Prediction of compressive strength of self-compacting concrete containing different fillers with the help Artificial Neural Networks

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Abstract

Self-compacting concretes with suitable rheological and mechanical properties, are among the new concretes that were considered by researchers and industrialists in the late 20th and early 21st centuries. Accuracy in pouring concrete, concrete density and also the appearance of concrete as an exposed material is always a concern of designers and executors of construction projects. Self-compacting concrete with weight compression properties can always be one of the options available to designers. The variety of materials used in self-compacting concrete, including recycled materials, with pozzolanic properties and fillers to achieve rheological and mechanical goals, is one of the challenges that designers face. Also, accurate determination of mixing ratios and their results is very time consuming and costly. Using soft computing and neural networks inspired by the biological structure of the human brain, computer science seeks to increase speed, accuracy, and cost reduction to prevent malicious experiments. In this study, with the help of ANN and LSTM networks, using 320 samples of self-compacting concrete with dispersion and comprehensiveness of common materials used in it by various researchers, tried to predict 28-day compressive strength of self-compacting concrete, evaluate performance and increase accuracy by 6 The training algorithm is different. In total, about 200 repetitions of training were performed on 320 samples of self-compacting concrete with 14 characteristics, which by comparing the best results obtained from training algorithms, best performance with root mean square error of 4.97 and correlation coefficient of 0.9484 in the test, for the network. ANN was reported with the Beyesian Regularization training algorithm, which indicates the high accuracy of that network.

Keyword

Self-compacting concrete - Compressive strength prediction - ANN neural network - LSTM neural network

1. Introduction

Concepts and architectural complexities of new structures, if considered as basic materials, face challenges, which are related to the efficiency and psychologicality of concrete while maintaining its strength and durability. Self-compacting concrete to address the concerns of designers and business owners, such as: The difficulty of concreting in high volumes and compacting it, as well as the use of concrete as a final and visible material in construction projects, was first developed by Okamura in the late 1980s to achieve sustainable structures in Japan[1]. Later, in 2002, the European Institute EFNARC published a guide to self-compacting concrete in order to maintain coherence in the design process of this type of concrete[2]. In order to achieve the optimal mixing ratios in order to achieve the desired results in the tests of self-compacting concrete in fresh and hardened state according to the relevant standards by changing each of the parameters including aggregate (sand), water to cement ratio (W / P), superplasticizers, etc., perform trial and error and perform destructive tests such as compressive strength test of concrete. Given the quality and performance of self-compacting concretes and the large number of additives and alternatives to cement in this type of concretes, researchers are looking for a solution to prevent wastage of time and energy and also to achieve high-reliability results based on previous experience[3]. Computer science and neural networks allow us to establish relationships between variables and outputs by creating nonlinear functions that are not traditionally possible to formulate. The aim of this study was to predict the 28-day compressive strength of self-compacting concrete with the focus on the study of fillers and viscosity and psychological modifiers using ANN and LSTM neural networks with the nature of post-diffusion learning and deep learning.

2. Description of neural networks

2-1. ANN Network

ANN with MLP structure or multilayer perceptron layers is a feed-forward artificial neural network with Backpropagation training method. This method is based on reducing the gradient or derivative in each step. In general, the network has three parts: input layer, hidden layer and output layer. The function of the network is that the samples are entered with any number of features from the input part, and after receiving random weights in the first iteration, it enters the hidden layer and the activation function and deviation value are applied to it, and then it goes to the output

$$\sum_{j=1}^{m} w_{ij} x_j + b_j \tag{1}$$

$$\frac{1}{1+e^{-x}} \; or \; \frac{e^{x} - e^{-x}}{e^{x} + e_{-x}} \; and \; \ldots \tag{2}$$

$$w_i = w_j(t) + 2\eta(t_p - f_p).Gradient\ activation\ function.x_{ij} \tag{3}$$

2-2. LSTM Network

Lstm or short-term stable memory is a recursive neural network, meaning that the network outputs re-enter the network as input in the next iteration. Lstm was first introduced by Hochreiter in the early 1990s and expanded by Hochreiter and Schmidhuber in the late 1990s[4]. Using it, the problem of zeroing and infinity of derivative networks, the so-called networking, was somehow solved. The Lstm output consists of two parameters, which represent the network memory and the target output, respectively, both of which are entered and entered into the network in the next step. So unlike our feed network, it has an RNN network, which is used in deep learning.

$$f_t = \sigma_g\left(W_f x_t + U_f h_{t-1} + b_f\right) \tag{4}$$

$$i_t = \sigma_g\left(W_i x_t + U_i h_{t-1} + b_i\right) \tag{5}$$

$$o_t = \sigma_g\left(W_o x_t + U_o h_{t-1} + b_o\right) \tag{6}$$

$$\tilde{c}_t = \sigma_c\left(W_c x_t + U_c h_{t-1} + b_c\right) \tag{7}$$

$$c_t = f_t \circ c_{t-1} + i_t \circ \tilde{c}_t \tag{8}$$

$$h_t = o_t \circ \sigma_h\left(c_t\right) \tag{9}$$

3. Results and Discussion

Now if we want to compare the best state of LSTM network with ANN network according to the path we did in this particular case, the performance of Beyesian Regularization training algorithm in ANN network will be better than

Sgdm algorithm in LSTM network only according to RMSE index. Was. It should also be noted that this does not mean denying the LSTM network and other training algorithms, and only in this particular case this result is achieved (Table 1, Figure 1).

Table 1: Comparison of ANN and LSTM network performance

Neural network	Training Algorithm	RMSE
		Test
ANN	Beyesian Regularization	4.9700
LSTM	Sgdm	7.1850

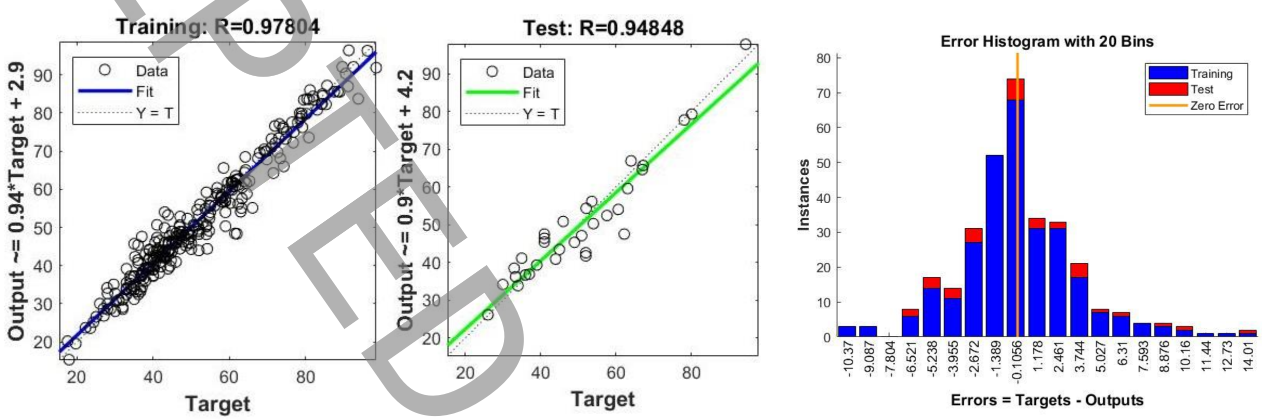

Figure 1: Error Diagrams and Correlation Coefficient of ANN Network Considering Beyesian Regularization Algorithm

4. Conclusion

Although the results of ANN network with Beyesian Regularization training algorithm are better than the other two training algorithms in this network (Levenberg Marquardt and Scaled Conjugate Gradient), this does not mean that the other two training algorithms can not perform prediction, Rather, the accuracy of the prediction during training is less with the other two training algorithms, which even in this particular issue, there was little difference.
Neural network training with Beyesian Regularization training algorithm takes more time than the other two training algorithms, and the more data and features of each input, the training time to correct the weights increases, on the other hand, Scaled Conjugate Gradient training algorithm spends less time and consequently It is also less accurate.

5. References

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