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Artificial neural network with adaptive moment estimation training approaches for prediction of punching shear capacity of steel fibre reinforced concrete slabs

Sử dụng mạng nơ-ron thần kinh nhân tạo với phương pháp huấn luyện ước tính mô men tự thích nghi cho việc tính toán lực cắt chọc thủng của sàn bê tông có cốt bằng sợi thép

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Abstract

Estimating punching shear capacity (PSC) of steel fibre reinforced concrete slabs (SFRCS) is a crucial task in structural design. This study investigates the performances of artificial neural networks trained by the adaptive moment estimation (Adam) method in dealing with the task of interest. To alleviate overfitting problem, decoupled weight decay (AdamW) and L_2 regularization (AdamL_2) are used. A dataset including 140 samples has been used to train and verify the machine learning approaches. In terms of root mean square error (RMSE), Experimental results including 20 independent runs point out that predictive performances of the AdamW (RMSE = 30.60) and AdamL_2 (RMSE = 31.74) are better than that of the Adam (RMSE = 36.62). However, performance of a combination of AdamW and AdamL_2 (RMSE = 32.31) is worse than those obtained from the individual AdamW and AdamL_2.

Keywords: Punching shear capacity; steel fibre-reinforced concrete slabs; artificial neural network; adaptive moment estimation; weight decay; L_2 regularization.

Tóm tắt

Ước tính khả năng chịu cắt chọc thủng (PSC) của tấm bê tông cốt sợi thép (SFRCS) là một nhiệm vụ quan trọng trong thiết kế kết cấu. Nghiên cứu này khảo sát các mô hình mạng nơ-ron nhân tạo được huấn luyện bởi thuật toán Adam trong tính toán PSC của SFRCS. Để hạn chế vấn đề quá khớp trong quá trình huấn luyện, phương pháp AdamW và AdamL_2 đã được sử dụng. Một tập dữ liệu bao gồm 140 mẫu đã được sử dụng để đào tạo và kiểm chứng các phương pháp học máy. Xét về chỉ số RMSE, kết quả thí nghiệm bao gồm 20 lần chạy độc lập chỉ ra rằng khả năng dự đoán của mô hình AdamW (RMSE = 30,60) và AdamL2 (RMSE = 31,74) tốt hơn so với Adam (RMSE = 36,62). Tuy nhiên, độ chính xác một mô hình kết hợp giữa AdamW và AdamL_2 (RMSE = 32,31) lại kém hơn các mô hình AdamW và AdamL_2.

Từ khóa: Khả năng chịu cắt chọc thủng; tấm bê tông cốt sợi thép; mạng lưới thần kinh nhân tạo; Adam; sự phân rã trọng số; chuẩn hóa L_2.

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1. Introduction

In civil engineering, reinforced concrete flat slabs are structural elements found in many types of structures such as parking stations, office blocks, and residential buildings [1-3]. Flat slabs offer various advantages including the ease of formwork installation/removal, reduced works in rebar installation, enhanced architectural features, and reduction of story height [4-6]. In recent year, steel fibers have been increasingly used in concrete flat slabs because this type of reinforcement can help improving the PSC [7-10]. Nevertheless, estimating the PSC of SFRCS based on existing experimental data remains a challenging task and various formula-based methods cannot deliver satisfactory outcomes [1, 6, 11].

This study investigates data-driven methods for predicting the PSC of SFRCS based on ANN models trained by the state-of-the-art Adam method [12, 13]. The ANN has been selected in this study due to its excellent capability of modeling nonlinear and multivariate data [14-18]. The Adam has also been demonstrated to be effective in optimizing various machine learning models [19, 20]. In addition, the two approaches of AdamW [21] and L_2 regularization [22] are employed for overfitting mitigation. Six influencing factors including the slab depth (X_1), effective depth of the slab (X_2), length or radius of the loading pad or column (X_3), compressive strength of concrete (X_4), the reinforcement ratio (X_5), and the fibre volume (X_6) are taken into account. In addition, a dataset including 140 experimental tests compiled in [6] has been used to train and verify the data-driven approaches. To evaluate predictive capability of each ANN model trained by the Adam, AdamW, AdamL_2, and the integration of AdamW and AdamL2 (denoted as AdamW-L_2), this study relies on experimental results obtained from 20 independent runs.

2. Methodology

2.1. Artificial neural network regression (ANNR)

ANNR, as a powerful nonlinear function estimator, is widely used in civil engineering [18, 23-28]. An ANNR model is known for its capability of mimicking the information processing and knowledge generalization in human brain. The advantage of this model lies in its interconnected network of individual neurons. This network provides means of universal learning of ANNR [29]. Put it differently, an ANNR model with a sufficient number of neurons in its hidden layer can approximate any known function with arbitrary accuracy.

To fit a dataset, an ANNR model is trained with a set of feature vectors and their corresponding target outputs. A training algorithm is used to identify a suitable set of this model's parameters including the weight matrix of the hidden layer (W_1), the weight matrix of the output layer (W_2), the bias vector of the hidden layer (b_1), and the bias vector of the output layer (b_2). The framework of error backpropagation is used to gradually update those model's parameters [30]. In case an ANNR is used for predicting the punching shear capacity of steel fibre reinforced concrete slabs, the Mean Square Error (MSE) loss function is often used. In addition, to deal with the problem of nonlinear functional mapping, the sigmoid function is often used [31] as an activation function for an ANNR model.

2.2. Adaptive moment estimation (Adam) method

Adam, put forward in [12], is a popular method for first-order gradient-based optimization of stochastic objective functions. Adam is recognized as an extension of the commonly used stochastic gradient descent used to train ANNR models via an iterative weight updating process [32]. Adam utilizes information attained from the average of the second moments of the gradients. In greater detail, this method computes an exponential moving average of the gradient and the square gradient. Furthermore, a set of parameters (β_1 - and β_2) is employed to determine the decay rates of these moving averages [32]. Generally, to train an ANNR model used for predicting the punching shear capacity of steel fibre reinforced concrete slabs, the following steps are implemented:

(i) Calculate gradient g_t

(ii) Revise the biased first and second raw moment estimates

(iii) Calculate the bias-corrected moment estimates

(iv) Update the optimized parameters

Furthermore, to deal with overfitting issue, the L_2 regularization [22] and decoupled weight decay (AdamW) [21] can be employed. In case the L2 regularization is applied, the equation used for calculating the gradient is as follows:

$$g_t = \nabla_\theta f_t(\theta_{t-1}) + \lambda\theta_{t-1} \quad (1)$$

In case the AdamW is used, model parameters are updated as follows:

$$\theta_t = \theta_{t-1} - (\alpha \times \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \varepsilon} + \omega \times \theta_{t-1}) \quad (2)$$

where $\hat{m}_t$ is bias-corrected first moment estimate.; $\hat{v}_t$ is bias-corrected second moment estimate; α = 0.001 and ε = 10^{-8} are the parameters of the Adam optimizer; λ and ω are the tuning parameters of the L_2 regularization and AdamW method, respectively.

3. Experimental result and comparison

In this section, the models of AdamW, AdamL2, and AdamW-L_2 are trained and validated by a dataset containing 6 influencing factors and 140 samples. The factors are of the slab depth (X_1), effective depth of the slab (X_2), length or radius of the loading pad or column (X_3), compressive strength of concrete (X_4), the reinforcement ratio (X_5), and the fibre volume (X_6). The ANN models trained by of AdamW, AdamL2, and AdamW-L_2 are developed in Visual C# by the author. Via several trial and error runs, the number of neurons in the hidden layer of those ANN models is set to be 10. In addition, the step size α used in the Adam optimizer is 0.001; exponential decay rates β_1 and β_2 are 0.9 and 0.9999, respectively. The parameters of λ and ω are 0.001 and 0.0001, respectively.

Table 1. Experimental results

Phase	Indices	Adam		AdamW		AdamL$_2$		AdamW-L$_2$	
		Mean	Std	Mean	Std	Mean	Std	Mean	Std
Training	RMSE	24.72	5.89	24.22	3.54	25.03	3.39	27.58	2.36
	MAE	18.83	4.43	18.52	2.93	18.83	2.48	21.04	1.87
	MAPE (%)	9.37	1.92	8.94	1.65	8.75	1.35	9.79	1.18
	R^2	0.94	0.03	0.95	0.02	0.94	0.02	0.93	0.01
Testing	RMSE	36.62	10.04	30.60	7.93	31.74	8.29	32.31	7.34
	MAE	27.27	7.76	23.32	6.17	24.89	6.77	24.76	5.45
	MAPE (%)	13.44	4.86	12.04	3.57	10.76	1.74	10.97	1.84
	R^2	0.86	0.09	0.89	0.06	0.90	0.04	0.88	0.06

In addition, a repetitive random subsampling including 20 training and testing times has been used for model assessment. In each run, 90% of the data is used for model training and 10% of the data is used for model testing. The indices of RMSE, the mean absolute percentage error (MAPE), the mean absolute error (MAE), and the coefficient of determination (R^2) are employed to quantify the model predictive performance. The model prediction results are reported in Table 1. It is observable that the implementation of AdamW has yielded the most desired performance. The AdamW, AdamL_2, and the hybrid AdamW-L_2 are better than the Adam. However, the implementations of AdamW, AdamL_2 separately deem to be better than the utilization of the AdamW-L_2. Therefore, the ANN model trained by the AdamW optimizer is recommended for performing the task of interest.

4. Conclusion

This study has constructed ANN models used for predicting PSC of SFRCS. The models are trained by the Adam optimizer with the help of the decoupled weight decay (AdamW) and L_2 regularization (AdamL_2). The implementations of AdamW and AdamL_2 aim at alleviating model overfitting. A dataset including 140 samples and 6 predicting variables has been used to train and verify the machine learning approaches. The research finding is that predictive performances of the AdamW and AdamL_2 are better than that of the Adam. Nevertheless, performance of the AdamW-L_2 is worse than those attained from the individual AdamW and AdamL_2.

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