Development of Deep Neural Network-Based Strain Values Prediction Models for Full-Scale Reinforced Concrete Frames Using Highly Flexible Sensing Sheets

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ABSTRACT

Structural Health monitoring systems (SHM) are commonly used to identify and assess structural damage. In terms of damage detection, SHM needs to periodically collect data from sensors placed in the structure as damage-sensitive features. These include abnormal changes due to strain fields and abnormal symptoms of the structure, such as damage and deterioration. At present, large-scale deployment of sensors in existing structures to cover large areas is still difficult to overcome, while increasing maintenance costs. In this study, a strain sensing sheet with high tensile strength is used to collect the strain data set generated on the concrete surface of the full-scale reinforced concrete (RC) frame structure when the cyclic load is applied to its limit. On this basis, two prediction models of deep neural network for frame beam and frame column are established. The training results show that they can predict the strain value accurately and have good generalization ability. These two deep neural network prediction models will also be deployed in SHM systems in the future as part of the intelligent strain sensor system.

INTRODUCTION

The structural life of an infrastructure degrades with use and time after construction, resulting in either internal damage (failure of structural elements) or external damage (cracks in the surface of the structure). Therefore, it is very important to successfully monitor structural performance, detect structural damage, completion and safety, and feedback in real-time and effective information.

In recent years, algorithms proposed in the field of Machine Learning (ML) and Deep Learning (DL) are widely applied to SHM. For instance, the structural damage identification framework based on an auto-encoder obtains the optimal solution of modal identification of highly nonlinear structures through a deep neural network [1]. Genetic algorithms (GA) and artificial neural networks (ANN) are used to simplify the modal shapes of structures and apply them to the layered recognition of composite plates [2]. [3] propose a new artificial intelligence-based structural health monitoring strategy based on neural network modelling.

In addition, most of the research focuses on the failure of a single structural element

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or material using deep neural networks. Therefore, a prediction model based on DL is developed in this study to predict the change of strain value of full-scale reinforced concrete frame structure, which is also the preparation study for the deployment of the prediction model into the flexible wireless smart sensor in the future work.

STRAIN-BASED SENSING TECHNOLOGY IN SHM

The civil structure is designed according to the standard of stress and deflection in the building code. However, due to the limitation of structural material performance, sensing technology and other factors, stress and deflection cannot be directly measured in the real application. Strain is a parameter directly related to stress and deflection. In other words, abnormal symptoms of structures, such as damage and deterioration, are usually manifested as strain field anomalies. Besides, in SHM applications, the problem that small damage is difficult to detect can be solved by the strain-based method. The basic idea is that although minor damage cannot be detected by changes in displacement it can be identified by changes in strain [4]. In this study, a stretchable strain sensing sheet prototype is used for large-scale structure strain value monitoring.

STRAIN SENSING TECHNIQUES

This study focused on two types of strain sensor configurations, half-bridge and full bridge. The Wheatstone bridge (Fig.1) itself is equivalent to two parallel voltage divider circuits. The general principle is based on the Wheatstone bridge which consists of four resistance sensing arms (R1, R2, R3, R4).

A constant excitation voltage V_ex, 3.3V in this study, is applied between the two electrodes. Therefore, when the bridge is in an equilibrium state under ideal conditions, i.e., R1 = R2 = R3 = R4, at which time the sensor does not produce any deformation, and the voltage output V_out is zero. On the contrary, any change in resistance (such as the strain sensor being stretched) will lead to unbalance of the bridge, and the resulting strain change can be obtained according to the (1):

$$Vout = (\frac{R4}{R4 + R3} - \frac{R1}{R1 + R2})Vex \tag{1}$$

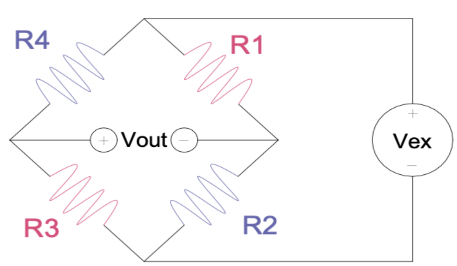


Figure 1. A typical Wheatstone bridge circuit

The sensor subjected to strain changes will cause a change in resistance wire length (tension or compression), which is ultimately reflected in the change of circuit resistance.

The quantitative expression of its strain sensitivity is the gauge factor (GF), which is the ratio of the change of resistance value to the change of length:

$$GaugeFactor(GF) = \frac{\Delta R/R}{\Delta L/L} \tag{2}$$

In this study, according to [4], since Cu/Ni(Constantan) is used as the conductive layer of the strain sensing sheet, the GF value is assumed to be 2.1.

OVERVIEW OF THE STRAIN SENSING SHEET PROTOTYPE

The strain sensing sheet prototype is composed of a 2-dimensional (2d) resistive Wheatstone bridge. It's fabricated on a stretchable material with multiple layers (Fig.2): substrate layer – Polyimide (25um); conductive layer – Constantan, also known as Cu/Ni (20um) and adhesive layer (25um).

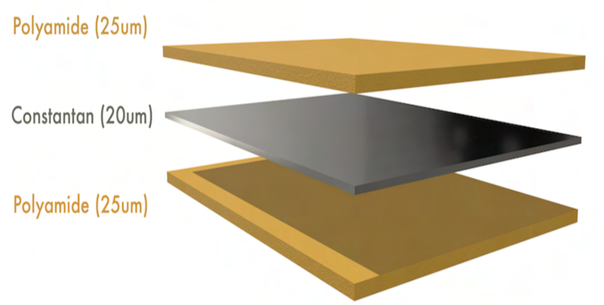
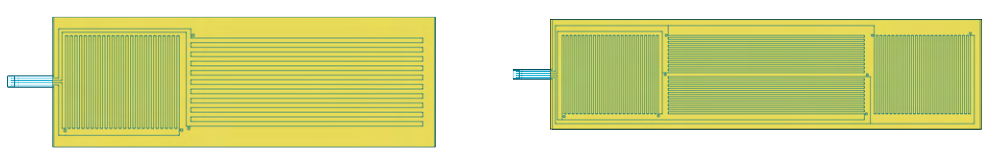


Figure 2. Schematic illustrations of strain sensing sheet layer composition

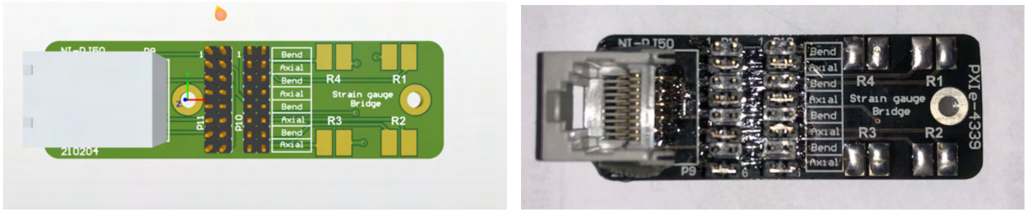
Two configurations, full-bridge and half-bridge were used in the study (Fig.3). To achieve temperature compensation, the half-bridge is connected to the full bridge through a strain sensor configuration selector (Fig.4). The purpose is to meet the bending strain measurement by mounting it on both sides of the structural elements (Fig.**??**).



(a) Half-bridide configuration **(b)** Full-bridge configuration

Figure 3. Top view of sensing sheets

DEEP NEURAL NETWORKS (DNNS) MODEL



(a) PCB 3D top view **(b)** PCB prototype

Figure 4. Strain sensor configuration selector for half-bridge configuration

As a kind of exploration and analysis technology with high prediction accuracy, the deep neural network can provide very good insights into complex nonlinear data in the scientific research field. DNN is a multi-layer sequence architecture composed of a collection of neurons. The neuron accepts neuron activation from the previous layer as input to the current layer and then performs a calculation that results in a complex nonlinear mapping from input to output. In this study, the back-propagation (BP) [5] learning method was also used to adjust the weights of each neuron learning from the tested data set. It minimizes the difference between the predicted output vector and the expected output vector by repeatedly adjusting the weighted value in the neural network.

MODEL EVALUATION

Evaluation and detection model is an important part of model building, indispensable. This study, in order to verify the accuracy of the established model, this study adopted two model evaluation methods, mean square error (MSE) and R-Squared (R^2).

MEAN SQUARE ERROR (MSE)

As a signal fidelity unbiased estimation, MSE aims to identify the accuracy of the model by comparing the fidelity (similarity) or distortion (error) between two signals. MSE has several significant advantages [6]:

1. The calculation results are based on a single sample, so they are independent of other samples.
2. MSE has a definite physical meaning and remains unchanged after any orthogonal linear transformation. For example, the Fourier transform.
3. When considering model optimization problems, MSE can be used as an excellent indicator due to its symmetry and differentiability.
4. MSE can also be used as an excellent metric in statistical and estimation models.

As one of the evaluation criteria of the regression model, the MSE of the model relative to the test set is the mean square prediction error of all samples in the test set. Here, the prediction error is mainly the difference between the real value of the test sample and the predicted value of the model [7]:

$$MSE = \frac{SSE}{dfE} = \frac{\sum_{i=1}^{D}(x_i - y_i)^2}{n - (k+1)} \tag{3}$$

Where y_i is the true target value of the data test set, $\hat{y}_i$ is the predicted target value in the ith case, and n is the number of the test? The root mean square is estimated from the standard deviation σ of the random error term, and the mean value in the mean square error is obtained by the primary degree of freedom.

R-SQUARED (R^2)

R^2 (Coefficient of Determination) is used to represent the proportion of variance of the dependent variable to the variance of the independent variable in the regression model:

$$R^2 = 1 - \frac{SSE}{SST} = 1 - \frac{\sum_{i=1}^{D}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{D}(y_i - \bar{y}_i)^2} \tag{4}$$

Where SST is the sum of squares, R^2 as an important indicator to measure the fitting data of the regression model, can be used to explain the difference between variable x and dependent variable y.

R^2 does not directly quantify the dataset itself; it represents the correlation between dependent variables and independent variables. Therefore, in ML or DL, it is often used to identify the correlation between the predicted value of the model and the target value of the actual training sample. Usually, the value is between [0, 1]. In some cases, R^2 will also be negative, which may be due to improper algorithm or over-fitting of the model.

EXPERIMENTAL TEST

The test object of this study is a full-size (beam length 2950mm, column height 2650mm) precast reinforced concrete frame structure (Fig.5). The frame beam section is rectangular, 230mm*220mm, and the compressive strength of concrete used for the frame structure is 25MPa. A full bridge sensor plate is installed near the beam-column joint. Two half-bridge sensors are installed on both sides of the right column near the bottom. In addition, to provide higher precision and multidimensional reference for the experiment, there were 14 linear variable differential transformers (LVDT) are installed, the right end of the beam is also equipped with a draw-wire displacement sensor, which serves as the baseline of lateral displacement caused by the load applied to the frame. As shown in Fig.6, MTS Hydraulic Actuator was used in the experiment to horizontally reverse load the frame structure. Hydraulic actuators apply a load of up to 1000kN and a static stroke of up to 500m. The hydraulic actuator gradually applies cyclic loads to the transverse frame beams. LVDTs were used in each loading step to measure the vertical displacement of the beam and the transverse displacement of the column. Strain sensing sheets are used to measure the strain value of the concrete surface of the beam and column respectively.

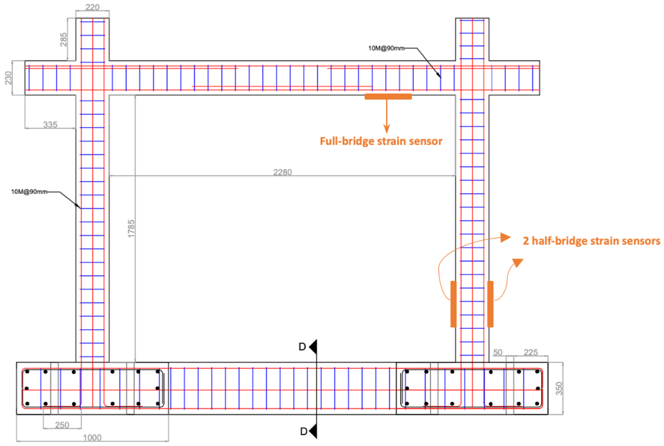
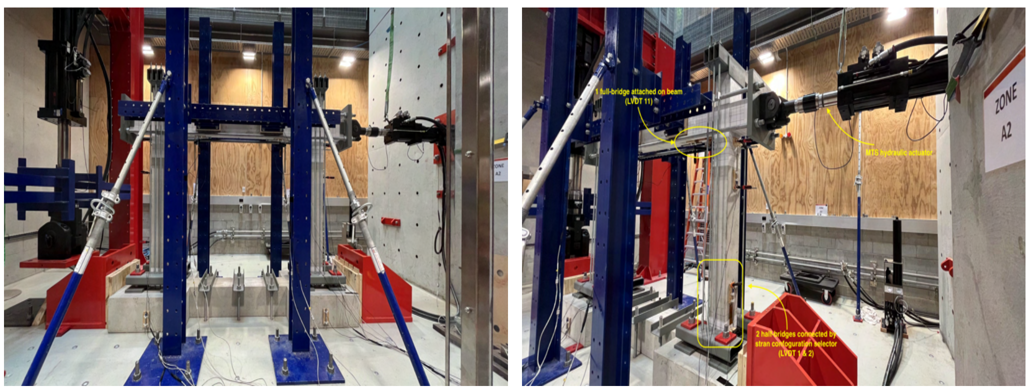


Figure 5. Front view of the RC frame and steel reinforcement(all dimensions in millimetres)



(a) Front view of the experimental test setup **(b)** Side view of the experimental test setup

Figure 6. Frame setup of the experimental test

As shown in TableI, in the experiment, the reinforced concrete frame was gradually loaded from an initial drift of 0.25% (5.3mm) to a drift of 1.25% (26.3mm) in 0.25% increments with each test.

TABLE I. Cyclic Test Procedure

Test Cycle	Drift (%)	Max Load (kN)
Test 1	0.25 (5.3mm)	75
Test 2	0.50 (10.5mm)	95
Test 3	0.75 (15.8mm)	125
Test 4	1.00 (21.0mm)	140
Test 5	1.25 (26.3mm)	168

TEST RESULTS

GLOBAL RESPONSE OF RC FRAME

The response of the whole structure is brought about by the increasing drift of the whole frame after the load is applied in the experiment. As can be seen from the RC Frame horizontal load-displacement cyclic response curve shown in Fig.7, the specimen was close to symmetric in the horizontal direction of push and pull, and the maximum horizontal force it resisted was 161kN and 145kN, respectively.

Although the results show different peaks in both directions, the shape of the hysteretic response curves throughout the frame is almost similar, and the scenario applies to the attenuation of loads between each test period.

Under yield strength, the relationship between beam and column load and concrete strain is shown in Fig.8 It can be seen that the relationship between the applied load and the measured strain of the component is highly nonlinear. This is also one of the important considerations for the deep neural network to build the prediction model in this study.

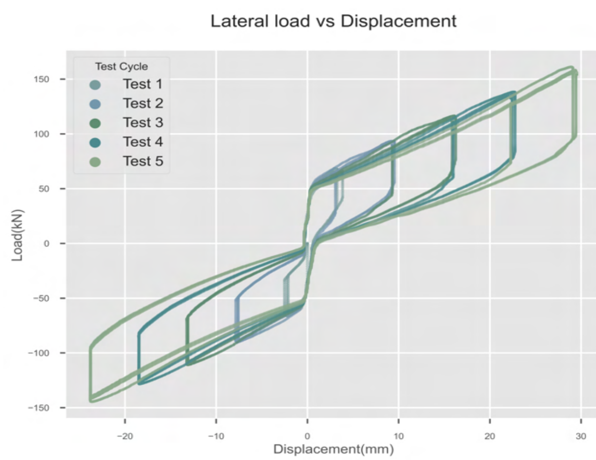
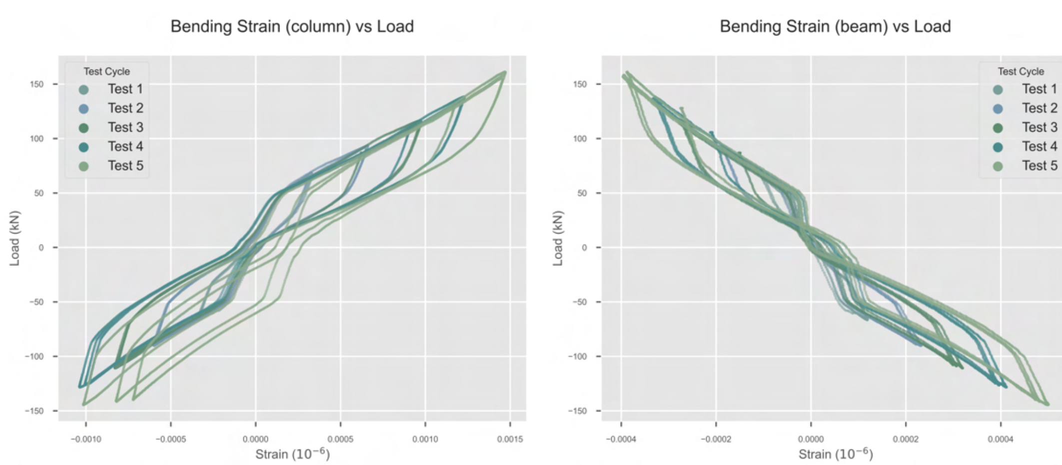


Figure 7. Load–displacement response curves of the RC Frame



(a) Strain sensing sheets on column (2 half-bridges) **(b)** Strain sensing sheet on beam (1 full-bridge)

Figure 8. Strain vs Load diagram

Deep Neural network design consideration

If the neural network is not complex enough, it will lead to under-fitting. On the other hand, if it is too complicated and provides too many unnecessary inputs to the network, it will lead to over-fitting. In order to avoid the occurrence of the above two situations, before establishing the network, this study classifies and filters the input data to find the correlation between variables. The collected data of 19 channels are preliminary analysed to determine which sensor data of nodes can be used as input to train the model The steps are as follows:

1. Use a correlation heatmap to determine the correlation between variables.
2. According to the relational values in (1), select appropriate inputs for the outputs (strain values at the two locations - beam and column).
3. Build a deep neural network based on input and output.
4. Conduct group training, verify the model, and adjust and improve the accuracy of the model.

First of all, correlation is used here to determine the input characteristics of the training set. Correlation is widely used in statistics and usually refers to the degree of linear correlation between two or more variables. The most common measure to judge the degree of correlation between variables is the Pearson correlation coefficient, but it is only sensitive to the linear relationship between two variables. Spearman's Rank correlation is more sensitive to nonlinear relations [8].

Figure 9 shows the correlation among 19 data channels. This heatmap can visualize the relative strength between numerical variables, each variable is represented by a column, and each row represents the relationship between the corresponding two variables. The value in the small cell unit directly reflects the relationship between a pair of variables corresponding to the row and column, and the value range is [-1, 1]. The larger the value is, the higher the correlation degree is, which can be selected as input values to train models and predict target values.

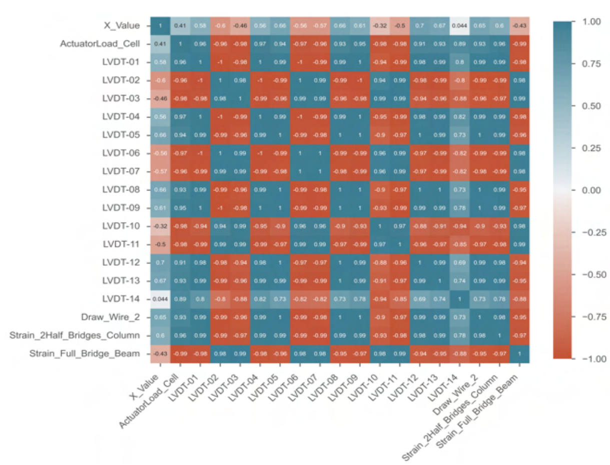


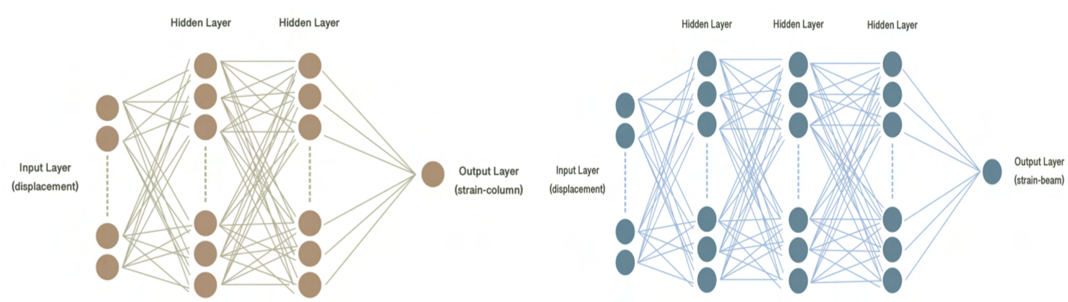
Figure 9. Correlation heatmap of 19 data channels.

Training network establishment

The strain data measured by experiments have high nonlinear characteristics, and the deep neural network has an excellent ability to deal with nonlinear relations. In this study, a fully connected strain value prediction model based on a deep neural network is designed and trained. As part of the Structural Health Monitoring System (SHM), the prediction model can be used as a threshold monitoring system for strain sensors to pre-process the collected raw data. This reduces the pressure on sensor data internal storage and SHM system data processing.

The determination of hidden layers and the number of neurons is complex and usually requires an iterative process. Studies on damage recognition show that the number of hidden layers and neurons in neural networks is usually determined by model trial and error. Early studies [9–11] indicated that one hidden layer was enough, but such studies did not prejudge the correlation of input values, so the reliability of input variables would be reduced, thus affecting the selection of the number of hidden layers. This study found that the model with two hidden layers can better carry out feature recognition and extraction, thus improving the accuracy of the model.

Figure 10 shows the model architecture adopted in this study, which is a fully connected multi-layer deep neural network. Built-in the PyTorch framework, the network is trained using feed-forward and BP which is also a technique of supervised learning. Gradient descent (GD) is used to optimise the accuracy of the model. As a strain prediction model, it needs to be applied to nonlinear data, so the activation function selection of neurons must also be nonlinear. Therefore, the Sigmoid function is chosen as the activation function. It can help the neural network to discover the nonlinear relationship between data features.



(a) 2 hidden layers deep neural network for the sensor on column **(b)** 3 hidden layers deep neural network for the sensor on beam

Figure 10. Architecture of the proposed neural network

The data set is divided into three groups: training, and testing/validation, where 80% of the total data set is used to train the network and 20% to test/validate the network. The train and validation datasets are divided into x_train, x_test, and y_test, y_train. Each training process is randomly assigned in accordance with the above ratio. To avoid overfitting, the generalization ability of a deep neural network is tested by using test samples. The training and verification process of the model built in this study is shown in Fig.11.

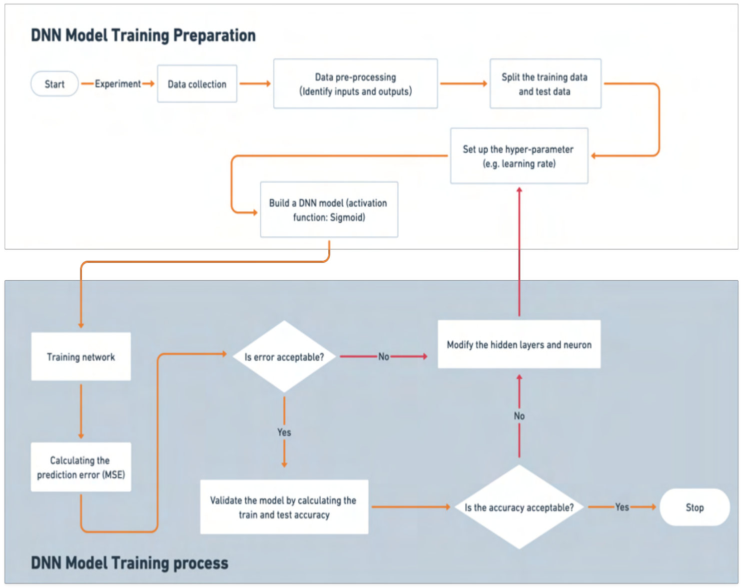


Figure 11. Flowchart of DNN model preparation and training

TRAINING RESULTS

As mentioned above, strain prediction results of the trained deep neural network are evaluated by two methods, MSE and R-squared, as part of verifying the accuracy of the model. The results are shown in Fig.12 The neural network established in this study accurately estimated the concrete surface strain value located near the bottom of the column.

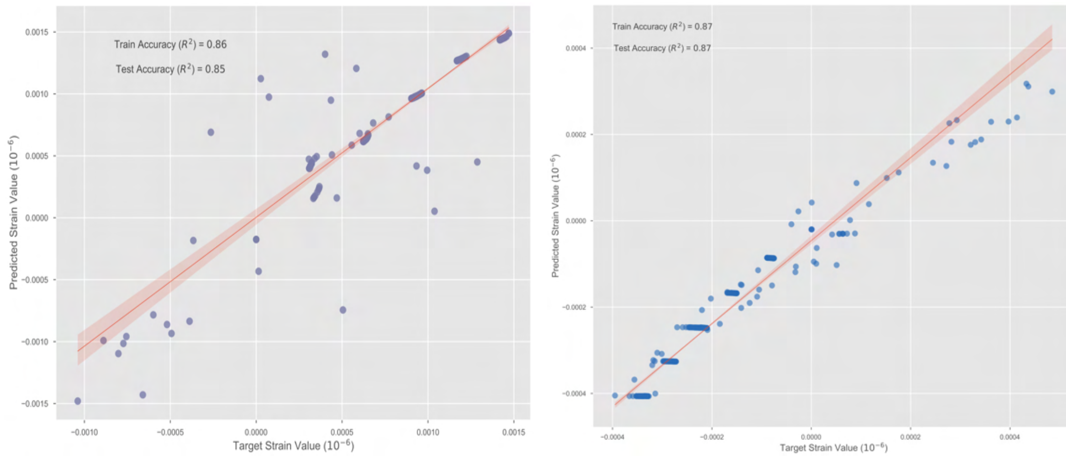
It is also obvious that the trained network model can successfully predict the strain value in the linear range and the strain trend in the non-linear range.

The results obtained from Fig.12 (a) show that for strain gauges installed on both sides near the bottom of the column, the accuracy of training and strain prediction of this deep neural network can reach 86%, test accuracy is 85%, and the root mean square deviation (RMSE) of the whole training is only 0.016%, and the mean absolute error (MAE) is 0.0089%. (b) Figure (b) shows the strain prediction results installed on the beam. The training accuracy and test accuracy both reach 87%. RMSE of the whole training result is 0.0042% and MAE is only 0.0036%.

Fig.13 shows the comparison results of experimental data and predicted data. Eighty samples are randomly selected from the experimental data set and the predicted data set respectively. It can be seen that there is a high linear correlation between the real strain value and the predicted strain value, indicating that both two DNN models for beam and column elements proposed in this study have great generalization ability.

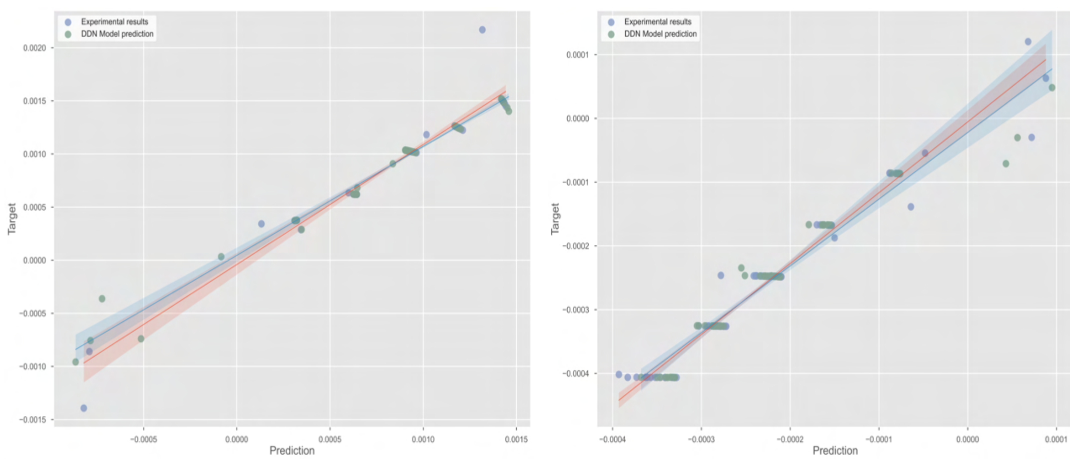
CONCLUSION

In this study, deep neural networks are applied to predict the strain values of full-size concrete frame structural members. The data set used to build the deep neural network was derived from the cyclic loading of the RC Frame to its limit, and a highly



(a) Sensing sheets installed on the column **(b)** Sensing sheets installed on the beam

Figure 12. Training and Testing accuracy of proposed deep neural networks



(a) Strain sensor on column measurements vs predictions **(b)** Strain sensor on beam measurements vs predictions

Figure 13. Comparison between experimental measurements and predictions

stretchable strain gauge was used to collect the strain values of the concrete surface. The two network architectures are suitable for beam and column respectively, and the prediction accuracy is 86% and 87%. Furthermore, random sampling is carried out in the predicted data set, and then compared with the real strain value, to prove the high generalization of the proposed deep neural network.

It is worth mentioning that in this study, gradient descent was used to train the network. According to [12] , Eighty-Five Percent Rule for optimal learning, the best training point for the neural network was when the training accuracy was about 85% and the training rate and difficulty were moderate. Optimization improves the most. It also avoids over-fitting due to the pursuit of high accuracy.

In addition, the proposed two neural networks will serve as the basis for future research. As part of the SHM system, the proposed neural network prediction model is deployed in the wireless sensor system to establish the threshold value for strain measurement and realize the data pre-processing and outlier alarm of the sensor board.

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