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Property Prediction of Ductile Iron (DI): Artificial Neural Network Approach

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Abstract : Mechanical properties of ductile cast iron (DI) depend on its microstructure, which is influenced by addition of alloying elements. Artificial Neural Network (ANN) technique with multilayer back propagation algorithm is used as a predictive tool for predicting UTS & 0.2%YS of ductile iron with respect to variation in wt% of alloying elements. Effect of Carbon Equivalent (%CE) and Mg wt% on UTS and 0.2%YS on 3MM & 12MM sections are studied. Comparison between predicted and experimental value shows good correlation with acceptable percentage of error.

1. Introduction

Ductile cast iron is one of the versatile materials adopted for applications in automotive industry, agricultural, nuclear area and many more due to its excellent mechanical properties, such as high ductility, toughness, elongation and strength, and low production costs. The strength correlates with the microstructure which is directly affected by addition of alloying elements like Cu, Ni, Cr, Mo, V etc. The typical microstructure contains nodular graphite instead of flake type, obtained when magnesium (Mg) or cerium (Ce) is added with molten iron. Nodularity is the ratio between volume content of spherical graphite spots and the total number of graphite spots, and in nodular cast iron it is usually above 90%. Nodularity is directly proportional to mechanical properties i.e. higher nodularity results increase in tensile strength, yield strength and ductility.[1] For optimization of properties correct chemical composition and/or process parameter is necessary. Predicting the properties based on chemical and physical processes involved during melting and subsequent solidification is an unrealistic task due to the complexity in processing. Hence numerical models or techniques have to be introduced which will reduce production cost.

Artificial neural network is a self learning tool which solves nonlinear problems by relating input data to the output (result). It has three major layers named as input layer, hidden layer and output layer, with a basic unit called neuron. Each neuron of the input layer correlates with hidden layer from the previous data available and establishes a nonlinear function which gives the possible output when an unknown set of input (whose result is to be predicted) is fed to the system. Zmak, Filetin [1] have applied ANN tool to predict the mechanical properties of ductile iron using error back propagation training algorithm applied to train the multilayer networks. The predicted result found was less than 2% which is the acceptable experimental error when measuring mechanical properties of ductile iron. Sterjovski [2] has applied three back propagation ANN model to predict the mechanical properties of steel. The result reported well match between predicted and experimental value for each three types of model constructed. He also discussed about the multiple prediction capability of ANN. Perzyk, Kochanski [3] investigated the possibility of predicting ductile cast iron qualities with the help of neural network applied for modelling of melting process under conditions of typical foundry.

Current paper approaches to predict the tensile strength and 0.2% yield strength using ANN technique developed by back propagation algorithm with the help of NEURONELE software. Effect of change in %CE and Mg wt% is also reported.

2. Methodology

2.1 *Experimental data*

Ductile iron specimens used in this study were melted in 250kg capacity coreless medium frequency induction furnace. The molten metal was tapped in a preheated ladle containing Ferro silicon magnesium alloy of size 15-25mm (Si=45.50%, Mg=5.85%, Ca=1.08%, Al=0.91%) at the bottom covered with steel scrap. The tapping temperature of molten metal was 1450°C. Commercial argon gas was punched through steel pipe to the melt for proper mixing with addition of 1% Ferro silicon inoculants (3.5kg) of size 2-6mm (Si=73.52%, Al=1.06%, P=0.035%, S=0.004%, Ca=0.19%, Ba=2.00%). Five different compositions were used for training of the neural network model, shown in table 1. Carbon Equivalent was calculated using equation- 1;

$$\%CE = \%C + 0.3\%Si + 0.33\%P + 0.4\%S - 0.027\%Mn \tag{1}$$

Tensile testing specimens were made from casting obtained from step bars and their tensile strength; yield strength and elongation were measured using Universal Testing Machine (model- UTE 100, max.capacity-1000 KN, Make-Fuel Instruments & engineer's pvt.ltd, Maharahstra, India) as per ASTM E8 standard.

Table 1. Chemical Composition of Specimens Used for ANN Training

Melt No.	C%	Si%	Mn%	S%	P%	Cr%	Ni%	Mo%	Cu%	Mg%
M-1	3.50	2.05	0.18	0.010	0.021	0.024	0.020	0.002	0.030	0.050
M-2	3.55	2.15	0.19	0.009	0.023	0.028	0.021	0.001	0.026	0.045
M-3	3.60	2.25	0.18	0.011	0.025	0.022	0.022	0.002	0.028	0.040
M-4	3.65	2.35	0.20	0.009	0.027	0.023	0.020	0.001	0.030	0.035
M-5	3.70	2.45	0.21	0.012	0.029	0.022	0.021	0.001	0.029	0.030

2.2 *Artificial neural network*

Artificial neural network is one type of soft computing model, based on interrelationship between different input and output parameters and learning from data set through iteration, without requiring a prior knowledge on the relationships between the process variables; (Friis *et al.,* 2001). [4] A basic type of neural network modelling comprises of three steps;

1. Collection and pre-processing of data available.
2. Training of neural network (this includes choice of architecture, training function, training algorithms and parameters of the network).
3. Testing of the model. [5]

ANN of simple processing elements (neurons) typically organized by input layers, hidden layers and output layers, shown in Figure-2. The aim of an ANN is to normalize an input output relationship of the form of,

$$\mathbf{y^m = \mathit{f}(x^n)}$$

Where, x^n is an n-dimensional input vector represents variables $x^1, x^2, \ldots x^i, \ldots, x^n$ and y^m is an m-dimensional output vector represents the resulting variables $y^1, y^2, \ldots, y^i, \ldots, y^m$ [4]**.** NEURONELE software developed by back propagation algorithm, to decrease the error, as the prediction tool for output is used for neural computing. Multi-Layer Perceptron type architecture with one hidden layer is chosen for constructing and training of two similar type network considering %CE, Cr, Ni, Cu, Mg wt% as input layer and UTS for the first network and 0.2% YS for the second network as output layer. Tension test result with input parameters used to train the network is shown in table: 2.

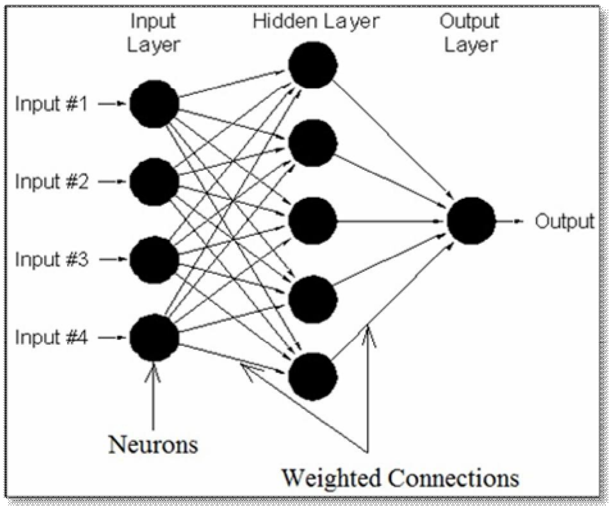


Fig: 2. Architecture of Artificial Neural Network

Table 2. Tension test result with input parameters used to train the network for 3MM section

Melt No.	%CE	%Cr	%Ni	%Cu	%Mg	UTS (MPa)	0.2% YS (MPa)
M-1	4.12	0.024	0.020	0.030	0.050	675.22	471.95
M-2	4.20	0.028	0.021	0.026	0.045	633.88	447.85
M-3	4.28	0.022	0.022	0.028	0.040	599.43	425.80
M-4	4.36	0.023	0.020	0.030	0.035	551.20	399.62
M-5	4.44	0.022	0.021	0.029	0.030	516.75	385.84

3. Result and discussion

With varying number of neurons in the hidden layer are tested at constant cycles, learning rate, error tolerance, momentum parameter and noise factor and slope parameter. Based on least error criterion, one structure given in Table-3 is selected for training of the input-output data. The learning rate is varied in the range of 0.002-0.100 during the training of the input-output data. The network optimization process (training and testing) is conducted for10^7 cycles for which stabilization of the error is obtained. The number of cycles selected during training is high enough so that the ANN models could be rigorously trained. Neuron numbers in the hidden layer is varied and in the optimized structure of the network this number is 8.

Table 3. Input parameter selected for training

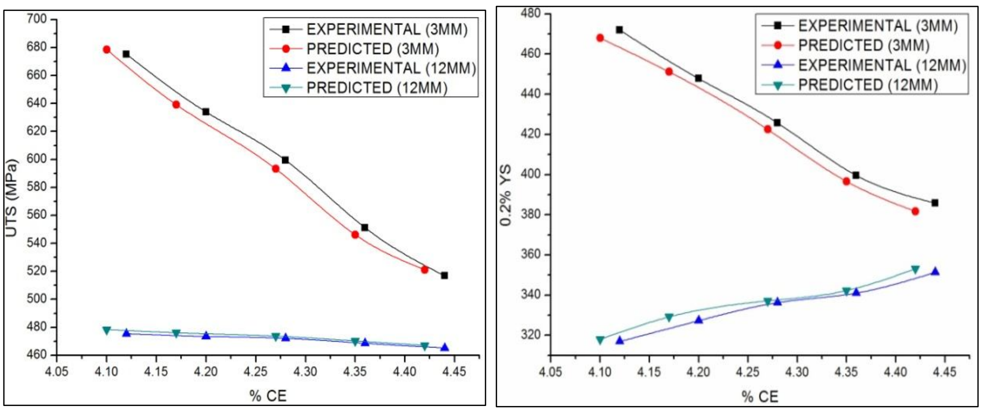
Input Parameter for Training	Values
Error tolerance	0.003
Learning parameter (ß)	0.002
Momentum parameter (α)	0.002
Noise factor (NF)	0.001
Maximum cycles for simulation	1,00,00,000
Slope parameter (£)	0.6
Number of hidden layer neurons	8
Number of input layer neurons (I)	5
Number of output layer neurons (O)	1

3.1 *Result for UTS: Comparison of ANN with experimental value*

Comparison of the experimental data with the predicted value showing the effect of %CE on the UTS & 0.2% YS is shown in Fig: 3(a) & Fig: 3(b) respectively. Result shows very less percentage of error between experimental and predicted value, i.e. a good generalization of the input parameter is achieved and hence properties can be optimized by varying the inputs. The mean square error is calculated using equation-(2) & it is found to be E=0.03.

$$E = \frac{1}{2}\sum_{i=1}^{N}\ \sum_{j=1}^{C}(t_{ij} - t_{ij})^2 \qquad (2)$$

Where N is the total number of training cases, C is equal to the number of network output, t_{ij} is the observed output for ith training case and the jth network output, and $\hat{t}_{ij}$ is the network's forecast for this case. It is evident that tensile strength decreases with the increase in Carbon Equivalent and so as the 0.2% yield strength, because of the increase in ferrite content due to high Silicon percentage. At elevated temperatures Si enhances ductile iron properties by stabilizing ferrite and forming rich surface layer. Also manganese, sulphur and phosphorus have detrimental effect on promoting pearlite content and hence decreasing the ductility as well as tensile and yield strength [6-8]. While comparing between 3MM and 12MM sections the UTS is found to be unaffected, Fig: 3(a) but in case of 0.2% YS, Fig: 3(b) the 12 MM section shows opposite nature as compared to 3MM section i.e. YS for 12MM section increases with increase in %CE where as there is decreasing nature in 3MM section. The reason behind this phenomenon is high precipitation of carbon in graphite phase causing by the slower cooling rate in 12MM section than 3MM section. Combination of slow cooling rate and high %CE produces large nodules during solidification resulting in graphite flotation, consequently depletion of large nodules in the lower part of the casting .[6]

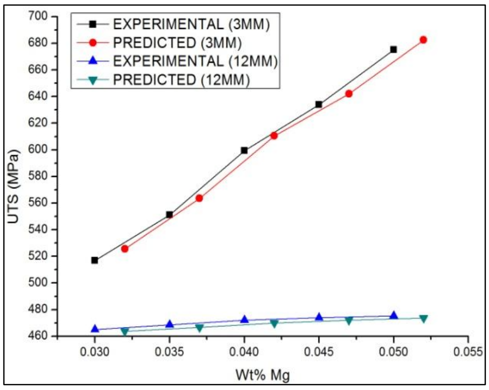


(a) **(b)**

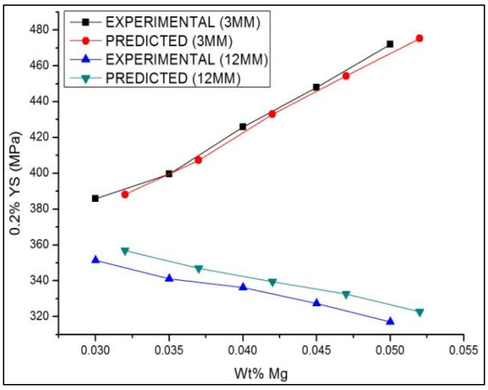
Fig: 3 - (a) Effect of Carbon Equivalent (%CE) on UTS

(b) Effect of Carbon Equivalent (%CE) on 0.2% YS

Similar type of phenomenon was occurred when Mg wt% was decreased i.e. for 3MM section the yield strength decreases where as it increases for 12MM section, Fig: 4 (b) . Mg nodularizes the graphite and increases ductility and yield strength, but lesser the section thickness higher is the cooling rate and nodule count resulting decrease in ductility and YS [9]. Whereas in Fig: 4 (a) the tensile strength doesn't show any change i.e. for both the case it decreases with decrease in Mg wt%. The compared result of ANN with experimental value does not show much variation.



(a)



(b)

Fig. 4: (a) Effect of Mg wt% on UTS,

(b) Effect of Mg wt% on0.2% YS

4. Conclusion

The results indicate that neural network analysis can yield fairly accurate results and can be used as a practical tool in ductile cast iron manufacturing process. The most popular advantage is its parallel mechanism; that is once an ANN is trained, it can provide the ability to solve the mapping problems much faster than conventional methods & can be used a control mechanism for deciding the wt% of alloying element during the production of ductile iron. %CE & Mg wt% were found to have noticeable effect on UTS & 0.2% YS, hence can be considered as one of the major factors while manufacturing ductile cast iron. Also it was observed that specimen thickness plays a vital role in predicting qualities of ductile iron & hence should be considered during production.

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