Frontiers in Computing and Intelligent Systems
ISSN: 2832-6024 | Vol. 10, No. 1, 2024

Application Research of Neural Network in the Tensile Constitutive Relationship of Carbon Steel

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Abstract: Most carbon steels are multi-phase alloys with high specific strength, good mid-temperature properties and corrosion resistance, which lead to great differences in mechanical properties. The traditional model has some limitations and only reflects the mechanical behavior of the forming process in a certain range of temperature and strain rate. In this paper, a constitutive model of carbon steel based on neural network is established by using the high precision nonlinear fitting ability and strong generalization ability of neural network, reflect its different stages of mechanical properties. The model is trained, studied and simulated, and the results of the model are compared and analyzed. It is found that the model has high fitting precision and practical application value.

Keywords: Neural Network; Generalization Ability; Carbon Steel; Constitutive Relation.

1. Introduction

Steel is the most widely used and recycled metal material on Earth. From stainless steel and high-temperature steel to flat carbon products, various forms of alloy steel have different properties and are widely used. Many countries in the world have recognized the importance of steel materials and have conducted research and development on them, which have been practically applied. Carbon steel has many excellent physical and chemical properties and is widely used in fields such as construction, transportation, energy, packaging, home appliances, and industry. Due to its high specific strength (high strength, low density), good thermal stability and heat resistance at high temperatures, carbon steel is suitable for making rolling bearings and machinery. Carbon steel is widely used in manufacturing fields such as aerospace, rail transit, ocean transportation, and automobiles. In recent years, the steel consumption in the manufacturing industry has shown significant growth in Asia [1-2].

The theoretical research of neural computing is an emerging interdisciplinary field, and its emergence and development are influenced by other disciplines on one hand, and on the other hand, it will inevitably affect the development of other disciplines in turn. The research content of artificial neural networks is extremely rich, generally including five aspect, basic theory, models, algorithms, applications, and implementation [3-10]. Often used in fields such as prediction, analysis, optimization, control, diagnosis and recognition, classification and identification [11-15]. Therefore, research on the application of neural networks is obviously of great significance.

Carbon steel is mostly a multiphase alloy with high specific strength, good medium temperature performance, and corrosion resistance [16-19]. During high-temperature deformation, the forming temperature is narrow, and the deformation resistance and microstructure properties are sensitive to temperature and deformation rate, making it a typical difficult to deform material [20]. When subjected to cold and hot processing in complex environments, the microstructure of carbon steel components may vary, resulting in significant differences in their mechanical properties. Traditional constitutive relationships can be divided into two categories: phenomenological constitutive relationships and mechanistic constitutive relationships, both of which have certain limitations. This article utilizes the deep learning and strong fitting capabilities of neural networks, combined with the complexity and nonlinearity of carbon steel tensile experiments, to propose a neural network-based constitutive relationship model for carbon steel tensile testing. By using experimental data as samples to train, learn, and simulate the model, and comparing and analyzing the results, it is concluded that the model has high fitting accuracy and predictive ability, and has certain practical application value.

2. Research Materials and Methods

2.1. Research Materials

Carbon steel is mostly a multiphase alloy, with main alloying elements including silicon, manganese, chromium, nickel, molybdenum, tungsten, vanadium, titanium, niobium, zirconium, cobalt, aluminum, copper, boron, rare earths, etc. Their composition ratios have a significant impact on the constitutive relationship. The excellent corrosion resistance and high temperature resistance of carbon steel have also attracted attention in military, pharmaceutical, and chemical industries, and its good biocompatibility has made it widely used in new energy and other fields [21]. In recent years, the application of carbon steel in human daily life has been continuously expanding and developing rapidly, and the application technology has become more mature and perfect [22]. Many countries in the world have recognized the important position of carbon steel materials, and have conducted research and development on them, which have been widely applied in practice.

2.2. Test Methods

The tensile test is one of the most important experiments in material mechanics, and the test uses an electronic universal testing machine (CMT5105 type). The CMT5105 testing machine is a new type of testing machine that combines mechanical technology, sensing technology, electronic (computer) measurement, and data processing technology. It can use computers to control the testing process and automatically collect and process measurement data.

The carbon steel specimen adopts a circular cross-section specimen, according to the national standard GB/T228-2002, with the shape shown in Figure 1 and the parameters shown in Table 1-2. The tensile test was conducted on the CMT5105 electronic universal testing machine for uniaxial tensile testing at room temperature, with a constant tensile rate until the tensile fracture occurred. The deformation process is controlled by a computer, which automatically collects data such as stress, strain, displacement, etc.

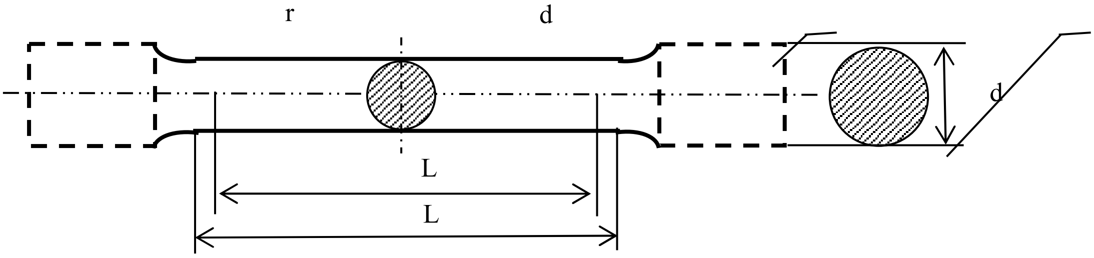

Figure 1. Schematic diagram of carbon steel specimen

Table 1. Parameters of Carbon Steel Specimens

Original gauge length L_o	Parallel length L_e	Original diameter of cross-section d	Excessive arc radius r	End diameter d'
50mm	70mm	10	8mm	20mm

Table 2. Dimensional tolerances of carbon steel specimens

Dimensional tolerance	Form tolerance
+/-0.05mm	+/-0.04m

2.3. Data Analysis

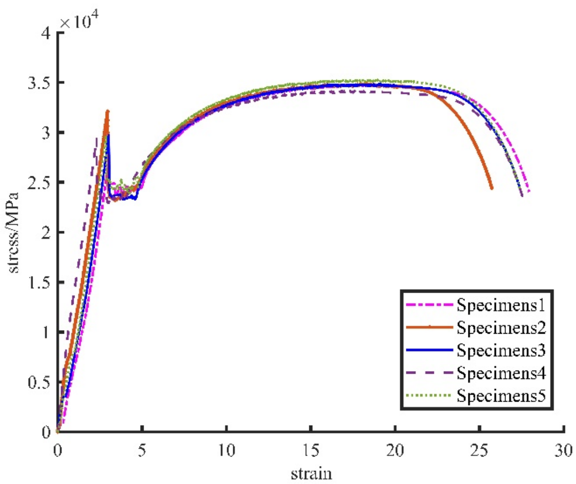

Figure 2. Stress strain curve of carbon steel specimen under tension and compression

Carbon steel specimens are subjected to normal stress during tensile testing, manifested by shrinkage of the fracture section and a total length of the specimen greater than the original length after fracture. Figure 2 shows the stress-strain curves of five sets of carbon steel specimens in tensile experiments. From the figure, it can be seen that yielding, strengthening, and necking phenomena occur during the stretching process. In the initial loading stage, there is a certain degree of slip, and the material mainly exhibits linear elasticity; As the load increases, the elongation of the specimen increases sharply, and the stress-strain curve exhibits significant nonlinearity. After the specimen reaches a certain load-bearing capacity, the curve enters the strengthening stage. After the specimen elongates to a certain extent, the load reading gradually decreases, and the cross-sectional area of a certain section of the specimen significantly shrinks, resulting in a "necking" phenomenon, until the specimen is pulled apart.

From the curve in the figure, it can be seen that the carbon steel specimen exhibits a very obvious nonlinear constitutive relationship when stretched to a certain extent, that is, the nonlinear nature of the stress-strain curve, and the stress-strain relationship at different stages is very complex.

2.4. Research Methods

The constitutive relationships exhibited by carbon steel specimens in various stages of tensile testing are very complex, and theoretical models cannot be described by a unified formula. The calculation of constitutive relationships in different stages is difficult and the accuracy is not high. Based on the theoretical foundation of solid mechanics and the structural principle of neural network framework, an intelligent constitutive relationship system model based on multi-layer neural network is constructed. In order to explore the learning and generalization ability of the model, we use L-M (Levenberg Marquardt backpropagation) optimization algorithm to dynamically adjust and optimize the model parameters to improve the model fitting ability and prediction accuracy, and minimize the mean square error of the model. Then, using deep learning methods, relevant algorithms are automatically improved through model experience accumulation to fit the constitutive relationships of carbon steel specimens at various stages of tensile experiments, and to establish a unified tensile constitutive relationship model for carbon steel structures, thereby improving the prediction accuracy and application value of the model.

3. Model Construction

Due to the structural differences of carbon steel, its compressive and tensile bearing capacities are not the same. From the stress-strain curve of carbon steel specimens under tensile load, it can be seen that the stress-strain curve of carbon steel specimens consists of four parts: linear elastic stage, yield stage, strengthening stage, plastic deformation stage, and necking deformation stage. The constitutive relationships exhibited in each stage are very complex, and the theory cannot be described by a unified formula. Neural networks have high-precision nonlinear fitting ability and strong generalization ability. Through the learning process of error back-propagation, the weights of each layer are continuously corrected to improve the accuracy of the model. We applied it to the constitutive relationship of carbon steel and constructed a neural network-based constitutive model to fit the constitutive relationship of the entire process of carbon steel tensile testing.

3.1. Data Processing

Firstly, the stress-strain data of tensile experiments on 5 groups of carbon steel specimens were analyzed and studied. The stress-strain curves are shown in Figure 2, and some invalid data were removed. The experimental data of the 5 groups of specimens were extracted to form a knowledge base for the network model, which was divided into two groups. The 88426 sets of data from specimens 1-4 were used as learning samples, and the 17429 sets of data from specimen 5 were used as testing samples.

Next, normalize the data in the knowledge base using the following normalization method [10-11]

$$D' = \frac{D - D_{\min}}{D_{\max} - D_{\min}} \times 0.8 + 0.1 \tag{1}$$

where D' is the normalized data value with a range of [0.1, 0.9], and D is the value of the data before normalization is a positive real number.

3.2. Model Structure

The constitutive relationship of carbon steel is influenced by various factors such as loading speed, carbon content, alloying elements, and heat treatment process. In the elastic stage, there is a linear relationship between the stress and strain of carbon steel. As the stress increases, carbon steel enters the yield stage, and the relationship between the stress and strain of carbon steel no longer remains linear. Therefore, the constitutive relationship of carbon steel is a complex and important topic, which involves the relationship between stress and strain of carbon steel and the effects of various influencing factors. Based on the characteristics and requirements of the tensile test of carbon steel at room temperature, combined with the characteristics of neural networks, the constitutive model of carbon steel tensile based on neural networks is determined as $\varepsilon = f(\sigma, t)$, and its system structure is shown in Figure 3, where t is the loading time, σ is the stress, ε is the strain, and the hidden layer is set to 100 layers.

3.3. Model Training and Learning

The training and learning of the model are to seek the optimal analytical solution of the objective functional. By learning and training the learning samples, the weight vectors W1 and W2 of the model are continuously adjusted to minimize the output error.

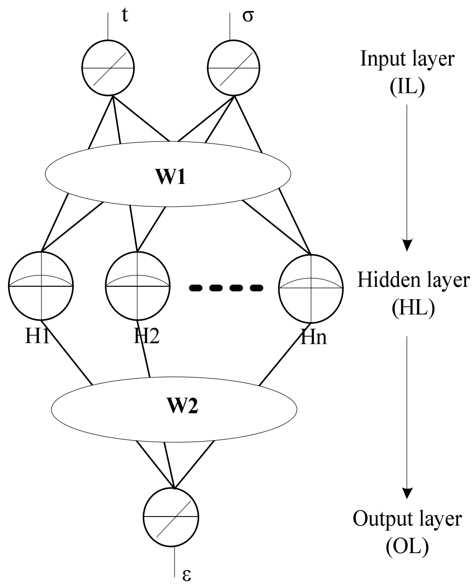

Figure 3. Architecture of the model

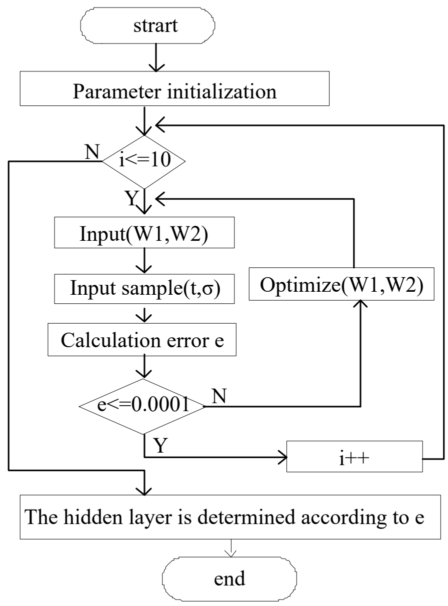

Figure 4. The training and learning process of the model

From the perspective of neural computing, this learning is an asymptotic process [23], and therefore the implementation of its objectives tends towards iterative optimization. The important feature of this learning process is that the objective functional tends to be extremely small. Here, the optimal number of hidden layers is designed to be 100 and trained using the Levenberg Marquardt algorithm. The transfer function of the neurons in the middle layer of the network adopts the S-shaped tangent function tangsig(), and the transfer function of the neurons in the output layer adopts the S-shaped logarithmic function logsig(). The training frequency is set to 1000 times, and the training objective is set to 0.0001. The specific learning process of the training is shown in Figure 4, and the training state and performance are shown in Figures 5-6. The best performance is achieved in the 126th round, with a mean square error of 8.9431e-05.

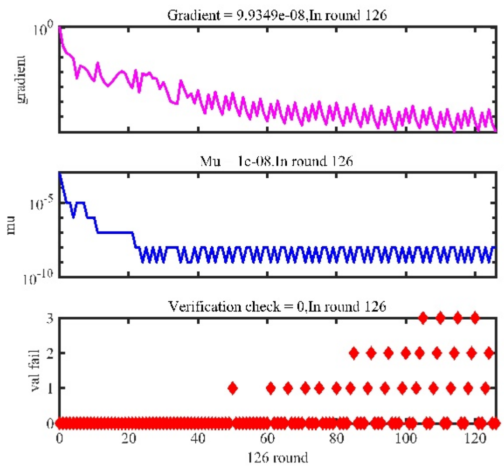

Figure 5. Training status of the model

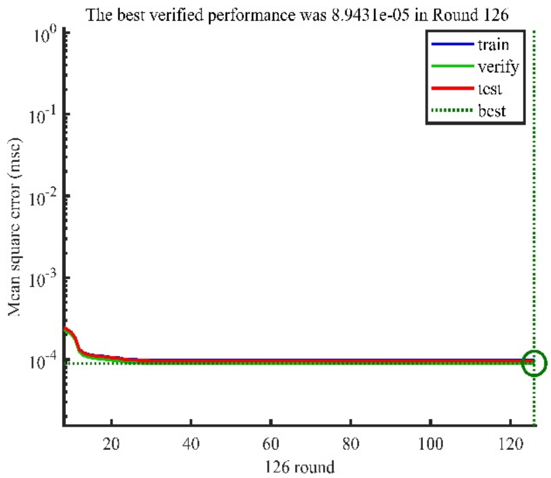

Figure 6. Training performance of the model

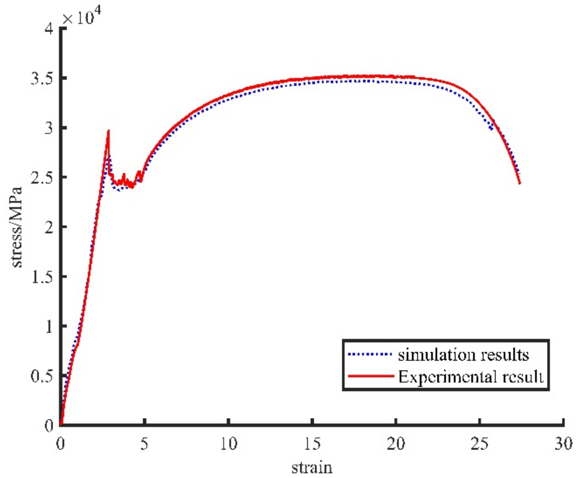

Figure 7. Comparison of simulation results

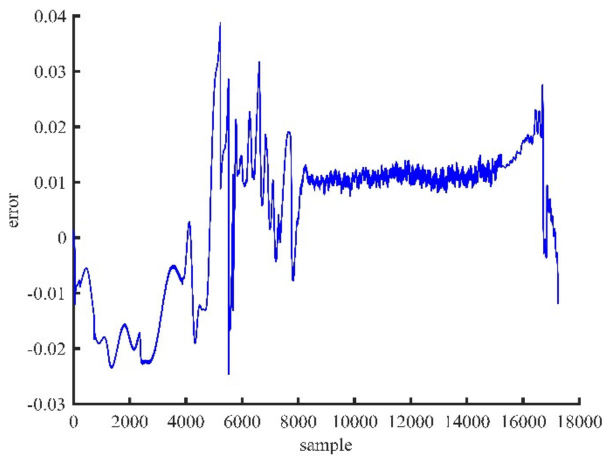

Figure 8. Error distribution

4. Analysis of Simulation Results of the Model

Now, 17429 sets of data extracted from the knowledge base for specimen 5 are used to form a test sample. The trained neural network-based tensile constitutive model of carbon steel is simulated and tested, and the simulation results are compared and analyzed with the experimental values. The situation is shown in Figure 7.

From the comparison in the figure, it can be seen that using a neural network-based tensile constitutive relationship model for carbon steel can effectively predict the entire process strain of carbon steel during tensile testing at room temperature, and the predicted curve can fit the experimental value curve well.

At the same time, a comprehensive comparison was made between the predicted values of the neural network model and the experimental values of the specimens. The distribution of the error curve of the tensile constitutive relationship of carbon steel at room temperature is shown in Figure 8. From the figure, it can be seen that the overall accuracy of the carbon steel tensile constitutive relationship model based on neural networks is within the range of -0.0246-0.0386, with a mean square error of 0.0011. The formation of errors is influenced by multiple factors such as experimental conditions, data processing, and model parameters. Overall, it meets the predetermined goals, and the model simulation results have high accuracy and reliability.

5. Conclusion

A neural network-based tensile constitutive relationship model for carbon steel was constructed by analyzing the tensile constitutive relationship of carbon steel at room temperature, taking into account multiple factors such as material properties, experimental conditions, data processing, and model parameters. Continuously optimizing model design and improving learning and training algorithms, the error between the predicted and experimental values of the model is controlled within an effective range, which can well fit the constitutive relationship of carbon steel at different stages of tensile testing at room temperature. Therefore, the application of neural networks in the study of constitutive relationships of carbon steel can achieve satisfactory results, and compared with traditional model calculations, it has the characteristics of accuracy and simplicity. At the same time, artificial neural networks have learning, self-organization, and certain generalization abilities, which can predict some performance data under unknown conditions, thus compensating for equipment and financial deficiencies, minimizing the generation of errors, and improving the accuracy and reliability of constitutive relationships.

Acknowledgments

The authors deeply appreciate the support from the key scientific research projects of Hunan Provincial Education Department (21A0601), and the National Natural Science Foundation of China (32371807).

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