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Simulation of Elastoplastic Behavior of Casting Aluminium Alloy Using Artificial Neural Network

Bin Chen[1, 2], Quan Yuan[1], Gang Chen[3] and Hongcao Liu[1]

[1]College of Resources and Environmental Science, Chongqing University, Chongqing 400044, China

[2]Key Laboratory for the Exploitation of Southwest Resources and Environmental Disaster Control Engineering, Ministry of Education, Chongqing University, Chongqing 400044, China

[3]College of Automation, Chongqing University, Chongqing 400044, China

Neural network is of an important efficiency in the simulations of the mechanical behaviors of engineering materials. In this work, a radial basis function neural network is used to the simulation of the nonlinearly elastoplastic behavior of casting Aluminium alloy. A radial basis function neural network is adopted for that it is of the characteristic of fast and exactly completing the simulations of the behaviors of the material. The neural network is trained based on a set of simple experimental data of the material. In the training process, a strain-controlled mode and the iterative method of the data are employed. The obtained model of the neural network is used to the prediction of the relationship between the stress and the strain of A101 and A104 casting Aluminium alloys. It is shown that the obtained neural network model can well simulate the nonlinearly elastoplastic behaviors of the materials.

Keywords: *Casting Aluminium alloy; elastoplastic behavior; neural network; simulation.*

1. Introduction

An important content in the investigations of material behaviors is to construct models of the materials. True material models can reasonably describe the experimentally observed results of the materials and predict their yet untested stress-strain relationships. The general models described the relationship between the stress and strain of a material are with mathematical rules and expressions. Up to today, most of material models are just effectual and exact in the elastic scope of the materials. Namely, the description of the material behaviors is limited in the elastic scope with linear characteristic. It is because, in a general way, there is considerable model error in the description of the nonlinearly mechanical characteristic of a material [1]. For example, there is a large error in the description of the nonlinearly elastoplastic behaviors of many key engineering materials. An alternative is to use a neural network to model the nonlinear characteristics of the materials [2]. The main benefits using the approach of a neural network are that all material behaviors can be represented within a unified environment of the neural network and that the network can be built directly from simply experimental data using the self-organizing capabilities of the network. Namely, the neural network can be presented with the experimental data of the material and "leans" the nonlinear relationships between the stress and the strain of the material. Such a modeling strategy has important implications for modeling the behaviors of those materials with nonlinear behavior and characteristic.

The simulations and descriptions of the behaviors of some materials using the techniques of neural networks have been reported by some researchers [1-5]. Ghaboussi et al. [1] reported the results of their researches in using a back-propagation neural network as a computational tool for capturing the behavior of a concrete material. Abendroth and Kuna [2] presented an approach to describe the plastic and failure properties of several steel materials with a back-propagation algorithm of a neural network. Furukawa and Hoffman [3] built a new material model using a multi-layer perceptron neural network that has the ability to describe the monotone and cyclic plasticities of Cr-Mo steel. Genel et al [4] employed the artificial neural network model with a multiple-layer-feed forward characteristic for simulating the complex properties of a alumina-fiber-reinforced zinc-Aluminium composite. Liu et al [5] acquired the constitutive relationship of thermal viscoplastic materials using a back-propagation neural network. In this paper, a radial basis function neural network model is built and trained for describing the nonlinearly elastoplastic behavior of casting aluminium alloy materials under large elastoplastic deformation. It is shown that the obtained model of the radial basis function neural network can well describe the nonlinearly elastoplastic behavior of the casting Aluminium alloy materials.

2. Elastoplastic behavior of casting Aluminium alloy

Casting Aluminium alloys are attracting increasing attention in transport vehicle field for their excellent properties in reducing vehicle weight and to be recycled. For example, casting Aluminium alloy A101 and A104 are currently being considered for automotive applications such as engine blocks and cylinder heads. The research on the material behaviors of the casting Aluminium alloys is very significant to develop new light-alloy materials of transport vehicle with high performances [6, 7]. In this section, the relationship between the stress and the strain of casting Aluminium alloys is investigated with a tensile experiment. The obtained test data will be transferred to a radial basis function neural network to obtain the material model of the casting Aluminium alloys.

In order to experimentally obtain the relationship between the stress-strain of the casting Aluminium alloy materials, cylindrical specimens of the materials were fabricated and experimentally tested with a Instron material test system. The measurable input is the load applied on the specimens and the measurable output is their displacement. The curve of the relationship between the load and the displacement provides the main information of the material behavior and can be easy transferred into the curve of the relationship between the stress and the strain of the material. Fig. 1 shows the obtained curve of the relationship between the stress and the strain of casting Aluminium alloy A101. It can be found from Fig. 1 that the relationship between the stress and the strain of the material is of nonlinearly elastoplastic characteristic and the stress-strain curve can be divided to linearly elastic and nonlinearly plastic parties. The dividing line between the elastic and plastic parties can be seen in Fig. 1. The nonlinearly elastoplastic behavior of the casting Aluminium alloy can be simulated using a neural network model with a radial basis function in the following section.

3. Simulation of material behavior

3.1 Extended radial basis function neural network

Radial basis function (RBF) was originated in 1964 as a potential function [8], but was first used for

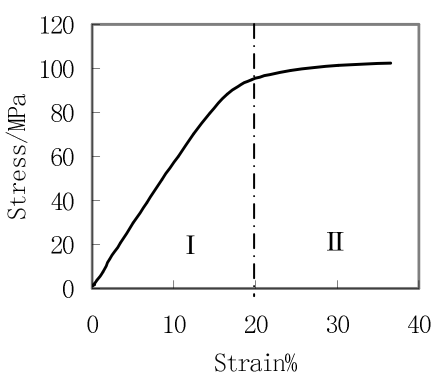

Fig. 1. Stress-strain curve of A101

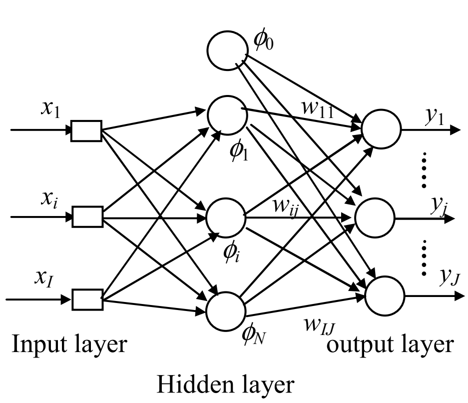

Fig. 2. Radial basis function neural network

the description of nonlinear regression by Sprecht in 1968 [9]. The neural networks with radial basis function (RBFNN) were brought to widespread attention by Moody and Darken [10] in 1989. It has been found that the architecture and training algorithm of the RBFNN is relative simple and the training of the RBFNN is more quickly than that of the multiple-layered perceptron (MLP) [10, 11]. So, in this research, we use an extended radial basis function neural network (ERBFNN) to simulate the elastoplastic behavior of the casting Aluminium alloy materials.

The ERBFNN consists of three layers: input layer, hidden layers and output layer (Fig. 2). The input layer has *I* neurons and anyone of the neurons can be expressed as *i*. The hidden layer includes *N* neurons, and anyone of the neurons can be expressed with *n*. The output layer has *J* neurons and anyone of the neurons can be expressed as *j*. The basis function of the network is $\phi(X, X_i)$ which is the inspiriting output of the *i*-th hidden unit. The connection weight between the hidden layer and the output layer is w_{ij} $(i = 1,2,...I;\ j = 1,2,...,J)$. In the hidden layer of the network, a basis function $\phi(0)$ is added and its corresponding weight is w_{0j}. When a training sample X_k of the network is inputted, the output of the *j*-th outputting neuron is

$$Y_{kj}(X_k) = w_{0j} + \sum_{i=1}^{N} w_{ij}\phi(X_k, t_i), \quad (j = 1,2...,J), \tag{1}$$

where t_i is the center of the radial basis function of the network. When the Green Function [10, 11] is adopted as the basis function of the network

$$\phi(X_k, t_i) = G(\|X_k - t_i\|), \tag{2}$$

following relationship can be given

$$\varphi(X_k, t_i) = \exp(-\frac{1}{2\sigma_i^{\ 2}}\|X_k - t_i)^2\|) = \exp(-\frac{1}{2\sigma_i^{\ 2}}\sum_{m=1}^{M}(x_{km} - t_{im})^2) \tag{3}$$

where $t_i = [t_{i1}, t_{i2}, ..., t_{iM}]$ is the center of the Gaussian Function and σ_i is the square error of the Gaussian Function. The centers of the network and other parameters can be determined by "learning" under surveillance. In the "learning" course, an aim function is defined as

$$E = \frac{1}{2}\sum_{k=1}^{N} e_k^2 , \tag{4}$$

where *N* is the number of samples, e_k is error signal and can be expressed as

$$e_k = d_k - Y_k(X_k) = d_k - \sum_{i=1}^{I} w_i G(\|X_k - t_i\|_{C_i}), \tag{5}$$

where d_k is the distance between the selected centers. The weight w_i of the output layer can be determined by:

$$\frac{\partial E(n)}{\partial w_i(n)} = \sum_{k=1}^{N} e_k(n) G(\|X_k - t_i(n)\|_{C_i}), \tag{6}$$

$$w_i(n+1) = w_i(n) - \eta_1 \frac{\partial E(n)}{\partial w_i(n)}, \quad i = 1,2,...I, \tag{7}$$

and the center t_i of the hidden layer can be calculated with

$$\frac{\partial E(n)}{\partial t_i(n)} = 2w_i(n)\sum_{k=1}^{N} e_k(n) G'(\|X_k - t_i(n)\|_{C_i} \textstyle\sum_i^{-1}(X_k - t_i(n)), \tag{8}$$

$$t_i(n+1) = t_i(n) - \eta_2 \frac{\partial E(n)}{\partial t_i(n)}, \qquad i = 1,2,...I\,. \tag{9}$$

The extended parameter $\sum_i^{-1}$ can be determined with

$$\frac{\partial E(n)}{\partial \Sigma_i^{-1}(n)} = -w_i(n)\sum_{k=1}^{N} e_k(n) G'(\|X_k - t_i(n)\|_{C_i}) Q_{ki}(n) \tag{10}$$

where $G'(\cdot)$ is the differential coefficient of $G(\cdot)$

$$Q_{ji}(n) = (X_k - t_i(n))(X_k - t_i(n))^T\,, \tag{11}$$

$$\Sigma_i^{-1}(n+1) = \Sigma_i^{-1}(n) - \eta_3 \frac{\partial E(n)}{\partial \Sigma_i^{-1}(n)}\,, \tag{12}$$

3.2 Training and test of neural network model

The experimentally obtained curves of the stress-strain relationship of the casting Aluminium alloys were used for training the constructed ERBFNN. A stress-controlled training mode was adopted [1]. In the training mode, stress increments were presented to the network as input and strain increments as output. The network was trained to predict strain increments given the current state of the strain, stress and stress increment. This is done by starting at a known stress-strain state, increasing small stresses and using the ERBFNN to predict the strain increments. These strain increments can then be added to get the new strain state which can be used to predict the strain increment for another stress increment. The predicted result of the curve of the stress-strain of casting Aluminium alloys A101 is shown in Fig. 3. It can be found from Fig. 3 that the predicted result is consistent with the experimental data, which shows that the ERBFNN can well describe the elastoplastic behavior of the material.

The trained material model of the ERBFNN was also used for predicting the elastoplastic behaviors of casting Aluminium alloy A104. The predicted and the experimental results of the stress-strain relationship of the material are shown in Fig. 4. It can be seen from Fig. 4 that the predicted values of the ERBFNN are also very close to the experimental results of the material, which shows that the ERBFNN is of reliable ability for describing the nonlinearly elastoplastic behavior of the casting Aluminium alloy materials.

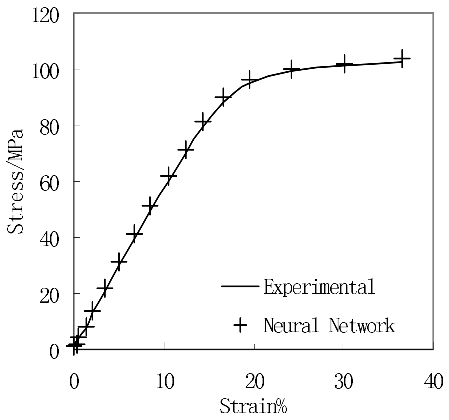

Fig. 3. Stress-strain curve of A101

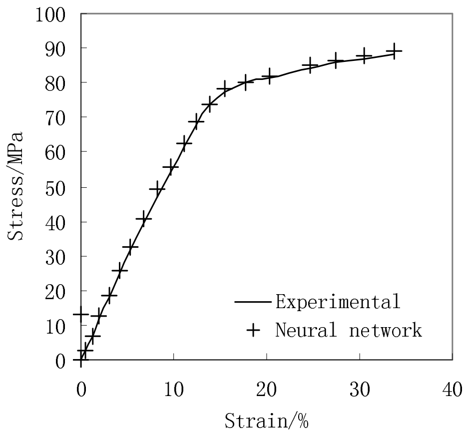

Fig. 4. Stress-strain curve of A104

4. Conclusions

The nonlinearly elastoplastic behavior of casting Aluminium alloys was simulated using an extended radial basis function neural network. The neural network is of the characteristic of fast and exactly completing the simulation of the material behaviors. The neural network was trained by directly using the experimental data of the stress-strain relationship of the materials. A stress-controlled mode and a data-iterative method were adopted in the training process. The trained neural network model was used to the prediction of the elastoplastic behavior of the materials. It is shown that the obtained material model of the extended radial basis function neural network can satisfactorily simulate the nonlinearly elastoplastic behavior of the materials.

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