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FUZZY MODELING OF TEMPERING PROCESS OF CAST STEEL

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Abstract: Tempering is a heat treatment process to achieve maximum toughness and ductility at a specified hardness and strength. It is important to develop an intelligent model for tempering process to satisfy requirement of mechanical properties with low cost. This paper presents a fuzzy model to predict Charpy-V notch toughness during tempering process of steel. The influence of processing parameters of steel casting, hot working and heat treatment on toughness of tempered steel was investigated. Fuzzy model for prediction od Charpy-V notch toughness of steel was established. In order to validate the model, it is employed to predict the tempering of EN GS-42CrMo4 steel. The calculated results show a good agreement with the experimental ones. This agreement indicates that the fuzzy logic is effective for modeling of tempering process of steels.

Keywords: modeling, tempering, cast steel, fuzzy logic.

1. INTRODUCTION

Tempering is a combined heat treatment process used in the manufacture of steel components. The final properties of a tempered steel part depend on the microstructure that evolves during the tempered process [1]. In practice, the tempering process is designed by analytically determining methods.

A lot of analytically methods were also developed and used for predicting mechanical properties during tempering process of steel. In the early nineties, Hodgson and Gibbs have developed a mathematical model that predict the final mechanical properties of hot rolled steels [2]. Around the same time, Ju and Inoue proposed analytical model to predict the kinetics of quenching-tempering process [3]. Denis and Aubry have developed the model for calculating phase transformation kinetics in steel mainly for taking into account the chemical composition variation of the steel and the tempering/self-tempering kinetics [4]. This model was coupled to the calculation of temperature, stress and strain evolutions in a massive specimen submitted to chemical composition gradients.

Techniques of artificial intelligence, such as Artificial Neural Network (ANN) [5], Genetic Algorithm (GA) [6], Fuzzy Logic (FL) [7] and their combinations, provide an alternative solution for predictive learning and modelling of weld quality without any mathematical model. Recently, some initial investigations in applying the basic artificial intelligence approach to model Charpy impact toughness of tempered processes, have appeared in the literature. Dunne et al. have been applied artificial neural networks to the prediction of the Charpy impact toughness of quenched and tempered steels and ferrous weld metals [8]. They demonstrated that the Charpy impact toughness can be accurately predicted using the selected input variables and their range of values. Chen and Linkens established generic toughness prediction neural network models which link materials compositions and processing conditions with Charpy impact properties.

In the literature, the effect of the different parameters on the Charpy impact toughness was researched. However the modeling with the fuzzy logic is still a scarce. In this study, influence of processing parameters of steel casting, hot working and heat treatment on toughness of tempered steel as tempering conditions were selected. A fuzzy logic model was developed and validated using these tempering parameters. Fuzzy logic (FL) is a theory used to describe the relationship between system inputs and outputs. It is widely used to develop rule–based expert systems in modeling of complex processes that are difficult to be modeled analytically under

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various assumptions [9]. In the present study, an intelligent model is developed to predict the Charpy-V notch toughness during the tempering process of cast steel by modifying the previous model in [10].

The toughness of cast steel is dependent on pouring temperature, cooling rate during the casting, as well as application of hot working, normalisation, and homogenisation [11]. The experiments have been carried out on cast steel EN GS-42CrMo4. The chemical components of this material can be found in the literature [10]. The experiments were conducted according to the specified experiment plan. The experiment was carried out for different combinations on the influence of casting temperature, cooling rate during the casting, as well as hot working, normalisation, homogenisation on yield strength and Charpy-V notch toughness according to the Table 1.

2. EXPERIMENTAL SETUP

The toughness of cast steel is dependent on pouring temperature, cooling rate during the casting, as well as application of hot working, normalisation, and homogenisation [11]. The experiments have been carried out on cast steel EN GS-42CrMo4. The mechanical properties of this material are shown in Table 1. The experiments were conducted according to the specified experiment plan. The experiment was carried out for different combinations on the influence of pouring temperature, cooling rate during the casting, as well as hot working, normalisation, homogenisation on yield strength and Charpy-V notch toughness according to the Table 1.

Table 1. Mechanical Properties of EN GS-42CrMo4

Quantity	Value	Unit
Young's modulus	200000 - 200000	MPa
Tensile strength	650 - 880	MPa
Elongation	8 - 25	%
Fatigue	275 - 275	MPa
Yield strength	350 - 550	MPa

The most commonly used method of assessing toughness of cast steels is the Charpy V-notch impact test. The Charpy impact test, also known as the Charpy V-notch test, is a standardized high strain-rate test which determines the amount of energy absorbed by a material during fracture.

3. FUZZY LOGIC MODELING

There are three types of fuzzy inference systems in wide use: Mamdani-type, Sugeno-type and Tsukamoto-type (Mamdani and Assilian, 1975; Sugeno and Kang, 1988; Tsukamoto, 1979). These three types of inference systems vary somewhat in the way outputs are determined [12]. Mamdani-type is used in this paper.

In this experiment, the input variables considered are casting temperature, cooling rate during the casting, as well as hot working, normalization and homogenization. The output variable is Charpy-V notch toughness. The elementary stage in fuzzy logic is the selection of appropriate shapes of the membership function for developing the algorithm in order to select the machining parameters. The membership function is a graphical representation of the magnitude of participation of each parameter. It associates a weighting with each of the inputs that are processed, defines functional overlap between inputs, and ultimately determines an output response.

Fuzzy expressions for input variables have been divided into two membership functions. The number of membership functions used for the output response is eight, Figure 1. Fuzzy logic uses membership functions which is an arbitrary curve. Though there are many numbers of membership functions available like triangular, trapezoidal, Gaussian, etc. The modeling of the Charpy-V notch toughness in this paper is using the Gaussian type as described in literature [13].

The concept of fuzzy reasoning for five-input and one output fuzzy logic unit is described as follows: The fuzzy rule base consists of a group of IF- THEN statements with for inputs, x_1 (casting temperature), x_2 (mold temperature), x_3 (warm deformation), x_4 (normalization) and x_5 (homogenization) one output y (Charpy impact toughness). General form of rule base systems with multiple inputs and one output is:

$$\begin{array}{l}
Input: \; x_1 \; is \; A_i \; and \; x_2 \; is \; B_i \; and \; x_3 \; is \; C_i \; and \; x_4 \; is \; D_i \; and \; x_5 \; is \; D_i \\
\hline
R_1: \; x_1 \; is \; A_1 \; and \; x_2 \; is \; B_1 \; and \; x_3 \; is \; C_1 \; and \; x_4 \; is \; D_1 \; and \; x_5 \; is \; E_1 \;\; THEN \; y \; is \; F_1 \\
R_2: \; x_1 \; is \; A_2 \; and \; x_2 \; is \; B_2 \; and \; x_3 \; is \; C_2 \; and \; x_4 \; is \; D_2 \; and \; x_5 \; is \; E_2 \;\; THEN \; y \; is \; F_2 \\
\vdots \\
R_i: \; x_1 \; is \; A_i \; and \; x_2 \; is \; B_i \; and \; x_3 \; is \; C_i \; and \; x_4 \; is \; D_i \; and \; x_5 \; is \; E_i \; THEN \; y \; is \; F_i \\
\hline
\qquad\qquad\qquad\qquad Output: \;\; y \; is \; F^{'}
\end{array} \tag{1}$$

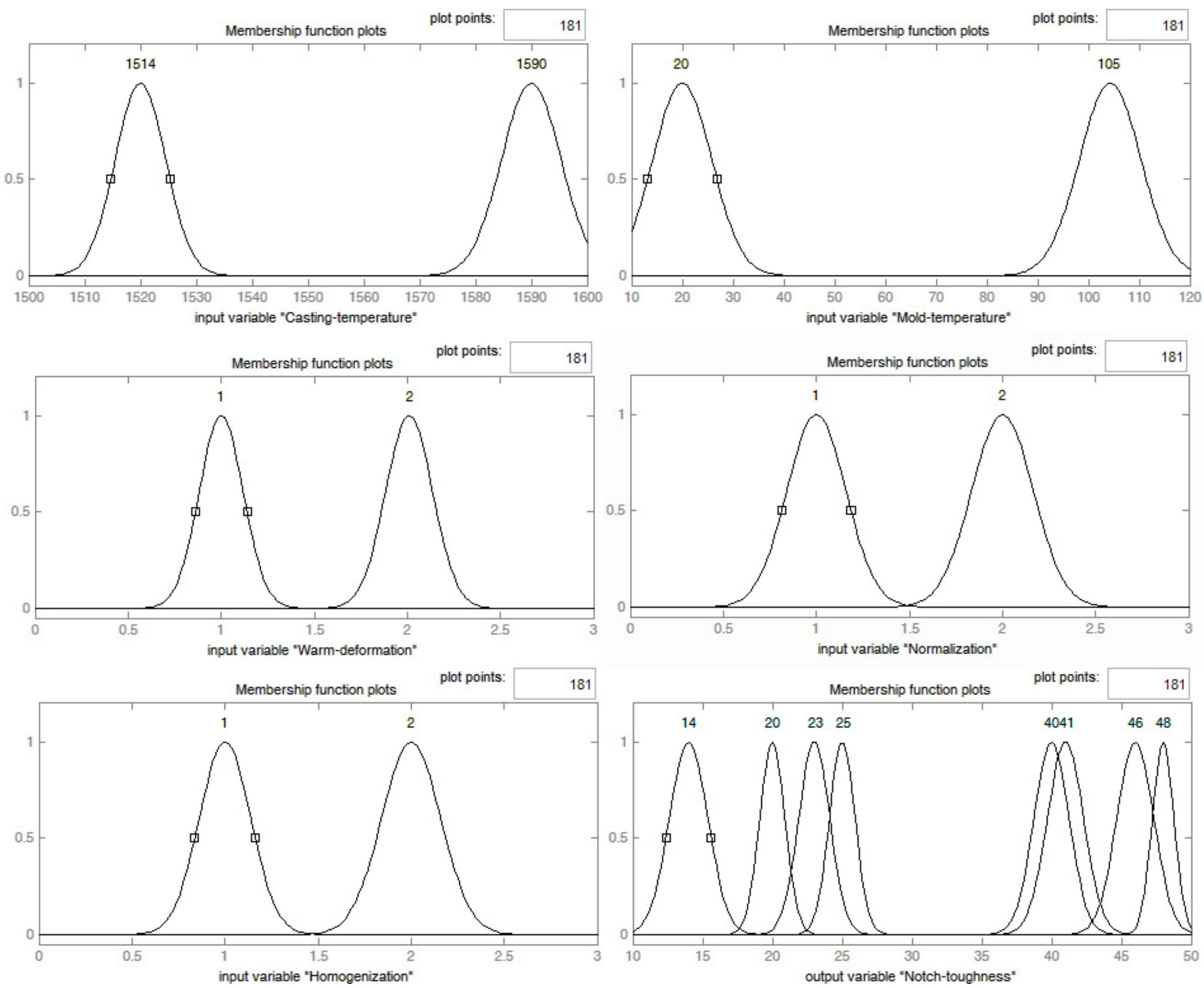

Figure 1. Membership functions for input and output parameters

Where x_1 , x_2, x_3, x_4 and x_5 state variables that describe the state of the process and represent the input size of a fuzzy system and y is the output of a fuzzy system with A, B, C, D, E and F are linguistic values defined by fuzzy sets on the ranges, x_1, x_2, x_3, x_4, x_5 and y respectively. After that the implication function modifies that fuzzy set to degree specified by the antecedent. The most common way to modify the output fuzzy set is truncation using the MIN function. Each rule from the previous set of rules can be viewed as a fuzzy implication, so that the i-th rule can be written as:

$$\mu_{Ri} = \mu_{(Ai\wedge Bi\wedge Ci\wedge Di\Rightarrow Ei)}(x_1,x_2,x_3,x_4,y) == [\mu_{Ai}(x_1)\wedge \mu_{Bi}(x_2)\wedge \mu_{Ci}(x_3)\wedge \mu_{Di}(x_4)]\Rightarrow \mu_{Ei}(y) \tag{2}$$

Mamdani *MIN* (∧ <=> *AND*) implication operator is used. Where an implication operators take~~s~~ as an input membership function of antecedent $\mu_{Ai}(x_1)\wedge\mu_{Bi}(x_2)\wedge\mu_{Ci}(x_3)\wedge\mu_{Di}(x_4)\wedge\mu_{Ei}(x_5)$ and $\mu_{Fi}(y)$ is consequent. Every rule has a weight (number between 0 and 1) which is applied to the number given by the antecedent. Finally, a defuzzification method is used to transform the fuzzy output into a non-fuzzy value y0. Defuzzification is carried out using centroid defuzzification method. It produces the center area of the possibility distribution of the inference output. It is also one of the more frequently used defuzzification method that uses for calculating the centroid of the area under the membership function:

$$y' = \frac{\sum_{i=1}^{n} y\mu_{Fi}(y)}{\sum_{i=1}^{n} \mu_{Fi}(y)} \tag{3}$$

Where *y'* the defuzzified output (the output for a given input vector, which was the predicted by Charpy impact energy value in this study.), $\mu_{Fi}(y)$ the aggregated membership function and *y* the output variable (the centre value of the regions).

The non-fuzzy value *y'* gives the output Charpy impact toughness value in numerical form. For example, the value of Charpy impact toughness at condition, casting temperature is 1514, mold temperature is 19, as well as, warm deformation - no, normalization - yes and homogenization – yes, is obtained as 20 KV [J]. MATLAB fuzzy logic tool is used for the calculation. Fuzzy predicted values are given in Table 2. In this work Mamdani MAX–MIN approach is used as an inference engine. Fuzzy rule base is shown of figure 2.

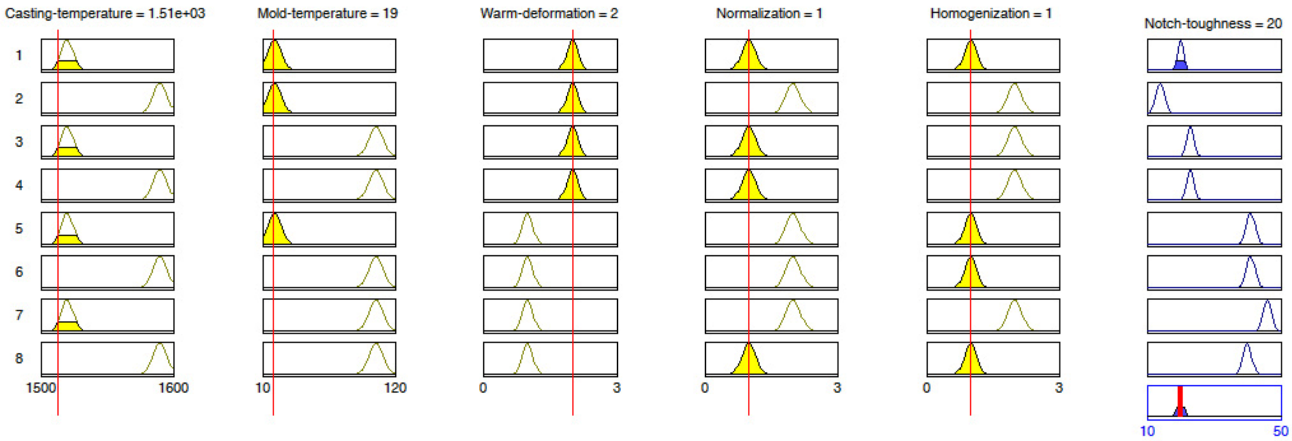

Figure 2. Fuzzy rules of model

4. RESULTS AND DISCUSSION

The present investigation was conducted to evaluate the level of impact toughness of cast steel. The proposed fuzzy modeling approach has been used to construct composition-processing-property models for Charpy impact toughness prediction of EN GS-42CrMo4 steel.

Exactly 32 experimental data were used to develop the prediction model. Two different set of data patterns are prepared for fuzzy model development; one set is comprised of 24 patterns (75% of total patterns) for design fuzzy rules, second set is comprised of 8 patterns (25% of total patterns) for validating of design.

Results obtained by Mamdani fuzzy system of reasoning, using rules that are defined on the basis of experimental data, show agreement with experiment. Table 2 shows the compared values obtained by experiment and estimated by fuzzy logic model. The average deviation of data for design rules is 7.85% while average deviation of validation data is 9.98 %.

Results obtained by Mamdani fuzzy system of reasoning, using rules that are defined on the basis of experimental data, show agreement with experiment. This shows that the selected types of membership functions (gaussmf) type reasoning mechanism by the method of MIN - MAX and selected defuzzification centroid method (center of gravity) are a good choice.

Table 2. Data for design rules and validation data

No.	Casting temperature [°C]	Mold temperature [°C]	Warm deformation [yes-1/no-2]	Normalization [yes-1/no-2]	Homogenization [yes-1/no-2]	Notch toughness KV [J]	Fuzzy Notch toughness KV [J]	Abs. Error %
Data for design rules								
1.	1514	20	2	1	1	20	20	0.00
2.	1590	20	2	2	2	14	14.2	1.42
3.	1514	105	2	2	1	23	26.8	16.52
4.	1590	105	2	1	2	25	23	8.00
5.	1514	20	1	1	2	48	46.6	2.91
6.	1590	20	1	2	1	41	39.6	3.41
7.	1514	105	1	2	2	46	46	0.00
8.	1590	105	1	1	1	40	40	0.00
9.	1513	20	2	1	1	24	20	16.66
10.	1591	20	2	2	2	15	14	6.66
11.	1513	105	2	2	1	26	30	15.00

No.	Casting temperature [°C]	Mold tem-perature [°C]	Warm deformation [yes-1/no-2]	Normalization [yes-1/no-2]	Homogenization [yes-1/no-2]	Notch toughness KV [J]	Fuzzy Notch toughness KV [J]	Abs. Error %
12.	1591	105	2	1	2	26	23	11.53
13.	1513	20	1	1	2	47	39.7	15.53
14.	1591	20	1	2	1	37	39.5	6.75
15.	1513	105	1	2	2	44	46	4.54
16.	1591	105	1	1	1	38	40	5.26
17.	1514	21	2	1	1	23	20	13.04
18.	1590	19	2	2	2	14	14	0.00
19.	1514	104	2	2	1	25	30	20.00
20.	1590	106	2	1	2	20	23	15.00
21.	1514	21	1	1	2	50	48	4.00
22.	1590	19	1	2	1	44	40.7	7.50
23.	1514	104	1	2	2	49	48	2.04
24.	1590	106	1	1	1	37	36	2.70
							Average error of training data:	**6.55**
				Validation data				
25.	1513	19	2	1	1	24	20	16.66
26.	1591	21	2	2	2	14	14	0.00
27.	1515	106	2	2	1	26	32	15.3
28.	1589	104	2	1	2	20	23	15.00
29.	1513	21	1	1	2	47	46.6	0.85
30.	1591	20	1	2	1	37	39.5	6.75
21.	1513	104	1	2	2	42	40	4.76
32.	1589	106	1	1	1	40	39	2.50
							Average error of validation data:	**7.72**

5. CONCLUSIONS

Error results obtained by using "Mamdani" model is not dependent on the amount of data that were used to obtain the model, but error model depends on the defined rules and to avoid their overlapping. Selecting membership function, its parameters selected are a good choice phase fuzzification and defuzzification. The adequacy of the model is checked and is found to be adequate at about 90% confidence level and the model can be used for predicting Charpy-V notch toughness.

Figure 3 depicts the comparison of experimantal and fuzzy test results for the Charpy impact toughness. It proved that the method used in this paper is feasible and could be used to predict the Charpy impact toughness in an acceptable error rate. The compared lines seem to be close to each other indicating with good agreement.

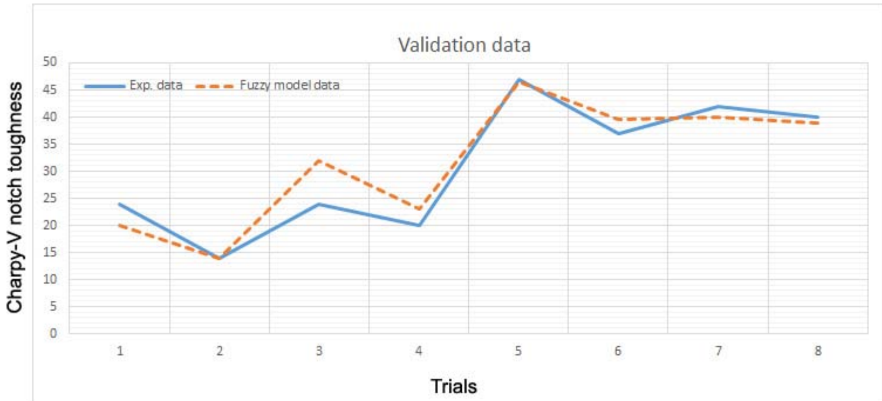

Figure 3. Correlation between experimental value and fuzzy predicted

The effectiveness of the model is only within the range and factors studied. The model adequacy can be further improved by considering more variables and ranges of parameters. It is necessary to define the membership function for each set of rules which form and combination appear with too many solution. Implementation of fuzzy logic for this purpose can be applied successfully.

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МОДЕЛОВАЊЕ ПОБОЉШАЊА ЧЕЛИЧНОГ ЛИВА ПРИМЕНОМ ФАЗИ ЛОГИКЕ

Сажетак: Побољшање је поступак термичке обраде челика како би се постигла максимална жилавост и кртост за одређену тврдоћу и чврстоћу. Веома је важно развити интелигентан модел за процес побољшања који ће задовољити захтеве механичких својстава уз ниске трошкове. У овом раду је описан фази модел који предвиђа жилавост изражену ударним радом лома при процесу побољшања челика. Истраживан је и утицај појединих параметара обраде, као што су параметри ливења, обраде пластичном деформацијом у топлом стању и термичке обраде на жилавост побољшаног челика. Развијен је фази модел за предвиђање жилавости у зависности од улазних параметара. У циљу валидације модела извршено је поновно побољшање челика EN GS-42CrMo4. Резултати модела су показали добро слагање са експерименталним подацима. Ови резултати потврђују да се применом фази логике може успешно моделовати процес побољшања челика.

Кључне речи: моделовање, побољшање, челични лив, фази логика.