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Estimation of Screw's Physical Properties Using Neural Network

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In this paper, the estimation of a screw's physical properties using a neural network (NN) technique is presented. The aim of this research is to study the effects of various control parameters of heat treatment and spheroidization on the physical properties of an alloy steel wire in its manufacturing process. The NN model is used to analyze the data collected by the image sensor and temperature sensor for heating treatments of alloy steel wire. It is expected that an advanced screw manufacturing system with intelligent analysis ability can be developed. Then, this smart system will be able to provide the optimal control parameters in real time to produce an alloy steel wire with ideal physical properties so that high-quality screws can be produced in the later manufacturing process. The results of this study show that the NN model can indeed achieve a fairly accurate estimation of the physical properties of a steel wire after the spheroidization, quenching, and tempering heat treatments. This shows that the development of an artificial-intelligence-based screw process optimization mechanism is very feasible.

1. Introduction

The main function of screws is to fasten objects. In many applications such as machinery, civil engineering, construction, electronics, and automobiles, they are important and indispensable basic components. For instance, from the smallest IC chip to the largest aircraft, screws are always part of the products.

In fact, the screw industry is a traditional industry that uses little high technology, and many screw manufacturing processes still rely on the experience of senior technicians. However, with the advent of the Industry 4.0 era, reducing the reliance on the experience of senior technicians and making manufacturing equipment and control processes capable of intelligence and self-adaptive capability are the desired goals of every industry, even the traditional screw industry. The purpose of our research is to help screw companies improve their manufacturing process.

The general procedure for producing screws is shown in Fig. 1. In the production process, annealing and quenching are two procedures for changing the physical properties of steel by high-temperature heating, in which spheroidizing annealing is performed to aggregate the cementite of the steel into spheroids that are uniformly distributed in the ferrite matrix. Such an

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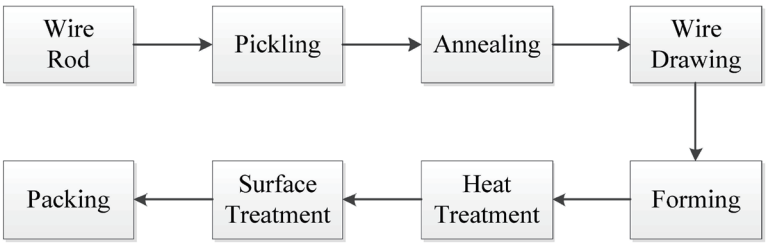

Fig. 1. Production flow chart of screws.

Fig. 2. (Color online) Bell-type spheroidizing annealing furnace (image provided by Fang Sheng Screw Co., Ltd.).

annealing process can improve the ductility of steel and reduce its hardness so that it can be easily machined or deformed. Figure 2 shows a bell-type spheroidizing annealing furnace, which is the main equipment used for the spheroidization.

In the spheroidization process, a thermocouple sensor is used to record the temperature changes. Figure 3 shows digital monitoring displays of the spheroidizing process.

The final heat treatment involves quenching and tempering. Quenching can increase the strength and hardness of steel. After quenching, the steel becomes brittle, so it is usually tempered again to reduce its brittleness. Basically, tempering is often accompanied by quenching. The tempering can eliminate or reduce the quenching stress, stabilize the shape and size of the steel, and prevent the deformation and cracking of quenched parts. Figure 4 displays the whole process of quenching and tempering.

2. Literature Review

To control the physical properties and quality of steel by heat treatment, the following related studies have been performed. Yu *et al.* studied the effects of the holding time during both austenitizing and spheroidizing on the microstructure and mechanical properties of the high-carbon martensitic stainless steel 8Cr13MoV.(1) Di *et al.* reported a spheroidizing procedure for the eutectic carbide in a twin roll-cast M2 high-speed steel strip by annealing, quenching, and tempering.(2) Studies on changes in the mechanical properties of steel after the spheroidizing process have also been performed.(3–11) In a study of quenching and tempering heat treatment, Ji

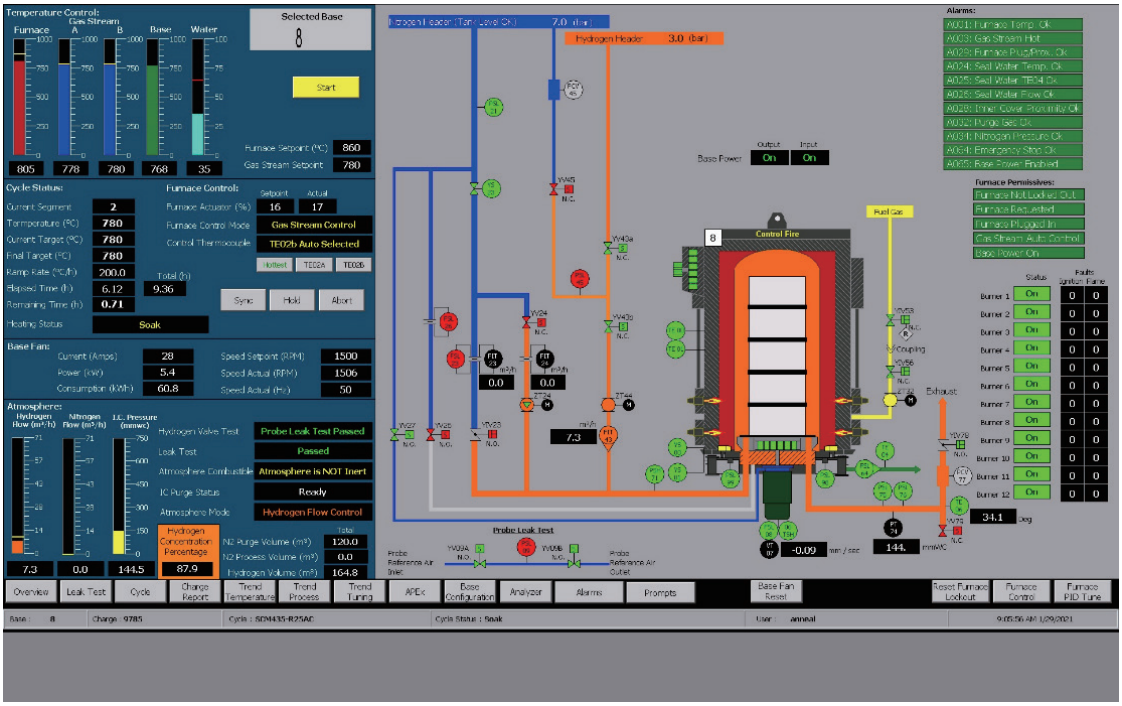

Fig. 3. (Color online) Digital monitoring displays of spheroidizing process (image provided by Fang Sheng Screw Co., Ltd.).

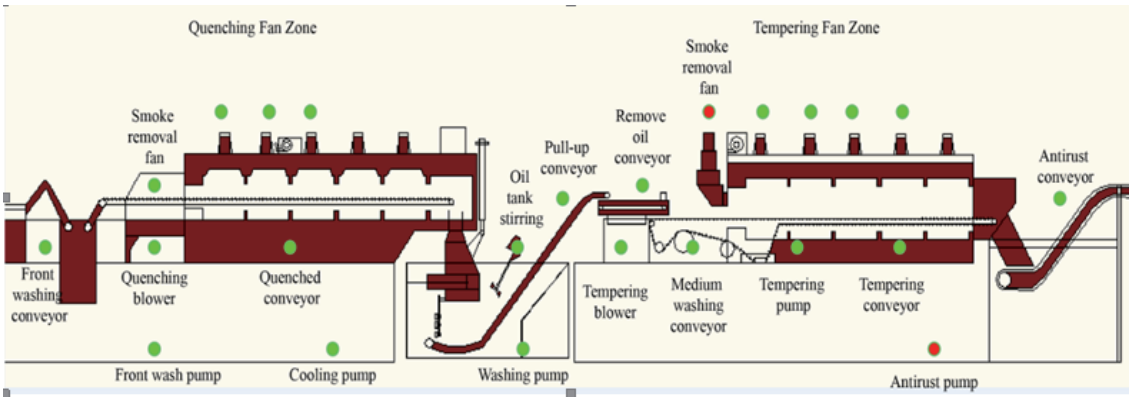

Fig. 4. (Color online) Process of quenching and tempering heat treatment (image provided by Fang Sheng Screw Co., Ltd.).

et al. used a thermal expansion analyzer, Thermo-Calc software, a scanning electron microscope, an X-ray diffractometer, and an ultrahigh-temperature confocal microscope to investigate the relationship between the microstructure and hardness of high-carbon martensitic stainless steel and temperature.[12–13] Luo *et al*. studied the effect of the subcritical quenching temperature on the microstructure of an EH36 ship plate steel of 15 mm thickness and the performance of controlled rolling and controlled cooling (TMCP). The results show that the mechanical properties of steel can be enhanced, i.e., its hardness and plasticity can be improved.[14] Other

related studies on the quenching and tempering of different steels have also been reported.[15–21]

From the past research, it is known that many factors in the heat treatment affect the properties of steel wires after heat treatment. For instance, the wire diameter, wire weight, heating temperature, heating time, and cooling rate in the heat treatment could all affect the properties. However, with the large amount of production data every day, factory technicians cannot carry out troubleshooting immediately when there are problems in the manufacturing process. Usually, the relevant control can only be done in accordance with experience and by trial and error. Therefore, not only is the heating process easily prone to errors, but inappropriate heating conditions also lead to the waste of raw materials.

In our study we use artificial intelligence technology to analyze the heat treatment process. The processes of spheroidizing, quenching, and tempering were studied and performed. For the case of a variety of different screw product orders, it is hoped that artificial intelligence technology can be used to accurately set the relevant control parameters of the heating process for the different steel wire materials.

3. Neural Network

In this study, a neural network (NN) model was used to analyze the spheroidizing, quenching, and tempering heat treatments. Data mining is a technique that can extract hidden useful information from a large database. In data mining techniques, regression is used to obtain the relationship between the output and input variables for a system and express the output as a function of the input variables. Model specification and parameter estimation are two common applications of regression analysis.

Our research is expected to lead to the development of an estimation model for a screw's physical properties after heating treatments. Owing to its powerful learning and adaptive capabilities, the NN technique has been widely applied to the field of nonlinear regression for unknown systems. Through the training of data, a model mapping the input/output data can be automatically developed. Then, the well-trained NN can perform tasks that the user wants it to do.[22–25]

The NN structure commonly known as a multilayered feedforward network is the topology selected in this research. An example of a three-layer feedforward NN model is shown in Fig. 5. Each layer is connected to the layer above it in a feedforward manner in the sense that there is no feedback from the same layer or a layer above, and the backpropagation (BP) learning algorithm is used to train the NN model.[24]

4. Experiments

4.1 Spheroidization

In the first experiment, the hardness and spheroidizing rate of an alloy steel wire were estimated. The real hardness value of the steel wire was measured using a Rockwell hardness tester, and the spheroidizing rate was sensed with a metallographic microscope. The data

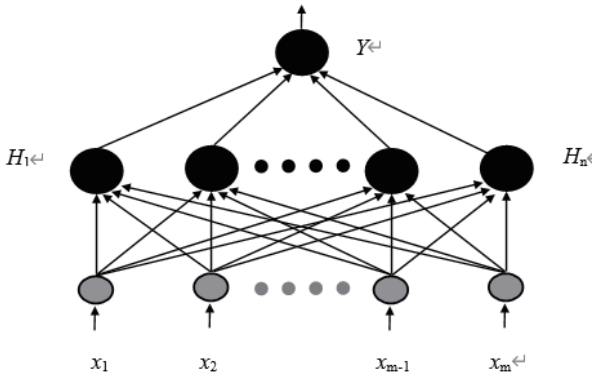

Fig. 5. Example of a three-layer NN structure.

Table 1
Number of data of each furnace for training and testing of NN.

Furnace	Number of data	Training	Test
A	83	55	27
B	70	47	23
C	90	60	30

collected by five spheroidizing furnaces were analyzed. All heating temperatures were sensed by a thermocouple sensor, which is a widely used type of temperature sensor. Table 1 lists the number of data of each furnace and the amount of data used for training and testing the NNs. For the estimations of the hardness and spheroidizing rate, the mean absolute percentage error (MAPE) and the accuracy are used, respectively. The size of the NN used for hardness estimation is 16-33-33-1, i.e., there are 16 nodes in the input layer, 33 nodes in the first hidden layer, 33 nodes in the second hidden layer, and one node in the output layer. The size of the NN used for spheroidizing rate estimation is 16-33-33-2. Three levels (1, 2, 3) of the spheroidizing rate are coded as (01,10,11). The inputs and outputs for both NNs are listed as follows.

Inputs: status, wire diameter, total weight, number of pieces, total spheroidizing time, five heating segment times, and five heating segment temperatures

Outputs: hardness and spheroidizing rate

Table 2 presents the estimation results of the hardness and spheroidizing rate of the three furnaces. Figures 6 and 7 respectively show the hardness estimated during training and testing of the NN for furnace A, where the solid line is the desired hardness and the dashed line is the estimated hardness.

4.2 Quenching and tempering

In the second experiment on quenching and tempering, the tensile strength and hardness were estimated. The values of tensile strength and hardness were respectively measured using a universal testing machine and hardness tester. The quenching and tempering temperatures were sensed by thermocouple sensors. The amounts of data collected by quenching and tempering treatments A, B, C, and D are 1346, 1008, 1113, and 2297, respectively. For each treatment, two-

Table 2
Data for the first experiment.

Furnace	Hardness (MAPE) (%)		Spheroidizing rate (Accuracy) (%)	
	Training	Testing	Training	Testing
A	0.006161	0.876	100	96
B	0.0013	0.0040	100	97.77
C	0.0017	0.0021	100	95.55

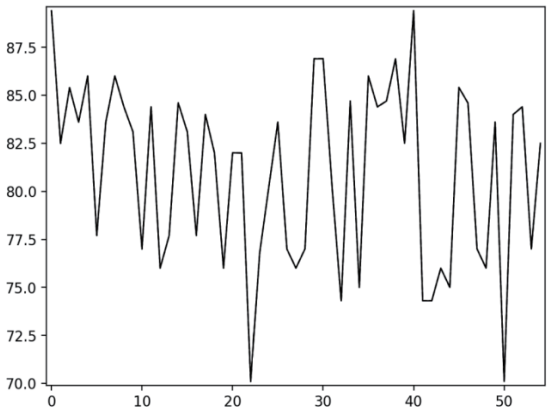

Fig. 6. Hardness during NN training.

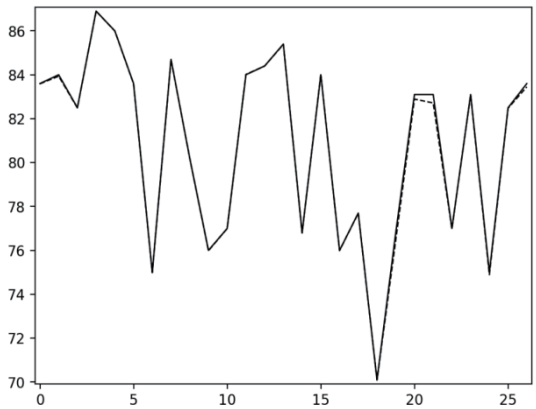

Fig. 7. Hardness during NN testing.

Table 3
Tensile strength and hardness prediction error of four treatments (A, B, C, D).

Treatment	Tensile strength (%)		Hardness (%)	
	Training (MAPE)	Test (MAPE)	Training (MAPE)	Test (MAPE)
A	0.695	1.790	0.833	1.196
B	1.177	1.679	0.995	1.325
C	0.670	1.322	0.912	1.488
D	0.548	1.396	0.815	1.245

thirds of the data are used for training the NN and the other one-third are used for testing. The size of the NN used for each treatment is 14-20-15-1, i.e., 14 nodes in the input layer, 20 nodes in the first hidden layer, 15 nodes in the second hidden layer, and one node in the output layer. The inputs and outputs of the NN for both estimations are listed as follows.

Inputs: belt speed, quenching time, two quenching temperatures, tempering time, four tempering temperatures, C, Mn, Cr, and Mo

Outputs: tensile strength and hardness

Table 3 presents the estimation results of the tensile strength and hardness for the four quenching and tempering treatments. Figures 8 and 9 respectively show examples of the estimated tensile strength for treatment A during the training and testing of the NN. Examples of the estimated hardness during the training and testing for treatment A are respectively shown in Figs. 10 and 11. Again, the solid line is the desired value and the dashed line is the estimated value. The results clearly show that the NN model can indeed estimate the screw's physical properties after the heating processes of spheroidization, quenching, and tempering.

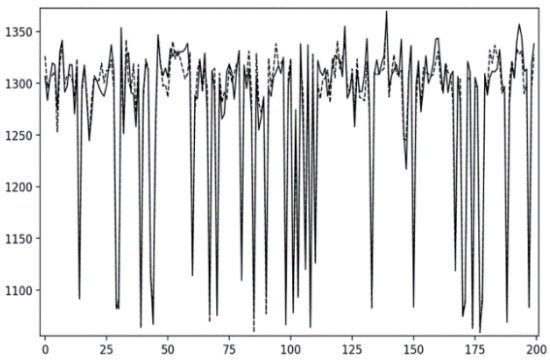

Fig. 8. Example of tensile strength estimated during training of NN.

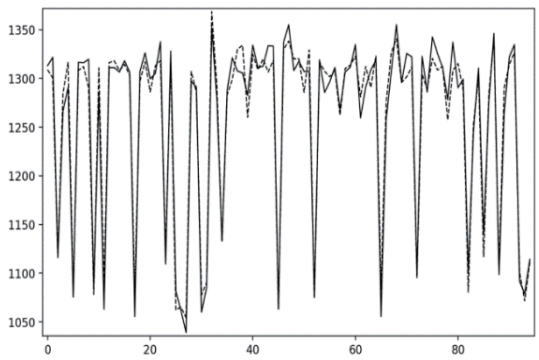

Fig. 9. Example of tensile strength estimated during testing of NN.

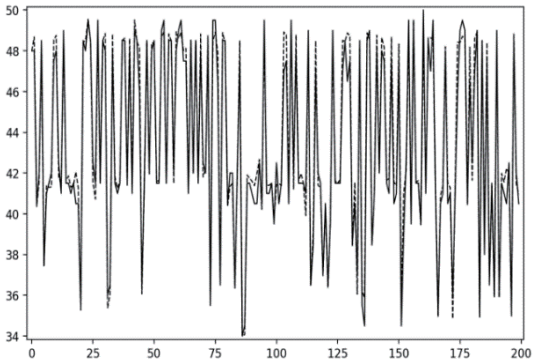

Fig. 10. Example of hardness estimated during training of NN.

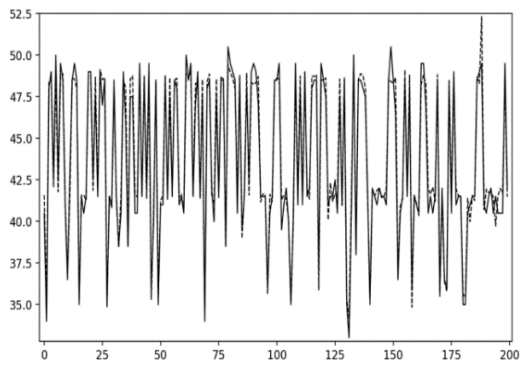

Fig. 11. Example of hardness estimated during testing of NN.

5. Conclusions

The main purpose of this research is to develop techniques to meet the needs of the screw industry. The NN technique is used to generate an estimation model that can predict a screw's physical properties after heating treatments. A good physical property estimation model for a screw can be used to determine appropriate control parameters in the screw manufacturing process.

In the heating treatments, temperature control and the heating time play very important roles in determining the characteristics of the screw steel. To obtain information effectively and accurately, a temperature sensor and image sensor were used to collect the relevant signal values for the learning of the NN and the construction of estimation modules.

Therefore, we hope that in the case of a variety of different product orders and raw materials with different chemical compositions, the relevant control parameters of heating processes can be set accurately through the use of artificial intelligence technology, enabling the production of high-quality screws.

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