PREDICTION OF HARDNESS DISTRIBUTION IN PLASMA ARC SURFACE HARDENING USING NEURAL NETWORK

Mohd Idris Shah Ismail[1*] and Zahari Taha[2]

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Abstract

In this paper, an attempt has been made to develop neural network models to predict the hardness distribution of hardened zone in plasma arc surface hardening process. The back propagation method with the Levenberg-Marquardt algorithm was used to train the neural network models. Hardness distributions were collected by the experimental setup in the laboratory and the associated data were used to train the neural network models. Furthermore, the prediction of neural network models were compared with those obtained from a statistical regression models. It is confirmed experimentally that the hardness distribution can be accurately predicted by the trained neural network models. The accuracy of hardness distribution prediction using neural network is superior to that using other statistical regression models.

Keywords: Plasma arc, surface hardening, neural network, hardness

Introduction

Plasma arc surface hardening is quite effective in achieving higher surface hardness, and keeping the modification of the surface down to a minimum. Owing to the high energy transfer efficiency of plasma arc (about 75%) (Yan and Zhu, 1998), the surface layer is heated above its austenite transformation temperature (A_{c3} temperature), but below the melting temperature, martensite structure can be produced in a short interaction time. Various types of steel such as cast iron, medium carbon steel and tool steel can be hardened by plasma arc to increase their hardness, wear resistance and corrosion resistance (Yan and Zhu, 1997; Bourithis *et al*., 2002; Yan, 2003; Pan *et al*., 2005). Plasma arc surface hardening is a promising technology in manufacturing, such as in the automobile and metal working industries (Krasposhin *et al*., 1989). The rapidity, flexibility and lower cost of the method can improve the competitiveness of these industries.

Hardness distribution in the vertical distance from the hardened surface can be applied to verify the hardened depth (JIS, 1996). To predict hardness distribution, researchers used empirical phase-property relationships to

[1] *Department of Mechanical and Manufacturing Engineering, Faculty of Engineering, University of Putra Malaysia, 43400 Selangor, Malaysia. E-mail: ms_idris@eng.upm.edu.my*

[2] *Engineering Design and Manufacture Department, Faculty of Engineering, University of Malaya, 50603 Kuala Lumpur, Malaysia.*

[*] *Corresponding author*

express hardness as a function of microstructure and chemical composition (Ashby and Easterling, 1984; Ion and Anisdahl, 1997). However, little work has been reported concerning the relationship between process parameter and hardness distribution. The relationship between process parameters and hardness distribution in the plasma arc surface hardening process are not known completely. Hence, a new practical prediction method is desired. Neural networks have provided a means of successfull prediction studies in surface hardening processes (Woo and Cho, 1998; Stich *et al.*, 2000).

Recently, neural networks have been widely utilized to tackle problems which cannot be satisfactorily handled by traditional analytical approaches. The advantages of neural networks include extreme computation, powerful memory and rapid learning morever it can predict an output with accuracy even if the variable interactions are not completely understood. Neural networks have been applied successfully in various fields of mathematics, engineering, medicine, economics, meteorology, psychology, neurology and many others (Kim *et al.*, 2003).

In this paper, the relationship between the process parameters and hardness distribution during plasma arc surface hardening is established using neural network analyses. In addition, statistical regression models were used in this study to be compared with the proposed neural network models.

Neural Network

Neural network simulates the behavior of human brain neurons. It is a parallel processing structure, which can be divided into several processing procedures, which can be trained simultaneously. A neural network model is constructed by using a set of data consisting of input and output variables. In the training process, the structure of the model adjusts itself to the data, and the final model can be used for prediction. One of the most important applications of neural networks is modeling a system with an unknown input–output relation (Zhang *et al.*, 1999). To date, many kinds of neural network architecture have been proposed. Neural network using the back-propagation training methodology is most prevalent in modeling and controlling applications, owing to its capability of learning system characteristics through non-linear mapping (Wang *et al.*, 1999). The operation of the neural network model can be divided into two main phases: forward computing and backward learning (Cheng and Lin, 2000).

Forward Computing

The input patterns applied to the neurons of the first layer are just a stimulus to the network. On the other hand, there is no computation in the input layer. As depicted in Figure 1, each neuron in the hidden layer determines a net input value based on all its input connections. The net input is calculated by summing the input values multiplied by their corresponding weight. Once the net input is calculated, it is converted to an activation value. The weight on the connection from the ith neuron in the forward layer to the jth neuron is indicated as w_{ij}. The output value Y_j of neuron j is computed by the following equation:

$$net_j = \sum_{i=0}^{n} w_{ij} x_i \tag{1}$$

$$Y_j = f_{act}(net_j) \tag{2}$$

where net_j is the linear combination of each of the x_i values multiplied by w_{ij}, n is the number of inputs to the jth neuron, and f_{act} is the activation of neuron j. Sigmoid functions (S-shaped curves), such as logistic function and hyperbolic tangent function, are commonly adopted for the activation functions (Ezugwu *et al.*, 2005). The activation functions of logistic and hyperbolic tangent functions are, respectively.

$$Y_j = \frac{1}{1+\exp(-net_j)} \tag{3}$$

$$Y_j = \frac{1-\exp(-net_j)}{1+\exp(-net_j)} \tag{4}$$

Backward Learning

The generated output of the network is compared to the desired output, and an error is computed for each output neuron. The error vector E between desired values and the output value of the network is defined as:

$$E = \sum_j E_j = \sum_j \frac{1}{2}\left(T_j - Y_j\right)^2 \qquad (5)$$

where Y_j is the output value of the jth output neuron, T_j is the desired value of the jth output neuron. Errors are then transmitted backward from the output layer to each neuron in the forward layer. The process repeats layer by layer. Connection weights are updated by each neuron to cause the network to converge. The network was trained with Levenberg-Marquardt algorithm. This training algorithm was chosen due to its high accuracy in similar function approximation. The adjustment of weights and biases are done according to transfer function

$$\Delta w_{ij} = -\left(J^T J + \mu I\right)^{-1} J^T E \qquad (6)$$

where J is Jacobian matrix of derivation of each error, μ is a scalar and E is error function.

Experimental Work

Plasma arc surface hardening process was performed using a plasma arc machine with torch diameter of 1.6 mm, which integrated with a six degree-of-freedom articulated robot. The negative terminal of the power supply is connected to the cathode located inside the plasma torch and the workpiece is connected to the positive polarity of the power supply. Argon gas was used at 6 bar as plasma and shielding gas, to minimize oxidation. The nozzle–workpiece standoff distance was kept constant at 13 mm. The selected currents of plasma arc were 30 A and 60 A. The scanning velocities of plasma arc were each set to 0.1, 0.2, 0.3, 0.4, and 0.5 m/s. ASSAB 618 and ASSAB DF3 steels were used in this study with carbon content of 0.37 wt.% and 0.90 wt.%, respectively.

Prior to the experiment, specimens of size $60 \times 40 \times 10$ mm^3 were cut, ground and polished to 1,000 grit silicon carbide paper in order to remove oxides and obtain a smooth surface. After the experiment, the hardened specimens were cut perpendicular to the scanning direction, polished, etched in 2% Nital and then used for hardness measurements. The hardness distribution over the depth of hardened zone was measured using the microhardness tester with a load of 200 g and an indentation time of 15 s. The hardness distributions of the hardened zone and base material were measured from a distance of 0.03 mm from the surface up to 0.25 mm (Line 1) as shown in Figure 2.

Network Training

In this study, the development and the training of the network is carried out using MATLAB Neural Network Toolbox (Demuth and Beale,

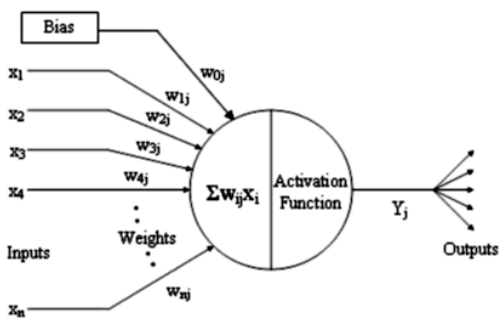

Figure 1. Architecture of an individual neuron for back propagation network

2004). The input/output dataset of the model is illustrated in Figure 3. Here, there are four neurons in the input layer of network. The inputs are arc current, carbon content of material, scanning velocity and hardness location. The output layer has only one neuron, which gives the values of hardness. In this study, networks with one and two hidden layer(s) were used. With a learning rate of 0.1, the network was trained for 2000 iterations. The error between the desired and actual outputs is less than 0.001 at the end of the training process. The four variables data sets could not be trained by neural network in their original form due to the wide range of values among them. In order to become feasible input neurons, all the values in the input neurons had to be pre-processed by normalizing and transformed within the range of ± 1, using the MATLAB subroutine premnmx. The normalized value (X_i) for each raw input/output dataset (d_i) was calculated as:

$$X_i = \frac{2}{d_{\max} - d_{\min}}(d_i - d_{\min}) - 1 \qquad (7)$$

where d_{max} and d_{min} are the maximum and minimum values of the raw data.

To evaluate the performance of the model, a total of 192 data pairs of hardening conditions with hardness locations; and corresponding hardness values were used. Among them, 128 pairs were used for modeling and the total data set including the remaining 64 pairs was used to assess the performance of the models. The criterion used to judge the efficiency and the ability of the model to predict hardened zone performances was the percentage error or deviation (Δ) which is defined in Equation (8). With this criterion, it would be much easier to see how the proposed model fit and how the predicted values are close to the actual ones.

$$\Delta = \frac{|\,\text{Predicted value} - \text{Actual value}\,|}{\text{Actual value}} \times 100\% \qquad (8)$$

Results and Discussion

In the first model, the network has one hidden layer and the number of neurons is examined between one and eight. The hyperbolic tangent function (*tansig*) was used in the hidden layer as an activation function. In addition to the previous model, a second model was considered. Here, the hidden layer comprised two layers with the number of neurons were between one and eight for each layer. The hyperbolic tangent function (*tansig*) and logistic function (*logsig*) were used for the first and second hidden layer, respectively. For both models, linear transfer function (*purelin*) was used in output layer. In order to reform the activation of network, one bias for each layer can be added. There is one bias for each layer of network except the output layer. After having finished the neural network training, neural network was tested using the different data from the trained data.

The performance of the neural network depends on the number of hidden layers and the number of neurons in the hidden layers. Therefore, many attempts have been carried out in choosing the optimal structure for the neural network by changing the number of hidden layers as well as the number of neurons in each of these hidden layers. To examine the effect of the different structure of the neural network models, the RMS errors were determined. Table

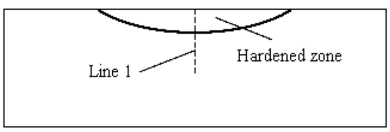

Figure 2. Schematic illustration of hardness distribution measurement

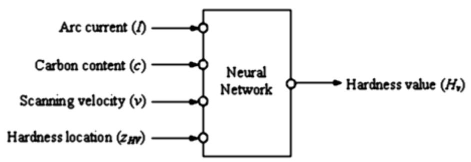

Figure 3. Schematic model of neural network for prediction of hardness distribution

1 lists the results based on the RMS error of the training and testing sets. It is clear that the 4-8-1 structure had the lowest RMS error among all the structures with one hidden layer, and 4-8-7-1 was better than other structures with two hidden layers. Table 2 summarizes the percentage deviation of the above two structures.

In addition, two statistical models with the same input data were also employed to evaluate the results with neural network models. The linear regression and non-linear regression models are, respectively.

$$H_v = 919 + 4.46\bullet(x_1) - 357\bullet(x_2) - 476\bullet(x_3) - 4174\bullet(x_4) + 5.06\bullet(x_1x_2) - 28.6\bullet(x_1x_4) + 1670\bullet(x_3x_4) + 9410\bullet(x_4^2) \quad (9)$$

$$H_v = \frac{12.46 \cdot x_1^{0.522}}{x_2^{1.27} \cdot x_3^{0.135} \cdot x_4^{0.56}} e^{0.274 \ln x_1 \cdot \ln x_2} \quad (10)$$

where H_v is the hardness value in [HV], x_1 is arc current [A], x_2 is the specimen carbon content [wt.%], x_3 is the scanning velocity [m/s], and x_4 is hardness location in thickness direction [mm]. In order to guarantee the reliability of the regression analysis, the regression model coefficients were determined using a backward elimination procedure in which insignificant terms were eliminated based on significance level of ≤ 0.05. Table 3 summarizes the percentage deviation of the training and testing data for each regression model. It was apparent that the linear model had a higher R^2 value and a lower percentage deviation between the predict values and the actual values.

Figure 4 shows the prediction error for the neural network models and regression models. Compared with the experimental results, the maximum error obtained by neural network model with 4-8-7-1 structure is not more than 10%, showing better accuracy than those of linear regression, non-linear regression and neural network 4-8-1 model with the maximum error of 75.3%, 62.3%, and 24.9%, respectively. To ensure the accuracy of the developed regression and neural network models for prediction of hardness distribution, all the measured and predicted results using the developed models were compared and represented in Figure 5. In the neural network, it can be seen that the distribution of data points for model with 4-8-1 structure is similar and close to the 'A = T' line. However, the predicted values obtained using the model with 4-8-7-1 structure is more accurate with accuracy of 99.7%. The prediction accuracy of other models was 98.5%, 87.1%, and 78.1% for the 4-8-1 one hidden layer neural network model, linear regression model and non-linear regression model, respectively. In all of them, the 4-8-7-1 two hidden layer neural network model was found to be the best in terms of predictive ability.

The experimental results have been graphically compared with the testing results obtained from neural network models and regression models as shown in Figure 6. The values with the neural network models prediction were able to follow the trend better than those optained from the regression models prediction. Since the neural network models and the statistical models are both generated by back propagation and regression, respectively, a brief comparison is made between them. It is apparent that the neural network models generally have better predictive ability of both training and testing relative to their percentage deviation. The comparison chart confirms this finding as shown in Table 4. The predicted hardness values of the neural network models are much closer to the actual hardness values than those of the regression models. This is thought to be because the neural network expresses the non-linear relationship of the hardness values which is formed through the input variables better than the statistical regression.

Conclusions

Two models of back propagation neural network with one and two hidden layers for predictions of hardness distribution in plasma arc surface hardening process have been established, and compared with two models of statistical regression i.e. linear and non-linear. The neural

Table 1. Summary of neural network with different structures and their training and testing RMS error

Number of hidden Layer	Structure RMS error	Training RMS error	Testing
1	4 – 1 – 1	0.19264	0.16722
	4 – 2 – 1	0.17074	0.16357
	4 – 3 – 1	0.11960	0.10920
	4 – 4 – 1	0.11629	0.10268
	4 – 5 – 1	0.10308	0.09023
	4 – 6 – 1	0.09640	0.08395
	4 – 7 – 1	0.08257	0.03556
	4 – 8 – 1	**0.07585**	**0.03162**
2	4 – 1 – 1 – 1	0.19246	0.16194
	4 – 2 – 1 – 1	0.14295	0.12475
	4 – 2 – 2 – 1	0.14087	0.10820
	4 – 3 – 1 – 1	0.11173	0.08992
	4 – 3 – 2 – 1	0.10802	0.06721
	4 – 3 – 3 – 1	0.06898	0.03702
	4 – 4 – 1 – 1	0.09612	0.07376
	4 – 4 – 2 – 1	0.07956	0.04223
	4 – 4 – 3 – 1	0.06864	0.03570
	4 – 4 – 4 – 1	0.05836	0.03259
	4 – 5 – 1 – 1	0.09057	0.07634
	4 – 5 – 2 – 1	0.07492	0.03654
	4 – 5 – 3 – 1	0.07608	0.04148
	4 – 5 – 4 – 1	0.06859	0.03935
	4 – 5 – 5 – 1	0.05280	0.03161
	4 – 6 – 1 – 1	0.07092	0.05806
	4 – 6 – 2 – 1	0.06961	0.03552
	4 – 6 – 3 – 1	0.06880	0.04027
	4 – 6 – 4 – 1	0.04933	0.03160
	4 – 6 – 5 – 1	0.04574	0.03159
	4 – 6 – 6 – 1	0.04051	0.03138
	4 – 7 – 1 – 1	0.07230	0.04681
	4 – 7 – 2 – 1	0.04904	0.03489
	4 – 7 – 3 – 1	0.03628	0.03142
	4 – 7 – 4 – 1	0.03987	0.03162
	4 – 7 – 5 – 1	0.03411	0.03162
	4 – 7 – 6 – 1	0.03175	0.03136
	4 – 7 – 7 – 1	0.03162	0.03097
	4 – 8 – 1 – 1	0.06607	0.03311
	4 – 8 – 2 – 1	0.04963	0.03241
	4 – 8 – 3 – 1	0.03635	0.03147
	4 – 8 – 4 – 1	0.03139	0.03125
	4 – 8 – 5 – 1	0.03161	0.03116
	4 – 8 – 6 – 1	0.03161	0.03000
	4 – 8 – 7 – 1	**0.03043**	**0.02382**
	4 – 8 – 8 – 1	0.03122	0.03052

Table 2. Summary of 4–8–1 and 4–8–7–1 neural network models

Result	4–8–1	4–8–7–1
Training cycle	2,000	2,000
Percentage deviation of the training data	3.98%	1.68%
Percentage deviation of the testing data	1.58%	1.02%

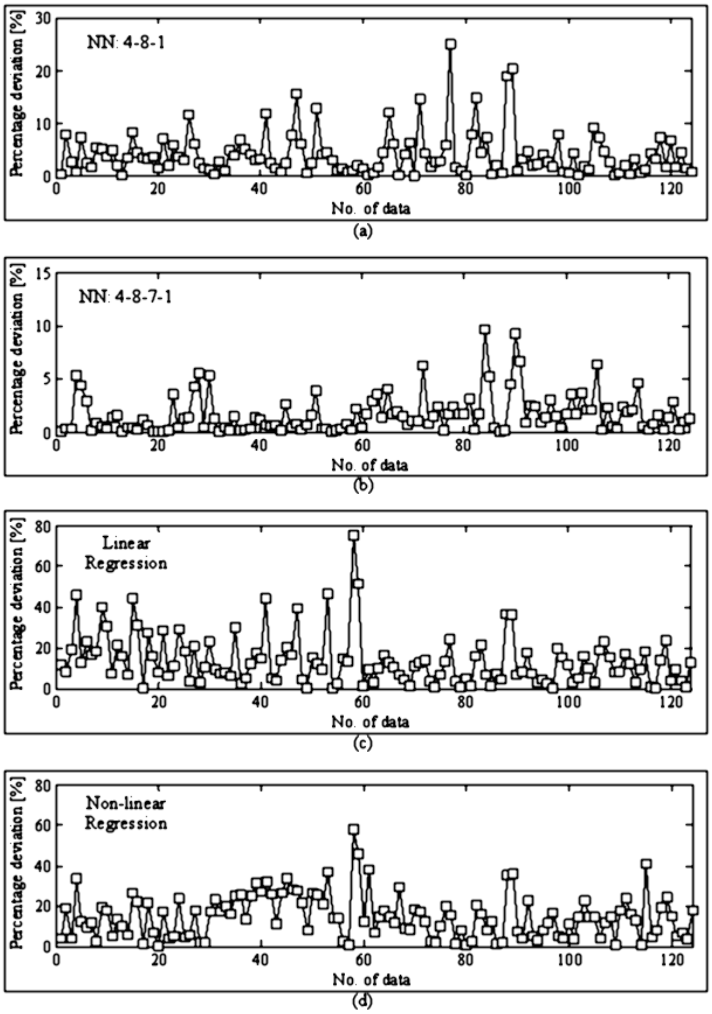

Figure 4. Prediction error of hardness distribution using (a) neural network 4-8-1, (b) neural network 4–8–7–1, (c) linear regression and (d) non-linear regression model

Table 3. Summary of statistical regression models

Result	Linear regression model	Non-Linear regression model
R^2	0.8710	0.7814
Adjusted R^2	0.8698	0.7797
Percentage deviation of the training data	13.72%	14.98%
Percentage deviation of the testing data	14.76%	18.40%

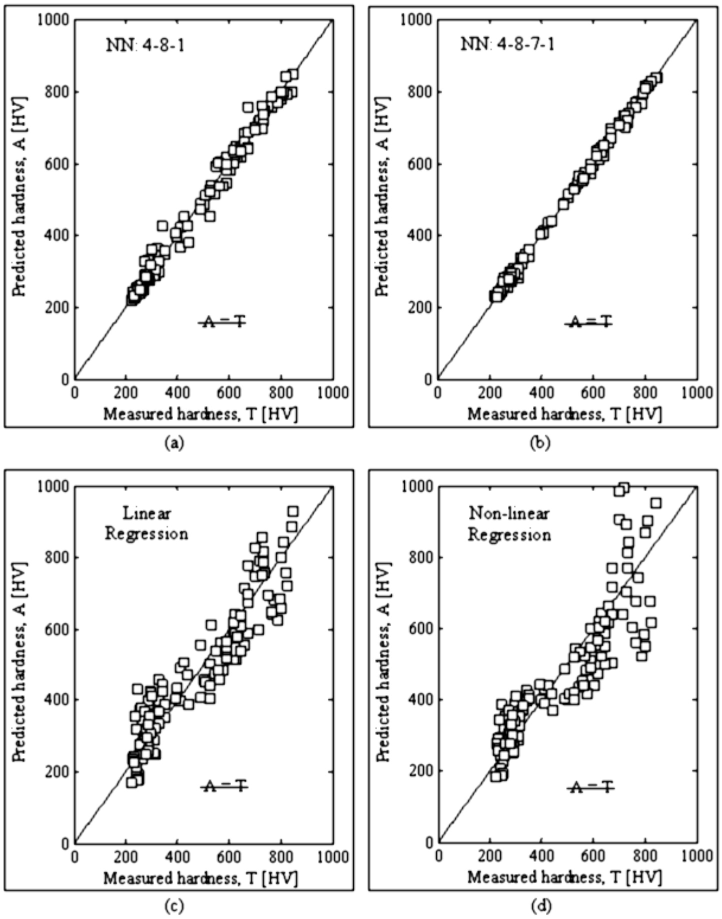

Figure 5. Comparison of measured and predicted results using (a) neural network 4-8-1, (b) neural network 4-8-7-1, (c) linear regression and (d) non-linear regression model

Table 4. Comparison between the regression modes and neural network model

Result	Regression		Neural network	
	Linear	Non-Linear	1 hidden layer (4–8–1)	2 hidden layers (4–8–7–1)
Training data				
Max error	184.48	287.74	85.70	30.03
Min error	0.46	0.53	0.01	0.04
Δ	13.72%	14.98%	3.98%	1.68%
Testing data				
Max error	222.83	456.40	22.18	31.37
Min error	3.30	1.09	0.02	0.08
Δ	14.76%	18.40%	1.58%	1.02%

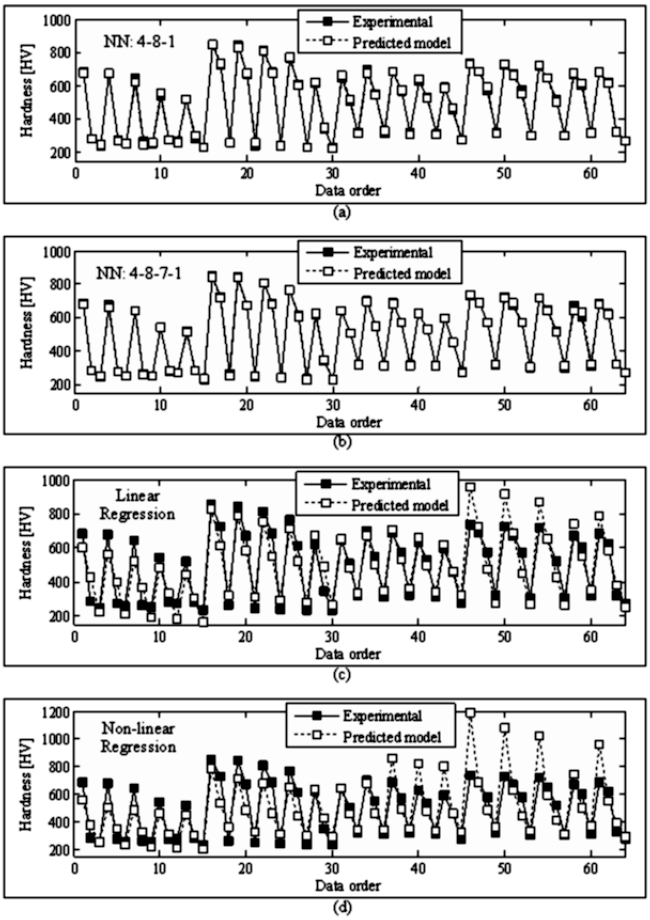

Figure 6. Prediction models trend with experimental data order. (a) neural network 4-8-1, (b) neural network 4-8-7-1, (c) linear regression and (d) non-linear regression model

when network models have better predictive ability compared with the regression models in predicting hardness distribution. The predicted hardness values of the neural network models are much closer to the actual hardness values than those of the regression models.

In the neural network models, after training with 2000 cycles, the one hidden layer 4-8-1 structure model could achieve an accuracy of 98.5% precision. In addition, a two hidden layer 4-8-7-1 structure produces an accuracy of prediction of 99.7%. Thus, the two hidden layer was more accurate and effective in predicting the hardness distribution than the one hidden layer neural network model. Neural network is a powerful tool, easy-to-use in complex problems. Neural network can be used reliably, successfully and very accurately for the prediction of hardness distribution in surface hardening process.

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