Research on quasi-dynamic calibration model of plastic sensitive element based on neural networks

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Abstract. Quasi-dynamic calibration accuracy of the plastic sensitive element depends on the accuracy of the fitting model between pressure and deformation. By using the excellent nonlinear mapping ability of RBF (Radial Basis Function) neural network, a calibration model is established which use the peak pressure as the input and use the deformation of the plastic sensitive element as the output in this paper. The calibration experiments of a batch of copper cylinders are carried out on the quasi-dynamic pressure calibration device, which pressure range is within the range of 200MPa to 700MPa. The experiment data are acquired according to the standard pressure monitoring system. The network train and study are done to quasi dynamic calibration model based on neural network by using MATLAB neural network toolbox. Taking the testing samples as the research object, the prediction accuracy of neural network model is compared with the exponential fitting model and the second-order polynomial fitting model. The results show that prediction of the neural network model is most close to the testing samples, and the accuracy of prediction model based on neural network is better than 0.5%, respectively one order higher than the second-order polynomial fitting model and two orders higher than the exponential fitting model. The quasi-dynamic calibration model between pressure peak and deformation of plastic sensitive element, which is based on neural network, provides important basis for creating higher accuracy quasi-dynamic calibration table.

1. Introduction

Copper cylinders as a sensitive element of crusher gauges are widely used for measuring the peak pressure in weapon chamber. Since the 1860s Nobel invented the copper cylinders for pressure measuring so far, with its convenience, simple operation, without drilling of the gun barrel as well as the consistency, copper crusher method has always been the main technical means of chamber pressure measuring in “practical ballistics” area and has been widely used in the world by far [1-4].

In order to ensure the accuracy of the chamber pressure test, copper cylinders need to be calibrated before use. If a static calibration method is used, an obvious dynamic error (up to 5% to 30% of the measured value) will be produced when measuring rapidly changing chamber pressures [4-6]. In the late 1970s, the quasi-dynamic calibration technology was first used by the United States to eliminate this dynamic error. This method was subsequently adopted by European countries, and became one of the most important methods for the calibration of plastic sensitive element. The so-called quasi-dynamic calibration refers to use a half-sine pressure pulse, which is similar to the chamber pressure waveform and has known peak value and pulse width, to calibrate sensitive elements of crusher gauges (copper cylinders or copper sphere), and obtain corresponding relationship between the pressure and deformation of the sensitive elements. In order to accurately calibrate a copper cylinders or a copper sphere with a drop-weight quasi-dynamic calibration device, it is necessary to know the
relationship between the operating parameters of drop-weight device (such as weight, drop height, piston area, initial volume of oil cylinder, the diameter of the piston, the starting diameter of the copper sphere, etc.) and the pressure peak and pulse width by the device. And in order to ensure the accuracy of quasi-dynamic calibration, the relationship between the deformation of the plastic sensitive elements and the peak of the pressure pulse must meet certain precision requirements. Zhu Mingwu carried out a quasi-dynamic calibration practice aimed at the $4mm \times 8mm$ copper cylinders [9] and analyzed the characteristics of quasi-dynamic calibration of copper cylinders and the problems which should be paid attention to. In Reference [11], a corresponding mechanics-mathematical model is established to guide the research work by using the method of theoretical analysis and according to the laws of physics which play a dominant role in the working process of the device. In Reference [12], based on the dimensional analysis theory, the dimensional analysis of copper sphere’s dynamic calibration process is carried out, and a dimensionless model between drop height, peak pressure and pulse width is established. The maximum relative error of the model for peak pressure is less than 3%.

Based on the excellent nonlinear mapping ability of RBF neural network [13-15], a quasi-dynamic calibration test on copper cylinders is carried out based on drop-weight device. The relationship between the deformation of copper cylinders and the peak of pressure pulse is established, and the accuracy of the neural network fitting model is compared with the accuracy of the traditional fitting model.

2. The Principle of Quasi-Dynamic Calibration for Plastic Sensitive Element

The quasi-dynamic calibration device mainly consists of the pressure pulse generator and the reference pressure measurement system. The principle of the half-period sine pressure pulse generator [7] is shown in Figure 1. The pressure pulse generator consists of a piston and a mass that can be dropped onto the piston from various heights. When the mass is released from a certain height, it transmits its Kinetics energy through the piston to the fluid inside the oil-filled cylindrical chamber. The drop weight and the piston move downward with the same velocity. At the same time, the piston skins rapidly into the oil-filled chamber into which the crusher gauges and the reference transducers are mounted. Its energy is then transformed to the fluid as compression energy which causes a pressure increase. After releasing the total energy, the maximum pressure is reached and the reverse motion of the piston and drop weight starts. They are pushed upwards with the same velocity until the piston is stopped and the falling mass rebounds, and is generally caught. During this process, a pressure pulse is generated, which is similar to a single half cycle of a sine wave. This pressure curve pattern is quite similar to real gas pressure variation inside fired ammunition; both in its duration and in its shape. Hence, the pressure pulse generator is still used for a comparison calibration based on a reference sensor which provides the reference pressure measurements. The aim of this method is to check that the dynamic behavior of the crusher gauge can mimic the real gas pressure which certainly improves the accuracy of the measurement. The plastic sensitive element is calibrated by this method, which can eliminate or reduce the static and dynamic difference produced by the past static calibration and the dynamic use. The peak value $P_m$ and pulse width $\tau$ of the pressure pulse can be changed by adjusting the falling mass $m$, the drop height $h$, the piston area $S$, the initial volume of the oil-filled chamber $V_0$, etc. [8, 10].

![Figure 1. The principle of the hydraulic pressure pulse generator.](image-url)
Four crusher gauge mounting holes (A, B, C, D) and four reference sensor mounting holes (1, 2, 3, 4) are evenly distributed around the cylinder chamber as shown in Figure 2. To perform a quasi-dynamic calibration, the reference transducers should be installed into the sensor mounting hole on the cylinder. The plastic sensitive elements should be placed into the crusher gauge, and the crusher gauges should be tighten in its mounting holes. In the crusher gauge measuring range, 7 to 9 pressure points are set evenly for calibration. The average pressure value of four reference pressure sensor which is measured by the reference pressure measurement system is regarded as the standard pressure. The piezoelectric pressure transducers Kistler type 6213BK (RS) delivers low amplitude and high impedance charge signal, generally expressed in pico-Coulomb (pC). Thus, a charge amplifier Kistler type 5018A1000 with scale factor of 100 MPa/V is used. The data acquisition (DAQ) board consists in a multi-channel device of four high speed digitizers. Each digitizer has 4 channels of parallel with a resolution of 14 bits and a maximum sampling rate of 10 MHz. The major conversion occurring in the DAQ board is an analog to digital conversion. In addition, signal processing was performed with programs developed with the LabVIEW software [16]. A Butterworth phaseless filter was used. For all signals, the frequency domain transform was computed by DFT for optimizing the filter cut off to the signal. After the experiment, the relationship between the standard pressure and the mean value of the deformation of the plastic sensitive element is established. Using the polynomial regression technique, the regression equation between the peak pressure and deformation of copper cylinders (height after compression for copper sphere) can be obtained. According to this, the dynamic pressure conversion table of the plastic sensitive element is compile. [8-10].

![Figure 2. The position of the mounting hole of crusher gauges and reference sensors.](image)

3. The Neural Network Model of Crusher Gauges Based on Quasi - Dynamic Calibration

3.1. The Basic Principles of RBF Neural Network

(1) The structure of RBF neural network

RBF neural network is a kind of multi-layer forward network structure with single hidden layer. RBF neural network includes the input layer, the hidden layer and the output layer [17]. The structure of typical RBF neural network is shown in Figure 3.
Figure 3. Structure of radial-based function (RBF) neural network.

The network has \( n \) inputs, \( h \) hidden nodes, \( m \) outputs, in which \( x = (x_1, x_2, ..., x_n)^T \in \mathbb{R}^n \) is the input vector of the neural network, \( W \in \mathbb{R}^{h \times n} \) is the weight matrix, \( y = [y_1, y_2, ..., y_m]^T \) is the output of the RBF neural network, \( \Phi_i(*) \) is the activation function of the \( i \)-th hidden layer node, and the radial-based function is used as the activation function of the hidden layer neuron. Generally, the Gauss function is chosen as the radial-based function.

The output of hidden layer neurons is:

\[
\Phi_i(x, c_i) = \exp \left( -\frac{1}{2\sigma_i^2} \| x - c_i \|^2 \right)
\]

(1)

Where \( c_i \) the center of Gaussian basis is function and \( \sigma_i \) is the variance of the Gaussian basis function.

The output layer neuron nodes use the Purelin function to weight the output generated by the neurons of the hidden layer, which can be expressed as:

\[
y_k = \sum_{i=1}^{h} w_i \Phi_i(x, c_i)
\]

(2)

Where \( w_i \) represents the weight between the \( i \)-th neurons in the hidden layer to the one in the output layer, and \( h \) represents the number of neurons in the hidden layer.

(2) The training process of RBF network

There are two types of parameters to be determined in the network: center \( c_i \) and width \( \sigma_i \) of the radial basis function, and the weights between the hidden layer and output layer. The training process of the network is composed of two steps: the determination of the center and width of the radial basis function, and the training of the weights \( W \) between the output layer and the hidden layer. The K-means clustering algorithm is usually adopted to determine the center and the width of the radial basis function, and improved LMS algorithm is applied to tune the weight.

3.2. Establishment of RBF Neural Network Fitting Model

According to the basic principle of the RBF neural network, the peak pressure \( mP \) is selected as the input parameter of the RBF neural network based on quasi-dynamic calibration model. The output parameter is the deformation of the plastic sensitive elements \( y \). So that it can be determined that the number of the nodes in input layer is 1, and that in output layer is the same. The structure of RBF neural network model for the plastic sensitive element based on quasi-dynamic calibration is shown in Figure 4.
Figure 4. Structure of RBF neural network for quasi-dynamic calibration model.

The quasi-dynamic calibration experiments will be carried out for a batch of copper cylinder in order to test the prediction effect of the neural network model for quasi-dynamic calibration.

4. Quasi - Dynamic Calibration Experiments

4.1. Quasi-Dynamic Calibration Experiment and Data Processing

The quasi-dynamic calibration device which was developed by our research group is used as experimental equipment. The four Kistler 6213BK quartz high-pressure sensor are used as the "standard pressure sensor", and its calibrated range is 0 to 800MPa. The objects to be calibrated are 3.5mm × 8.75mm copper cylinder. The experimental temperature is 20℃ ± 1℃. The pulse width of the half-sine wave pressure pulse is 6 ± 0.6ms. 9 pressure points are set approximately in the range of copper cylinders, in which the peak pressure and deformation of plastic sensitive elements are measured.

The experimental data of the copper cylinders in the pressure range of 200MPa to 700MPa (that is, the training sample of neural network) are listed in Table 1. Among them, \( P_\text{m} \) is the average peak pressure of four "standard pressure sensors", and \( y \) is the average of deformation of four copper cylinders.

| Calibration point | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   |
|-------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| \( P_\text{m} \)/(MPa) | 214.78 | 269.24 | 379.95 | 429.85 | 486.25 | 528.49 | 563.22 | 655.96 | 689.31 |
| \( y \)/(mm)       | 0.073 | 0.391 | 1.063 | 1.378 | 1.746 | 2.011 | 2.219 | 2.750 | 2.962 |

In order to further test the accuracy of the neural network model, the test samples shown in Table 2 are given.

| Table 2. The testing samples |
|-----------------------------|
| \( P_\text{m} \)/(MPa) | \( y \)/(mm) |
| 331.51 | 0.767 |
| 612.73 | 2.530 |

4.2. Training and Learning of Neural Network Model

In order to improve the training efficiency of the network, the training samples are normalized, and the data in Table 1 and Table 2 are mapped to [0,1] by using formula (3).

\[
\hat{P} = \frac{P - P_{\text{min}}}{P_{\text{max}} - P_{\text{min}}}
\]
After training, we also need to use the formula (4) to restore the data.

\[ P = \hat{P} \left( P_{\max} - P_{\min} \right) + P_{\min} \]  

(4)

where \( P \) is the original data; \( P_{\min} \) and \( P_{\max} \) are the minimum and maximum of the sample; \( \hat{P} \) is the data after normalized pretreatment.

Under the environment of MATLAB R2013a, the RBF neural network prediction model is designed, trained and tested for the network after training. Set the training accuracy to 0.00001. Use the training sample data to train the model. During the training process, adjust the expansion factor to tend to the correct value and minimize the error. K-means clustering algorithm is used to select the center and width of the neural network, and the iterative LMS algorithm is used to adjust the connection weights between the output layer and the hidden layer. The RBF neural network model is trained by the newrb function provided by MATLAB neural network toolbox. The training results for the RBF neural network model of copper cylinders based quasi dynamic calibration are shown in Figure 5. It can be seen that the training goal can be achieved with a smaller number of iterations.

![Figure 5. Training results of RBF network.](image)

Finally, the parameters of RBF neural network prediction model with the best prediction effect are listed in Table 3.

| Parameters                                      | Parameter Value |
|-------------------------------------------------|-----------------|
| Neural Network Structure                        | 1-2-1           |
| Training function                               | newrb function  |
| Radial basis function                           | Gaussian function|
| Test Function                                   | sim function    |
| The mapping function between hidden layer and output layer | Purelin function |
| Maximum number of neurons in hidden layer       | 100             |
| Target error(Goal)                              | \(1 \times 10^{-5}\) |
| Spread factor                                   | 1.9             |

### 4.3. Comparison of the Fitting Accuracy between the Neural Network Model and the Traditional Empirical Model

According to the polynomial regression model in references [10], the relationship between the peak pressure \( P_m \) and the deformation \( y \) of the copper cylinders can be obtained by polynomial fitting to the data in Table 1 as shown in formula (5).
The residual standard deviation of the model is 0.0145mm and the correlation coefficient is 0.9999.

According to the modeling method in references [11], the exponential fitting relation between $P_m$ and $y$ can be obtained as shown in formula (6).

$$y = -1.2939 + 0.0064 \times P_m - 2.5855 \times 10^{-7} \times P_m^2$$

(6)

In order to verify the generalization ability of constructed neural network, two test samples are selected to test the training accuracy. The relative error between the test sample values and the corresponding fitting values of neural networks, polynomial fitting values and exponential fitting values are given in table 4.

|                          | Peak pressure 331.51(MPa) | Peak pressure 612.73(MPa) |
|--------------------------|---------------------------|----------------------------|
|                          | deformation of copper cylinders /mm | Relative error/% | deformation of copper cylinders /mm | Relative error/% |
| Test samples              | 0.767                      | —                         | 2.530                      | —                         |
| Neural network model      | 0.764                      | 0.39                      | 2.518                      | 0.47                      |
| Second order polynomial fitting | 0.785                      | 2.35                      | 2.504                      | 1.03                      |
| Exponential fitting       | 0.492                      | 35.85                     | 2.903                      | 14.74                     |

From the comparison results in Table 4, the maximum relative error predicted by the neural network model of copper cylinders based on quasi-dynamic calibration is no more than 0.5%. The fitting value of RBF neural network is closest to the experimental value, and the precision of the second order polynomial fitting model is second, the precision of the exponential fitting model is the worst.

5. Conclusion
1) Based on the characteristic of RBF neural network that can approximate any nonlinear function with arbitrary precision, a neural network fitting model is established, which takes the peak value of pressure pulse as the input and the deformation of the plastic sensitive element as the output.

2) According to the neural network model of a batch of copper cylinder based on quasi-dynamic calibration, the prediction value of the neural network model is closest to the test sample value, and the accuracy of the prediction model is better than 0.5%. The predicted value of the second-order polynomial fitting model is close to the experimental sample value, and prediction accuracy of the second-order polynomial fitting model is better than 3%. Hence the exponential fitting model has the worst prediction accuracy. Therefore, applying the neural network in the quasi-dynamic calibration experiment of plastic sensitive elements can obtain a quasi-dynamic calibration model with higher accuracy, which lays a foundation for making the high accuracy pressure conversion table.

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