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The Performance Study of Metal Rubber Based on Neural Network

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Abstract: Coefficients of relationship of metal rubber were studied by Artificial Neural Network (ANN) as an alternative to mathematical model. Artificial neural network was introduced and how to predict design model of rubber metal was discussed. Artificial neural network parameters were chosen. Through parameter identification of experimental data of metal rubber, neural network models inputs were obtained in five cases, including: density, diameter of wired, external radius of metal rubber, internal radius of metal rubber and height. The result from ANN showed a good agree internal radius cement with the experiment data. Now ANN has been successfully used in our process of design and is helpful to reduce the cost.

Key words: Metal rubber, artificial neural network, experimental data, density

INTRODUCTION

Metal rubber's wires are molded and pressed into required shape. It has the elasticity and damping characteristics like rubber material and at the same time keeps the broad adaptability of the metal material to the environment. It can be used as sealing component in severe environment with extremely high and low temperature, high pressure, high vacuum and erosive medium as shown in Fig. 1.

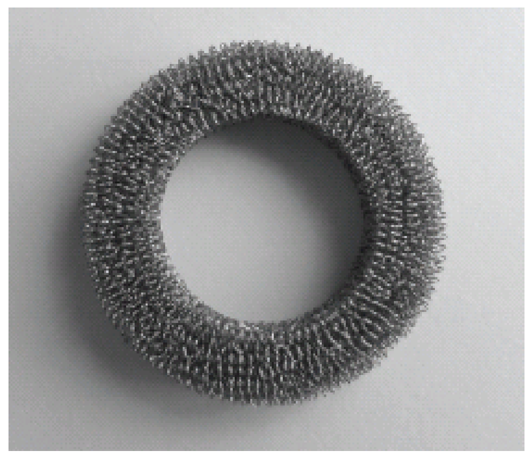

Fig. 1: A sample of metal rubber

Up to now metal rubber is mainly used in national defense industry. This situation can be explained by its complex characteristics. The inner structure of metal rubber is similar with macromolecule and the constitutive equation of metal rubber is nonlinear (Zhongying, 2000). And theoretical model of metal-rubber was studied (Guo *et al*., 2004), the paper presents the constitutive relation of metal rubber and application research of metal rubber was studied (Zhao *et al*., 2006). Therefore its elasticity and damping characteristics are very complicated. Previous attempts on prediction of metal rubber performance are mostly based on mathematical model of constitutive equation. Although much progress has been made, it is hard to describe its characteristics with sufficient accuracy. In our research of metal rubber, it nearly impossible to find an appropriate mathematical model as shown in Fig. 2.

Fig. 2: A set of molds for metal rubber

Without the help of mathematic model, a lot of experiments are necessary for the design of metal rubber. Yet this leads to great cost. To make a new type of metal rubber for sealing, for example, a set of new molds has to be made for laying wires, stamping semi-finished product and wrapping with polytetrafluoroethylene. And then experiments have to be done to test the performance of

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samples made by the new molds. The new product cannot be massively produced until the samples satisfy the requirement. Usually five or six sets of molds have to be made in this process. This leads to great waste of time and resource and outlays are considerable. That is why it is mostly used in national defense industry which cares less about the cost. However the metal wire, the material of metal rubber, is cheap. If the cost of design process can be reduced, undoubtedly metal rubber will have more applications (Bai, 2002).

In this work, artificial neural network is introduced for the design of metal rubber. ANNs are used in a wide range of engineering and non-engineering applications, such as, pattern recognition, as well as behavior prediction and function approximation. The characteristic feature of ANNs is that they are not programmed; they are trained to learn by experience. It can be seen that ANNs can be used as an alternative to mathematical models of metal rubber. In this paper coefficients of constitutive equation of metal rubber are predicted by ANNs. If the coefficients cannot fulfill the requirements. The design can not be modified in advance. Therefore the success rate of design can be improved (Irie and Miyake, 1988).

COEFFICIENTS OF CONSTITUTIVE EQUATION

In the design process, the most important work is to find the coefficients of constitutive equation of metal rubber. Once the coefficients are gotten, mechanical, sealing and other performance can be deduced. Usually the constitutive equation of nonlinear material can be expressed as follows:

$$F(x) = a_0 \operatorname{sgn}|x| + \sum_{i=1}^{n} a_i |x|^{i-1} x + b_0 \operatorname{sgn}|\dot{x}| + \sum_{i=1}^{n} b_i |\dot{x}|^{i-1} x \tag{1}$$

where, x is the compressive displacement, F (x) is the force exerted on metal rubber and a_0, a_i, b_0, b_i are coefficients respectively. In Eq. 1 the first and second terms describe the fourth terms which describe the dynamic characteristics.

Up to now metal rubber is mainly used as sealing component and the dynamic characteristic is mostly of little importance. Omitting the third and fourth term, then:

$$F(x) = a_0 \operatorname{sgn}|x| + \sum_{i=1}^{n} a_i |x|^{i-1} x \tag{2}$$

For static characteristic, it is found that cubic nonlinearity of displacement is enough to describe the characteristic of material. So Eq. 2 becomes to:

$$F(x) = a_0 + a_1 - a_1 x + a_3 x^3 \tag{3}$$

Due to the memory characteristic, the forces of loading and unloading stage are different from each other. Equation (3) was displaced with:

$$F_1(x) = a_{0l} + a_{1l} x + a_{2l} x^2 + a_{3l} x^3 \tag{4}$$

and

$$F_{tl}(x) = a_{0tl} + a_{1tl} x + a_{2tl} x^2 + a_{3lt} x^3 \tag{5}$$

where, the index notation, l represents the loading stage and t represents the unloading stage, respectively.

In our research, the least-squares method was used for the parameter identification of experiment data. It finds the coefficients of polynomial F (x) that fits the experiment data in a least squares sense. For each set of N force-displacement data (x_1, y_1), (x_2, y_2),... and (x_n, y_n) obtained in the static experiments, the approximated by a polynomial of degree 3: The coefficients a_0, a_1,...a_3 were obtained by minimizing the function:

$$Q = \sum_{i=1}^{n} [F(x_i) - y_i]^2 \tag{6}$$

NEURAL NETWORK PREDICTOR MODEL

The coefficients of constitutive equation had to be obtained from experiment data. In this paper ANNs are introduced to predict those coefficients before a new set of molds are made. If the coefficients cannot fulfill the requirements, the design can not been modified. Therefore the success rate of design can be improved (Li *et al*., 2011a).

An artificial neural network can be regarded as a black box which is able to produce certain output data as a response to a specific combination of input data. It is an information processing paradigm that is inspired by the way biological nervous systems process information. By receiving the data for an existing system, ANN can be trained to learn the internal relationships that govern that system and predict its behavior without any physical equations (Li *et al*., 2005). The major advantage of ANNs, compared to traditional polynomial mapping, is that they are able to perform non-linear mapping of multidimensional functions, i.e. relationships from many inputs to many outputs. It can be seen that design of metal rubber just belongs to this problem (Zhang *et al*., 2007).

One ANN which has received most attention is the Backpropagation Network (BPN) (Li *et al.*, 2011b), as is shown in Fig. 3. BPNs have hierarchical feed forward network architecture. In the classical structure of a BPN, output of each layer is sent directly to each neuron in the layer above. While there can be many layers, the processing can be done with a minimum of three layers: one layer receives and distributes the input pattern, one middle or hidden layer captures the nonlinearities of the input/output relationship and one layer produces the output pattern (Wang *et al.*, 2011). BPNs are trained by repeatedly presenting a series of input/output pattern sets to the network. The network gradually learns the input/output relationship of interest by adjusting the weights to minimize the error between the actual and predicted output patterns of the training set. The trained network is usually examined through a test set of data to monitor its performance and validity. When the mean squared error of the test set reaches a minimum, network training is considered completely and the weights are fixed.

The back propagation neural network with three layers, input-hidden *i* output, is used. It has 5 inputs, 15 intermediate nodes and 6 outputs. The input variables are: average density of metal rubber ρ_a, diameter of wired d_w, external radius of metal rubber r_e, internal radius of metal rubber r_i, height of metal rubber r_h. The outputs are coefficients of constitutive equation according to the formula:

$$Y_i = s\left(\sum_{i=1}^{N} \overrightarrow{W_{ij}}\overrightarrow{Zj} - \theta_j\right) \quad (7)$$

where, $\vec{z}_j$ are the input vectors, $\vec{w}_{ij}$ are the connection weights between layers and θ_j are bias weights. And activation function s is a Sigmodial function as follows:

$$s\left(Net_{kj}\right) = \frac{1}{1 + e^{-Net_{kj}}} \quad (8)$$

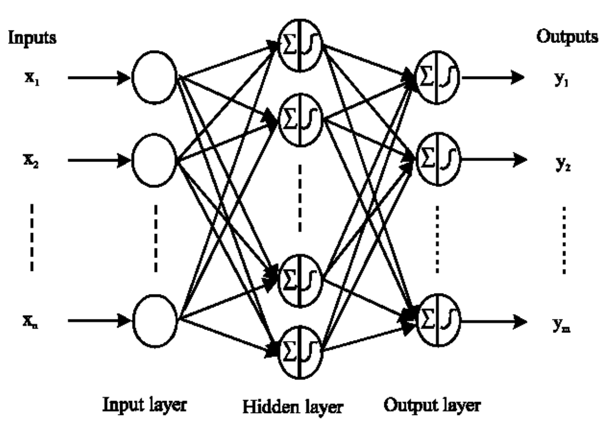

Fig. 3: The structure of BPN with a hidden layer

By using the algorithm-generalized gradient descent search technique, BPA adjusts the eights of the network and the threshold of each neuron recurrently according to the criterion that the cost function is minimized. The cost function is mean-squared error between the actual outputs:

$$O_m = s\left(\sum_{l=1}^{L} \vec{w}_{lm}\vec{z}_l - \theta_m\right) \quad (9)$$

And the target outputs:

$$y_l = s\left(\sum_{l=1}^{N} \vec{w}_{nl}\vec{z}_n - \theta_l\right) \quad (10)$$

Metal rubber constitutive relation coefficient material density, shape, the relation of the factor, it is difficult to describe accurate mathematical model. This paper is ready to BP neural network based on the constitutive relation coefficient estimates, resulting in the constitutive relationship of metallic rubber following BP neural network estimated metal rubber material constitutive Method.

EXPERIMENTS AND RESULTS

The experiments were carried out on a MTS810 universal testing machine. The article has been applied about material density changes of the estimate of the constitutive relation of metal rubber material. To the metal rubber material do static experiment, specimen for without heat, r_i = 4 mm, r_e = 12.5 mm (Li, 2006; Liu, 1997).The metal wire is made of 1Cr18Ni9Ti and its elastic modulus is 198,000 Mpa. A total of 19 groups of experiment data are used. Fifteen groups of data are used for the training of the network and the others are used for validation. Static equipment adopted in the experiment for WDW-1002 type electronic universal testing machine, precision grade of 0. 5, maximum load of 100 kN, load measuring accuracy can reach 0. 1 n, displacement of measuring accuracy can reach 0. 001 mm.

As a rule of thumb, optimization of the neural network condition was performed by trial-and-error by adjusting various parameters. These include the learning epoch size, the learning rate and momentum constants. The controlled error is 0.005. The ANN achieved a stable state after 1298 cycles of training. Finally, the trained network was tested through four groups of experiment data. The results are shown in Fig. 4-7.

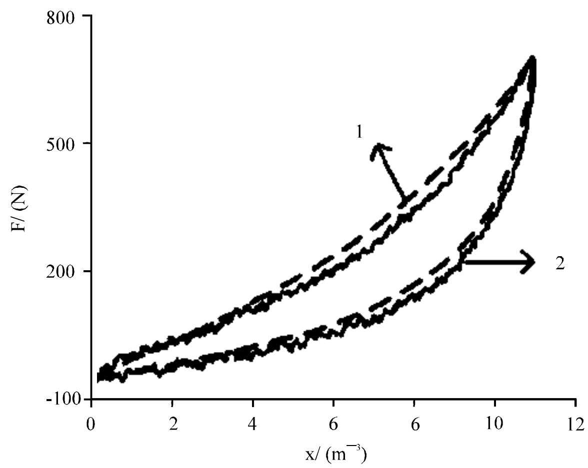

Fig. 4: Force-displacement relationship for a metal rubber product with $\rho_a = 2.11 g\ cm^{-3}$, $d_w = 0.10$ mm, $r_e = 5.0$ cm, $r_i = 4.6$ cm, $r_h = 0.4$ cm: 1-pridiction, 2-experiment

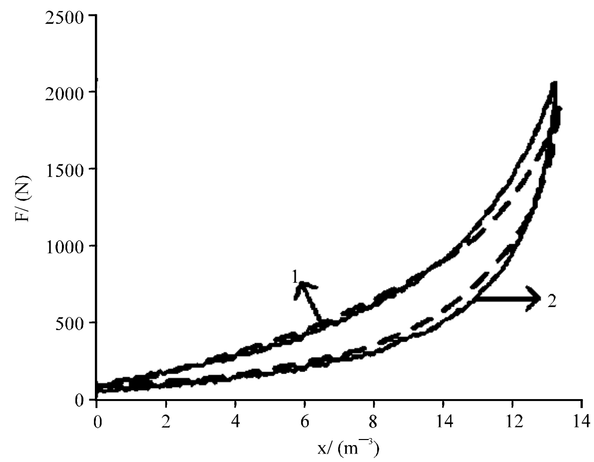

Fig. 6: Force-diaplacement relationship for a metal rubber product with $\rho_a = 2.516$ g cm^{-3}, $d_w = 0.12$ mm, r_e = 8.0 cm, r_i = 7.2 cm, r_h = 0.8 cm: 1-pridiction, 2-experiment

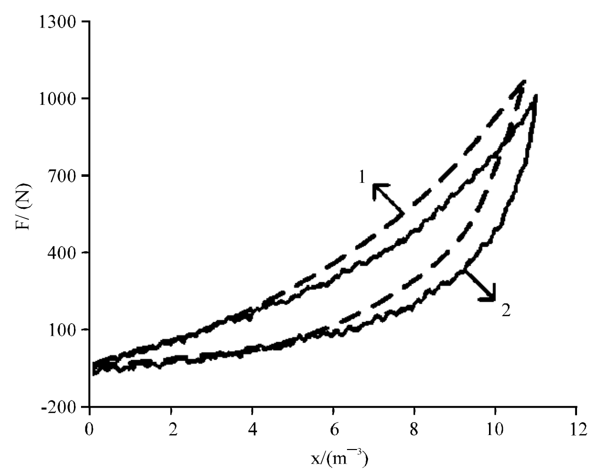

Fig. 5: Force-diaplacement relationship for a metal rubber product with ρ_a = 2.11 g cm^{-3}, d_w = 0.10 mm, r_e = 6.0 cm, r_i = 4.6 cm, r_h = 0.4 cm: 1-pridiction, 2-experiment.

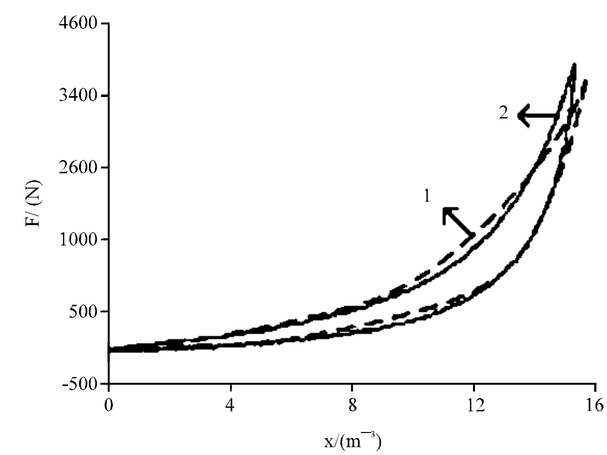

Fig. 7: Force-diaplacement relationship for a metal rubber product with $\rho_a = 2.977$ g cm^{-3}, $d_w = 0.15$ mm, r_e = 10.0 cm, r_i = 9.0 cm, r_h = 1.0 cm:1-pridiction,2-experiment

It can be seen that the prediction from the ANN shows agreement with experiment data. The accuracy can satisfy the requirement of the design of metal rubber.

Now ANNs have been used in our design process and play an important role. Before a new set of molds is made, coefficients of metal rubber made by the molds will be predicted. If the result does not satisfy the requirement, the design will be modified. In most cases one set of molds is enough for the production of new type of metal rubber with the help of ANN. Only in a few cases two sets are needed. ANN reduces the cost of molds and the need for extensive experiments.

CONCLUSION

In the past, the main method of designing metal rubber was the mathematical model. However, they cannot describe the performance of metal rubber with sufficient accuracy. In this paper, artificial neural network was used to predict the coefficients of constitutive equation and showed a good congruence with the experiment data. ANN method is suitable for the design of metal rubber. Besides the ANN model is much faster and easier to use. It has been used in our design process and is helpful to reduce the cost.

For future work in the direction of this study the main concern is integration of more parameters as inputs and enhancing the accuracy of the model.

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