fig. 1(b).

Metallographic examination of the specimens was carried out on samples deformed to the selected reduction ratios. The specimens were prepared following standard procedures and were etched with a solution of 6 mL H_2O, 50 mL HCl, and 6 g $CuCl_2$. The grain size of the material was reported by direct comparison following the ASTM standard E112-96 (Ref 25) as such method is standard at the factory in which this work was carried out.

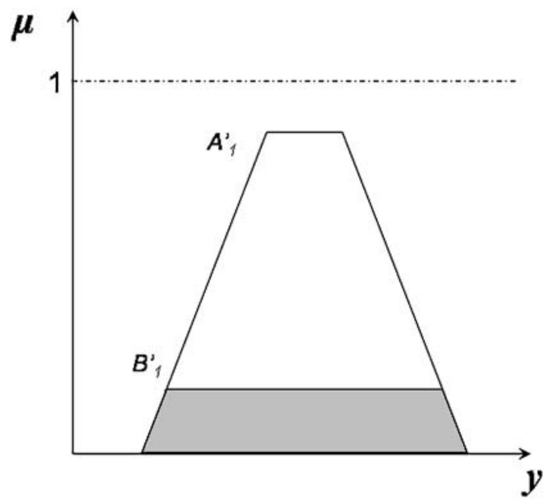

Fig. 6 Resultant fuzzy sets from the evaluation of rule 1

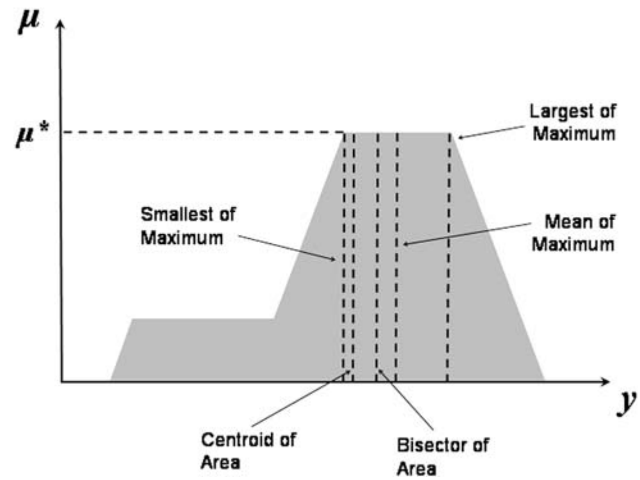

Fig. 7 Output fuzzy set with the defuzzification methods

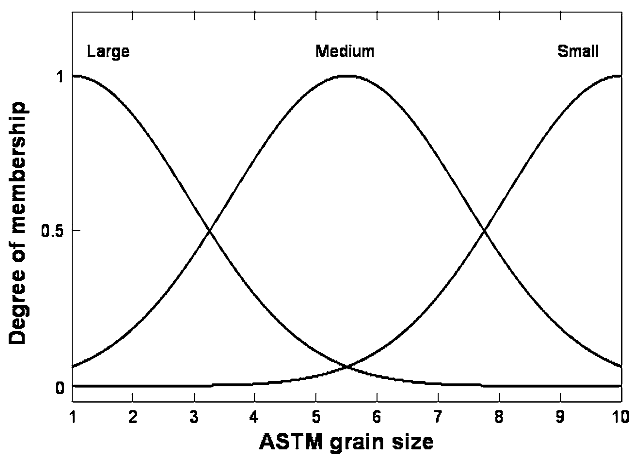

Fig. 8 Fuzzy sets for the initial grain size (G_i)

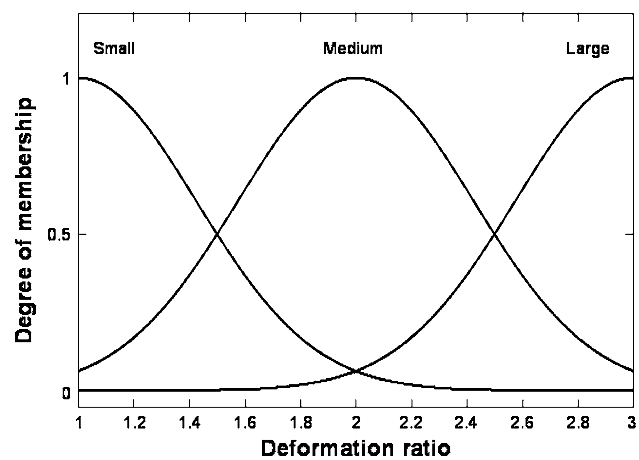

Fig. 9 Fuzzy sets for the reduction ratio (D_r)

3. Fundamentals of Fuzzy Logic

As was mentioned, an empirical rule-based FIS designed to estimate changes in grain size of a superalloy IN718 after upset forging is presented in this work. In this section, the basic principles of FL systems are presented, since it is a well-established methodology, the reader should consult Ref 10 and 11 for a deeper insight.

3.1 Fuzzy Variable and Fuzzy Sets

Fuzzy logic was first introduced by Lofti Zadeh in the 1960s as a means to model natural language. In traditional logic, a variable takes deterministic values (crisp values) to model any characteristic from a natural process. However, when human judgment is involved, an uncertain value which depends on the criterion of the individual appreciation is assigned to these variables. Such uncertainty is modeled by the so-called fuzzy sets.

A fuzzy set is described by a function and gives a degree of membership (DM) of the variable to the fuzzy set. This function is called membership function (MF). Typically, the MFs are chosen to be triangular, trapezoidal, or Gaussian. Figure 2 shows a triangular MF in which the maximum DM is one.

A typical example is modeling the age of a human being, which is depicted in Fig. 3. Three fuzzy sets are used to model a human being aged fuzzy variable. This example shows the fact that a fuzzy variable does not take crisp values but it is rather relative. As it can be seen, there is not a clear border between a young and a middle-aged individual, a 35-year-old person for example may lay in both fuzzy sets, young and middle aged, however, with different degrees of membership.

3.2 Fuzzy Set Operations

The fuzzy set operations more commonly used are intersection and union, these are depicted in Fig. 4. The intersection of two fuzzy sets A and B is a fuzzy set C denoted by (see Fig. 4b):

$$C = A \cap B = A \text{ AND } B$$

The membership function of C is related to those of A and B as follows:

$$\mu_C = \min(\mu_A, \mu_B) = \mu_A \wedge \mu_B \quad \text{(Eq 1)}$$

where μ_C, μ_A, and μ_B denote the DM of fuzzy set C, A, and B, respectively. The union of two fuzzy sets A and B is a fuzzy set C denoted by:

$$C = A \cup B = A \text{ OR } B$$

The membership function of C is related to those of A and B as follows (see Fig. 4c):

$$\mu_C = \max(\mu_A, \mu_B) = \mu_A \vee \mu_B \quad \text{(Eq 2)}$$

3.3 Fuzzy Inference

A fuzzy inference maps an input fuzzy space into an output fuzzy space. Such mapping is defined by a set of If-Then rules and fuzzy set operations. The fuzzy intersection operation is usually performed by the minimum operator or algebraic product and is called t-norm. While the fuzzy union operation is carried out by the maximum operator or the algebraic sum, it is usually called t-conorm.

The fuzzy inference is defined by a set of rules of the type: If x is A then y is B. In this case, an entry fuzzy space, defined by the entry variable and the entry fuzzy set A, is mapped into an output fuzzy space, defined by the output variable and the output fuzzy set B. The entry part of the rule is called antecedent while the output is called consequent.

Figure 5 depicts the following two-rule fuzzy inference case:

Rule 1: IF x_1 is A_1 AND x_2 is B_1 then y is C_1
Rule 2: IF x_1 is A_2 AND x_2 is B_2 then y is C_2

For every particular input value, the rules are evaluated, i.e., the DM of every input from the corresponding fuzzy set is computed. Then the specified operation is performed. As it can be seen, for the case depicted in Fig. 5, the operation required by the rules is an intersection expressed by the AND operator, which for this case was implemented by the minimum operator; therefore the t-norm inference operation is performed for antecedent. The intersection operation performed by the minimum operator for Rule 1 is shown in Fig. 6.

The output inference operation chosen in the example is a union operation, implemented by the max operator; therefore, the t-conorm operation is performed for the consequent. Note that this is not obvious from the rules. The selection of the MF and the fuzzy set operation as well as the structure of the rules depends on the particular problem.

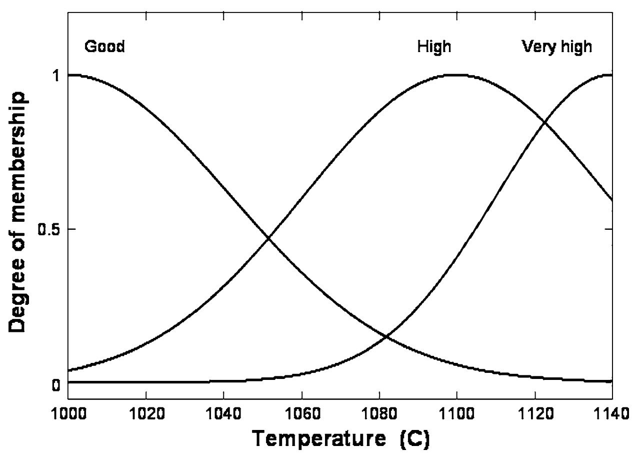

Fig. 10 Fuzzy sets for the reheating temperature (T_i)

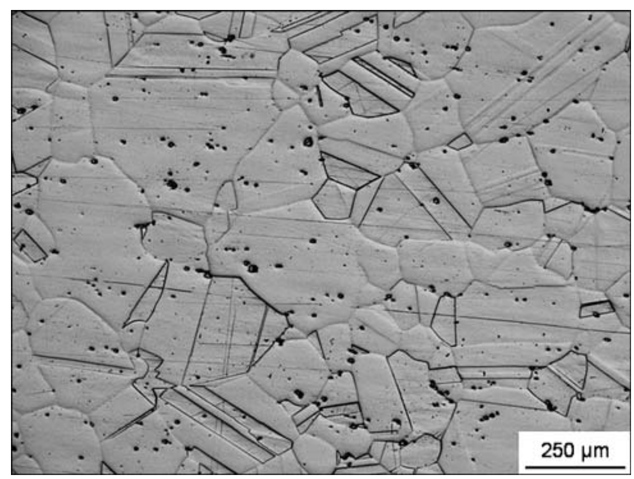

Fig. 11 Microstructure of a sample held for 2 h at 1040 °C; grain size 1

Table 1 First set of empirical fuzzy rules

Rule	Initial temperature		Deformation ratio		Initial grain size		Final grain size
1	If T_i is good	AND	D_i is small	AND	G_i is large	Then	G_f is medium
2	If T_i is good	AND	D_i is medium	AND	G_i is large	Then	G_f is small
3	If T_i is good	AND	D_i is large	AND	G_i is large	Then	G_f is small
4	If T_i is good	AND	D_i is small	AND	G_i is medium	Then	G_f is small
5	If T_i is good	AND	D_i is medium	AND	G_i is medium	Then	G_f is small
6	If T_i is good	AND	D_i is large	AND	G_i is medium	Then	G_f is small
7	If T_i is good	AND	D_i is small	AND	G_i is small	Then	G_f is small
8	If T_i is good	AND	D_i is medium	AND	G_i is small	Then	G_f is small
9	If T_i is good	AND	D_i is large	AND	G_i is small	Then	G_f is small
10	If T_i is high	AND	D_i is small	AND	G_i no matter	Then	G_f is large
11	If T_i is high	AND	D_i is medium	AND	G_i no matter	Then	G_f is medium
12	If T_i is high	AND	D_i is large	AND	G_i no matter	Then	G_f is small
13	If T_i is very high	AND	D_i is small	AND	G_i no matter	Then	G_f is large
14	If T_i is very high	AND	D_i is medium	AND	G_i no matter	Then	G_f is large
15	If T_i is very high	AND	D_i is large	AND	G_i no matter	Then	G_f is large

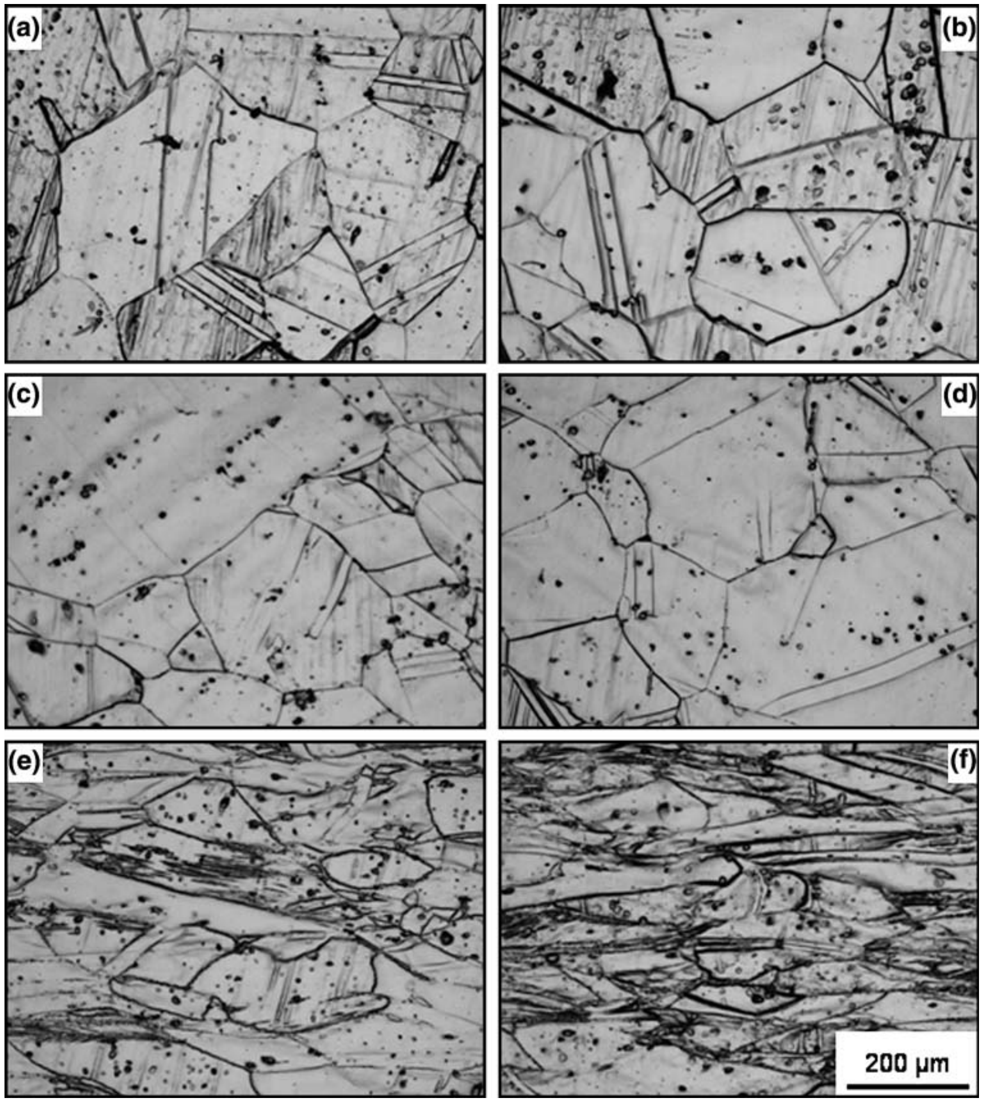

Fig. 12 Microstructures from a sample reheated at 1020 °C and reduction ratios of 1.1 (a), 1.4 (b), 1.8 (c), 2.2 (d), 2.6 (e) and 3 (f)

3.4 Defuzzification

The output of the fuzzy inference is an aggregated fuzzy set as it is shown in Fig. 5 and 7. However, engineering applications required a crisp value. Therefore the output has to be converted into a fixed value. Several methods have been proposed. These are as follows:

Centroid of Area y_{COA}:

$$y_{\mathrm{COA}} = \frac{\int_y \mu_C(y) y dy}{\int_y \mu_C(y) dy} \qquad \text{(Eq 3)}$$

where $\mu_C(y)$ is the aggregated output MF.

Bisector of Area y_{BOA} satisfies:

$$\int_{y_{\min}}^{y_{\mathrm{BOA}}} \mu_C(y) dy = \int_{y_{\mathrm{BOA}}}^{y_{\max}} \mu_C(y) dy \qquad \text{(Eq 4)}$$

where $y_{\min} = \min\{y|y \in Y\}$ and $y_{\max} = \max\{y|y \in Y\}$.

Mean of Maximum y_{MOM} is the average of the maximizing y, i.e., the value of y at which $\mu_C(y)$ reaches the maximum value μ^+. It is given by:

$$y_{\mathrm{MOM}} = \frac{\int_{Y'} y dy}{\int_{Y'} dy} \qquad \text{(Eq 5)}$$

where $Y' = \min\{y|\mu_C(y) = \mu^+\}$

Smallest of Maximum y_{SOM} is the minimum in terms of absolute value of the maximizing y.

Largest of Maximum y_{LOM} is the maximum in terms of absolute value of the maximizing y.

4. Fuzzy Inference System Design

The FIS designed to estimate the grain size of superalloy IN718 after upset forging assumes that the final grain size (G_f) depends on the initial grain size (G_i), the amount of

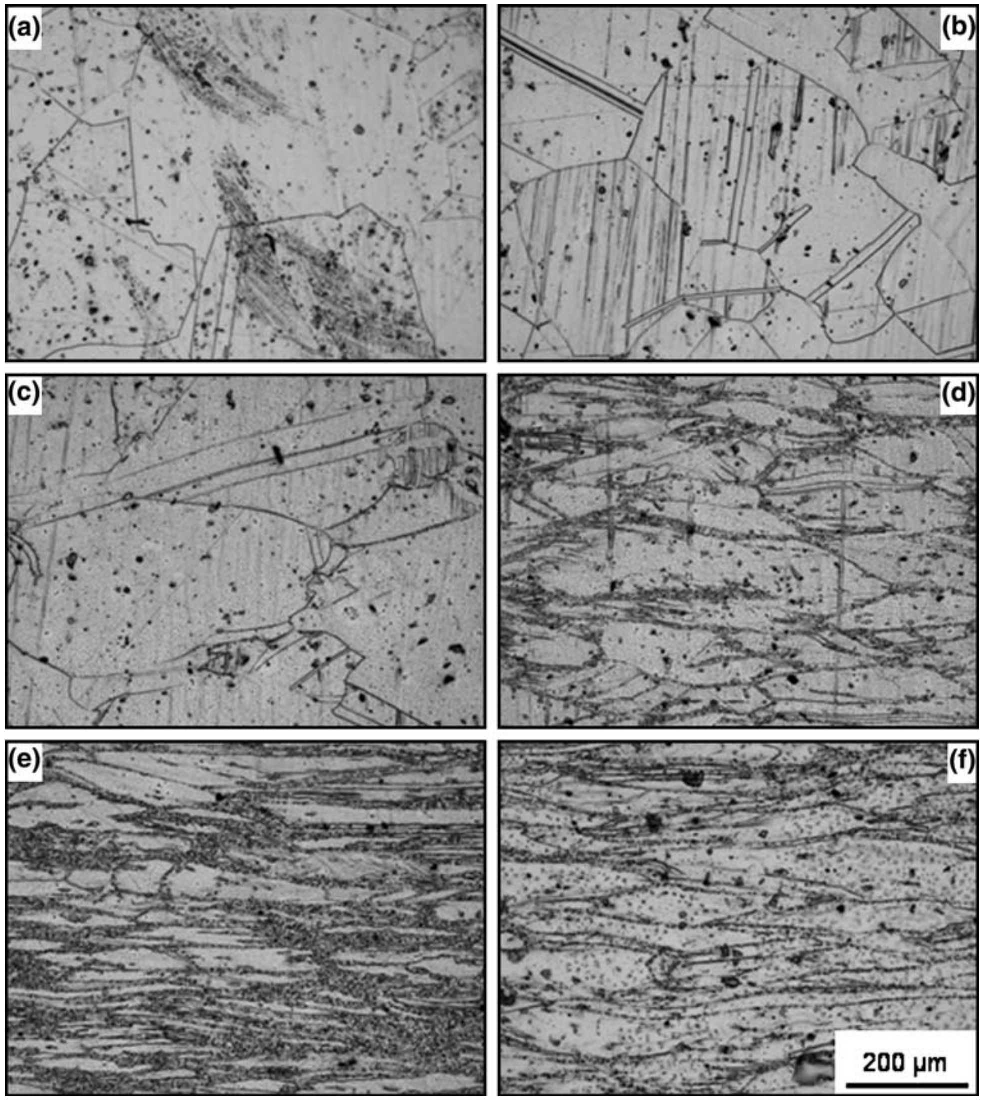

Fig. 13 Microstructures from a sample reheated at 1120 °C and reduction ratios of 1.1 (a), 1.4 (b), 1.8 (c), 2.2 (d), 2.6 (e) and 3 (f)

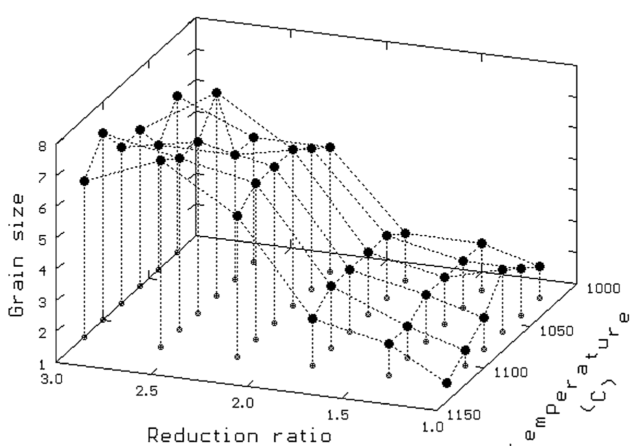

Fig. 14 Grain size (G_f) as measured at the sample as a function of temperature and reduction ratio

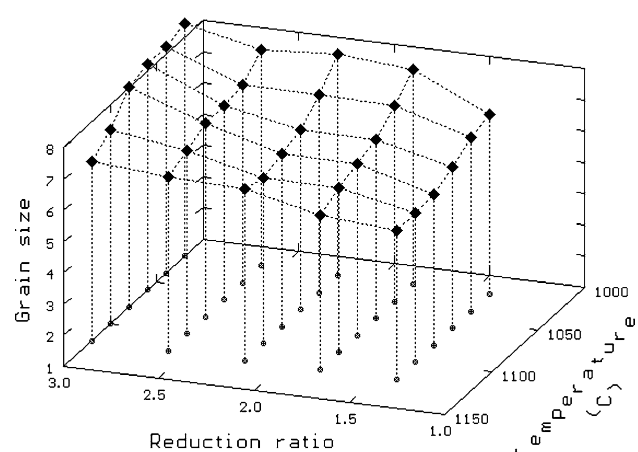

Fig. 15 Grain size (G_f) predicted as a function of temperature and reduction ratio with the set of rules shown in Table 1

deformation (D_r), which is given by the reduction in height ratio, and forging temperature (T_i). Therefore, the system has three inputs: T_i, D_r, and G_i while the only output is G_f.

In this work, open gaussian functions are used as membership functions since they are considered to represent the behavior of the process to a better extent. Inference is

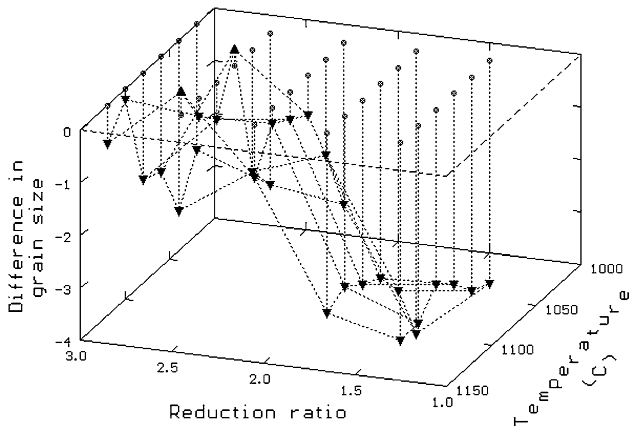

Fig. 16 Difference in grain size measured and predicted with the rules shown in Table 1

Table 2 Estimation error for the first set of rules

	Reduction ratios				
Temperature, °C	**3:1**	**2.6:1**	**2.2:1**	**1.8:1**	**1.4:1**
1020	−2.41	−2.89	−3.08	−5.37	−4.23
1040	−3.24	−2.32	−1.82	−4.25	−4.07
1060	−2.2	0.31	−0.75	−3.7	−3.63
1080	−2.03	−0.71	−0.52	−3.5	−3.32
1100	−0.2	−0.35	−0.3	−3.25	−3.76
1120	−0.73	0.44	−1	−3.42	−3.76

performed by t-norm operators for antecedents while for the consequent t-conorm operator is used. Defuzzification is carried out by the centroid of area method as given in Eq 3.

G_i is given in terms of the ASTM number and ranges from 1 to 10; values close to 1 are considered to be large while those close to 10 are to be small. Three uniformly distributed fuzzy sets on G_i range to represent "large," "medium," and "small" are used, as depicted in Fig. 8. D_r ranges from 1.1:1 to 3:1. Three fuzzy sets are uniformly distributed along the D_r range to represent "small," "medium," and "large" deformation, see Fig. 9.

Temperatures up to 1040 °C T_i are considered to be "good" for forging. Above this temperature, most of the alloying elements start to dissolve into the matrix and promote grain coarsening. Because of this, forging at temperatures in the neighborhood of 1040 °C is not being carried out at the plant, hence the fuzzy sets were distributed in such a way that the DM is low at such T_i range, see Fig. 10. The resulting fuzzy sets for G_f are modeled in a similar way as G_i within the range from 3 to 10. The rules shown in Table 1 were selected to obtain the final grain size.

5. Results and Discussion

The samples were reheated to the testing temperature for 2 h; an extra piece (witness) was kept together with the wedge-shaped specimen to measure the grain size resulting from the treatment. Figure 11 shows the microstructure obtained in the sample reheated to 1040 °C; the grain size was assessed to be of ASTM size 1. The samples that were compressed were left to

Table 3 Final set of fuzzy rules

Rules	Weight	Initial temperature		Deformation ratio		Initial grain size		Final grain size
1	1	IF T_i is good	AND	D_i is small	AND	G_i is large	Then	G_f is large
2	1	IF T_i is good	AND	D_i is medium	AND	G_i is large	Then	G_f is small
3	1	IF T_i is good	AND	D_i is large	AND	G_i is large	Then	G_f is small
4	1	IF T_i is good	AND	D_i is small	AND	G_i is medium	Then	G_f is medium
5	1	IF T_i is good	AND	D_i is medium	AND	G_i is medium	Then	G_f is small
6	1	IF T_i is good	AND	D_i is large	AND	G_i is medium	Then	G_f is small
7	1	IF T_i is good	AND	D_i is small	AND	G_i is small	Then	G_f is small
8	1	IF T_i is good	AND	D_i is medium	AND	G_i is small	Then	G_f is small
9	1	IF T_i is good	AND	D_i is large	AND	G_i is small	Then	G_f is small
10	1	IF T_i is high	AND	D_i is small	AND	G_i is large	Then	G_f is large
11	1	IF T_i is high	AND	D_i is medium	AND	G_i is large	Then	G_f is medium
12	1	IF T_i is high	AND	D_i is large	AND	G_i is large	Then	G_f is small
13	1	IF T_i is high	AND	D_i is small	AND	G_i is medium	Then	G_f is medium
14	1	IF T_i is high	AND	D_i is medium	AND	G_i is medium	Then	G_f is small
15	1	IF T_i is high	AND	D_i is large	AND	G_i is medium	Then	G_f is small
16	1	IF T_i is high	AND	D_i is small	AND	G_i is small	Then	G_f is small
17	1	IF T_i is high	AND	D_i is medium	AND	G_i is small	Then	G_f is small
18	1	IF T_i is high	AND	D_i is large	AND	G_i is small	Then	G_f is small
19	1	IF T_i is very high	AND	D_i is small	AND	G_i is large	Then	G_f is large
20	1	IF T_i is very high	AND	D_i is medium	AND	G_i is large	Then	G_f is large
21	1	IF T_i is very high	AND	D_i is large	AND	G_i is large	Then	G_f is medium
22	1	IF T_i is very high	AND	D_i is small	AND	G_i is medium	Then	G_f is large
23	1	IF T_i is very high	AND	D_i is medium	AND	G_i is medium	Then	G_f is medium
24	1	IF T_i is very high	AND	D_i is large	AND	G_i is medium	Then	G_f is small
25	1	IF T_i is very high	AND	D_i is small	AND	G_i is small	Then	G_f is medium
26	1	IF T_i is very high	AND	D_i is medium	AND	G_i is small	Then	G_f is medium
27	1	IF T_i very high	AND	D_i is large	AND	G_i is small	Then	G_f is small
28	0.8	T_i no matter	AND	D_i is large	AND	G_i no matter	Then	G_f is small

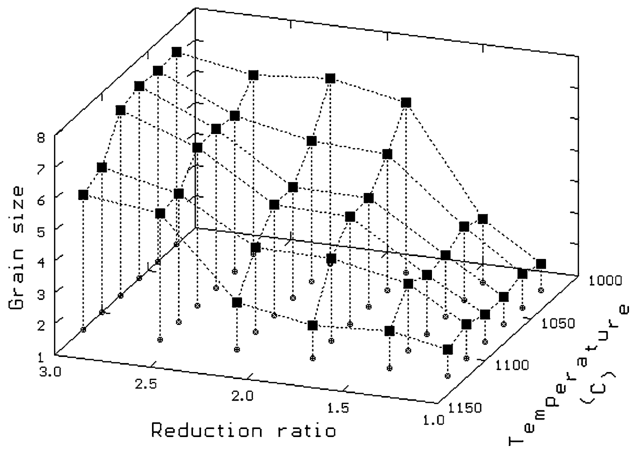

Fig. 17 Grain size (G_f) predicted as a function of temperature and reduction ratio with the set of rules shown in Table 3

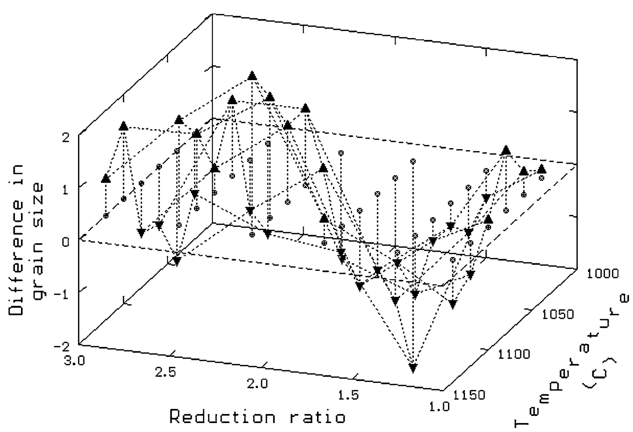

Fig. 18 Difference in grain size measured and predicted with the rules shown in Table 3

cool in air and were sectioned to obtain the grain sizes at the different places of the sample. This procedure was carried out at the regions corresponding to the reduction ratios shown in Fig. 1(b). Figures 12 and 13 show the microstructures at the center of specimens reheated at 1020 and 1120 °C, respectively. Figure 14 was traced with information available from these trials. This last figure indicates the strong dependence of the grain size as a function of reduction rate.

A run of the FIS described in the previous section was performed with the experimental entry data to estimate G_f and compare it against the measured values from the experiments. Figure 15 shows the surface graph of the FIS results. It was found that the initial grain size, G_i, was always close to 1; therefore, the results shown in Fig. 15 do not consider the effect of G_i on G_f, which implies that the only rules used in this case, Table 1, are the ones corresponding to large grain sizes, i.e., rules 1 to 3 and 10 to 15. Figure 16 shows the difference between the measured and predicted grain sizes; the corresponding estimating error is calculated by:

$$e = |G_{fe} - G_{fm}| \qquad \text{(Eq 6)}$$

where e is the estimation error, G_{fe} is the estimation of G_f by the FIS and G_{fm} is the measured G_f from the experiments. Table 2 shows the estimation error, which averages 2.32.

Table 4 Estimation error for the final set of rules

	Reduction ratios					
Temperature, °C	**3:1**	**2.6:1**	**2.2:1**	**1.8:1**	**1.4:1**	**1.1:1**
1020	−1.14	−1.72	−1.9	−3.93	−0.53	0.16
1040	−2.1	−0.96	0.03	−2.34	−0.86	0.43
1060	−1.11	1.43	1.45	−1.45	−0.45	1.13
1080	−0.93	0.46	1.46	−1.43	−0.4	0.13
1100	1.37	1.42	2.29	−0.62	−1.13	−0.6
1120	0.71	1.99	3.01	0.45	−0.2	−0.84

It can be appreciated in Fig. 15 that the estimation by FIS does not reproduce the strong effect caused by the reduction rate, so it was decided to establish the new set of rules shown in Table 3. As with the previous case, the large size of the initial grain, G_i, forced the system only to use rules 1 to 3, 10 to 12, 19 to 21, and 28, this last rule with a lower weight. Figure 17 shows the grain size predicted, G_f, by this new set of rules, which result in a better estimation of the error, Fig. 18. The changes made to the set of rules resulted in a better prediction, Table 4, that results in an average error of 1.18 ASTM that is considered to be adequate for the prediction of grain size in preforms to be used in the production of rolled rings.

6. Conclusions

A fuzzy inference system was developed to predict the grain size resulting from the upsetting of IN718 alloy. The system was designed to take into account the influence of reduction rate, temperature, and initial grain size, although the experimental trials did not allow for the evaluation of this last variable.

A system based in 15 rules was not able to reflect the effect of reduction rate, and resulted with a large estimation error (2.32 ASTM). The system was modified to take into account a new set of 28 rules that contributed to reduce the estimation error close to half of the previous value (1.18 ASTM).

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