Fuzzy neural network analysis on gray cast iron with high tensile strength and thermal conductivity

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Abstract: To develop a high performance gray cast iron with high tensile strength and thermal conductivity, multivariable analysis of microstructural effects on properties of gray cast iron was performed. The concerned parameters consisted of graphite content, maximum graphite length, primary dendrite percentage and microhardness of the matrix. Under the superposed influence of various parameters, the relationships between thermal conductivity and structural characteristics become irregular, as well as the effects of graphite length on the strength. An adaptive neuro-fuzzy inference system was built to link the parameters and properties. A sensitivity test was then performed to rank the relative impact of parameters. It was found that the dominant parameter for tensile strength is graphite content, while the most relative parameter for thermal conductivity is maximum graphite length. The most effective method to simultaneously improve the tensile and thermal conductivity of gray cast iron is to reduce the carbon equivalent and increase the length of graphite flakes.

Key words: high performance gray cast iron; fuzzy neural network; tensile strength; thermal conductivity

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Despite having weaker tensile strength and fatigue resistance compared with that of compacted or spherical graphite iron^[1], pearlitic gray cast iron (GCI) is still the optimal choice for production of vital engine components due to lower cost, higher thermal conductivity and better castability^[2, 3]. However, the service life of these components becomes increasingly problematic due to the higher performance demanded by increased load carrying capability and the thinner thickness required by energy conservation^[4]. Since the main failure patterns of these components relate to high cycle fatigue and thermo-mechanical fatigue^[4, 5], it is necessary to develop the high performance GCI with improved ultimate tensile strength (UTS) and thermal conductivity.

Previous studies showed that the tensile strength and thermal conductivity of GCI are usually contradictory to each other. The tensile strength of pearlitic GCI can be improved by decreasing the graphite content

(carbon equivalent) and length of graphite flakes, increasing primary dendrite and microhardness (MH) of the matrix^[6-9]. On the other hand, the GCI with high thermal conductivity was linked to the increase of carbon equivalent and graphite length but the reduction of scattering of alloying elements^[10-13]. Bertodo also reported that reducing solutes in the matrix can improve the thermal conductivity of GCI^[5]. However, the corrections mentioned above were mainly carried out by considering the variation of single parameters. Optimizing the UTS and thermal conductivity requires the multivariable analysis.

Various models were also developed to model the structural influence on properties of GCI. Hecht et al.^[14] predicted the thermal transport property by considering the effect of maximum graphite length. Fourlakidis et al.^[8] considered the UTS of pearlitic GCI as the function of primary dendrite content. Holmgren et al.^[12] developed a relationship between thermal conductivity and structure of GCI by linear multiple regression analysis. However, the conventional regression model cannot provide satisfactory prediction due to the narrow structural variables and crisp treatment of measured values. Adaptive neuro-fuzzy network system (ANFIS) was reported as an available method to map the complex relationship between inputs and outputs by considering

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the measured data as fuzzy numbers^[15]. Qian et al.^[16] built an ANFIS structure to link the UTS of GCI with various structural parameters. It was also confirmed that ANFIS can provide better learning precision for modeling complex non-linear system with limited dataset than multiple linear regression and other forms of neural network^[16,17].

The aim of this work was to find out the most effective method for improving GCI properties with high tensile strength and thermal conductivity. Multivariable investigations on the tensile and thermal properties from graphite content, maximum graphite length, primary dendrite content and MH of the matrix were discussed depending on experimental data. The relationships between properties and parameters were linked using a standard fuzzy neural network. Then the sensitivity level was analyzed respectively to determine the dominant parameter for tensile strength and thermal conductivity.

1 Methods

1.1 Materials

Thirty-six specimens used in this work were melted in a 25 kg medium-frequency induction furnace. The charges consisted of 70wt.% steel scrap and 30wt.% pig iron. Ferro-molybdenum, ferro-manganese, ferro-silicon and carburizer were used to meet the requirement of chemical composition. After superheating to 1,500–1,530 °C, the liquid was poured into a ladle with inoculant at the bottom. ZrFeSi (2.6wt.%Zr), SrFeSi (2.0wt.% Sr), and SiC inoculants were used respectively in order to obtain different structural morphologies. For each composition, an EN-1564 Type II mould was poured. The compositions and corresponding inoculation details are shown in Table 1. Carbon equivalent (CE) is calculated by $CE = C\% + 0.31Si\% + 0.33P\%$.

Table 1: Chemical composition of samples and corresponding inoculants (wt.%)

No.	C	Si	Mn	S	P	Cu	Ni	Mo	Sn	CE	Inoculant
1	3.44	1.44	0.48	0.026	0.030	0.53		0.26	0.059	3.90	ZrFeSi
2	3.58	1.20	0.51	0.026	0.029	0.54		0.24	0.059	3.96	ZrFeSi
3	3.57	1.40	0.51	0.027	0.029	0.51		0.24	0.059	4.01	ZrFeSi
4	3.57	1.59	0.51	0.024	0.026	0.54		0.24	0.058	4.07	ZrFeSi
5	3.58	1.62	0.50	0.029	0.028	0.54		0.33	0.059	4.09	ZrFeSi
6	3.67	1.51	0.51	0.029	0.028	0.54		0.34	0.059	4.15	ZrFeSi
7	3.58	1.19	0.50	0.025	0.029	0.54		0.35	0.059	3.96	ZrFeSi
8	3.62	1.19	0.52	0.027	0.027	0.54		0.44	0.058	4.00	ZrFeSi
9	3.58	1.41	0.50	0.027	0.026	0.53		0.44	0.057	4.03	ZrFeSi
10	3.54	1.64	0.51	0.027	0.026	0.53		0.44	0.058	4.06	ZrFeSi
11	3.43	1.65	0.49	0.024	0.031	0.53		0.26	0.057	3.95	ZrFeSi
12	3.39	1.81	0.48	0.025	0.029	0.53		0.26	0.058	3.96	ZrFeSi
13	3.66	1.90	0.48	0.026	0.030	0.55		0.36	0.060	4.26	ZrFeSi
14	3.39	1.64	0.46	0.025	0.030	0.55		0.35	0.057	3.91	ZrFeSi
15	3.53	1.59	0.51	0.028	0.029	0.54		0.34	0.060	4.03	ZrFeSi
16	3.49	1.47	0.50	0.029	0.030	0.54		0.45	0.061	3.96	ZrFeSi
17	3.50	1.72	0.50	0.030	0.029	0.53		0.45	0.061	4.04	ZrFeSi
18	3.48	1.94	0.50	0.027	0.029	0.53		0.44	0.060	4.09	ZrFeSi
19	3.52	2.14	0.36	0.025	0.031				0.030	4.19	ZrFeSi
20	3.54	1.66	0.49	0.028	0.026	0.53		0.44	0.056	4.06	SrFeSi
21	3.32	1.80	0.50	0.020	0.028	0.58		0.41	0.060	3.89	SrFeSi
22	3.42	1.63	0.49	0.027	0.028	0.58		0.35	0.061	3.93	SrFeSi
23	3.52	1.62	0.50	0.028	0.027		0.11	0.34	0.057	4.03	SrFeSi
24	3.54	1.62	0.51	0.028	0.025	0.58		0.35	0.060	4.05	SrFeSi
25	3.33	1.62	0.51	0.028	0.025		0.21	0.34	0.060	3.84	SrFeSi

No.	C	Si	Mn	S	P	Cu	Ni	Mo	Sn	CE	Inoculant
26	3.36	1.96	0.39	0.027	0.032	0.42			0.030	3.98	SrFeSi
27	3.36	1.60	0.52	0.028	0.025		0.32	0.37	0.060	3.86	SrFeSi
28	3.69	1.59	0.51	0.030	0.027	0.58		0.35	0.061	4.19	SrFeSi
29	3.43	1.84	0.52	0.020	0.028	0.58		0.41	0.060	4.01	SrFeSi
30	3.49	1.89	0.51	0.020	0.026	0.58		0.40	0.060	4.08	SrFeSi
31	3.56	1.94	0.52	0.020	0.026	0.56		0.41	0.060	4.17	SrFeSi
32	3.63	1.83	0.51	0.091	0.029	0.58		0.40	0.060	4.21	SrFeSi
33	3.61	1.93	0.49	0.025	0.028		0.11	0.34	0.060	4.22	SrFeSi
34	3.53	1.70	0.52	0.026	0.028	0.58		0.36	0.061	4.07	SiC
35	3.64	1.61	0.51	0.028	0.028	0.58		0.36	0.060	4.15	SiC
36	3.34	1.80	0.50	0.025	0.028	0.58		0.36	0.061	3.91	SiC

Tensile tests were performed according to Chinese Standard GB/T T228.1-2010 using dog-bone shaped bars with a 20 mm diameter in the gauge section, 60 mm gauge length and 3.2 μm surface finish. Three tests were performed for each composition and the average UTS was calculated as the final value. Dish specimens (12.5 mm in diameter and 2.5 mm in thickness) were cut from the gripped end and then used to determine the thermal diffusivity (α) and heat capacity (c_p) with a NETZSCH LFA 457 laser flash apparatus. The density (ρ) was calculated by weighting the specimen and dividing by the volume. Then the thermal conductivity (λ) was calculated by equation (1).

$$\lambda = \alpha \rho c_p \quad (1)$$

The dish specimens were then polished and prepared for microstructural analysis. The size and percentage of graphite flakes were evaluated in an unetched condition by quantitative metallography with the software Image J Pro. The primary dendrites were revealed by color etching. The color etchant was 100 g NaOH and 8 g picric acid dissolved in 200 mL

distilled water. The etching was performed at 98 °C for about 6 minutes. The volume percentage of a phase (graphite or primary austenite) is simply approximated as the area percentage occupied by the phase on the metallographic specimen. The maximum graphite length was measured according to Chinese Standard GB/T 7216-2009. A total of eight fields were measured and the average value was taken. Typical metallographs showing graphite and primary dendrites are provided in Fig. 1. Microhardness of the matrix, which represents the effect of alloy strengthening, was obtained by an automatic Qness Q60 tester under a 500 g load for 10 s. Ten tests were performed for each composition and the average value was taken. In order to obtain precise MH of the matrix, only the value without graphite in the indentation was recorded.

1.2 Fuzzy neural network structure

A fuzzy model was developed to map the complex relationship between inputs and outputs which cannot be measured or collected as precise information. The adaptive neuro-fuzzy

Fig. 1: Metallographs showing graphite (a) and primary dendrites (b)

network system, which is a fuzzy form of the classical artificial neural network, models the dependent and independent variables by membership functions and associated parameters. In this work, an ANFIS based on the zero-order Takagi-Sugeno^[18] method was built as shown in Fig. 2. The inputs and outputs are treated as fuzzy numbers, and the IF-THEN rules are formed as follows:

$$R_i: \text{If } x_1 \text{ is } A_i, x_2 \text{ is } B_i, x_3 \text{ is } C_i, x_4 \text{ is } D_i, \text{ then } y_i \text{ is } E_i \quad (2)$$

where R_i is the i -th rule, x_1, x_2, x_3 and x_4 are input variables, y_i is the output in the i -th rule, A_i, B_i, C_i, D_i and E_i are fuzzy sets defined for inputs and output.

For a given input data set X_0 , the output Y_0 is calculated by taking the weight average of y_i :

$$Y_0 = \frac{\sum_i w_i y_i}{\sum_i w_i} \quad (3)$$

The firing strength w_i in i -th rule can be represented as:

$$w_i = u_{i1} \wedge u_{i2} \dots u_{im} \quad (4)$$

where $\wedge$ denotes a fuzzy T-norm operator, which describes a generalized AND operator, u_{im} is the membership function (MF) of x_m .

Gaussian membership functions were used for each input variable. The form of the MF was defined as follows:

$$u = e^{-\frac{(x-c)^2}{\sigma^2}} \quad (5)$$

where c and σ are the corresponding parameters, whose initial values were defined by grid partition depending on the range of inputs. In the learning process, these parameters were adjusted by the combination of back-propagation algorithm and least squares method.

Fig. 2: Schematic diagram of ANFIS structure

2 Results and discussion

2.1 Experimental results

The microstructural characteristics and the properties of samples are summarized in Table 2. Fully pearlitic matrix and A-type graphite were observed for each sample. Considering

most of the flakes cannot be displayed completely in a random 2-D section, the three longest flakes were measured and the average value was taken as the maximum graphite length. All the properties were obtained at room temperature. The ranges of graphite percentage, maximum graphite length, primary dendrite percentage and MH of the matrix are respectively (8.2%, 10.3%), (195.8 μm , 288.0 μm), (8.6%, 20.5%) and (208.3 Hv, 303.2 Hv), which are all wide enough to reflect their influences on the properties. The relationships between the property and structural parameters are shown in Figs. 3 and 4. It is clear in Fig. 3 that the UTS is improved by the decrease of graphite content and the increase of primary dendrite content or MH of the matrix, which was indeed expected since many similar correlations have been reported previously^[6, 8]. No distinct relationship between UTS and graphite length is observed. As shown in Fig. 4, a general increase of thermal conductivity can be found with the increase of maximum graphite length, which can be explained by the fact that longer graphite provides more basal plane of graphite and thus higher thermal transport. However, there is no special relationship between thermal conductivity and other parameters.

Even though SrFeSi can inoculate more primary dendrite and thus provide higher UTS^[19], an overall linear relationship between graphite content and UTS still exists. It implies that the impact of the change of CE is greater than that of inoculation, which means graphite content has greater effects on UTS than primary dendrite refinement. However, it is difficult to distinguish the relative importance between graphite content and MH of the matrix just relating to Fig. 3. As for thermal conductivity, the irregular relationship between graphite content and thermal conductivity cannot deny the effect of graphite content since it is obvious that more graphite phase can improve the thermal transport property due to its higher thermal conductivity. It can be explained by the disturbance of other parameters. A similar explanation can also be used for the undistinguishable impacts on thermal conductivity from primary dendrite and MH of the matrix. Therefore, the mutual interference of these parameters on both UTS and thermal conductivity cannot be linked. That means it is difficult to optimize the microstructure for the high performance CGI just depending on the results shown in Figs. 3 and 4.

2.2 ANFIS and sensitivity test

Based on the parameters summarized in Table 2, an ANFIS was appropriately trained to find an approximate relationship between parameters and UTS or thermal conductivity. The inputs consisted of graphite percentage (x_1), maximum graphite length (x_2), primary dendrite percentage (x_3) and MH of the matrix (x_4). Since the number of input variables is 4, 32 cases in Table 2 were chosen as training data to avoid an overfitting problem, and 1/8 of training cases were used as testing data. Figure 5 depicts the comparisons between the outputs of the trained ANFIS and the measured values. It can be clearly observed that the UTS and the thermal conductivity calculated by ANFIS are in line with the experimental data. The coefficient of determinations (R^2) are respectively 0.89 and

0.84 for comparisons of UTS and thermal conductivity. These comparisons indicate that the ANFIS provides a satisfactory learning process to link the tensile and thermal properties of GCI with the parameters.

In order to more clearly see the influence of the key

parameters on the properties, the relative significance was analyzed by the sensitivity level method. In this method, all the input variables were changed step by step at a certain rate (5% and 10% in this work), and the outputs were recalculated by the established ANFIS. The sensitivity level Sen_j to input x_j was

Table 2: Microstructural information and properties of samples (Errors are $\pm$ one standard deviation)

No.	P_G^1 (%)	L_G^1 (μm)	P_P^1 (%)	MH of thematrix (Hv)	UTS (MPa)	λ^1 ($\text{W}\cdot\text{m}^{-1}\cdot\text{K}^{-1}$)
1	8.7 ± 0.4	217.6 ± 13.3	16.5 ± 0.5	277.2 ± 11.2	291.7 ± 6.5	51.5 ± 0.6
2	9.0 ± 0.5	229.9 ± 24.7	15.2 ± 0.4	268.7 ± 7.3	281.3 ± 6.1	54.1 ± 0.3
3	9.1 ± 0.6	238.2 ± 14.1	12.4 ± 0.8	264.5 ± 17.1	288.3 ± 2.6	54.2 ± 0.2
4	9.2 ± 0.6	246.8 ± 9.4	12.8 ± 0.7	263.5 ± 14.8	284.3 ± 2.4	52.4 ± 0.3
5	9.4 ± 0.5	221.3 ± 20.8	12.5 ± 0.4	249.8 ± 10.7	293.7 ± 4.0	51.4 ± 0.4
6	10.1 ± 0.6	259.1 ± 25.9	11.5 ± 0.6	238.6 ± 14.9	259.7 ± 5.4	55.7 ± 0.4
7	9.9 ± 0.4	241.2 ± 19.3	14.7 ± 0.7	258.8 ± 9.5	281.3 ± 6.1	55.6 ± 0.6
8	9.1 ± 0.5	246.4 ± 12.1	11.6 ± 0.7	280.5 ± 13.3	313.0 ± 1.4	52.4 ± 0.7
9	9.5 ± 0.6	216.9 ± 10.9	12.7 ± 0.4	283.0 ± 12.9	300.7 ± 7.0	50.1 ± 0.5
10	9.4 ± 0.4	232.2 ± 15.6	10.1 ± 0.6	303.2 ± 13.2	305.7 ± 1.3	49.4 ± 0.4
11	9.3 ± 0.3	234.7 ± 28.4	13.2 ± 0.2	300.8 ± 13.9	305.7 ± 1.3	51.4 ± 0.4
12	9.1 ± 0.3	219.2 ± 19.6	12.9 ± 0.3	282.8 ± 7.4	299.7 ± 1.7	49.8 ± 0.5
13	8.7 ± 0.3	195.8 ± 19.3	14.2 ± 0.6	266.2 ± 16.1	309.7 ± 0.5	50.3 ± 0.2
14	10.1 ± 0.4	254.4 ± 16.1	10.7 ± 0.3	267.3 ± 15.8	265.7 ± 4.2	58.4 ± 0.5
15	8.6 ± 0.5	214.2 ± 8.9	16.7 ± 0.7	288.3 ± 13.6	315.5 ± 5.7	47.8 ± 0.3
16	8.9 ± 0.4	238.8 ± 23.2	13.3 ± 0.6	271.5 ± 11.8	301.7 ± 2.8	50.2 ± 0.3
17	8.8 ± 0.3	231.0 ± 11.3	15.9 ± 0.4	280.5 ± 16.2	317.3 ± 6.0	53.7 ± 0.4
18	9.5 ± 0.3	227.8 ± 19.4	13.1 ± 0.7	297.8 ± 18.7	315.7 ± 1.0	52.3 ± 0.3
19 ²	10.2 ± 0.7	259.3 ± 20.2	9.9 ± 0.5	232.8 ± 10.6	245.9 ± 1.7	52.8 ± 0.4
20	9.2 ± 0.4	276.9 ± 14.0	14.6 ± 0.5	296.1 ± 17.7	321.3 ± 3.4	61.6 ± 0.4
21	9.0 ± 0.7	267.1 ± 4.2	18.8 ± 0.4	272.0 ± 18.3	340.0 ± 5.1	58.0 ± 0.5
22	8.5 ± 0.4	233.0 ± 13.3	18.2 ± 0.5	272.1 ± 16.5	338.2 ± 10.3	55.5 ± 0.3
23	8.9 ± 0.5	265.1 ± 19.4	14.8 ± 0.3	281.6 ± 8.2	326.3 ± 8.0	61.3 ± 0.3
24	9.0 ± 0.2	272.9 ± 19.0	15.6 ± 0.9	290.3 ± 6.6	326.3 ± 8.0	58.8 ± 0.3
25	8.2 ± 0.7	274.2 ± 21.4	20.5 ± 0.6	265.1 ± 12.2	346.0 ± 6.7	56.3 ± 0.3
26 ²	8.8 ± 0.6	246.8 ± 16.7	16.4 ± 0.6	261.2 ± 22.8	308.6 ± 13.8	59.7 ± 0.8
27	8.9 ± 0.3	267.3 ± 12.4	19.9 ± 0.4	263.2 ± 16.9	347.0 ± 7.1	57.9 ± 0.3
28	9.9 ± 0.3	288.0 ± 25.2	13.1 ± 0.5	269.1 ± 14.1	285.1 ± 3.4	61.8 ± 0.4
29	9.3 ± 0.5	250.3 ± 31.1	15.2 ± 0.7	287.4 ± 8.3	332.3 ± 6.9	58.7 ± 0.3
30	9.3 ± 0.4	251.2 ± 18.9	14.3 ± 0.4	269.3 ± 17.8	310.0 ± 2.9	53.7 ± 0.4
31	9.8 ± 0.7	277.7 ± 39.6	13.2 ± 0.3	261.6 ± 4.5	265.3 ± 5.6	63.7 ± 0.4
32	10.3 ± 0.5	266.1 ± 23.7	12.3 ± 0.4	285.7 ± 10.7	268.7 ± 1.2	61.5 ± 0.4
33	9.6 ± 0.3	270.3 ± 20.4	12.4 ± 0.5	270.3 ± 13.3	294.3 ± 2.6	64.6 ± 0.4
34	9.4 ± 0.6	243.9 ± 16.3	10.6 ± 0.6	208.3 ± 6.1	271.7 ± 8.1	57.8 ± 0.2
35 ²	10.0 ± 0.5	260.0 ± 19.8	8.6 ± 0.4	268.4 ± 13.6	255.3 ± 5.6	58.7 ± 0.4
36 ²	8.9 ± 0.2	242.1 ± 17.4	14.8 ± 0.5	301.7 ± 14.0	290.3 ± 3.3	51.5 ± 0.3

1. P_G is the percentage of graphite, L_G means the maximum graphite length, P_P represents the percentage of primary dendrite, λ is the thermal conductivity measured at room temperature.

2. These cases were chosen as testing data while the others were used as training data.

Fig. 3: UTS versus structural parameters

Fig. 4: Thermal conductivity versus structural parameters

Fig. 5: Comparison between calculated values and measured UTS values

then calculated as follows^[20]:

$$Sen_j = \frac{1}{n} \sum_i \left(\frac{\% \text{ change in output}}{\% \text{ change in } x_j} \right)_i \times 100 \quad (6)$$

where n is the total number of data set shown in Table 2. The comparisons of sensitivity level of the properties are shown in Fig. 6. It can be observed in Fig. 6(a) that the graphite content has the greatest effect on the UTS, successively followed by MH of the matrix, graphite length and primary dendrites amount. As shown in Fig. 6(b), the most important parameter for thermal conductivity is maximum graphite length, while

the significance of graphite content and MH of the matrix are slightly weaker. Obviously, the thermal conductivity of GCI is mainly influenced by the length of graphite flakes.

The sensitivity analysis provides a solution to optimize the UTS and thermal conductivity of GCI. The observations shown in Fig. 6 demonstrate that the most effective method to improve the UTS is to decrease the graphite content, while the most significant factor for thermal conductivity is maximum graphite length. It is thus implied that maintaining low carbon equivalent and increasing the graphite length are the most effective method to simultaneously improve the UTS and thermal conductivity of GCI.

Fig. 6: Sensitivity level of UTS and thermal conductivity to structural parameters

3 Conclusions

Effects and relative significance of different microstructural characteristics, consisting of graphite percentage, maximum graphite length, primary dendrite percentage and microhardness of the matrix, were studied to find out the optimized method for designing a high performance GCI with high tensile strength and thermal conductivity. The conclusions can be made as follows:

(1) Under the superposed influences of structural variation, the corrections between properties of GCI and structural

characteristics become complex. The effects of graphite content, primary dendrites and microhardness of the matrix on the thermal conductivity are irregular due to mutual disturbance, as well as the influence of graphite length on the UTS. Direct comparisons cannot provide enough information to develop high performance GCI.

(2) The built ANFIS provides a good prediction on the basis of the experimental measurements. The sensitivity level analysis shows that the order of relative importance for UTS are graphite content, microhardness of matrix, maximum graphite length and primary dendrites amount, while the ranking for thermal

conductivity is maximum graphite length, microhardness of matrix, graphite content and primary dendrites amount.

(3) The most effective method to simultaneously improve the UTS and thermal conductivity is to reduce the graphite content and increase graphite flake length.

References

- [1] Fragassa C. Material selection in machine design: The change of cast iron for improving the high-quality in woodworking. *P. I. Mech. Eng. C-J. Mec.*, 2017, 231: 18–30.
- [2] Lulian R, Mihai C, Stelian S. New developments in high quality grey cast irons. *China Foundry*, 2014, 11: 351–363.
- [3] Seifert T and Riedel H. Mechanism-based thermomechanical fatigue life prediction of cast iron. Part I: Models. *Int. J. Fatigue*, 2010, 32: 1358–1367.
- [4] Langmayr F, Zieher F, Lampic M. The thermo-mechanics of cast iron for cylinder heads. *Mtz Worldwide*, 2004, 65: 17–20.
- [5] Bertodo R. Grey cast irons for thermal-stress applications. *J. Strain Anal. Eng.*, 1970, 5: 98–109.
- [6] Collini L, Nicoletto G, Konecna R. Microstructure and mechanical properties of pearlitic gray cast iron. *Mat. Sci. Eng. A-Struct.*, 2008, 488: 529–539.
- [7] Liu Jinhai, Xiong Peng, Fu Binguo, et al. Effects of austempering temperature on microstructure and surface residual stress of carbide austempered ductile iron grinding. *China Foundry*, 2018, 18: 173–181.
- [8] Furlakidis V and Dioszegi A. A generic model to predict the ultimate tensile strength in pearlitic lamellar graphite iron. *Mat. Sci. Eng. A-Struct.*, 2014, 618: 161–167.
- [9] Xu Wangqian, Ferry M, Wang Y. Influence of alloying elements on as-cast microstructure and strength of gray iron. *Mat. Sci. Eng. A-Struct.*, 2005, 390: 326–333.
- [10] Rukadikar M C and Reddy G P. Influence of chemical composition and microstructure on thermal conductivity of alloyed pearlitic flake graphite cast irons. *J. Mater. Sci.*, 1986, 21: 4403–4410.
- [11] Holmgren D, Dioszegi A, Svensson I L. Effects of carbon content and solidification rate on thermal conductivity of grey cast iron. *China Foundry*, 2007, 4: 210–214.
- [12] Holmgren D and Svensson I L. Thermal conductivity - structure relationships in grey cast iron. *Int. J. Cast Met. Res.*, 2005, 18: 321–330.
- [13] Helsing J and Grimvall G. Thermal conductivity of Cast Iron - Models and Analysis of Experiments. *J. Appl. Phys.*, 1991, 70: 1198–1206.
- [14] Hecht R L, Dinwiddie R B, Wang H. The effect of graphite flake morphology on the thermal diffusivity of gray cast irons used for automotive brake discs. *J. Mater. Sci.*, 1999, 34: 4775–4781.
- [15] Chang Feijohn and Chang Yating. Adaptive neuro-fuzzy inference system for prediction of water level in reservoir. *Adv. Water Resour.*, 2006, 29: 1–10.
- [16] Qian Hancheng, Xia Bocai, LiShanzheng, et al. Fuzzy neural network modeling of material properties. *J. Mater. Process. Tech.*, 2002, 122: 196–200.
- [17] Al-Khedher M, Pezeshki C, McHale J, et al. Adaptive neuro-fuzzy modeling of mechanical behavior for vertically aligned carbon nanotube turfs. *J. Mater. Sci., Technol.*, 2011, 27: 301–308.
- [18] Takagi T and Michio S. Fuzzy identification of systems and its applications to modeling and control. *IEEE T.sys. man cyb.*, 1985, 1: 116–132.
- [19] Wang Guiquan, Chen Xiang, Li Yanxiang, et al. Effects of inoculation on the pearlitic gray cast iron with high thermal conductivity and tensile strength. *Materials*, 2018, 11: 1876–1887.
- [20] Yazdanmehr M, Anijdan S H M, Samadi A, et al. Mechanical behavior modeling of nanocrystalline NiAl compound by a feed-forward back-propagation multi-layer perceptron ANN. *Comp. Mater. Sci.*, 2009, 44: 1231–1235.