AE-BP Based Prediction Algorithm for Vibration Anomaly Detection and Intelligent Control of Civil Structures

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Abstract: *Intelligent structures utilize neural networks for intelligent controller prediction, allowing vibrating structures to adaptively adjust their state under dynamic loading. Intelligent structure technology plays a crucial role in preventing the loss of life and the destruction of structures, especially for large structures with hundreds or thousands of members, and their contents. Therefore, to address the problems of unknown time-varying characteristics of the structural system and uncertainty of the environmental loading of the structural system in the vibration control of large nonlinear structures, this paper designs a smart structure technique based on a self-encoder and BP neural network. The technique aims to detect vibration anomalies in civil structures and predict them for intelligent control. This paper firstly introduces the concept of structural vibration control, selects intelligent control for prediction, and proposes an anomaly detection algorithm based on AE to detect structural vibration anomalies. Through comparison experiments of BP neural networks and LSTM, the BP neural network is finally selected for the intelligent control prediction of civil structure vibration.*

Keywords: *Intelligent control prediction; AE; BP; LSTM*

1. Contexts

1.1 Structural Vibration Control

Structural vibration is usually caused by external loads (eg, wind, earthquake, etc.) or internal excitation (eg, mechanical motion). If the vibration amplitude is too large or the frequency is close to the intrinsic frequency of the structure, it may adversely affect the safety, comfort, and service life of the structure. Therefore, it is crucial to fully consider structural vibration during the phases of structural design, construction, and operation. By using vibration analysis and structural optimization methods, engineers can effectively assess the vibration response of a structure and take the necessary measures to reduce the vibration amplitude and ensure the safe operation of the structure.

Structural vibration control is an engineering technology aimed at reducing or suppressing the vibration of buildings, bridges, mechanical equipment, and other structures when they are subjected to external or internal excitation. This is achieved through the application of different control strategies and devices to improve the stability of the structure. The main goal is to ensure that the structure remains stable and safe under different excitations while providing a comfortable operating environment and increasing the structure's lifetime. Structural vibration control strategies can be passive, active, or semi-active. Passive vibration control uses energy dissipators (eg, dampers) to absorb vibration energy and thus reduce the vibration response. Active vibration control, on the other hand, utilizes actuators and sensors installed in the structure to sense the vibration response of the structure in real-time and apply the appropriate control forces to counteract or reduce the vibration. Semi-active vibration control combines characteristics of both passive and active control, using adjustable dampers or force elements to adjust control parameters based on real-time vibration response information. The three control strategies are shown schematically in Figures 1-3. These methods can often be used individually or in combination, depending on the characteristics of the structure, the environment in which it is used, and the complexity of the vibration problem.

The objectives of structural vibration control include:

Improving the stability and safety of the structure to ensure that the structure will not be

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destabilized or damaged by natural disasters or other external loads.

Improving the comfort of the structure and reducing the discomfort of vibration on people or equipment inside the building.

Increasing the service life of the structure, reducing vibration-induced fatigue damage, and extending the life of the structure.

Structural vibration control technology is widely used in civil engineering, aerospace, mechanical engineering, and other fields, providing an effective means to improve the performance, reliability, stability, safety, and comfort of structures, meeting their design requirements and usage needs.

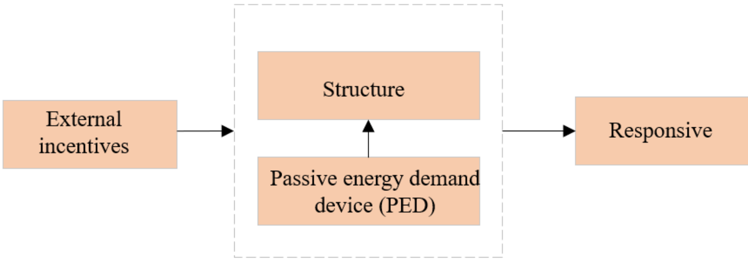

Figure 1: Active control

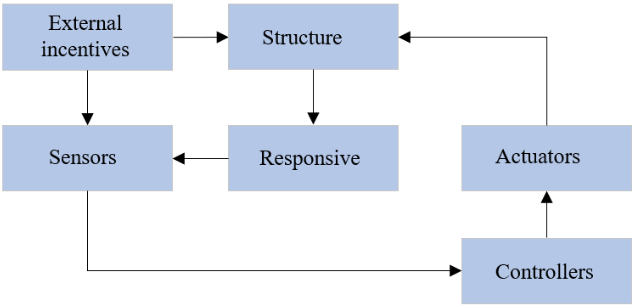

Figure 2: Passive control

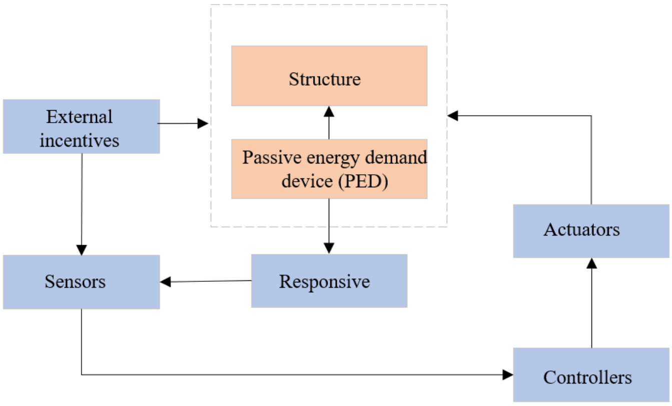

Figure 3: Hybrid control

1.2 Intelligent control

The concept of intelligent control was first introduced by Fu with the aim of enhancing and extending the applicability of automatic control systems[1]. As the design of civil engineering structures became more flexible, their increased complexity drove the development of controllers. Unlike traditional control systems, intelligent control systems do not require complex mathematical models but rely on knowledge bases and rule bases to simulate and replicate human thinking and decision-making processes. Unlike traditional active control, intelligent systems do not need to deal with lengthy mathematical models of the controlled structure; they only need to set up a simple control method based on engineering experience. Therefore, intelligent control has an important role in complex

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structural control systems.

In a broad perspective, intelligent systems are based on soft computing technology. Intelligent control integrates computational processes, reasoning and decision making and uses the level of accuracy or uncertainty in the available information as a design parameter. As a result, intelligent control systems are more realistic and multiple solutions usually exist to choose from. This requires the designer to choose from a set of non-dominated solutions. Currently, the best known hybrid systems are neuro-fuzzy and genetic fuzzy systems.

Fuzzy controllers do not involve complex mathematical computations and the entire fuzzy controller can be easily implemented on a parallel fuzzy digital signal processing (DSP) board[2], which ensures immediate response time and reduces time lag. Fuzzy systems use fuzzy set theory to represent linguistic and structured knowledge, but it is still up to the experts to build the knowledge base used by the system, so constructing suitable fuzzy IF-THEN rules and affiliation functions remains a tricky problem. In addition, static fuzzy rules and affiliation functions are susceptible to changes in the parameters of the system, and one way to eliminate this sensitivity to parameter changes is to combine a fuzzy system with an artificial neural network (ANN), called hybrid neuro-fuzzy control[3][4].The ANN is capable of learning the changes in the inputs of a given system and adapting to the outputs of of these changes.

1.3 Neural network

The performance of a traditional machine learning model depends on the quality of feature extraction and its workflow is shown in Figure 4.

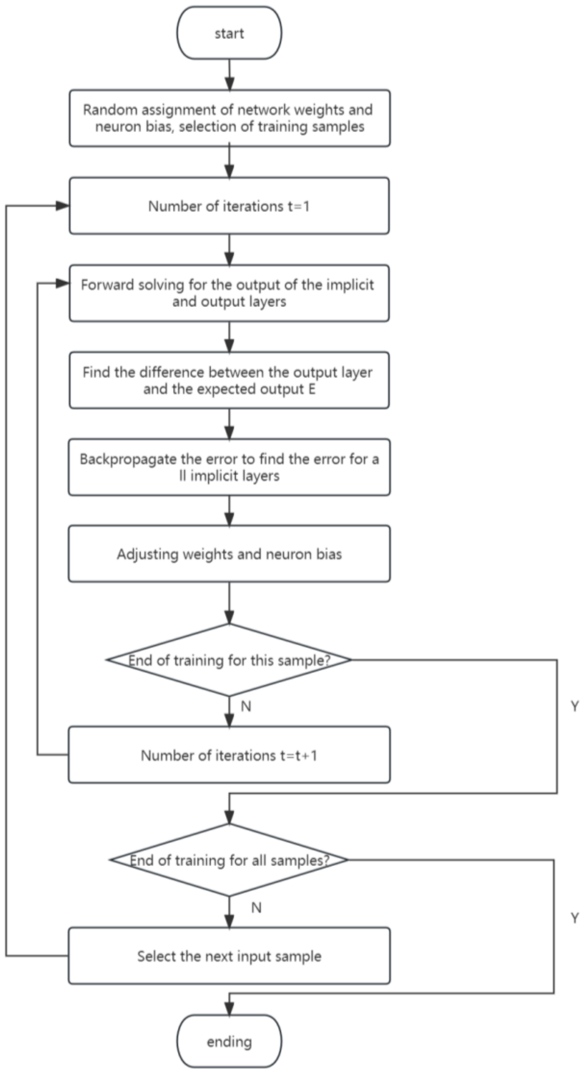

Figure 4: Machine Learning Based Prediction Workflow

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In contrast, deep neural networks have a great advantage in feature learning, i.e., they can automatically transform initial "low-level" feature representations into "high-level" features through multi-layer and non-linear transformations. A fully connected feed forward neural network can approximate any continuous function with any desired accuracy [5].

A neural network is a mathematical model that mimics the transfer of information between neurons in the human brain. In civil engineering vibration control, neural networks can be used to build vibration prediction models to predict future vibration response based on historical vibration data. At the same time, neural networks can also be used for intelligent control to learn and optimize through real-time collected vibration data, and dynamically adjust the control strategy to reduce the vibration response.

Neural networks play an important role in intelligent control prediction of civil structures, and the technology provides civil engineers with an effective tool for real-time monitoring of structural condition, predicting structural performance, and achieving intelligent damage control and optimal design. By combining advanced technologies such as sensor technology, data acquisition system and BP neural network, the intelligent control prediction capability of civil structures will be continuously improved, bringing more benefits to engineering construction and structural safety.

1.4 Anomaly detection

Anomaly detection of civil structure vibration is an important structural health monitoring technology, which aims to monitor the changes of civil structure vibration in real time and detect abnormalities, such as structural damage, fatigue, cracks and other problems. Anomaly detection is particularly important in the intelligent control prediction of civil structures, which helps the intelligent controller to detect the abnormal state of the structure in time, and can assist the controller in adjusting the control parameters of the structure, enhancing the stability and seismic capacity of the structure, preventing accidents and damages, and guaranteeing the safety and reliability of the structure.

2. Research methodology

2.1 BP neural network

BP neural network was proposed by Rumelhart, Hinton and Williams (1986)[6] and is the earliest and widely used neural network. Because of its advantages of simple structure and ability to handle complex nonlinear problems[7], it has become one of the most widely used artificial neural network models for fitting tasks. Several studies have been conducted to confirm the advantages of BP neural networks in prediction. For example, Wong and Chan (2015)[8]found that BP neural networks perform significantly better than linear regression and SVR.Lee, Choeh (2014)[9] and Wong et al. (2017) [10]also found that the prediction performance of BP neural network models outperforms linear regression models.

BP neural network is a unidirectional multilayer feed-forward network, which consists of an input layer, an implicit layer and an output layer. The learning process includes forward propagation of the signal and backward propagation of the error. The structure of BP neural network is shown in Fig. 5.

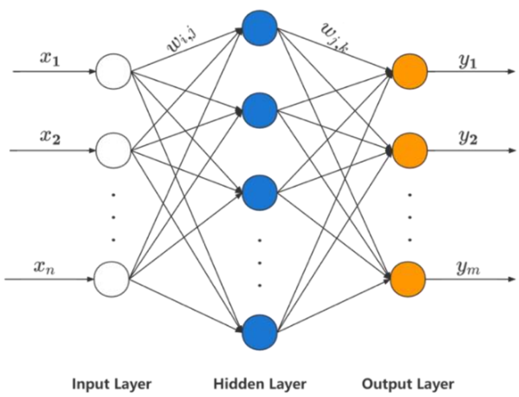

Figure 5: BP neural network structure

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Respectively, $x_1 x_2 \ldots x_n$ represents the input, $w_{i,j}$ denotes the connection strength between a neural in the input layer, and a neuron in that hidden layer, and $w_{j,k}$ denotes the connection strength between a neuron in the hidden layer and a neuron in the output layer. Then $y_1 y_2 \ldots y_n$ denotes the output of the neuron.

In civil engineering, intelligent control prediction is mainly used in structural health monitoring, structural damage diagnosis, structural performance prediction, etc. BP neural network has a wide range of applications in intelligent control prediction of civil structures.

Through the learning of structural vibration, strain or acceleration and other sensor data, the neural network can predict the state and behavior of the structure in real time. When the structure is abnormal or damaged, the BP neural network can quickly detect and send out warning signals, and it can be used as a part of the intelligent controller to optimize the control strategy and achieve the damage control of the structure. For example, adjusting the structure's dampers, mass dampers, or controls to reduce structural vibration or maintain structural stability for structural safety. Meanwhile, BP neural network can be used to predict the performance indexes of civil structures, such as bearing capacity, displacement, and vibration response. By learning historical performance data, BP neural network can predict the performance of the structure under different loading conditions and help engineers to design and optimize the structure.

2.2 Autoencoder

Autoencoder (AE) is a neural network model for unsupervised learning, the basic idea of which is to learn an effective feature representation of the data by putting the input data through the process of encoding and decoding so that the reconstructed data is as close as possible to the original input data.

The structure of the self-encoder consists of two parts: the Encoder and the Decoder. The Encoder is responsible for compressing the input data into a low-dimensional feature representation, while the Decoder reduces the encoded feature representation into reconstructed data of the same dimension as the original input data. The training process of the Self-Encoder is an unsupervised process that does not require labels or manually labeled outputs, but learns the feature representation of the data by minimizing the reconstruction error, the structure of which is shown in Fig. 6.

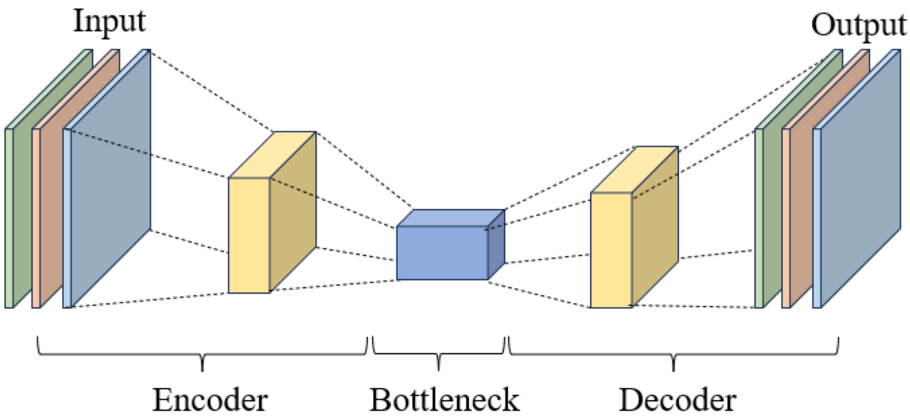

Figure 6: Self-Encoder

Self-encoder can provide effective feature extraction, anomaly detection, and structural condition monitoring functions in the intelligent control of vibration of civil structures, which uses the collected data preprocessed sensor data of civil structures as inputs, and its training objective is to minimize the reconstruction error, i.e., to make the output of the decoder as close as possible to the original inputs. After the training is completed, the new sensor data is reconstructed using the self-encoder. The reconstruction error between the original input and the reconstructed output is compared. If the reconstruction error is greater than a predefined threshold, then the data is labeled as abnormal. The selection of the threshold value can be determined by cross-validation or statistical-based methods to choose to optimize the performance of anomaly detection.

Applying the trained self-encoder to real-time civil engineering structure sensor data, once anomalies are detected, timely measures can be taken for the maintenance and upkeep of the structure to guarantee the safety and stability of the structure. Such an algorithm has strong applicability and

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flexibility in the anomaly detection of civil structures, and can effectively detect potential structural anomalies, helping engineers to understand the health status of the structure in real-time and take appropriate control measures. This helps to improve the stability, safety, and longevity of civil structures and optimize the design and O&M process of the structures.

2.3 AE-BP-based prediction algorithm for anomaly detection and intelligent control

Combining the theoretical feasibility of the above self-encoder and BP neural network in civil structure vibration, this paper constructs a model structure based on the combination of the self-encoder and BP neural network, which is shown in Figure 7 below.

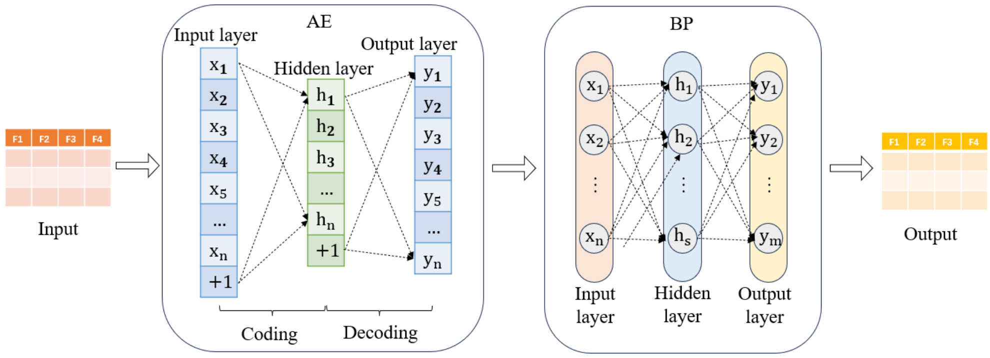

Figure 7: Model structure diagram

As can be seen from the figure, firstly in the first stage the self-encoder is used for anomaly detection and feature extraction, through the training of the self-encoder, the model can learn the feature representation of the normal structure and the reconstruction error increases when the structure is anomalous, thus it can be used for anomaly detection.

Then in the second stage, the extracted features are inputted into BP neural network for intelligent control prediction, through the training of the BP neural network, the model can learn the intelligent control strategy of the structure, and based on the input feature representations, it predicts the appropriate control parameters to realize the vibration suppression and stability control of the structure.

3. Experimental results and analysis

3.1 Datasets

To better evaluate the performance and robustness of the neural network, this paper uses the data generated by the Lorenz chaotic system to simulate the data collected by the sensors as a dataset. The Lorenz chaotic system is a dynamical system with complexity and nonlinear characteristics, which is extremely sensitive to the initial conditions, resulting in the outputs exhibiting unpredictable behavior. The dataset generated by this system is characterized by complexity and nonlinearity, which are exactly the data characteristics needed for the intelligent control prediction of nonlinear structural control investigated in this paper. Such a dataset provides a challenging test benchmark for the task of predicting the control of civil structures, and the use of the dataset can help the model to better capture nonlinear relationships. In addition, the data generated using the Lorenz chaotic system can also be used to evaluate and test the performance and generalization capabilities of the model, which is important in deep learning and machine learning research.

3.2 Results and Analysis

In this experiment, the data used for training is the data generated by the Loren chaotic system of length 20000, which starts and ends at [0.1, 1.0]. The BP model is divided into four layers, the activation function of the middle layer is sigmoid and relu, and the number of neurons in each layer is 128, 64, 32, and 1. The structure of the LSTM model is also divided into four layers, the activation function of the middle layer is relu, and the number of neurons in each layer is 64, 16, 4, and 1. The loading speeds of the BP model, the LSTM model, and the results of the model training are compared in Table 1 and Fig.8, respectively. Comparison are shown in Table 1 and Figure 8, respectively.

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Table 1: Loading time for BP and LSTM models

Method	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**AVG**
BP(ms)	398	399	423	403	464	410	430	395	399	495	421.6
LSTM(ms)	639	573	591	600	603	651	661	615	617	616	626.6

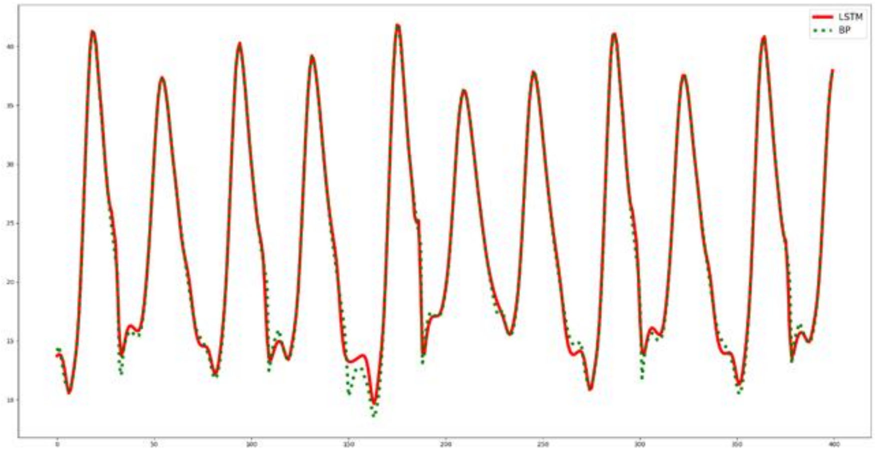

Figure 8: Training results of LSTM with BP

As can be seen in Fig. 7, in the BP neural network, the model training data change more drastically near the wave valley, i.e., the detection of abnormal data is more accurate and sensitive, and this sensitivity can help the controller better capture the dynamic characteristics and complex behavior of the civil structure under different working conditions, learn the subtle differences between normal vibration and abnormal vibration, find structural problems as early as possible, and take timely action when abnormal conditions occur. Necessary strategies are controlled to ensure the safe operation and reliability of civil engineering structures.

And from Table 1, it can be seen that the loading speed of the BP model is also faster than that of LSTM. Therefore, compared with LSTM, the BP network is a better choice for model generation.

4. Conclusion

This paper describes the application of a model based on combining a self-encoder and BP neural network for anomaly detection and intelligent control of vibration in civil structures. Although anomaly detection and intelligent control prediction are different tasks, they can be used in conjunction with each other in the field of civil engineering structures. Using a self-encoder, we can perform feature learning and dimensionality reduction of the vibration data of civil engineering structures, to obtain an effective feature representation of the structure and detect anomalies promptly. We can utilize these feature vectors with BP neural networks for structural prediction and intelligent control. This hybrid model can realize the anomaly detection of the structure and help to find the structural problems early, and at the same time realize the intelligent control of the structure to improve the stability and safety of the structure.

However, BP neural network, as a traditional artificial neural network, may have some limitations in complex and nonlinear civil structure control problems. In recent years, the development of deep learning technology has emerged more powerful neural network models, such as reinforcement learning, which can further enhance the effect and performance of civil structure control.

In future work, the field collection data will be used as the dataset, and at the same time, the fusion of multimodal data and other structural monitoring data, such as temperature and humidity, will be considered to improve the comprehensive capability of anomaly detection and intelligent control. We also consider introducing other deep learning techniques to further optimize the structure and parameter settings of the hybrid model, and explore more effective neural network structures and training algorithms to improve the accuracy and generalization ability of the model, to promote the continuous development and application of AI in the field of anomaly detection and intelligent control of vibration in civil structures.

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