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Prediction of Hydrogen Concentration in Annealing Furnace Using Neural Networks

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Spheroidizing annealing is a well-known heating method used for improving the ductility of steel so that the steel can be easily machined or deformed. In the annealing process, to avoid the high-temperature oxidation of steel, hydrogen and nitrogen are often used as protective reducing gases during annealing. A certain amount of hydrogen is allowed to flow continuously into the furnace. However, owing to the high cost of hydrogen and production safety, the flow and amount of hydrogen used in the annealing process should be effectively controlled. In this work, we present a study of hydrogen concentration prediction using neural networks (NNs). In the spheroidizing annealing process, three parameters, namely, base motor power, base motor speed, and inner temperature, are used for the immediate prediction of hydrogen concentration in the furnace. Once the hydrogen in the furnace reaches the specified concentration, the flow rate of hydrogen should be reduced. In this study, the data of hydrogen concentration was collected using an XMTC sensor, a thermal conductivity transmitter that can measure the concentration of binary gas mixtures containing hydrogen, carbon dioxide, methane or helium. From simulation results, it was found that the NN model can indeed provide a fairly accurate prediction of the hydrogen concentration on the basis of the physical characteristics of the motor. The results of this study showed that the application of artificial intelligence in predicting the hydrogen concentration in the annealing process is very promising and feasible.

1. Introduction

In the production of fasteners, annealing and quenching are two methods used to change the physical properties of steel bars. Generally, in spheroidizing annealing, when the steel in the furnace comes into contact with oxygen in air at a high temperature, oxidation will occur and affect the surface quality of the steel after annealing. To solve this problem, the spheroidizing furnace is filled with a protective gas when the steel is being annealed, and the oxygen concentration in the furnace is controlled to a value below 10 ppm. The purpose is to block the outside air and reduce the oxide layer on the steel surface. Generally, hydrogen and nitrogen are the two protective gases commonly used in the annealing process. To determine the differences

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and pros and cons of using these two gases, we conducted an experiment to compare the differences between using pure hydrogen and nitrogen as protective gases. Experimental results showed that if pure hydrogen is used as the protective gas, the cost of fuel, the amount of nitrogen, power consumption, and the amount of propane used can be reduced.

Table 1 lists the differences between using nitrogen and 100% pure hydrogen for the annealing of the same wire rod [JIS SCM435(AISI 4140), 13 mm diameter]. It was found that if pure hydrogen is used as the protective gas, the cost of fuel can be reduced by about 25%. In the entire spheroidizing annealing process, the cycle time required when using pure hydrogen is about half of that required when using nitrogen. Thus, the duration of the annealing process can be shortened and the purpose of saving energy can be achieved.

Metallographic analysis is an important method for inspecting the quality of metal materials after spheroidization. Many factors can affect the results of spheroidized metallography, including heating rate, heating temperature, temperature holding time, cooling rate, cooling temperature, steel alloy composition, and steel wire size. However, during heat treatment, one of the most important objectives is to achieve the temperature equalization of the material. The most effective gas that can achieve temperature equalization with efficient heat conduction is hydrogen.

To improve the product yield and reduce the waste of material, hydrogen is often used as a protective gas in the furnace during spheroidizing annealing. Generally, at the start of spheroidizing annealing, the furnace is filled with nitrogen at 2.5 times its volume, and the oxygen content in the furnace is sensed by an oxygen detector. When the oxygen content in the furnace is below 0.5%, hydrogen is allowed to flow at a rate of 40 m^3 per hour. Once the amount of hydrogen reaches twice the furnace volume, the flow rate of hydrogen is reduced to 25 m^3 per hour to save on hydrogen usage.

During the spheroidizing operation, the hydrogen concentration in the furnace is often estimated by an experienced engineer on the basis of personal experience. However, this estimation method often results in a large error relative to the actual value. Hence, the purpose of minimizing hydrogen usage cannot be achieved.

In the mechanism of heat conduction, the power of a stirring fan in the spheroidizing furnace is related to that of a rotating motor. Moreover, the power of the fan is related to the cross-sectional area and rotation speed of the fan; thus, we can conclude that the hydrogen concentration in the spheroidizing furnace must be related to the physical parameters of the fan. There must be a nonlinear and complex relationship existing between the gas concentration and

Table 1
Energy consumption of spheroidizing annealing process.

	N_2 Atm	100% H_2 Atm
Fuel	69 m^3	52 m^3
Nitrogen	18 m^3	5 m^3
Hydrogen	0 m^3	15 m^3
Electricity	10 kwh	3 kwh
C_3H_8	3 m^3	0 m^3
Cycle time	35 h	19 h
Spheroidization	$\geq$ 90%	$\geq$90%

the power of the fan motor, the rotation speed, and the furnace temperature. Therefore, in this study, we attempt to use the neural network (NN) model to predict the hydrogen concentration during the hydrogen filling process by using the relevant parameters of the stirring fan.

2. Research Purpose and Data Collection

In the operational process of the stirring fan, the wattage and current of the generator are used to calculate the completion rate of hydrogen and nitrogen replacement in the furnace. It is known that motor power ≈ fan work/efficiency; fan work = gas mass × speed; gas mass = density × volume; and speed = air volume/fan cross-sectional area. Consequently, fan work = gas density × volume × air volume/fan cross-sectional area, and because the thermal conductivity is proportional to the gas density, it can be seen that the stirring fan has a certain relationship with the hydrogen concentration. However, because the calculation of the whole process is complicated, it is very difficult, even for an experienced engineer, to estimate precisely and immediately the hydrogen concentration. If a hydrogen sensor is added into the system, the cost and complexity of the system will be increased.

In this study, we attempt to predict the hydrogen concentration using the NN model on the basis of the motor power, motor rotation speed, and inner temperature of the furnace. To collect the true and correct data for NN learning, the hydrogen concentration in the furnace was measured using the XMTC thermal conductivity binary gas transmitter, which is a compact, rugged, and fixed thermal conductivity transmitter that measures the concentration of binary gas mixtures containing hydrogen, carbon dioxide, methane or helium.(1) Table 2 shows the sample data collected in this study.

If the NN can obtain the relationship between the above parameters and the hydrogen concentration ratio accurately through learning, then the NN model could be used to predict the hydrogen concentration ratio in real time to control the hydrogen intake flow to minimize hydrogen usage. There would be no need to set sensors in each spheroidization system for the measurement, and thus, the cost and complexity of the system can be effectively reduced.

3. Literature Review

Spheroidizing annealing is a well-known heating method for improving the ductility of steel, reducing its hardness, and making the steel easy to process or deform, and the spheroidizing furnace is a commonly used equipment in industry.

Over the past few decades, the properties and advantages of spheroidized steel with hydrogen as the protective gas have been investigated. Chang and Hirth presented the mechanical test results for spheroidized AISI 1090 steel after precharging or dynamically charging with hydrogen at a high fugacity.(2) Onyewuenyi and Hirth explored the interaction of hydrogen using macroscopic plastic flow parameters.(3) Jiang *et al.* conducted work on the effects of rolling and annealing on the microstructures and mechanical properties of V–Ti–Ni alloy for hydrogen separation.(4) Yang and Lu carried out a series of experimental tests on cold-drawn SCM435 alloy steel wires in a bell furnace with a protective hydrogen atmosphere.(5) These experiments

Table 2
Sample data collected.

Base motor power (kW)	Base motor speed (rpm)	Temperature (°C)	H_2 concentration (%)
0	0	96.2	0
6.585201	500.5611	202.6	0
7.424463	571.0449	309.8	0
9.436195	743.0854	344.1	0
11.83855	957.2896	396.3	8.067364
14.37921	1192.649	452.4	38.51395
16.66061	1422.143	507.8	56.3782
17.84694	1590.966	562.1	65.59544
18.49709	1709.977	601.7	70.47108
16.5345	1764.459	601.7	76.70687
13.62083	1762.064	600.1	81.80132
11.80485	1760.505	599.8	85.15209
10.74458	1759.573	600.5	87.0763
10.05714	1758.972	613.6	88.3168
9.406506	1758.408	681.9	88.72612
8.928579	1757.954	715.1	88.9195
8.667954	1757.759	736.9	88.98829
7.679138	1707.029	756.2	89.1923
5.447103	1505.669	769.9	88.21623
5.440005	1505.66	770.3	88.12253

revealed that the spheroidized annealing temperature, heating time, and holding temperature significantly affect the quality of annealed cold-drawn SCM435 alloy steel wires.

Studies on the changes in the mechanical properties of steel after spheroidization have also been carried out.(6–10) Yu *et al.*(6) proposed a study on the effects of holding time during both austenization and spheroidization on the microstructure and mechanical properties of the high-carbon martensitic stainless steel 8Cr13MoV. Ko *et al.*(7) proposed a method of continuous shear drawing (CSD) for industrial applications in steel-wire manufacturing. In their study, they compared the spheroidization behavior of medium carbon steel processed by CSD to that processed via conventional drawing. Luo *et al.*(8) studied the effects of subcritical quenching on the microstructure and mechanical properties of EH36 alloy. Their study results showed that the comprehensive property of EH36 alloy can be markedly enhanced, and that its hardness and plasticity can be obviously improved. Other studies on spheroidization effects have also been conducted.(9–14)

4. Hydrogen vs Spheroidization

The traditional spheroidizing annealing system uses nitrogen as the protective gas (usually 2–4% C_3H_8 and 96–98% N_2). However, current spheroidizing annealing systems use hydrogen as the protective gas. The density of hydrogen is only 0.09 kg/m^3, which is 1/14 that of nitrogen. Its thermal conductivity of 0.163 W/mK is 7 times that of nitrogen. Hydrogen has the characteristics of light weight and small volume; thus, it can be uniformly distributed inside the furnace, making the product quality easier to control. Basically, the purpose of annealing is to soften the metal and is a key technology for the cold rolling of strips and wires. Pure hydrogen protects the metal and makes the process more efficient.

5. Research Methods and Experiments

In this study, we aim to create a hydrogen concentration prediction model for the spheroidizing annealing process. Owing to its excellent self-learning and self-tuning abilities, the NN technique has been widely used in various system identifications and signal predictions.[15–17] After simple training with historical data, the complex and nonlinear mapping function between the input and output pairs of training data can be created by NN automatically. At present, many new types of NN architecture have been developed, including the deep neural network (DNN), deep belief network (DBN), recurrent neural network (RNN), and convolutional neural network (CNN). However, the simple NN structure commonly known as a multilayered feedforward network was used in this study.

Two architectures of NN, named Model 1 and Model 2, were used and compared in this study. Model 1 is a four-layer NN model consisting of one input layer with three nodes, two hidden layers with five nodes each, and one output layer with one node. The Model 1 architecture is shown in Fig. 1. Model 2 is a five-layer NN model consisting of one input layer with three nodes, three hidden layers with five nodes each, and one output layer with one node, as shown in Fig. 2. Relu, linear, and sigmoid activation functions are used in the nodes of hidden and output layers for comparison. Thus, eight different NN modules could be generated. Figure 3 shows these eight different modules.

In total, 1358 data values for four parameters of annealing, namely, base motor power (kW), base motor speed (rpm), temperature (°C), and H_2 concentration, were collected. To demonstrate the superiority of NN in the study, cross-validation was performed in a fivefold manner during the simulations. In this method, we divide the data into five parts, and each time, one of them is taken in turn as the test data and the rest are used as training data. Thus, there are five simulations for each NN module. Table 3 lists the fivefold NN training and test combinations.

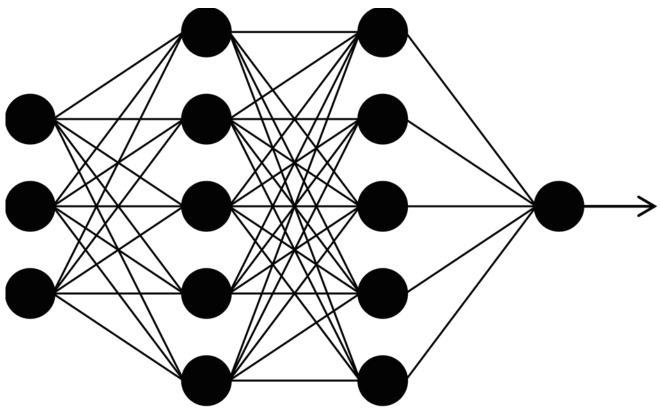


Fig. 1. Architecture of NN Model 1.

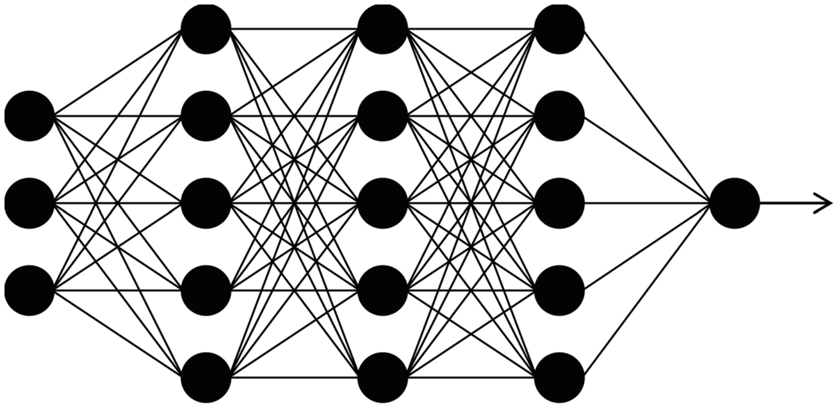


Fig. 2. Architecture of NN Model 2.

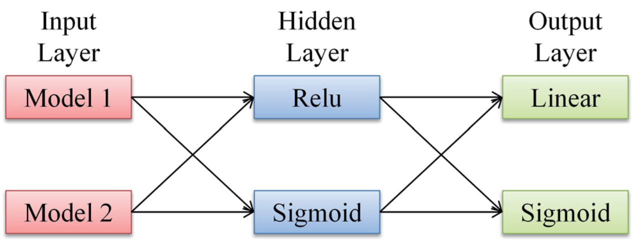


Fig. 3. (Color online) Eight modules.

Table 3
Fivefold NN training and test combinations.

Group 1	Group 2	Group 3	Group 4	Group 5
272	272	272	272	272
272	272	272	272	272
272	272	272	272	272
271	271	271	271	271
271	271	271	271	271

Table 4 shows the mean absolute percentage errors (MAPEs) of training and testing for Groups 1 to 5 obtained using the four-layer (3-5-5-1) NN model with different activation function combinations. The performance results obtained using the five-layer (3-5-5-5-1) NN model are listed in Table 5.

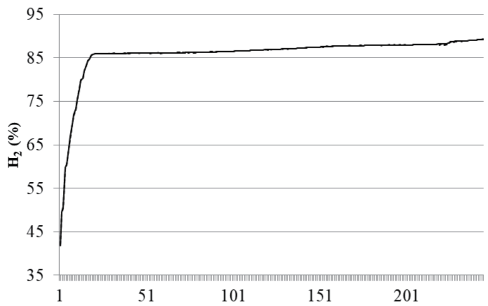
The results shown in Tables 4 and 5 revealed that all the NN modules have a sufficient ability to model the relationship between input and output, but the NN model with the sigmoid function as the activation function in the output layer exhibits the best performance. In other words, the output layer of the NN model that uses the sigmoid function as the activation function has a better nonlinear mapping ability. Figures 4(a)–4(e) are the superposition diagrams of NN tests for the data of Groups 1 to 5. These tests were all conducted using the NN model with the sigmoid activation function in its hidden and output layers. In the figures, the solid line is the actual hydrogen concentration in the annealing furnace and the dashed line is the hydrogen

Table 4
MAPEs of training and test for five groups obtained using 3-5-5-1 NN model.

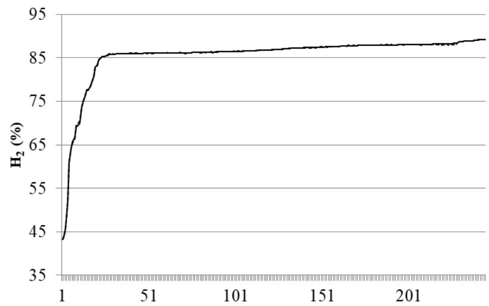
	Group 1	Group 2	Group 3	Group 4	Group 5	Average	Standard Deviation
Activation Functions: Relu (Hidden Layer), Linear (Output Layer)							
Training (%)	0.20	0.29	0.23	0.15	0.15	0.20	0.05
Testing (%)	0.17	0.26	0.19	0.17	0.14	0.19	0.04
Activation Functions: Sigmoid (Hidden Layer), Linear (Output Layer)							
Training (%)	0.13	0.14	0.12	0.13	0.26	0.16	0.05
Testing (%)	0.11	0.12	0.10	0.15	0.21	0.14	0.04
Activation Functions: Relu (Hidden Layer), Sigmoid (Output Layer)							
Training (%)	0.11	0.09	0.12	0.07	0.07	0.09	0.02
Testing (%)	0.10	0.09	0.09	0.10	0.09	0.09	0.00
Activation Functions: Sigmoid (Hidden Layer), Sigmoid (Output Layer)							
Training (%)	0.08	0.07	0.10	0.17	0.08	0.10	0.04
Testing (%)	0.06	0.07	0.09	0.21	0.09	0.10	0.05

Table 5
MAPEs of training and test for five groups obtained using 3-5-5-5-1 NN model.

	Group 1	Group 2	Group 3	Group 4	Group 5	Average	Standard Deviation
Activation Functions: Relu (Hidden Layer), Linear (Output Layer)							
Training (%)	0.35	0.08	0.22	0.10	0.12	0.17	0.10
Testing (%)	0.30	0.08	0.17	0.13	0.11	0.16	0.08
Activation Functions: Sigmoid (Hidden Layer), Linear (Output Layer)							
Training (%)	0.14	0.25	0.13	0.15	0.12	0.16	0.05
Testing (%)	0.15	0.24	0.12	0.21	0.10	0.16	0.05
Activation Functions: Relu (Hidden Layer), Sigmoid (Output Layer)							
Training (%)	0.09	0.08	0.11	0.08	0.09	0.09	0.01
Testing (%)	0.06	0.08	0.08	0.15	0.08	0.09	0.03
Activation Functions: Sigmoid (Hidden Layer), Sigmoid (Output Layer)							
Training (%)	0.07	0.10	0.08	0.11	0.08	0.09	0.01
Testing (%)	0.06	0.09	0.08	0.17	0.07	0.09	0.04

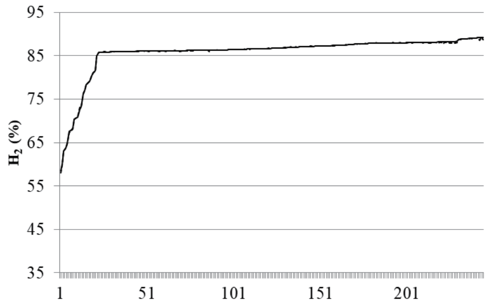


(a)

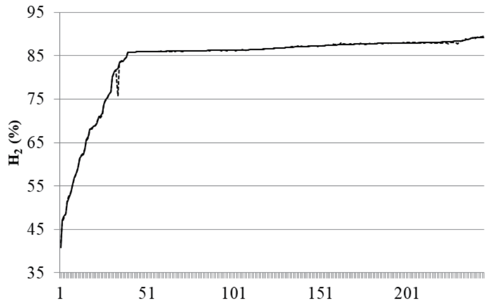


(b)

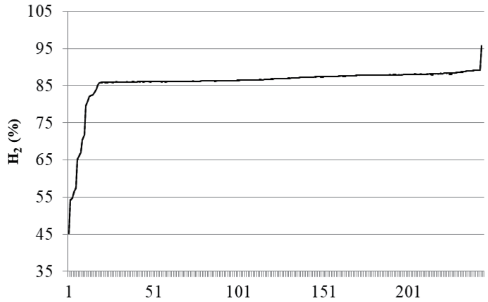
Fig. 4. Superposition diagram of NN tests results for the data of Groups 1 to 5. (a) Group 1. (b) Group 2. (c) Group 4. (d) Group 3. (e) Group 5 (solid line: desired output; dashed line: actual output).



(c)



(d)



(e)

Fig. 4. (Continued) Superposition diagram of NN test results for the data of Groups 1 to 5. (a) Group 1. (b) Group 2. (c) Group 4. (d) Group 3. (e) Group 5 (solid line: desired output; dashed line: actual output).

concentration predicted using the NN module. It can be seen that these two lines almost overlap, which means that the NN module has good prediction ability in this application.

6. Conclusion

In this paper, we presented a means of predicting the hydrogen concentration in an annealing furnace. To provide evidence that NN technology can be used for the immediate prediction of the hydrogen concentration, we collected the gas data sensed during an actual annealing process using an XMTC sensor. Three other furnace physical parameters, namely, motor power, motor speed, and inner temperature, related to gas concentrations were also recorded. Five randomly reorganized data groups were used to show the superiority of NN used in the study. From simulation results, the average test MAPEs obtained using the two modules of different sizes with the sigmoid activation function in the NN output layer are small. This shows that NN can indeed be used to identify the complex behavior of the annealing process, and this also indicates that the three parameters of the annealing furnace (base motor power, base motor speed, and temperature) exhibit important relationships with the hydrogen concentration. This also shows the feasibility of using the physical information of the motors to immediately predict the hydrogen concentration in the furnace.

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