Mechanical Behavior of Powder Metallurgy Steel—Experimental Investigation and Artificial Neural Network-Based Prediction Model

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Mechanical properties of high-density powder metallurgy (PM) steels have been evaluated using standard tests, and a theoretical model using the artificial neural network (ANN) has been developed. Various heat treatments were carried out to study their influence on mechanical properties, *viz.* endurance limit (EL), yield strength (YS), and hardness, and also on the carbon content in PM steel. The material containing 0.47% C that was quenched and tempered at 503 K (QT 503 K) showed the optimum combination of yield strength/ultimate tensile strength (YS/UTS) and EL. The ANN-based model showed excellent agreement with experimental results. Prediction models based on the ANN are demonstrated for YS as well as for the EL as a function of heat treatment (ranging from QT 400 K to QT 900 K) and percent carbon (%C) (between 0.1 and 0.5). This would help the materials engineer suitably design the heat-treatment schedule to obtain the desired/best combination of fatigue and strength properties.

Keywords artificial neural network, endurance limit, heat treatment, microstructure, PM steel, yield strength

1. Introduction

The powder metallurgy (PM) route offers the advantage of manufacturing near-net-shaped components at lower cost. Continued research efforts have resulted in a number of advanced PM materials with an optimum combination of properties for various service conditions. During the last few decades, the demand for lower production costs and the reduction of weight resulted in the use of PM iron and PM steel for highly stressed, fatigue-loaded components. The production of near-net shape at lower cost, with a reduction in metal scrap, and environmentally cleaner processes (*e.g.*, less/no need for cutting fluid and less energy consumption) are the distinct advantages over conventionally produced components.[1] The demand for lower production costs in the automotive and tool industries, resulted in the use of PM materials even for highly stressed, fatigue-loaded components (connecting rods, camshafts, parking gears, *etc.*), which are produced by PM route on a large scale.[2] The fatigue behavior of cast and wrought materials has been summarized in numerous publications.[2,3] However, the influence of high-density ($<$2% porosity) structure, with varying heat treatments/microstructure, on the cyclic properties still requires further investigation. Furthermore, about 80% of fatigue-exposed PM materials in current use are PM iron/steels so that a special emphasis on ferrous PM material seems justified. For a better understanding of the fatigue response of PM materials, it is necessary to consider their specific microstructure.[1,4] The aim of this investigation, therefore, is to evaluate the fatigue property of a high-density Fe-2% Ni based PM steel under different heat-treated conditions. The fatigue property of this material was evaluated using a rotating bending fatigue test at room temperature. Fe-2% Ni based PM materials are being developed for use, especially in automobile industries (for crankshafts, camshafts, and other moving parts). Successful application of this material would result in a significant reduction in cost apart from energy savings.

There has been no published literature available on the analytical prediction model for mechanical properties of PM steels. The artificial neural network (ANN) can be effectively used to develop models to analyze and predict mechanical properties of materials. Neural computing is a relatively new field of artificial intelligence, which tries to mimic the structure and operation of biological neural systems, such as the human brain, by creating an (ANN) on a computer. These ANNs are modeling techniques that are especially useful in addressing problems for which solutions are not clearly formulated[5] or for which the relationships between inputs and outputs are not sufficiently known. The ANNs have the ability to learn by example. Patterns in a series of input and output values of example cases are recognized. This acquired "knowledge" can then be used by ANN to predict unknown output values for a given set of input values. Alternatively, ANNs can also be used for classification. In this case, the ANN's output is a discrete category to which the item described by the input values belongs. The ANNs are composed of simple interconnected elements called processing elements (PEs) or artificial neurons that act as microprocessors. Each PE has an input and an output side. The connections on the input side correspond to the dendrites of the biological original and provide the input from other PEs, while the connections on the output side correspond to the axon and transmit

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Table 1 Mechanical properties of PM steel

Sol. no.	Heat treatment	YS (MPa)	UTS (MPa)	% El.	Hardness (HRC)	% Porosity	EL (MPa)	% C
1	AN	289	502	17	7		134	
2	QT 503 K	1044	1174	12	45		316	
3	QT 588 K	969	1052	14	40	1.84	290	0.13
4	QT 700 K	942	981	18	35		260	
5	QT 810 K	772	817	24	30		218	
1	AN	380	614	15	7		152	
2	QT 503 K	1332	1539	10	43		339	
3	QT 588 K	1214	1346	11	40	1.86	304	0.24
4	QT 700 K	1042	1145	12	33		276	
5	QT 810 K	918	994	13	29		240	
1	AN	531	690	9	7		160	
2	QT 503 K	1408	1628	5	44		348	
3	QT 588 K	1263	1442	5	40	1.84	317	0.36
4	QT 700 K	1083	1180	7	33		294	
5	QT 810K	938	1035	11	28		269	
1	AN	573	773	15	8		165	
2	QT 503 K	1497	1801	4	46		360	
3	QT 588 K	1352	1487	5	41	1.84	330	0.47
4	QT 700 K	1118	1221	6	35		312	
5	QT 810 K	987	1090	12	31		283	

the output. Synapses are mimicked by providing connection weights between the various PEs and transfer functions or thresholds within the PEs. One of the most popular neural network models is the back-propagation network. Currently, back-propagation is the most popular, effective, and easy to learn model for complex networks. To develop a back-propagation neural network, a developer inputs known information, assigns weights to the connections within the network architecture, and runs in the networks repeatedly until the output is satisfactorily accurate. The weighted matrix of interconnections allows the neural networks to learn and remember.[6]

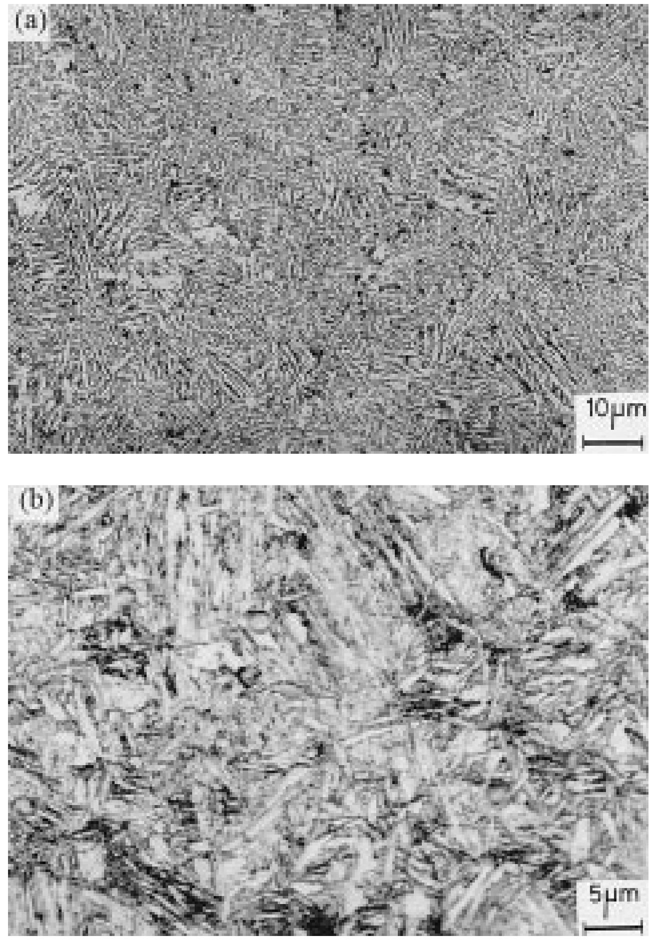


Fig. 1 (**a**) Optical microstructure of AS sample, revealing bainitic structure. (**b**) Optical microstructure of QT sample, showing tempered martensitic structure

2. Material, Heat Treatment, and Experimental Procedure

2.1 Material

Four Fe-2% Ni based PM steels (Table 1) were used in the present investigation, having percentages of carbon as of 0.13, 0.24, 0.36, and 0.47. Fe-2% Ni based PM powder was produced by the atomization process to obtain powders of size less than 10 μm. The green powder was sintered under vacuum at 1473 K. Nickel addition was made using a liquid-phase-sintering technique.

2.2 Heat Treatment

The material Fe-2% Ni based PM steel, was subjected to five different heat treatments. They are annealed at 1473 K (designed as "AN"), quenched and tempered (QT) at 503 K, QT at 588 K, QT at 570 K, and QT at 810 K, in a vacuum-controlled muffle furnace.

2.3 Tensile and Fatigue Tests

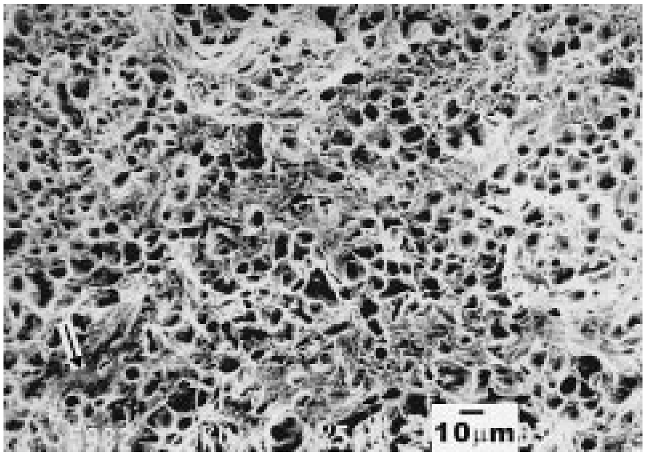
Tensile tests were carried out per ASTM standard E-9, on a microprocessor-controlled Instron-8032 (Instron Inc., USA) model UTM machine of capacity 100 kN. At least four specimens were tested for each heat treatment and the results are the average values.

The sintered bars were machined to form fatigue test specimens with 5 mm gauge diameter and 20 mm gauge length having a continuous radius. After turning, the portion of the specimen having a continuous radius was polished to get a mirror-finish. This was done to avoid the most likely influence of surface roughness on fatigue strength. Fatigue testing was carried out on a rotating bending fatigue-testing machine of capacity 6 Newton-Meter, at a frequency of 50 Hz and at room temperature. The tests were carried out up to 10^7 cycles to determine the endurance limit (EL). At least four specimens were tested to confirm the EL for each heat treatment.

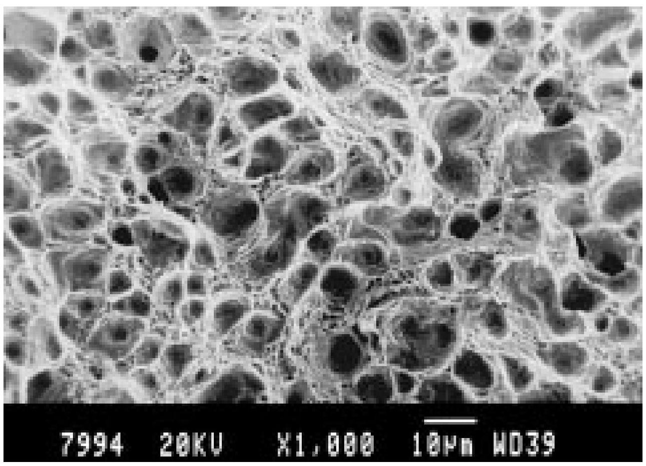
3. Test Results and Discussion

3.1 Influence of Heat Treatment on Microstructure

The typical optical microstructures of the material in the as-sintered and QT conditions are shown in Fig. 1(a) and (b),

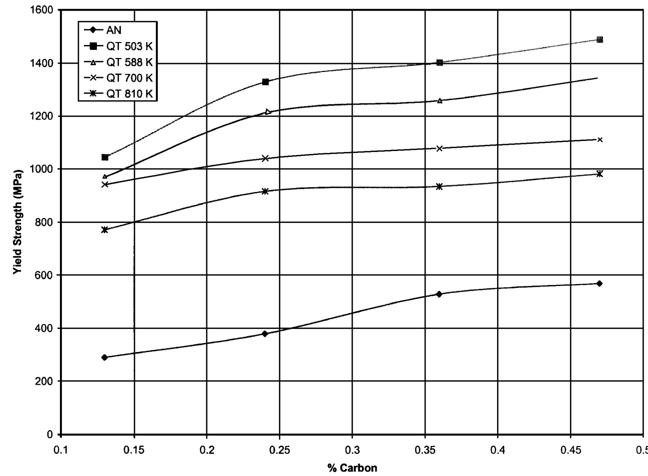


(a)

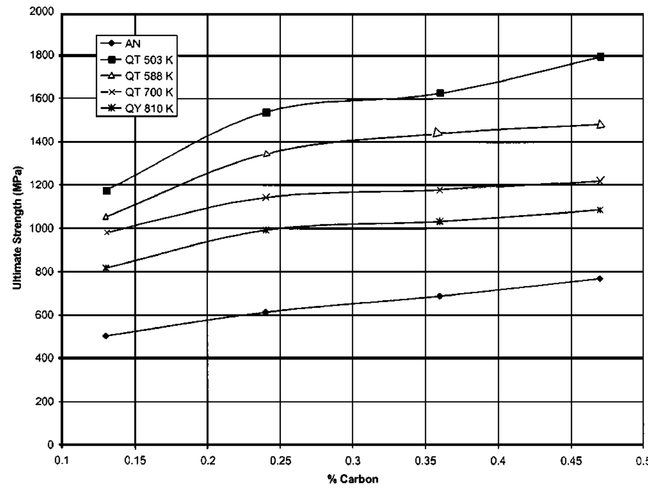


(b)

Fig. 2 (**a**) Fractographic features of AS sample, indicating cleavage facets along with dimples. (**b**) Fractographic features of QT 503 K sample, showing large density of dimple structure typical of ductile fracture



(a)



(b)

Fig. 3 (**a**) Experimental investigation—variation of YS as a function of heat treatment and %C content. (**b**) Experimental investigation—variation of tensile strength as a function of heat treatment and %C content

respectively. Typical SEM fractographs for the same are shown in Fig. 2. Figure 2(a) reveals cleavage facets in addition to dimples, whereas Fig. 2(b) shows the presence of a large number of dimples typical of ductile fracture. These fractographic features, as can be seen, are reminiscent of their microstructures. Bainitic structure, with its needlelike morphology, is known to offer easy paths for crack initiation and propagation as compared to the predominantly circular/round morphologies of carbon in ferrite (tempered martensite structure) of the heat-treated structure.

3.2 Influence of Heat Treatment on Tensile Properties

Figure 3(a) and (b) demonstrate the influence of heat treatment on yield strength (YS) and ultimate tensile strength (UTS), respectively, for high density Fe-2% Ni based PM steel, having carbon content between 0.13 and 0.47%. Quite expectedly, it may be observed that YS and UTS decreased with the increase in tempering temperature at all carbon levels, being least for annealed sample. Elongation of the material showed the reverse trend, which, of course, is due to the softening of the material with increasing tempering temperatures. Furthermore, YS, UTS, and hardness values increased (for any given heat treatment) with an increase in percent carbon (%C) content in the material. As is well known, a high carbon tempered martensite structure, being tougher and stronger, contributed to improved tensile properties.

3.3 Dependency of EL on Heat Treatment and Carbon Content

Figure 4 represents the variation of experimentally observed EL as a function of heat treatment and carbon content. The EL generally decreased with an increase in the tempering temperature. The heat treatment “QT 503 K” with 0.47% C recorded the maximum EL among all four materials discussed in this paper. This is attributed to the most effective crack initiation and crack propagation resistance offered by the microstructure containing tougher, high-carbon-tempered martensite.

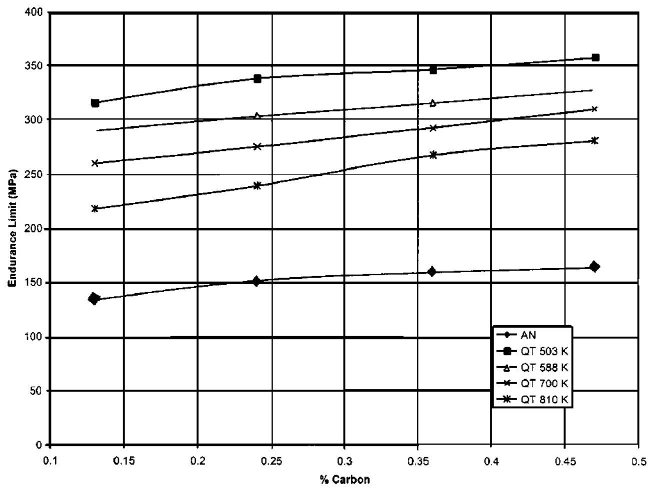


Fig. 4 Experimental investigation—influence of heat treatment and %C on EL

4. Proposed ANN Model Development Methodology

Back-propagation networks are most useful for problems involving forecasting and pattern recognition. Back-propagation training is one of the most popular methods for training ANNs with back-up/historical data. "NeuroShell 2" software by Ward Systems Group, Inc. (Frederick, MD) was used in the present analysis to implement back-propagation training. In essence, back-propagation training adapts a gradient-descent approach to adjusting the ANN weights. During training, an ANN is presented with the data of thousands of times (called cycles). After each cycle, the error between the ANN outputs and the actual outputs is propagated backward to adjust the weights in a manner that is mathematically guaranteed to converge.[6]

4.1 Training ANN Model

The major property that deems ANNs' superiority to algorithmic and other network-based systems is their ability to be trained on historical information as well as real-time data. Training is the act of continuously adjusting their connection weights until they reach unique values that allow the network to produce outputs that are close enough to the desired outputs. The accuracy of the developed model, therefore, depends on these weights. Once optimum weights are reached, the weights and biased values encode the network's state of knowledge. Thereafter, using the network on new cases is merely a matter of simple mathematical manipulation of these values.

4.2 Neural Network Architecture Used

The neural network used for the proposed model was developed with NeuroShell 2 software, using a back-propagation architecture with three layers (for the first model) and four layer jump connections (for the second model), as shown in

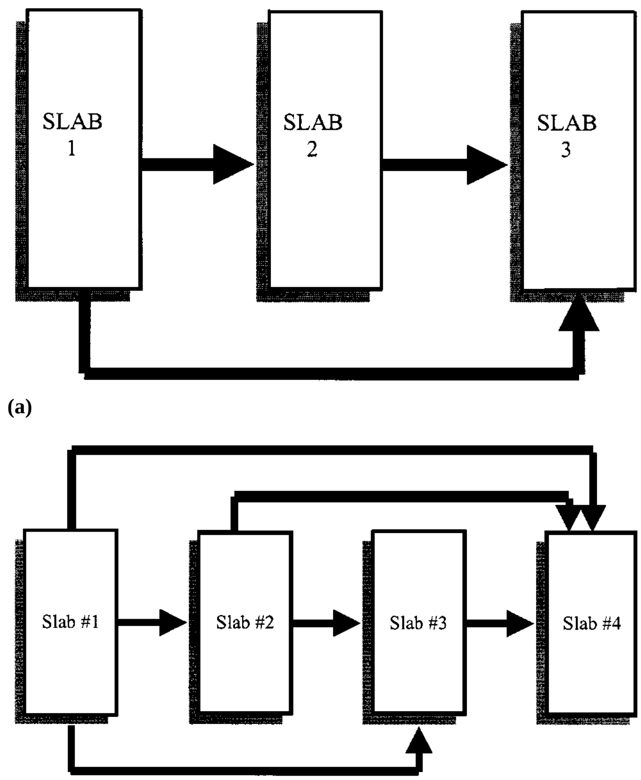


Fig. 5 (**a**) Three layer jump connections. (**b**) Four layer jump connections

Fig. 5(a) and (b), respectively. In this type of network architecture, every layer (slab) is connected or linked to every previous layer. The input parameters, heat treatment (QT) and %C, and output, YS, were stored in slabs 1, 2, and 3, respectively, for the first model. The input parameters, QT, %C, YS, and output parameter, EL, were stored in slabs 1, 2, 3, and 4, respectively, for the second model. The number of hidden neurons, for which the Gaussian activation function, $\{\exp(-x^2)\}$ was determined according to the following formula:[7]

$$\text{number of hidden neurons} = 0.5\,(\text{inputs} + \text{outputs}) + \sqrt{(\text{number of training patterns})}$$

Given the properties of the training data used, 2 inputs, 1 output, and 16 training patterns, the number of processing elements was determined to be 6. The other network parameters were set as follows:

learning rate: 0.10

momentum: 0.10

initial connection weights: 0.30

learning stopping criteria: 20,000 epochs

4.3 System Performance

The neural network used for the presented model demonstrated an excellent statistical performance,[7] as shown in Table

2 for the training model and the evaluation of the trained model. In Table 2, R squared is a statistical indicator usually applied to multiple regression analysis. It compares the accuracy of the model to the accuracy of a trivial benchmark model, wherein the prediction is just the mean of all of the samples. A perfect fit would result in an R-squared value of 1, a very good fit near 1, and a very poor fit near 0. The following formulas[7] were used to calculate R squared:

$$R^2 = 1 - (SSE/SS_{yy})$$

Table 2 Network system performance

Statistical indicator	Network training (model 1)	Network training (model 2)
R squared	0.9891	0.9896
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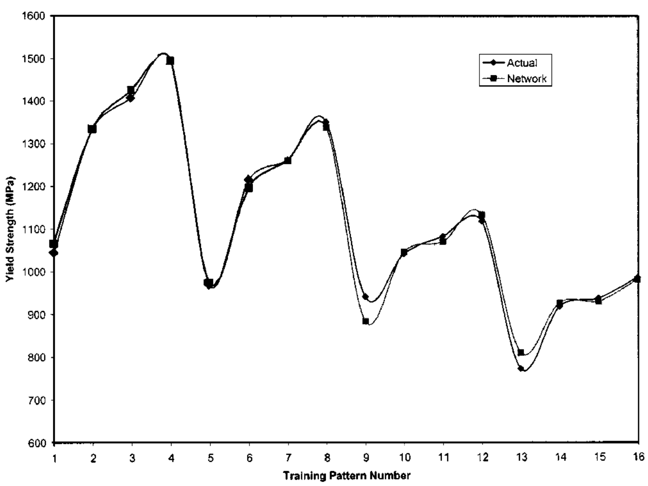
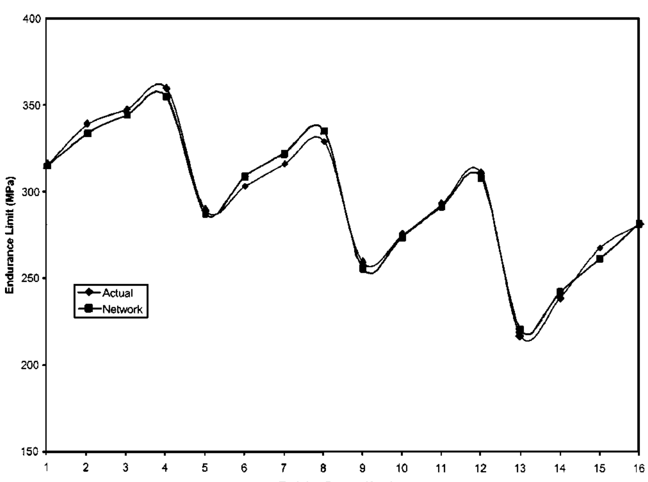
Correlation coefficient, r	0.9946	0.9375



(a)



(b)

Fig. 6 (**a**) Actual (experimental) and network YS vs training data pattern numbers. (**b**) Actual (experimental) and network EL vs training data pattern numbers

where $SSE = \Sigma(y - \bar{\bar{y}})^2$, $SS_{yy} = \Sigma(y - \bar{y})^2$, y is the actual value, $\bar{y}$ is the predicted value of y, and $\bar{\bar{y}}$ is the mean of the y values.

The correlation coefficient, r, is a statistical measure of the strength of the relationship between the actual versus predicted outputs. The r coefficient can range from -1 to $+1$. It will show a stronger positive linear relationship when r is closer to $+1$, and a stronger negative linear relationship when r is closer to -1. The following formulas[7] were used to calculate r:

$$r = SS_{xy}/\sqrt{(SS_{xx}SS_{yy})}$$

where

$$SS_{xy} = \Sigma xy - (l/n)\{(\Sigma x)(\Sigma y)\}$$
$$SS_{xx} = \Sigma x^2 - (l/n)(\Sigma x)^2$$
$$SS_{yy} = \Sigma y^2 - (1/n)(\Sigma y)^2$$

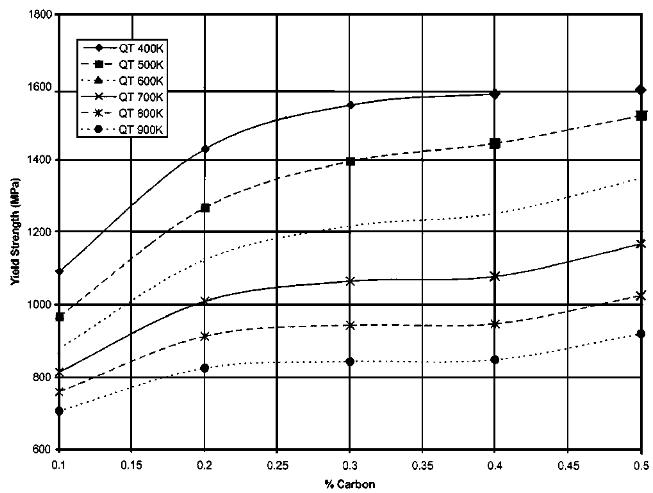


Fig. 7 ANN model predicted YS vs %C for QT 400 K through QT 900 K

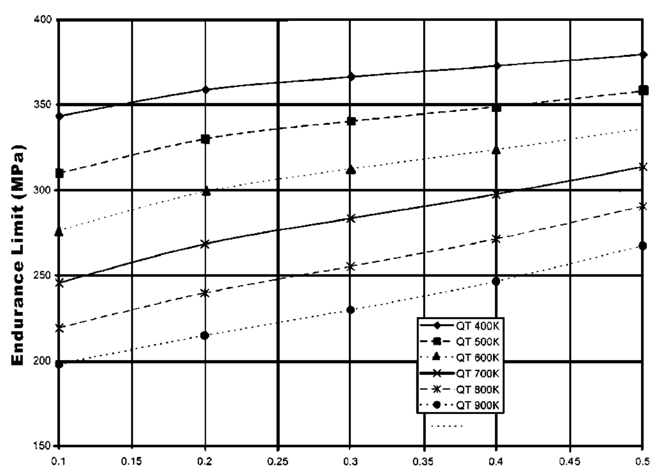


Fig. 8 ANN model predicted EL vs %C for QT 400 K through QT 900 K

where n equals the number of patterns, x refers to the set of actual outputs, and y refers to the predicted outputs.

Figure 6(a) and (b) represent the graphical comparisons between the actual experimental data and the network-predicted output for YS and EL, respectively. It clearly demonstrates an excellent statistical performance.

4.4 Prediction Model

From Table 1 (experimental results), it may be observed that the EL varied between 218 and 360 MPa for different heat treatments as a function of carbon content. At the outset, EL seems to be influenced directly by the increase in carbon content for a given tempering temperature. The prediction model for YS as a function of %C is presented in Fig. 7. The YSs were predicted from the first trained model based on three layer jump connections. These predicted YS values were used as an input parameter in the second trained model (four layer jump connections) to obtain predicted ELs. Since YS depends on QT as well as %C, the first prediction model was essential to obtain YS in order to use it as input for the second model. Figure 8 demonstrates the variation of EL as a function of heat treatment and carbon content of the material. In Fig. 7 and 8, YS and EL were predicted for the heat-treatment schedules between QT 400 K and QT 900 K, having carbon content varying from 0.1 to 0.5. Experimental and theoretical results on YS and EL exhibit close agreement with reference to Fig. 3, 4, 7, and 8.

5. Conclusions

The tensile properties and EL of Fe-2% Ni based PM steel were found to be sensitive to heat treatment. The sample containing 0.47% C, which was QT at 503 K, exhibited the best combination of fatigue and strength properties. The ANN-based model showed excellent agreement with experimental results. The ANN model can reduce the experimental efforts, which otherwise takes long hours of a tedious and complex fatigue test procedure. The ANN prediction model results (especially the fatigue property and EL) can be used as a "reference chart of data." The application of ANN becomes highly significant and beneficial in designing an optimum heat-treatment schedule to obtain the desired/best EL. The presently investigated Fe-2% Ni based PM steel is found to have a good potential to be used as a fatigue-loaded component.

References

1. A. Salak: *Ferrous Powder Metallurgy*, Cambridge International Science Publishing, Cambridge, UK, 1995.
2. M. Klesnil and P. Lukas: *Fatigue of Metallic Materials*, Elsevier, Amsterdam, 1980.
3. S. Suresh: *Fatigue of Materials*, Cambridge University Press, Cambridge, UK, 1991.
4. H. Danninger, G. Jangg, B. Weiss, and R. Stickler: *Powder Met. Int.*, 1993, vol. 25 (3), p. 111.
5. M. Chester: *Neural Networks—A Tutorial*, Prentice-Hall, Englewood Cliffs, NJ, 1993.
6. D. Rumelhart, G. Hinton, and R. Williams: *Parallel Distributed Processing*, MIT Press, Cambridge, MA, 1986.
7. *NeuroShell 2 User's Manual*, Ward Systems Group, Inc., Frederick, MD, 1996.