



The Efficiency of Hybrid BNN-DWT for Predicting the Construction and Demolition Waste Concrete Strength

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ABSTRACT

The current study focuses on two main goals. First, with the use of construction and demolition (C&D) of building materials, a new aggregate was produced and it was utilized for green concrete production. The compressive strength test confirmed the good function of C&DW aggregate concrete. This concrete did not show significant differences with natural sand concrete. Second, Backpropagation neural network (BNN) was adjusted for C&DW concrete strength prediction at different curing times. Although BNN has good accuracy for strength prediction, due to the importance of 28th day of concrete strength the need to improve the accuracy was felt. So discrete wavelet transform (DWT) was used on BNN and a hybrid network was produced. DWT by filtering the noises can improve the homogeneity of the dataset. The results of DWT-BNN showed that the regression can increase to 98% and the MSE index reduces to 0.001. Continued research has shown that increasing the number of filters to four steps leads to reduced accuracy and increased computational cost. So using DWT-BNN as a hybrid network with one filter can improve prediction ability to the desired level but adding up the number of filters not recommended.

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NOMENCLATURE

X_i	Input units	E	Error function
X	Sample	m, n	Scaling parameters
x_{\max}	Maximum sample	A	Approximation
x_{\min}	Minimum sample	D	detail
w_{ij}	Weight on the connections	Greek Symbols	
b_j	Bias of each neuron	ζ	Training parameter
n	Number of input units	$\psi(t)$	Mother function
O_z	Actual output value	Subscripts	
t_z	Output of the network	j	Neuron counter

1. INTRODUCTION

Concrete is one of the common building material that has a large volume of production and consumption in the building industry [1, 2]. It produces in almost all countries [3, 4]. Therefore, various ways have proposed

to reduce the cost of concrete production. One of the methods is the use of building waste in the manufacture process. Wastes such as glass, ceramic tiles, concrete, plastics, etc. are recommended materials for the construction of concrete. Researchers have evaluated the different dimensions of using these materials [5], whether

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cement or aggregate, as concrete ingredients or even soil stabilizers [6]. For example, in the case of C&D waste as concrete aggregate, laboratory studies indicated an increase in water absorption and, in some cases, a decrease in compressive strength of concrete [7]. However, the use of recycled aggregate concrete with low old cement paste adhering to them could increase the quality of aggregates and improve the mechanical properties of concrete [8]. The use of tile and ceramic waste were also used to replace cement and aggregate in the manufacture of concrete [9, 10]. The use of tile and ceramic waste in cement manufacturing were also investigated. The use of them is appropriate in accordance with the relevant standard for the production of cement and using up to a maximum of 35% is allowed [11]. The use of brick waste could be used in the construction of a lightweight concrete compound [12]. Today, due to the development of technology, significant changes have been made in the experimental studies. Previously, due to material and sample making limitations it was not possible to decisively decide on the high precision deductions. So it took a lot of time to build prototype and study about experimental samples. But with the help of computer simulations, it was possible for discrete laboratory results to be converted to continuous results and avoid spending additional time and cost [13]. In the construction of concrete materials, various researchers have also used statistical methods and computer modeling to increase deduction precision. Artificial neural networks are one of the statistical tools that have been used successfully to estimate concrete features such as shear resistance [14], compressive strength [15, 16], elastic modulus [17], and corrosion of bars in reinforced concrete [18]. It is also possible to use neural networks in concrete mix designs modeling [19]. A series of studies have also shown that various types of networks, such as artificial neural network (ANN), automated neural network search (ANS), radial basis function (RBF), Support vector machine, and Support vector regression (SVR and SVM) are capable of solving laboratory problems [20, 21]. Another computational method is wavelet transform which is able to evaluate the performance of concrete structures [22, 23]. A wavelet transform with data separation capabilities has the potential to facilitate data analysis for the network. Using some transformations, such as discrete wavelet transforms, can separate data using upper and lower frequencies [24]. This can be used as a positive point in neural networks to reduce the time of data analysis. To date, numerical results have shown that the use of wavelet transforms as the neural network functions have beneficial effects in the increasing of the prediction accuracy [25]. What has been researched by the authors so far, using both wavelet and BNN with serial function have not been investigated, although the DWT-fuzzy systems has been evaluated before [26]. In addition to,

the influences DWT filters on network answers has not been studied. In this regard, for estimating the compressive strength of concrete containing recycled aggregate, first a BNN with using 165 laboratory samples, including the samples in different age, was made. In the next step, in order to increase the precision of the estimation, the compressive strength results were filtered by the help of discrete wavelet transformation (DWT). The new up and low frequencies which were obtained by DWT were used as BNN output. Afterward, the predicted values were reconstructed and the results were evaluated. This paper has 7 sections. First at section (2) experimental program is explained. At sections (3) and (4), BNN and DWT structures are investigated respectively. In section (5) the BNN-DWT is described. In section (6) the results of the networks were evaluated. In addition, section (7) shows a summary of the most important results.

2. EXPERIMENTAL PROGRAM

For the construction of recycled aggregate (RA) concrete, portland cement type 1-525, potable water, the aggregate mixture of natural aggregate (NA) and construction waste, and superplasticizer based on polycarboxylate copolymer were used. The RA was produced by the destruction of the building which was included concrete, stone, brick, and ceramic. It was replaced by 0 to 100% of the total consumed aggregate. Table 1 shows the mix design of the samples. As can be seen, a total of 55 concrete samples with different amounts of sand to cement ratio and recycled to natural sand were made. In this table, R, W, C, and S are used as recycled aggregate,

TABLE 1. Mix design

NA*	RA*	Label	Superplasticizer by S/C ratio**				
			1	1.5	2	2.5	3
100	0	R0	0	0	0.3	0.2	0.7
90	10	R10	0	0	0.3	0.3	0.7
80	20	R20	0	0	0.3	0.5	0.8
70	30	R30	0	0	0.3	0.7	0.1
60	40	R40	0	0	0.4	0.8	0.14
50	50	R50	0	0	0.6	0.11	0.16
40	60	R60	0	0.1	0.8	0.14	0.17
30	70	R70	0	0.1	0.11	0.17	0.2
20	80	R80	0	0.2	0.14	0.19	0.2
10	90	R90	0	0.3	0.17	0.2	0.2
0	100	R100	0.3	0.4	0.19	0.2	0.2

*(% wt. of total aggregate)

**(% wt. of cement)

water, cement, and sand respectively. It should be noted that for the results section (parts 4 and 6) the name of samples for better understanding has changed. For this reason, R used as recycled sand, the number after that shows the substitute percent with natural sand, S as sand to cement abbreviation and the number following is sand to cement ratio. For example, R0S1 means a sample with 0% recycled sand and sand to cement ratio of 1.

To make concrete, dry compounds, cement, and aggregate, were first combined in 5 liters mixer for 3 minutes, and then a solution of water and superplasticizer was added to the mixture. The mixing process continued for another 3 minutes (ASTM C 94). Then concrete was poured into 5 cm cubic molds. After one day, the molds were opened and the concrete samples were cured by water for 7 and 28 days. It is worth noting that after 1, 7, and 28th days, samples were broken by using a 2000 KN concrete compressive strength jack and their results were taken (ASTM C 109). Figure 1 shows the concrete sample under jack for compressive strength. It should be noted that based on ASTM C 109, for each day three samples were ready and broken by jack. The average of three samples' compressive strength was used as the final result.

2. 1. Compressive Strength Test Figure 2 shows the compressive strength results. As shown in Figure 2, the maximum compressive strength at 1th day was 18.1 MPa for a sample containing 40% of the RA and the ratio of sand to the cement of 2.5. After 7 days, compressive strength was observed and the highest compressive strength was related to samples containing 0 and 20%

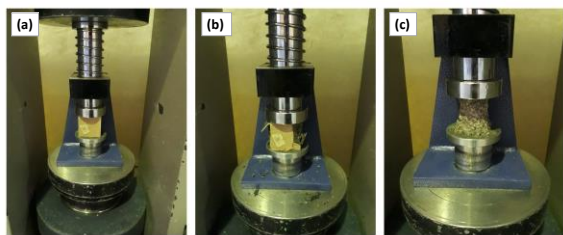


Figure 1. Process of the concrete sample breaking under hydraulic jack [27]

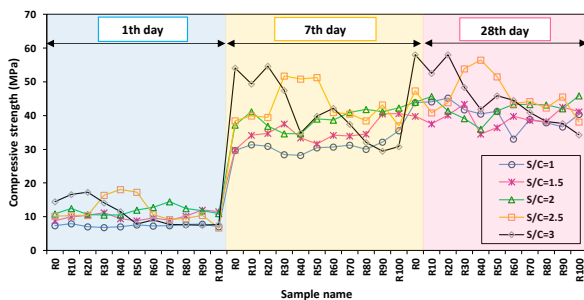


Figure 2. Compressive strength test results

of waste with sand to cement ratio of 3. The compressive strength of 7th day in both samples was 54.13 and 54.6 MPa, respectively. At 28th day, compressive strength in both samples were for samples with 40 and 20% recycled sand replacement and the sand to cement ratio of 2.5 and 3, with the compressive strength of 56.56 and 58.68 MPa, respectively.

3. BACKPROPAGATION NEURAL NETWORK

In this study, the Backpropagation neural network (BNN) is used to estimate the compressive strength of concrete at 1, 7, and 28 days. The neural network had three inputs: the recycled sand to sand ratio, the superplasticizer to cement ratio and the sand to cement ratio. This network had a hidden layer with 10 neurons. Also, the Levenberg Marquardt was used as a training function, and the Tangent Sigmoid and Linear functions were used as transfer functions. Therefore, the network had 3 inputs and 3 outputs (Figure 3). It should be noted that in this network 80% of the data was used for training and 10% was set aside for validation and 10% was used for the testing process. The BNN mechanism is as follows:

First, the inputs enter the network. Then, they processed based on the following equation:

$$Net_j = \sum_{i=1}^n x_i w_{ij} + b_j \tag{1}$$

In which x_i is used as input units, w_{ij} is the weight, i and j are the input and neuron counters, b_j is the bias of each neuron, and n is the number of input units. If the tangent sigmoid is used as a transfer function of the hidden layer, the following formula will be used:

$$O_j = f(Net_j) = \frac{-1+e^{-2Net_j}}{1+e^{-2Net_j}} \tag{2}$$

One more time, the data multiple by weight and sum with the bias. Then they entered into the second transfer function and enter into the output layer. This process is the same as before. In the end, the network error is calculated. The error general formula is as Equation (3):

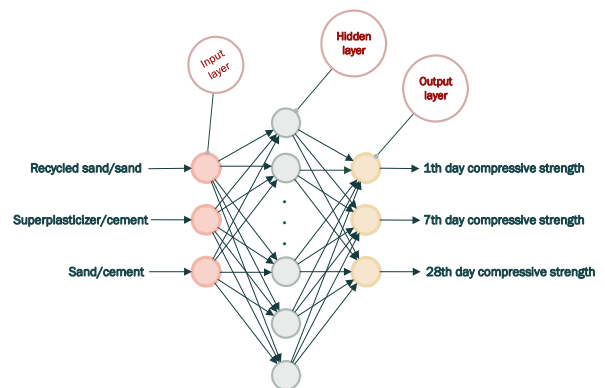


Figure 3. The BNN configuration in the current study

$$e_i = t_z - O_z \tag{3}$$

which t_z is the predicted value which is achieved by BNN and O_z is the real output value. For determining the error, the mean absolute error (MAE), mean square error (MSE), sum of squared error (SSE), and root-mean-squared error (RMSE) were used. The Equations (4)-(7) show the used error functions respectively.

$$E = \frac{\sum_{i=1}^n |e_i|}{n} \tag{4}$$

$$E = \frac{\sum_{i=1}^n e_i^2}{n} \tag{5}$$

$$E = \sum_{i=1}^n e_i^2 \tag{6}$$

$$E = \sqrt{\frac{\sum_{i=1}^n e_i^2}{n}} \tag{7}$$

The network training is the process of achieving the best-predicted value. To minimize the error, the weight parameter must be changed:

$$\nabla W_{jz} = -\xi (\delta E / \delta W_{jk}) \tag{8}$$

ξ and E are the training parameter and the error function respectively. The new weight for the next steps will be computed as:

$$W_{jz}(n + 1) = W_{jz}(n) + \nabla W_{jz}(n) \tag{9}$$

This process continues until the network error reaches the desired level [17].

4. DISCRETE WAVELET TRANSFORM (DWT)

Wavelet transform is a powerful tool for separating high and low frequencies. This transformation for data separation and reconstruction can be a useful tool for analysis [28-30]. One of the wavelet transforms is the discrete wavelet transform, which is used for analyzing the signal at various scales. A discrete wavelet transform is defined as:

$$DWT(m, n) = 2^{-\frac{(m-n)}{2}} \sum_{t=0}^{T-1} x(t) \psi\left[\frac{(t-n2^m)}{2^m}\right] \tag{10}$$

In the above equation, $x(t)$ is the function that is related to t , where t is the horizontal axis points, m and n are the scaling factors and the translation factor, respectively. T is the number of points and is the mother wavelet

function. In this study, Haar wavelet function is mother function and is used as follows.

$$\psi(t) = \begin{cases} 1 & 0 \leq t < \frac{1}{2} \\ -1 & \frac{1}{2} \leq t < 1 \\ 0 & \text{otherwise.} \end{cases} \tag{11}$$

In the discrete wavelet transformation, the primary wave is divided into two high-frequency and low-frequency. Then, the low frequency is divided into two new high and low-frequencies. This process continues for the n stage [22]. The following figure shows the wave separation. In Figure 4, D is an abbreviation of detail and A is used as an approximation. The number after D and A is illustrated as the step of filtration.

In this study, the results of compressive strength of concrete were filtered using discrete wavelet. The results of which were as follows:

As shown in Figure 5, with an increasing number of wave filtering levels, the low frequency is converted to a more smother wave. In the first phase filter, at the high-frequency wave, the first noise occurred in the compressive strength changes of 1st day to 7th day, which is associated with a jump. This jump is visible in

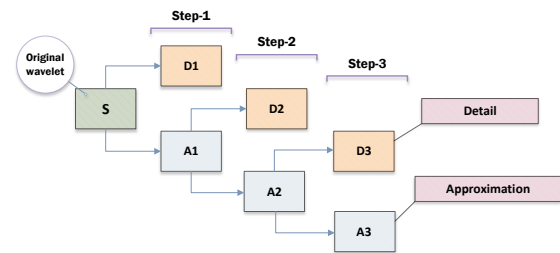


Figure 4. DWT mechanism

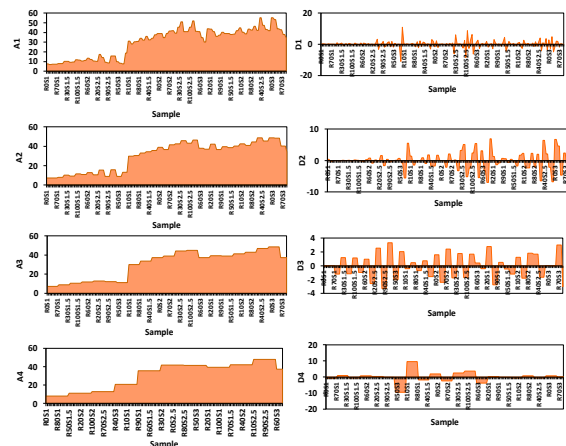


Figure 5. Using DWT in filtering the compressive strength function (4 step filtrations)

A1 (Figure 5). Afterward, the next noise occurred at a change in compressive strength of 7th day to 28th day, which was shown at a high frequency in the form of noise. But compared to the first noise, the second noise is less intense due to the more severe compressive strength on 7th day compared to the 28th day. The jumps due to compressive strength time are shown in Figure 6.

In the fourth stage filter, with lowering the compressive strength curve changes due to filtration, the high-frequency spectrum has fewer fluctuations, while the low frequency changes from oscillating shape to a relatively uniform state. It should be noted that the high-frequency curves have lower rates of variation. If the vertical axis of high-frequency changes as the same as the low-frequency axis, this curve has no significant variations.

5. DWT-BNN Analysis Since the compressive strength curve is highly noisy (Figure 2), for increasing the performance of the estimated data, a combination of a DWT and a BNN is used. The DWT-BNN methodology is as follows (see Figure 7).

In this method, first, the output data is entered into a discrete wavelet transform, and after filtering to up and down frequencies, the broken wave is given as a new output to the neural network. After training the neural network, the outputs are re-constructed. The reconstruction waves after 4 levels have done based on the following equation:

$$RC = A4 + D4 + D3 + D2 + D1 \tag{12}$$

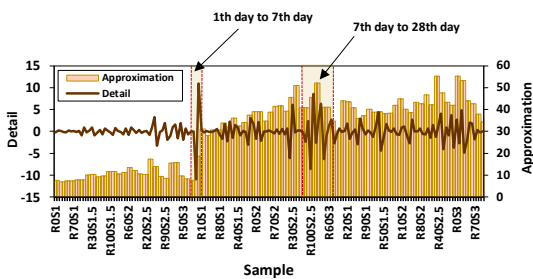


Figure 6. The presence of two main noises at 7th and 28th day of strength test

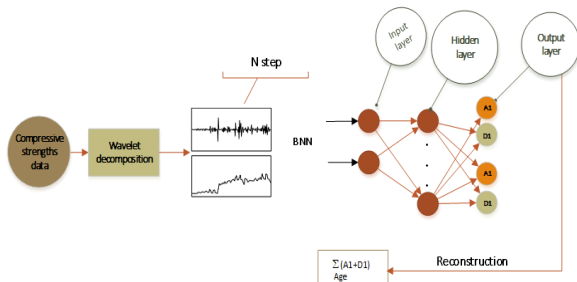


Figure 7. DWT-BNN mechanism

RC is the reconstructed wave, A and D are the approximation and detail, respectively. The number after them is used as a filtration step. Therefore, the compressive strength is again obtained from the above equation. Then the results of observations and predictions are compared with each other.

6. RESULTS AND DISCUSSION

6. 1. Backpropagation Neural Network In the first step, the linear regression method was examined by Excel software. The regression was 0.135. This amount indicates the failure of fitting. Therefore, a more powerful tool is needed. In the second step, the neural network was used. The recycled sand to the total sand, the superplasticizer to cement, and the sand to cement ratios were defined as the network input. Then compressive strength of 1st day, 7th day, and 28th day were considered as the network outputs. After analyzing the network around 38 to 40 times and ensuring complete training, the best result was chosen as its appropriate result. Figure 8 shows the result of fitting by BNN.

As can be seen, the neural network, having regression of 0.9722, has a good ability to estimate the compressive strength of concrete, which is approved by Alilou and Teshnehab [31]. But it seems that with the increase of noisy manner of 28th day strength, the neural network loses its ability (Figure 9).

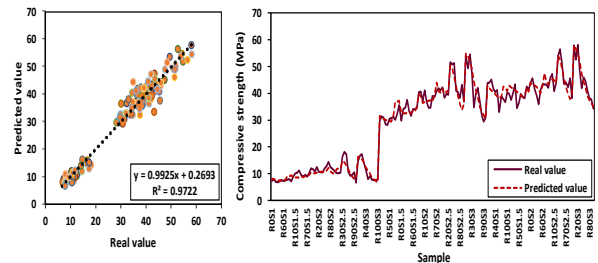


Figure 8. Regression and the real and predicted values by BNN

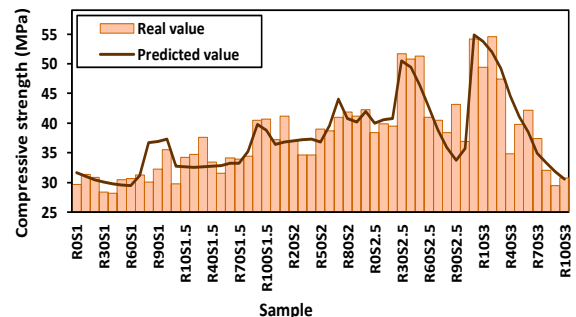


Figure 9. The lack of enough precision for predicting the 28th day compressive strength

The lowest error rate was observed for 1st-day concrete strength. At this time, the MSE error was 0.00056. Also, the error rate increases for the 28th day compressive strength. The MSE error rate is reached to 0.0021. The results are shown in Table 2.

6. 2. DWT 1-BNN In the next step, a DWT is used. For this, filtration of the compressive strength data (the desired output) was performed without reducing the number of data in just one level. Then the filtered data was entered into the neural network as a new output. From the combination of the neural network and the discrete wavelet (one filter level), the results of Figure 10 were obtained.

As shown in Figure 10, the new network regression was 0.9841 which had been 0.9722 before. At this stage, the MSE error index of the 28th day strength was decreased, and thus, the accuracy of the combination network improved. Providing a filtering tool by DWT can denoise the strength spectra and improve the homogeneity of the dataset. Increasing the R² factor is important proof for reducing the standard deviation and improving accuracy. The mean square error rate from 0.00157 reached the 0.000961 level (Table 3). Since the 28th day strength of concrete in many cases has a higher priority and importance than others ages for long term study, the combination of BNN and wavelet with a filtering stage is desirable from two perspectives: 1) having higher regression and less error index than BNN, 2) help to obtain more accurate estimation for 28th day compressive strength. It should be noted that the research conducted by Khademi et al. [32], ANN network with 91% R² factor is chosen as the best tool for predicting 28th day compressive strength. In the current work, the regression increases to 98% which is a more exact answer. So DWT can improve accuracy.

TABLE 2. Errors of BNN

Error	MAE	MSE	SSE	RMSE
1 st day	0.0184	0.0005	0.0306	0.1751
7 th day	0.0332	0.0021	0.1141	0.3378
28 th day	0.0362	0.0021	0.1156	0.3400
average	0.0293	0.0015	0.2604	0.5103

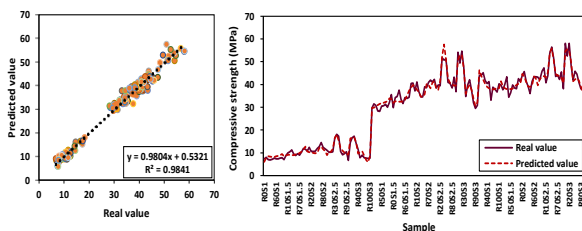


Figure 10. Regression and the real and predicted values differences by DWT 1-BNN

TABLE 3. Errors of DWT 1-BNN

Error	MAE	MSE	SSE	RMSE
1 st day	0.0188	0.0005	0.0284	0.1685
7 th day	0.0285	0.0012	0.0688	0.2624
28 th day	0.0276	0.0011	0.0612	0.2475
average	0.0249	0.0009	0.1585	0.3981

6. 3. DWT 2-BNN

In the next step, the DWT filtering was increased to two levels (Figure 11). In this step, the network error in the prediction of compressive strength of one day was decreased compared to the previous stage and the accuracy of the network was higher, but for the network at 7th and 28th days, the network error was increased. It seems that DWT removes important data instead of denoising them and it deviates BNN; which is approved by Altunkaynak and Wang [33] before. Filters are good for denoising. In this case that the error-index is not too high, using one filter is sufficient.

At one day, the MSE error index was reduced to 0.000255. The MSE error rate on 28th day was reached to 0.00183, while if the neural network had used with one filtering level, the MSE error-index could have been 0.001114. The results indicate an increase in the final errors of this method compared to the previous step (Table 4).

6. 4. DWT 3-BNN

Next, the 3 levels filtering effects were evaluated (Figure 12). The results of the data evaluation showed that the 7th day strength error decreases compared to the use of two levels filter, but at the age of 1st and 28th days, the error of this method is higher than the two levels filtration (Table 5).

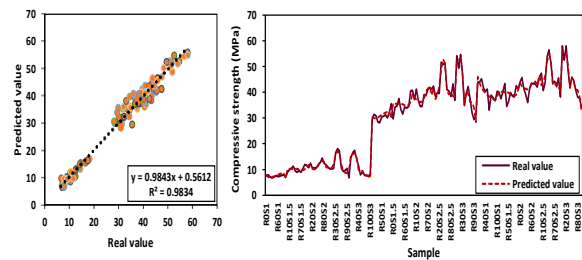


Figure 11. Regression and the real and predicted values differences by DWT 2-BNN

TABLE 4. Errors of DWT 2-BNN

Error	MAE	MSE	SSE	RMSE
1 st day	0.0123	0.0002	0.0140	0.1184
7 th day	0.0344	0.0018	0.1004	0.3169
28 th day	0.0341	0.0018	0.1006	0.3172
average	0.0269	0.0013	0.2151	0.4637

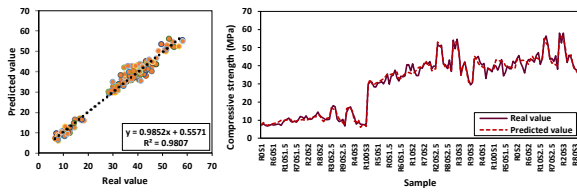


Figure 12. Regression and the real and predicted values differences by DWT 3-BNN

TABLE 5. Errors of DWT 3-BNN

Error	MAE	MSE	SSE	RMSE
1 st day	0.0183	0.0005	0.0254	0.1593
7 th day	0.0304	0.0015	0.0839	0.2896
28 th day	0.0387	0.0025	0.1371	0.3703
average	0.0291	0.0015	0.2464	0.4964

It should also be noted that the MSE error-index on 28th day was increased to 0.002493. While the MSE error index for BNN had been 0.002102. Therefore, the recent state is not recommended for the estimation of 28th day compressive strength due to an increase in error index.

6. 5. DWT 4-BNN In the last step, using four levels filtration, a new network was created. The results are shown in Figure 13. As can be seen, the regression has a value of 0.9658 which was lower than BNN. The network errors were also greater in all ages than the primary backpropagation neural network (Table 6).

Therefore, it is not recommended to use four level filtrations. So the analysis was stopped at 4 step filtrations and the BNN-DWT with 2 level filtrations was introduced as the best network.

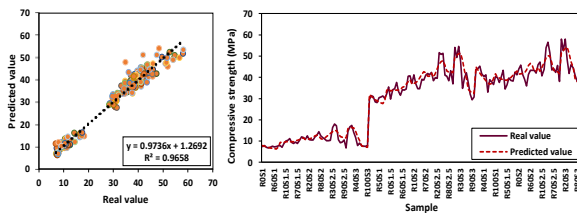


Figure 13. Regression and the real and predicted values differences by DWT 4-BNN

TABLE 6. Errors of DWT 4-BNN

Error	MAE	MSE	SSE	RMSE
1 st day	0.023325	0.000975	0.053622	0.231564
7 th day	0.056574	0.005304	0.291719	0.54011
28 th day	0.059223	0.005264	0.289517	0.538067
average	0.046374	0.003848	0.634857	0.796779

7. CONCLUSION

The current study focuses on the evaluation of DWT-BNN efficiency on C&DW concrete strength prediction. The main results are summarized as follows.

- Previously, the compressive strength prediction has been done for 28th day compressive strength as standard strength. In the current study, it was shown that providing the separated networks for each day is essential.
- The presence of noises on 28th day spectra, deviate BNN from predicting the values with good precision. So the supplementary tool (DWT) added to the BNN.
- Adding DWT with one filter produced a network that as approximately 50% lower MSE error in comparison with BNN. In addition, the R² factor, as the main parameter of network function, increased to 98% which shows the high correlation of real and predicted value.
- This regression and low error indexes in comparison to similar researches, confirm the DWT efficiency.
- The good results of using DWT on BNN encouraged authors to investigate the higher number of filters.
- Evaluating the filters' numbers showed that increment of filters can accumulate errors by removing main data instead of noises. Further, augmentation of low and high passes can decrease the RUN speed and provide computational cost.
- According to the current results, based on the deviation of real and predicted values by BNN, the authors should decide whether to use DWT on BNN or not. If it is necessary to use DWT, adding one (two) filters on DWT is suggested. If the results are not satisfactory, the filters should be added one by one.
- For further investigation, the authors suggested evaluating the mother functions, symmetric or asymmetric, and the shape of wavelets on BNN results.

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Persian Abstract

چکیده

مطالعه حاضر بر دو هدف متمرکز است. در بخش اول یک بتن دوستدار محیط زیست به کمک سنگدانه ساخته شده از ضایعات ساختمانی تولید شد. نتایج مقاومت فشاری نشان داد این نوع بتن تفاوت چندانی از لحاظ مقاومت فشاری با بتن ساخته شده از سنگدانه طبیعی ندارد. در بخش دوم با استفاده از شبکه عصبی مصنوعی انتشار برگشتی اقدام به پیش‌بینی مقاومت فشاری شد. نتایج نشان داد اگرچه مقاومت فشاری با کمک شبکه انتشار برگشتی قابل قبول است اما لازم است به دلیل اهمیت بالای مقاومت ۲۸ روزه بتن، دقت شبکه افزایش یابد. شبکه هیبریدی انتشار برگشتی-موجکی برای این امر پیشنهاد داده شد. استفاده از موجک توانست دقت شبکه را تا رگرسیون ۹۸ درصد بالا برده و خطا را تا ۰/۰۰۱ کاهش دهد. ادامه بررسی‌ها نشان داد افزایش تعداد فیلترها به جای کاهش نویزها منجر به افزایش خطا و زمان محاسبات می‌شود. بر این اساس شبکه هیبریدی انتشار برگشتی-موجکی با یک فیلتر برای پیش‌بینی مقاومت فشاری این نوع بتن مناسب است و افزایش بیشتر فیلترها پیشنهاد نمی‌شود.
