Dynamic Response Prediction of Underwater Explosion Vessels

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Abstract. In order to ensure the safety of the underwater explosive vessel in service, it is necessary to analyse the dynamic response of the underwater explosive vessel. The dynamic response model based on Classification and Regression Tree is established to simulate the mapping relationship between load and container strain. A reliable and stable model is obtained by cross validation. At the same time, compared with Multi-Layer Perceptron model, CART model is faster and more accurate in training, and the prediction effect is obviously better than Multi-Layer Perceptron model, which further explains the validity of CART model and provides a better method for dynamic response prediction of container.

Keywords: Dynamic response; Decision tree; Multi-layer perceptron; Prediction.

1. Introduction

The underwater explosion vessel simulates various water depth conditions by loading a certain hydrostatic pressure. In order to ensure the safety of underwater explosive vessel in service and prevent the damage of underwater explosive shock wave and other explosive products to experimental personnel and equipment, it is necessary to analyze the response and performance of underwater explosive vessel under load [1-2]. Because the uncertainties of the underwater explosion vessel itself also affect the control effect of the structure, the calculation process using theoretical analysis and numerical simulation [3-6] is complex and some parameters are difficult to obtain. The analysis results often fail to reflect the dynamic response state of the vessel during service. Using intelligent algorithm to simulate the mapping relationship between load and container, dynamic strain prediction is carried out, which provides a feasible method for dynamic response prediction of container.

With the further development of machine learning, more and more scholars have applied machine learning to the field of dynamic response analysis and prediction of Engineering structures. Du Yongfeng [7-11] and others use RBF, BP, convolution and other neural networks to model and predict. Wang Li [12-16] and others used optimization algorithm combined with neural network model and hybrid model combined with the two models to predict. CART [17-18] can be used for both classification and regression. When data sets often contain some complex relationships, the relationship between input data and target variables is non-linear. Tree structure is a feasible way to model these complex relationships. In this study, the regression tree algorithm of CART is used to realize dynamic response prediction of underwater explosive vessel. MLP [16-20] neural network model is established to compare with it, and the performance of the prediction model of CART regression tree is analyzed, which provides multi-model reference for dynamic response prediction of underwater explosive vessel.
2. Analysis of Influencing Factors and Data Acquisition

The cylindrical underwater explosive vessel \cite{21} with 10g TNT equivalent which can simulate the depth of 200 meters was taken as the research object. During the test, the main factors that affect the maximum strain of the container are the charge quantity and the loading hydrostatic pressure. At the same time, according to the different positions of the strain gauge at the test point (including the position of the container (3 positions), the mounting method (5 ways), and the lead position of the strain gauge (3 positions)), three corresponding variables are obtained. In order to establish the model, these three position variables are treated as virtual variables, which defines the virtual variable of vessel position, mounting method and lead position of strain gauge:

\[
P_{1i} = \begin{cases} 
1, & \text{contain position } i \\
0, & \text{others} 
\end{cases}, \quad i = 1, 2, 3,
\]

\[
P_{2i} = \begin{cases} 
1, & \text{mounting method } i \\
0, & \text{others} 
\end{cases}, \quad i = 1, 2, 3, 4, 5,
\]

\[
P_{3i} = \begin{cases} 
1, & \text{the lead position } i \\
0, & \text{others} 
\end{cases}, \quad i = 1, 2, 3
\]

They turn out to be 11 variables. Fourteen variables including time, charge amount, hydrostatic pressure and eleven dumb variables of the position of strain gauge, were used as the influencing factors of dynamic response in underwater explosion test. The underwater explosion tests of explosives with 0.8g and 2.4g TNT equivalent were carried out under 8 working conditions with hydrostatic pressure of 0, 0.3, 0.5, 0.8, 1, 1.3, 1.5, 1.8 and 2MPa. In order to reduce the test cost and obtain more test data, three strain test points are arranged at the top and middle sides of the vessel head, 15 strain test points are arranged at each position, and the dynamic monitoring of the vessel is carried out. Finally, 855 samples (2.4 g TNT equivalent explosive is tested twice at 1.5MPa hydrostatic pressure) should be obtained. The test data of underwater explosion under 18 working conditions are sorted out, and the uncollected data are removed. Only 782 samples are obtained from the actual test. The actual sample size under each working condition is shown in Table 2.1.

**Table 1.** Actual sample size per working condition.

| Dosage (g) | Pressure (MPa) | 0  | 0.3 | 0.5 | 0.8 | 1  | 1.3 | 1.5 | 1.8 | 2  |
|-----------|---------------|----|-----|-----|-----|----|-----|-----|-----|----|
| 0.8       |               | 43 | 42  | 43  | 43  | 42 | 39  | 42  | 43  | 42 |
| 2.4       |               | 43 | 41  | 43  | 43  | 41 | 43  | 65  | 43  | 41 |

3. Data Pre-processing

3.1. Missing Value Processing

The experimental data should collect 855 samples, but only 782 valid samples are obtained. Because each patch in the experiment can produce 3 data, 73 null sample data in the experiment. In order to avoid the possibility of introducing new noise data due to improper processing, the method of deleting the null value is directly used to process the missing value.

3.2. Abnormal Value Processing

Because the data are obtained by actual measurement, there are many uncertainties in the process of data acquisition. Some abnormal values may occur due to the noise interference of instruments, measuring systems and human factors, which may lead to errors in the accuracy of model prediction. In order to improve the accuracy of prediction, it is necessary to clean the experimental data. In this study, Isolation Forest method was used to detect and eliminate abnormal values of experimental data.
Isolation Forest make use of the characteristics of fewer and different outliers. Only a small part of training data is used to build an effective model to isolate outliers quickly. It has the characteristics of linear time complexity, high precision and low memory requirement, and can effectively process large data. This algorithm is suitable for dealing with abnormal data caused by experiment acquisition or recording problems, and can cluster multi-variables without setting label variables. In this study, the number of forests was set to 100, the maximum number of sampling was set to 256, and the proportion of outliers in the data set was set to 0.05. These parameters were brought into the program to run. The results showed that 40 outliers were removed and 742 sample data remained. The comparison of data before and after eliminating outliers is shown in Figure 1. After eliminating the outliers, the mean value of the sample decreased from 88.34 to 77.60, and the standard deviation decreased from 81.40 to 36.55, which reduced by 55.10%, making the data more concentrated on the mean value of the sample.

![Sample](image)

**Figure 1.** Treatment results of Isolation Forest.

### 3.3. Data Standardization
Because the value difference between different features is large and the distribution is discrete, it is necessary to unify the dimension of these data and standardize the data for later processing. In this paper, min-max normalization, also known as deviation normalization, is used to standardize the data. Its standardization is a linear transformation of the original data, which maps the result value to 0-1. The conversion function is as follows:

\[
x' = \frac{x - \min}{\max - \min}
\]

Among them, Max is the maximum value of sample data and min is the minimum value of sample data.

### 4. Construction of Dynamic Response Model
Fourteen variables including time, charge amount, hydrostatic pressure and eleven dumb variables of the position of strain gauge, were selected as input variables, maximum strain of container was taken as output variable, and the mapping relationship between load and strain of container was simulated, and the prediction performance of the model was verified by cross-validation method.
4.1. Classification and Regression Tree regression Model

4.1.1. Feature Selection. Fourteen variables including time, charge amount, hydrostatic pressure and eleven dumb variables of the position of strain gauge, were selected as feature vectors.

4.1.2 Generation of Classification and Regression Tree. Firstly, starting from the root node, 80% of the sample data are placed as training samples at the root node. By choosing the best feature, Boolean judgment is made at each node. If the judgment is true, it is classified as left subtree, and the rest is classified as right subtree, i.e. recursive dichotomy of each feature, so the training data set is divided into finite subsets.

The partition of subsets can be described as: for input variable $x$ and output variable $y$, when the $j$ eigenvector $x^{(j)}$ and its value $s$ are selected as partition points, two subsets are defined.

$$ R_i(j,s) = \{x \mid x^{(j)} \leq s\} $$  \hspace{1cm} (2)

$$ R_i(j,s) = \{x \mid x^{(j)} > s\} $$  \hspace{1cm} (3)

In the formula, $R_i(j,s)$ denotes the left subtree partitioned by the value $s$ of the $j$th eigenvector, $R_2(j,s)$ denotes the right subtree partitioned by the value $s$ of the $j$th eigenvector, and the best partitioning variable $j$ and the best partitioning point $s$ are obtained:

$$ \min_{j,s} \left[ \min_{x_i \in R_1(j,s)} \sum (y_i - \bar{y}_1)^2 + \min_{x_i \in R_2(j,s)} \sum (y_i - \bar{y}_2)^2 \right] $$  \hspace{1cm} (4)

$$ \bar{y}_1 = \text{ave}(y_i \mid x_i \in R_1(j,s)) $$  \hspace{1cm} (5)

$$ \bar{y}_2 = \text{ave}(y_i \mid x_i \in R_2(j,s)) $$  \hspace{1cm} (6)

$y_i$ is the output variable corresponding to the input variable $x_i$, $x_i \in R_1(j,s)$ is the input variable belonging to the left subtree under the value $s$ partition of the $j$ eigenvector. By traversing all input variables, the best partitioning variable $j$ and the best partitioning point $s$ are found and a pair $(j,s)$ is formed. Then the set is divided into two subsets, and the partitioning process is repeated until the stopping condition is satisfied.

4.1.3 Pruning of Regression Trees. In order to avoid the over-fitting phenomenon of the generated regression tree, it is necessary to restrict the growth of the tree in order to obtain better generalization ability of the model. In this study, pre-pruning method is used and cross-validation is carried out. The minimum number of samples required for partitioning is 5, i.e., the number of samples at a node is less than 5, and no further partitioning is carried out.

4.2. Multi-Layer Perceptron Model
Multi-Layer Perceptron model adopts the classical three-tier full connection mode, that is, it contains only one hidden layer, and its structure is shown in Figure2.
Figure 2. MLP model structural diagram.

Among them, 14 nodes in the input layer correspond to 14 input variables, 10 nodes in the hidden layer and one node corresponds to the output strain. The activation functions of the hidden layer and the output layer are tanh function and sigmoid function, respectively. Their formulas and images are shown in Figures 3 and 4. The value range of tanh function is between \([-1,1]\], and the mean value is 0. In fact, tanh function has the effect of normalization. The value range of Sigmoid function is between \([0,1]\), so it is better to calculate the output value.

\[
sigmoid : a = \frac{1}{1 + e^{-z}}
\]

\[
tanh : a = \frac{e^z - e^{-z}}{e^z + e^{-z}}
\]

Figure 3. Sigmoid images and formulas. Figure 4. Tanh images and formulas.

The training parameters of MLP neural network are chosen as default parameters, and the initial value of learning rate is 0.001, which is used to update the weight compensation. Using MATLAB tool to train the experimental data into the neural network, it is found that the number of hidden layer nodes and learning rate have the greatest impact on the convergence of the network and the speed of convergence. The more hidden layer nodes in a certain range, the greater the possibility of convergence and the smaller the learning rate. The training results show that the network converges when the number of hidden layer nodes is 10 and the learning rate is 0.002.

4.3. Model Evaluation Index

The fitting results of the two models for training samples are shown in Figure 5, and the prediction results for testing samples are shown in Figure 6. The training errors and testing errors of the two models are shown in Table 4.1. The evaluation indexes of the model include mean square error (MSE), mean absolute error (MAE) and mean absolute percentage error (MAPE). Their formulas are as follows:

\[
MSE = \frac{1}{N} \sum_{i=1}^{N} (\hat{y}_i - y_i)^2
\]  
(7)
\[ MAE = \frac{\sum_{i=1}^{N} |\hat{y}_i - y_i|}{N} \]  
\[ MAPE = \frac{\sum_{i=1}^{N} |\hat{y}_i - y_i|}{\sum_{i=1}^{N} y_i} \]  

Figure 5. Fitting results of training samples.  
Figure 6. Prediction results of test samples.
### Table 2. Comparison of training errors and testing errors between the two models.

| Model index | Training set MSE | Test set MSE | Training set MAE | Test set MAE | Training set MAPE | Test set MAPE |
|-------------|------------------|-------------|------------------|-------------|------------------|-------------|
| CART        | 1.42             | 1.90        | 0.98             | 1.17        | 1.73             | 1.79        |
| MLP         | 3.79             | 3.18        | 1.66             | 1.53        | 3.18             | 1.79        |

From the evaluation indexes of the two models in the table, it can be seen that the training and testing errors of CART are smaller than those of MLP. Therefore, the dynamic response prediction model of underwater explosive vessel is established by using CART in this study.

### 5. Conclusion

- This paper constructs a data pre-processing method and uses Isolation Forest method to eliminate abnormal data, which effectively improves the quality of sample data.
- In the analysis of the influencing factors, considering the service life of the vessel, the number of experiments is taken as the influencing factor of the dynamic response prediction of underwater explosion vessel.
- A prediction model of dynamic response of underwater explosion vessel based on CART regression tree is proposed in this paper. Compared with MLP neural network model, the prediction accuracy of CART model is higher and the prediction performance of CART model is obviously better than MLP model. This provides a reliable model for dynamic response prediction of underwater explosive vessel.

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