Analysis of 3D In-situ Stress Field and Query System’s Development Based on Visual BP Neural Network

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Abstract

In-situ stress field is very important in the numerical simulation and stability analysis as well as in the engineering design and construction. So it requests an effective analysis method. The typical in-situ stress analysis method is multivariate regression, which is based on 3-D FEM direct modeling, but it may be not so accurate to obtain the distribution of in-situ stress field of the project, because when the multivariate regression is carried out, the cross influence of the main factors of in-situ stress field is ignored, and the relationship of in-situ stress field and the main factors is too complicated to express by subharmonic multivariate function. This paper presents an improved method back propagation (BP) neural network back analysis of in-situ stress field, based on the calculated results of multivariate linear regression analysis. For in the ANN (Artificial Neural Networks) method, the training samples are difficult to generate, while combining the linear regression method with ANN method this problem can be solved perfectly. Linear elastic multivariate regression is carried out to determine the general bounds of optimized paraments, and uniform design method is carried out to settle different combinations of factor levels. Training samples are gained by FEM analysis. And the visual neural network by using ActiveX technology is realized in this paper, by taking full advantages of strong capability in computing of Matlab and features of friendly interface of VB perfectly. In fact, one needs to know the status of the in-situ stress field at some important location in the engineering, by using neural network method, intelligent expression method of the in-situ stress field is presented, and the developed man-computer interface has the property of easy use in the actual engineering.

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1. Introduction

In-situ stress field information is very important in the numerical simulation and stability analysis as well as in the engineering design and construction, as we know that, in situ measurement is the most direct way to get the in-situ stress field data, but it’s impossible to carry out in situ measurement in large scale. On the other hand, since the complexity of in-situ stress’ causes of formation and the excessive impact working on, the measured results are in fact only the reflection of a local stress field. Furthermore, since measured results are affected by the errors, they are discrete to some extent. So, to satisfy the need of engineering design and construction in a more reasonable way, it is necessary to carry out the in-situ stress regressive analysis combining the in-situ geological conditions, through effective analysis method, and based on in-situ measurements. The method proposed in this paper combines the advantages of the multi-factor regression analysis [1-5] and the back propagation (BP) artificial neural network theory[6-10]. The training samples of the neural network are generated by making use of the results of the multi-factor regression analysis, which can avoid the blindness of sample generation. And also it makes the network generalization into interpolation problem, which can improve the network learning speed and training precision. We can compute the displacement boundary conditions of the geological model by utilizing the highly nonlinear characteristics of the artificial neural network, and then apply the obtained boundary conditions to the main analysis program, so the simulation of the initial in-situ stress field in the engineering area can be done. Meanwhile, in order to take advantages of matlab in calculation and flexible of VB in convenient, ActiveX technology is introduced to realize visual neural network. Then, the query system is developed in the platform of the visual neural network. During training, take coordinates of the X, Y, and Z of each node in the finite element calculation model as input, and take the six corresponding stress components of the calculated result as output. After completing the learning function, take the coordinate of a certain position needed to know as input of the neural network that has been well trained. Then neural network will output the corresponding six stress components of the position. Furthermore, the principal stress, dip angle and azimuth of the position can be calculated according to them, and the developed man-computer interface has the property of easy use in the actual engineering.

As the methods of multi-factor regression analysis and back propagation (BP) artificial neural network are involved, so they are introduced briefly as follows.

2. Principle of multi-factor regression

On the basis of the geological mechanics analysis, the in-situ stress mainly comes from the self weight and the geological tectonic stress field. The analysis for the in-situ stress constructs the numerical computation model on the basis of such a viewpoint, and carries out fitting analysis using multivariate regression analysis method.

From the principle of multivariate regression method, we take the computational value of in-situ stress $\hat{\sigma}_k$ as the dependent variable, and take the self weight stress and the computational stress $\sigma^i_k$ which corresponding the FEM computation and the in situ measurement as the independent variable, then the regression equation take the form as :

$$\hat{\sigma}_k = \sum_{i=1}^{n} L_i \sigma^i_k$$

(1)

3. BP neural network model

As BP neural network has self-adapting and self-organization ability and such features as strong
generalization capability and strong fault tolerance capability, so we can say that BP neural network
embodies the essential part of artificial neural network. BP neural network extracts the implicit pattern
characters of input function, when the study pattern is provide to the network, neurons are activated and
propagated from input layer to output layer through hidden layer, and finally propagating the output
information of hidden nodes into the nodes of output layer upon the operation of activation function of
each unit and then obtaining the actual output value of each unit. Then, if the expected output value is not
obtained from the output layer, the difference (namely error) between the actual output value and the
expected output value shall be calculated and then the error signal returns along the original connection
route; the error signal is propagated into the input layer to be calculated by modifying the weight of each
layer of neurons and then reaches the allowable range through the continuous iteration of this forward-
propagating process[8].

In order to avoid the problem of slow convergence speed and falling into local minimum easily,
Levenberg—Marquardt algorithm is adopted to train BP neural network, in which Heun matrix is not
calculated directly, so the training computational and memory demand is reduced. As BP neural
network’s performance function is MSE (mean square error), Heun matrix can be obtained by Jacobian
matrix approximately, and the network weights can be adjusted by the following formula:

\[ \omega_{k+1} = \omega_k - (J^T J + \mu I)^{-1} J^T e \]

Where: \( e \) is error vector, \( J \) is the Jacobian matrix of error vector \( e \) to network weight \( \omega \), \( \mu \) is a scalar.
When \( \mu \) is very small, the algorithm becomes Newton method, but when \( \mu \) is very big, the algorithm turns
into steepest descent method (time step is \( \mu^{-1} \)). Because Newton method converges faster, the value of \( \mu \)
should be decreased after every successful iteration, otherwise it should be increased, and this ensures that
the error function is always reduced. Meanwhile, in order to improve training precision of BP neural
network, the samples are often processed pre-and postly. In this paper, "standardized approach" is used to
process the samples to make it in \([0,1]\).

4. Visual neural network model by mixed programming

ActiveX automation is one of ActiveX protocols, which permits the control of one application program
or component to another. It contains automatic servers and controllers. ActiveX component supplied by
Microsoft Corporation is a new protocol applied to module integration. Meanwhile, it is an extension of
the VB toolbox as well as some executable codes written according to the ActiveX criterion, such as a
document of .EXE, .DLL or .OCX. ActiveX will be a portion of the development and running
environment after it is added to the program. As a result it can provide new functions for the application
program. The attributes, events and methods of a few common VB controllers are reserved in ActiveX
assembly, and the specific methods and attributes of ActiveX assembly make the programming more
powerful and flexible.

Matlab is also software supporting ActiveX automation technique, which can be controlled by any
Microsoft programs that can be used as ActiveX program, including Excel, Access, Visual Basic and
Visual C++. User can use Matlab conveniently in his own programs by making use of this characteristic,
including executing Matlab commands, using its toolbox with rich functions, inputting data to it and
obtaining results. In this way not only beautiful visual Windows programs can be compiled by vb but also
various toolboxes of Matlab can be acquired to make assistant decision, design and simulation.

5. Application

5.1. Site description
Yangjiang Pumped Storage Plant is located in the Bajia Mountain across Yangchun City and Dianbai County, in southern China's Guangdong province. In order to study the in-situ stress distribution of the engineering area, the in-situ stress measurement was successively done in the underground powerhouse, and high pressure branch pipes by the deep-hole stress relief method, which can provide evidence for the arrangement scheme of the engineering structures, selection of the excavation methods, the stability analysis and supporting design of every building. Having taken many factors such as the characteristics of topography and geomorphology into account comprehensively, the calculation range can be determined. The range is that length×width=3000m×2000m, bottom elevation V-1000m. And it includes portion of the upper and lower reservoirs, diversion tunnel, high pressure branch pipe, underground powerhouse, tailrace surge tank, tailrace tunnel and so on. The measuring point is located at the center of the calculation range. Finite element meshes are shown in figure 1.

Fig. 1. FEM Mesh

5.2. Acquisition of neural network samples

It is generally considered that tectonic stress field and gravity stress field are the two main components of rock stress field, while tectonic stress is supposed in horizontal direction and decomposed as Ux, Uy and Uxy, corresponding to the tectonic stress in the north-south direction, tectonic stress in the east-west direction and shear stress in the horizontal plane respectively. Mathematical calculating model can be established according to this, in which gravity factor L1, tectonic displacement Ux, Uy and Uxy are regarded as undetermined factors. In order to determine its range approximately, multiple linear regression analysis can be done once at first, and then regression coefficients of the four independent variables (L1, L2, L3 and L4) can be calculated. So tectonic displacements should be L2×Ux, L3×Uy and L4×Uxy. It can be considered that the result of the regression analysis is an approximate solution, true value of the gravity coefficient and tectonic displacements change around the L1, L2×Ux, L3×Uy and L4×Uxy. So a suitable range can be selected by the experience. By doing this it avoids the blindness of sample generation. And it makes the network generalize into an interpolation problem, which can improve the network’s learning speed and training precision.

According to the measured values, the results of the finite element multiple linear regressions are: L1=1.05, Ux=0.185, Uy=0.19 and Uxy=0.05. So the ranges of L1, Ux, Uy and Uxy are determined as follows: L1 ∈ [0.85, 1.25], Ux ∈ [0.1, 0.4], Uy ∈ [0.1, 0.3], Uxy ∈ [0, 0.15]. Training samples of the neural network can be obtained by adjusting the values of L1, Ux, Uy and Uxy to do the feedforward calculation. Thought of the uniform design is adopted in the value adjustments of the training samples. Table U9*(9^4) is selected to do the design, and every factor takes nine levels.

For every combinatio, finite element forward calculation is done. The results are used as training samples, which will be trained by the BP neural network. 96 calculated values of the in-situ stress components of the 16 measured points arranged in the measuring hole of underground powerhouse and
high pressure branch pipes are used as input values, gravity coefficient L1 and three tectonic displacements Ux, Uy and Uxy are used as output values. Three layer networks are selected in the Network structure, hidden layer has 24 elements, the network structure is 96-24-4, and the Levenberg—Marquardt algorithm is adapted to train. The mapping relation among the stress values of the measured points, gravity coefficient and three tectonic displacements can be obtained, after the training is done. Now the measured value of the measurement points are taken as input value, so the output values are gravity coefficient L1, and tectonic displacements Ux, Uy, Uxy

5.3. Query system’s development

![Fig 2. The stress query system](image)

The result of the initial in-situ stress field is shown in the form of stress in the mesh points. But in real engineering we usually want to know the initial in-situ stress of a certain position or profile, when the interpolation calculation will be needed. As the result of the complexity of the structure model of the initial in-situ stress field, traditional interpolation method is more tedious and time-consuming; this can not meet the requirements of repeated taking value and calculation check. So it is necessary to search for a new method which is simple and suitable for operating to replace the traditional interpolation method. It suggests the method adopting neural network to express initial in-situ stress field, which provides a convenient and efficient intelligent expression method. It makes the complex interpolation work simple and feasible. The stress components of a certain point can be obtained in the VB visual interface by inputting the coordinates of it, which provides convenience for the engineering application. The calculations of the initial stress are used as training samples to train the network. During training, take coordinates of the X, Y, and Z of each node in the finite element calculation model as input, and take the six corresponding stress components as output. After completing the learning function, take the coordinate of a certain position needed to know as input of the neural network that has been well trained. Then neural network will output the corresponding six stress components of the position. Furthermore, the principal stress, dip angle and azimuth of the position can be calculated according to them. Transfer the calculated results to the vb to the human-computer interaction to visualize, as shown in figure 2.

6. Conclusion

The features of the method presented in this paper can be summarised as following:

1. It combines advantages of the multi-factor regression analysis and the artificial neural network theory. The training samples of the neural network are generated by making use of the result of the multi-
factor regression analysis. So, it does not need to adopt the elastic hypothesis of the linear regression and can avoid the blindness of sample generation. And it also makes the network generalize into interpolation problem, which can improve the network’s learning speed and training precision. So it has good development prospect.

(2) It combines the powerful calculation function of Matlab with the VB’s friendly user interface suitable for graphic developing. And ActiveX automation technology is used to carry on the BP neural network calculation by the mixed programming of the two. By doing this not only visualization of the interface is implemented, but also various network models of the Matlab neural network toolbox and many learning algorithms it has integrated are made full use of. Thus, the two can make up for each other’s deficiencies. So the whole performance of the software is improved, and the time and energy the development has taken is saved.

(3) The query system is developed in the platform of the visual neural network. From the query system one can know anyplace’s six stress components in the project. Furthermore, the principal stress, dip angle and azimuth of the position can be calculated according to them, and the developed man-computer interface has the property of easy use in the actual engineering.

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