Computers and Concrete, Vol. 10, No. 4 (2012) 379-390
DOI: http://dx.doi.org/10.12989/cac.2012.10.4.379

Using generalized regression neural network (GRNN) for mechanical strength prediction of lightweight mortar

S.V. Razavi*[1], M.Z. Jumaat[2], E.S. Ahmed H[3] and Mohammadi, P.[4]

[1]*Jundi-Shapur University of Technology, Dezful, Iran*
[2]*Civil Engineering Department, University Malaya(UM), Malaysia*
[3]*Civil Engineering Department, Universiti Kebangsaan Malaysia(UKM), Malaysia*
[4]*Islamic Azad University, Dezful Branch, Iran*

(Received June 17, 2011, Revised February 8, 2012, Accepted April 20, 2012)

Abstract. In this paper, the mechanical strength of different lightweight mortars made with 0, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70, 75, 80, 85, 90, 95 and 100 percentage of scoria instead of sand and 0.55 water-cement ratio and 350 kg/m^3 cement content is investigated. The experimental result showed 7.9%, 16.7% and 49% decrease in compressive strength, tensile strength and mortar density, respectively, by using 100% scoria instead of sand in the mortar. The normalized compressive and tensile strength data are applied for artificial neural network (ANN) generation using generalized regression neural network (GRNN). Totally, 90 experimental data were selected randomly and applied to find the best network with minimum mean square error (MSE) and maximum correlation of determination. The created GRNN with 2 input layers, 2 output layers and a network spread of 0.1 had minimum MSE close to 0 and maximum correlation of determination close to 1.

Keywords: mechanical strength; scoria; ANN; GRNN; MSE.

1. Introduction

Lightweight concrete and mortar with adequate mechanical strength reduces the weight of the construction (Wei *et al.* 2008), facilitates the transportation and provides thermal insulation (Lanzona and Garcia-Ruiz 2008). Many studies have been done to make lightweight concrete and mortar using new aggregates and chemical admixtures. The following methods are available to produce lightweight concrete and mortar:

1. Increase the volume of the mixture due to hydrogen gas production by adding lime and aluminium powder in the mixture of silica, cement and water (Short and Kinniburgh 1978).
2. Using lightweight aggregates, such as Perlite (Sanahi 1998), Vermiculite (Short and Kinniburgh 1978), Diatoms (Short and Kinniburgh 1978), Pumice (Shorabi and Rigi 2005) and Scoria (Famili 1997).
3. Use of artificial aggregates, such as expanded clay (Lica) (Merikallio and Mannonen 1996), lightweight residue of blast furnace (Shideler 1975).

The main objective of making lightweight concrete and mortar is a decrease in density and increase in workability (Lanzona and Garcia-Ruiz 2008). For example, an experimental study on using rigid polyurethane foam instead of sand to make lightweight mortar shows a decrease in

* Corresponding author, Lecturer, E-mail: vahidrazavy@yahoo.com

density and the mechanical properties and an increase in the workability (Gadea *et al.* 2010). Sari and Pasamehmetoglu (2004) investigated the effect of plasticizers and air-entrained agents to improve the workability of lightweight concrete. The results of experimental work on cubic samples showed the minimum compressive strength and density of 6.56 N/mm^2 and 1300 kg/m^3 respectively.

Topcu and Odler (1996) used volcanic slag as coarse aggregate to study the properties of semi-lightweight concretes. They reported that volcanic slag could decrease the specific gravity of concrete by as much as 20 per cent of normal concrete. However, decreased workability and low strength were some of the disadvantages of using volcanic slag as aggregate in concrete.

Unal *et al.* (2007) produced block elements with diatomite with different aggregate granulometries and cement contents. According to the results of the mechanical and physical properties in this study, using diatomite in lightweight concretes can be used in construction to reduce the service load and obtain high insulation in buildings.

Mannan *et al.* (2006) made lightweight concrete by using oil palm shell as coarse aggregate. The reason for this research was to determine slump, remoulded density and compressive strength.

Topcu and Uygunoglu (1996) studied the physical and mechanical properties of autoclaved lightweight aggregate concrete using diatomite and pumice. They used diatomite and pumice as lightweight aggregates after autoclave curing at different temperatures and curing times to make lightweight concrete.

Rajamane *et al.* (2007) performed research on lightweight concrete made with fly ash as a partial replacement of both Portland cement and sand. They determined an empirical equation for the 28-day compressive strength prediction of concrete. The results confirmed that the formula can assess the 28-day compressive strength of concrete.

Usually, the empirical equations used for material behaviour are derived from the results of experimental observation. The existing empirical models require solving of several numerical equations in situations where more than one parameter is required for prediction. Artificial Neural Networks (ANNs) are a quick and reliable alternative to such analytical models as they can predict the various parameters in one round network modelling. In ANN modelling, although the numerical relationship is captured between its nodes, no formal mathematical rules or formulae are to be observed within the model. Previous research of ANNs in Civil Engineering mainly focused on Feed-forward Back-propagation Neural Networks (FBNNs) using sufficient data for network generation.

When the number of data is not enough for FBNN generation, the Generalized Regression Neural Network (GRNN) is most useful when only a small number of training data are available (Specht 1990). This is because GRNN has the capability to connect to the primary function of the data. This makes GRNN an extremely useful tool to achieve predictions and comparisons of system performance in practice. GRNNs have been proven to be a capable method for the prediction of many scientific and engineering problems, such as sigma processing (Kendrick *et al.* 1994), chemical processing (Mukesh 1996), assessment of high power systems (Wehenkel 1996). However, the technique has not been widely applied to the field of Civil Engineering.

Williams and Gucunski (1995) have studied the development of GRNN and FBNN to predict the elastic modulus and layer thicknesses for pavement and soil systems. They developed the ANN by using ninety-eight cases of synthetic dispersion-curve data for network training and testing. The results of the generated neural networks were close to the practical outputs.

Mahmut and Gungor (2007) applied GRNN, FBNN and Adaptive Nero Fuzzy Inference System (ANFIS) for daily river flow prediction in the Seyhan catchment, which is located in the south of Turkey. They used 5114 daily river flow data for training and testing and 731 data for verification.

Mahesh and Surinder (2008) generated GRNN for pile capacity modelling. Totally, 105 data sets were collected from prestressed spun pipe piles made with precast high strength concrete and applied for network training and testing. A correlation of determination value of 0.977 was reached for the pile capacity prediction by GRNN.

In this research, the compressive and tensile strength of lightweight mortar made with different percentages of scoria instead of sand is studied. The scoria used in this experimental study, had a white to light grey colour, rough surface, angular particles and irregular open and closed pores. The specific gravity of the aggregate was less than 1 gr/cm^3. The main objective of this research is prediction of the compressive strength and tensile strength of lightweight mortar using GRNN.

2. Methedology

The GRNN architecture for predicting the compressive and tensile strength of lightweight mortar involves four following layers, as shown in Fig. 1:

(1) Input layer: Contains two neurons for the scoria instead of sand and curing time

(2) Pattern neurons: Includes two neurons for each training case

(3) Summation neurons: Includes one neuron equal to neuron in output layer

(4) Output layer: Contains two neurons for the compressive strength and tensile strength

The input layer of processing units is responsible for the reception of the information from the experimental work. For each input variable, a unique input neuron is defined in the model. No processing of data for scoria and curing is conducted at the input neurons. Then, the input neurons present the data to the pattern neurons. The data from the input layer are combined in the pattern layer and then the outputs are computed using the transfer function. The amount of the smoothing parameter plays an important role in the computed output from the pattern layer. The smoothing parameter determines how closely the function implemented by the GRNN fits the training data. A trial and error method was performed to find the optimum smoothing parameter.

After that, the output from the pattern layer was forwarded to the summation layer. The summation layer includes the numerator and denominator neurons, which compute the weighted and simple arithmetic sum, respectively. The denominator, S_d, and numerator, S_j, are defined by the following equations

$$S_d = \Sigma_i \theta_i$$

$$S_j = \Sigma_i w_i \theta_i$$

The calculated summation neurons are subsequently sent to the output neuron. Finally, the output

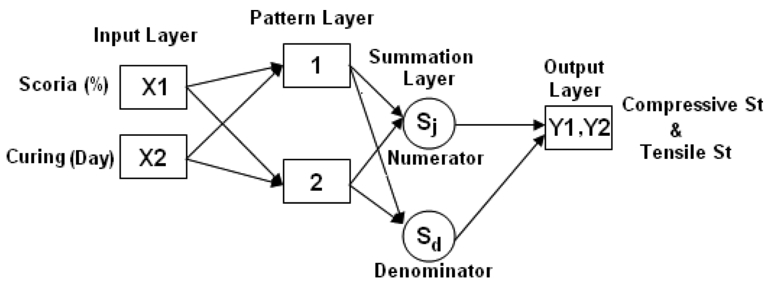

Fig. 1 The GRNN architecture for the lightweight mortar made with different percentage of scoria instead of sand

neuron carries out the following division to calculate the compressive strength and tensile strength of lightweight mortar.

$$Y_1 = S_j / S_d$$

2.1 Data

In order to study the mechanical strength of lightweight mortar made with scoria instead of sand, 210 mortar samples in the shapes of 15×15×15 (cm) cubes and 15×30 (cm) cylinders were made to determine the compressive strength and tensile strength, respectively. The water-cement ratio was 0.55 and the cement content was 350 kg/m^3. The materials mentioned above, were made according to the results of 288 lightweight concrete samples, which were made with scoria instead of sand with 0.55, 0.60 and a 0.65 water-cement ratio; and 300, 350 and 400 kg/m^3 cement content. The relationship between the compressive strength and the cement content for 35~50, 55~70 and 100% of scoria instead of sand for lightweight concrete are shown in Figs. 2, 3 and 4.

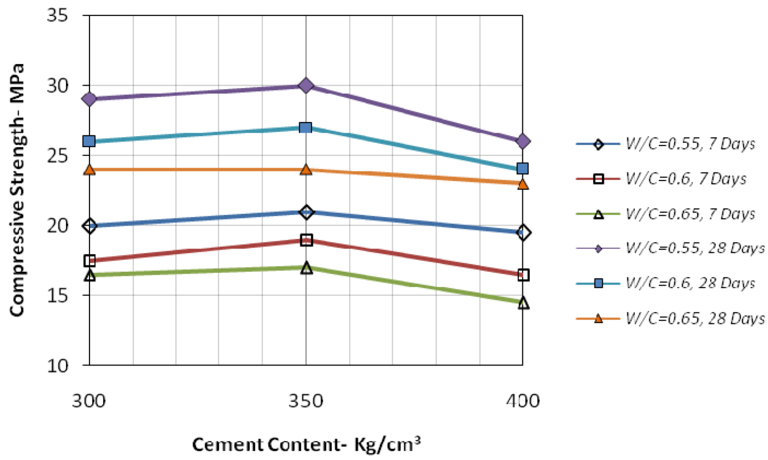

Fig. 2 Relationship between cement content and compressive strength with 35~50% Scoria

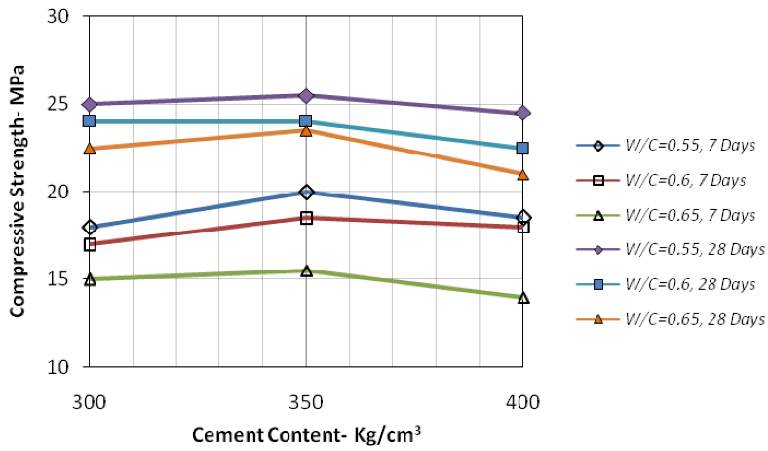

Fig. 3 Relationship between cement content and compressive strength with 55~70% Scoria

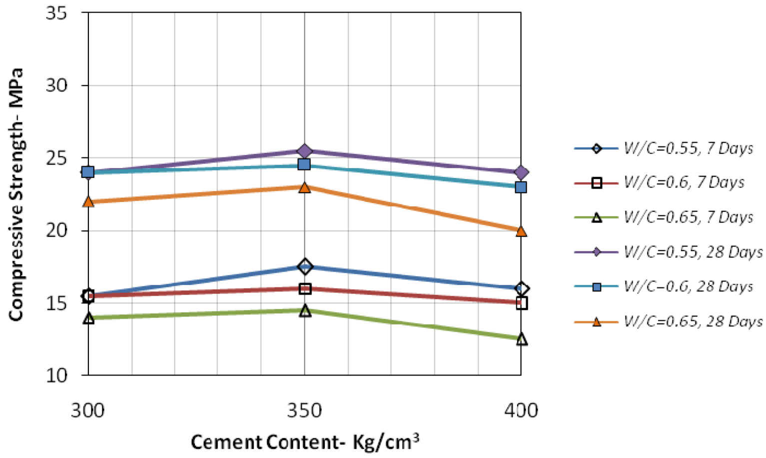

Fig. 4 Relationship between cement content and compressive strength with 100% Scoria

Table 1 Production schedule of lightweight mortar

Parameters	Mortar samples
Scoria instead sand in lightweight mortar - %	0, 5, 10, 15, 20, 25, 30, 35, 40 45, 50, 55, 60, 65, 70, 75 80, 85, 90, 95 and 100
Water-cement ratio	0.55
Cement content in compressive sample – kg/m^3	350
Cement content in tensile sample – kg/m^3	350
Curing time - days	3, 7, 14, 28 and 90

As we can see, the maximum compressive strength was with the 0.55 water cement ratio and 350 kg/m^3 cement concrete. By increasing the water cement ratio and cement content, the concrete compressive strength was decreased. The schedule of the experimental work is shown in Table 1. We consider different percentages of scoria instead of sand, which were studied to find the compressive and tensile strength after 3, 7, 14, 28 and 90 curing days.

All samples were made with normal water and the mean compressive and tensile strength was obtained from three similar samples.

The absolute volume method was applied as the mix design in this study. Knowing the water and cement amounts and by using the absolute volume method (shown as Eq. (1)) the amount of aggregates can be extracted. It is assumed that the volume of the compacted mortar is equal to the total absolute volume of its constituents.

$$\frac{C}{\gamma_C}+\frac{W}{\gamma_W}+\frac{A}{\gamma_A}=1 \tag{1}$$

In this formula C is the amount of cement, W is the amount of water and A is the amount of aggregate (sand + scoria) in kg/m^3 of mortar. The calculated amounts of sand and scoria in each mixture are shown in Table 2. The specific gravity of the sand, scoria, cement and water was 2,200, 760, 3,300 and 1,000 Kg/m^3, respectively.

Table 2 The calculated amounts of sand and scoria

Scoria %	0	5	10	15	20	25	30	35	40	45
Sand (Kg/m^3)	1543.2	1339.1	1167.6	1021.4	895.3	785.4	688.7	603.1	526.7	458.1
Scoria (Kg/m^3)	0.0	70.5	129.7	180.2	223.8	261.8	295.2	324.7	351.1	374.8

50	55	60	65	70	75	80	85	90	95	100
396.2	340.1	288.9	242.0	199.0	159.3	122.7	88.7	57.0	27.6	0
396.2	415.6	433.3	449.5	464.3	478.0	490.7	502.5	513.4	523.6	533.1

3. Results

3.1 Experimental results

First, the calculated amounts of sand, scoria and cement were weighed and mixed for about 60 sec. Then, after one quarter of the mixing time, water was added and the mixing process continued for 180 sec. Subsequently, the cubic samples 15×15×15 cm and cylinder samples 15×30 cm were cast in 3 layers to measure the compressive strength and tensile strength, respectively. Each layer was vibrated by a shaking table for 10 sec to compact samples properly. After keeping in the lab for 24 hours, the samples were opened and cured in water for 3, 7, 14, 28 and 90 days. After removal from the water tank and being kept in the laboratory for a few hours for drying and before testing, all samples were weighed. The specific gravity of all the samples is indicated in Fig. 5. The mortars made with ≥ 60% scoria instead of sand with a specific gravity ≤ 1300 Kg/m^3 (BS EN 992:1996) are lightweight mortars.

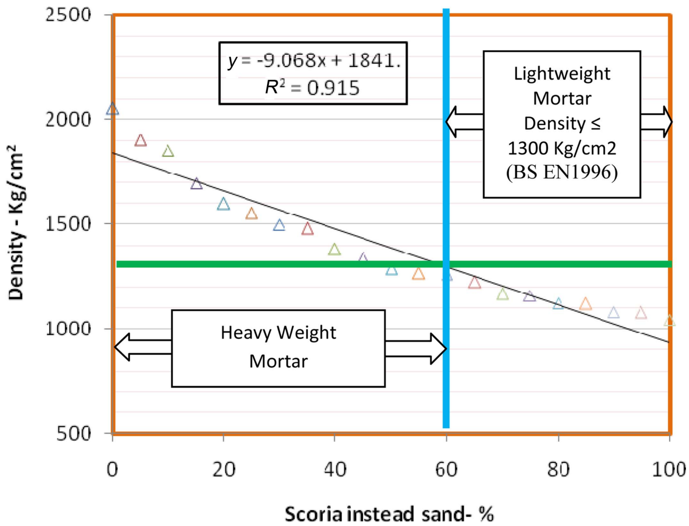

Fig. 5 The limitations of lightweight mortar

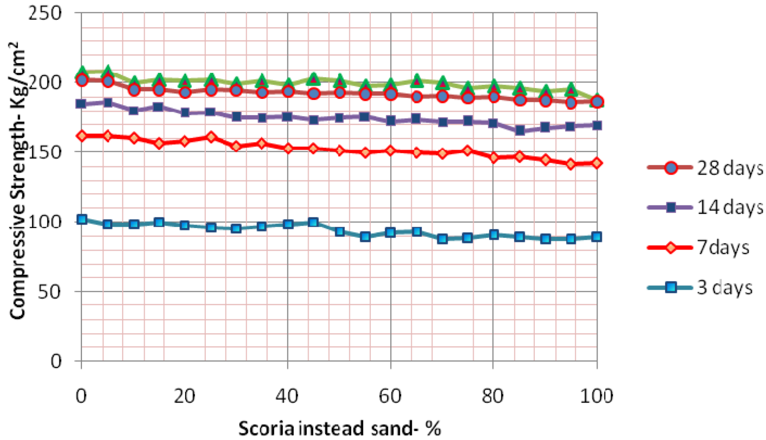

Fig. 6 Relationship between compressive strength and scoria percent instead of sand

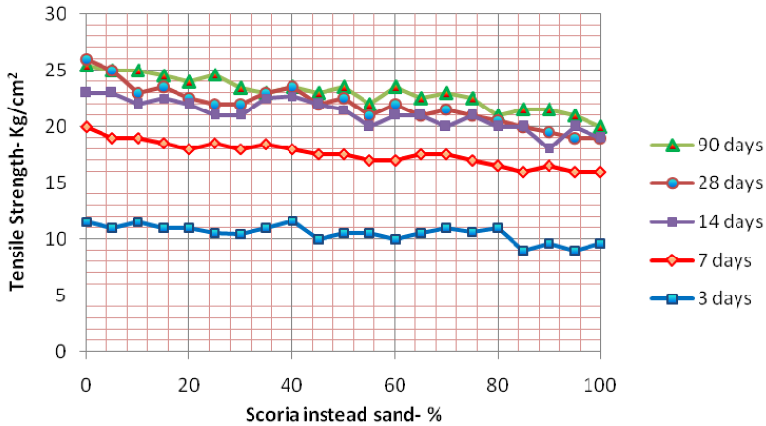

Fig. 7 Relationship between tensile strength and scoria percent instead of sand

Increasing the percentage of scoria instead of sand from 0 to 100% caused a 49% decrease in the specific gravity from 2051 to 1043 Kg/m^3. The relationship between the mechanical strength and the percentage of scoria instead of sand is shown in Figs. 6 and 7. It is observed that by increasing the percentage of scoria instead of sand in mortar from 0 to 100 the compressive strength and tensile strength of mortar decrease. The reasons for this are the low mechanical strength of scoria compared to that of sand (Aydin *et al.* 2010) and the increase in the degree of porosity of the aggregate (Lo and Cui 2004).

The compressive and tensile strength after 28 days curing were 202 and 24 Kg/cm^2, respectively, for 0% scoria instead of sand and 186.8 and 20 Kg/cm^2 for 100% scoria, respectively. By replacing the sand in the mortar with scoria, the results show a 7.52% and 16.67% decrease in the compressive and tensile strength, respectively.

3.2 Network results

Totally, 90 randomly selected data were applied for network creation by considering the 80 data

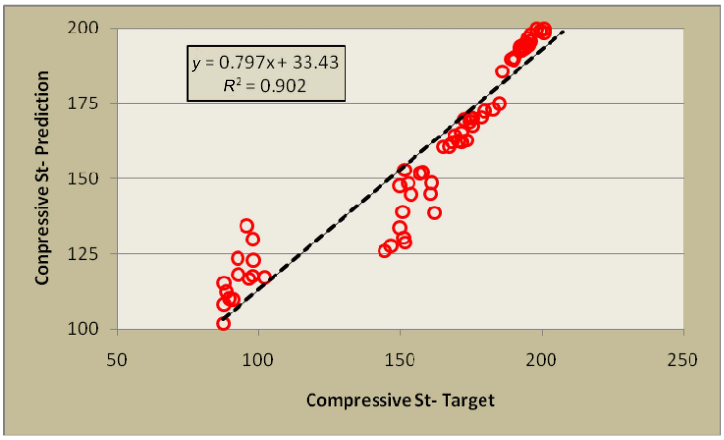

Fig. 8 Evaluation of predicted compressive strength of lightweight mortar in training phase

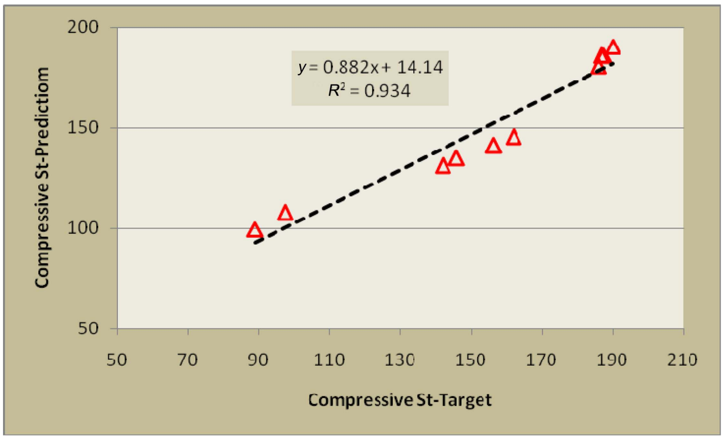

Fig. 9 The correlation of determination between target and predicted compressive strength of lightweight mortar in testing phase

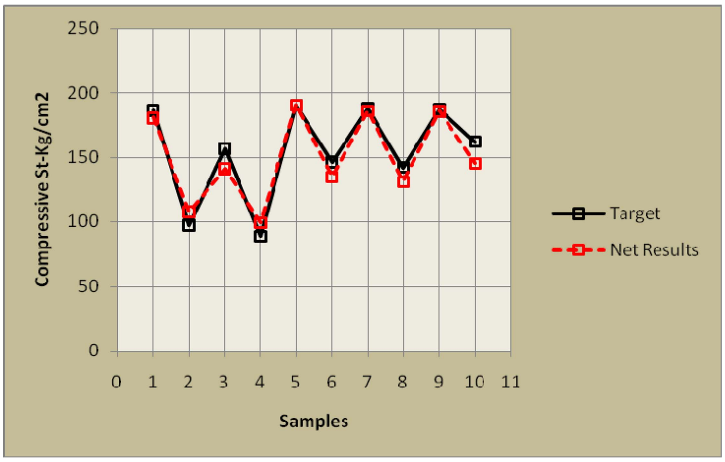

Fig. 10 GRNN response for compressive strength of lightweight mortar in comparison with target

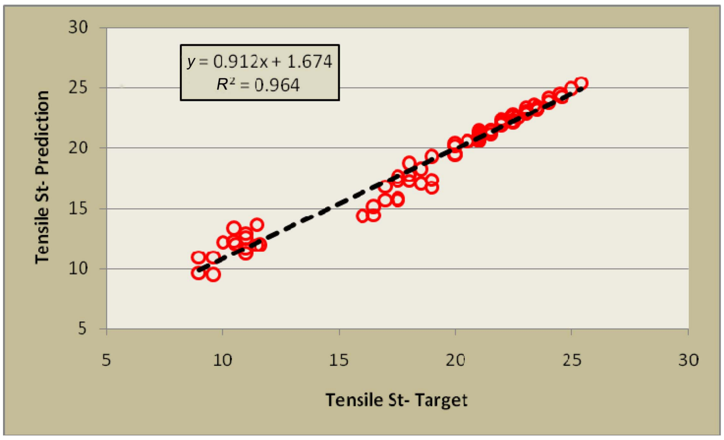

Fig. 11 Evaluation of predicted tensile strength of lightweight mortar in training phase

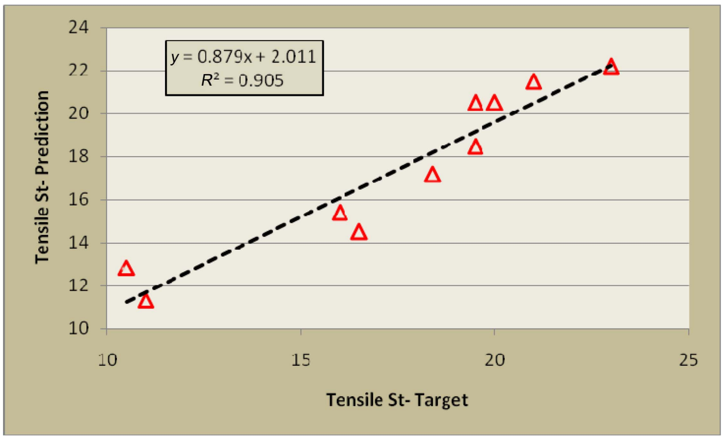

Fig. 12 The correlation of determination between target and predicted tensile strength of lightweight mortar in testing phase

used for network generation and 10 data for testing. The percentages of scoria instead of sand and curing time represented the input layers and compressive and tensile strength were the output layers. The good agreement between experimental compressive strength and predicted by network in training with a coefficient of determination of 0.902 is shown in Fig. 8.

The mean squared error (MSE) in the training stage was 0.69%. In the testing stage, the predicted compressive strength is in good agreement with the experimental results, as well as shown in Figs. 9 and 10. The correlation of determination between the experimental results as target and predicted compressive strength in the testing stage was 0.934. The MSE in the testing stage was 0.57%.

The GRNN response for the tensile strength compared with the experimental results is presented in Figs. 11, 12 and 13. In network training, the selected network represented 0.964 and 0.2% for correlation of determination and MSE respectively. The amount of correlation of determination and MSE in network testing was 0.905 and 1.06 % respectively.

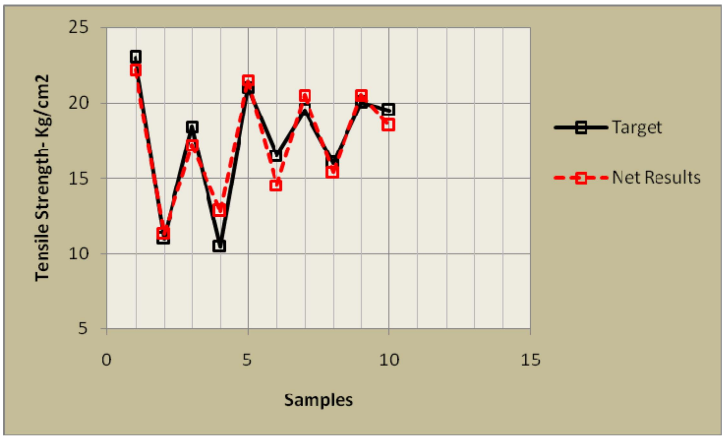

Fig. 13 GRNN response for tensile strength of lightweight mortar in comparison with experimental results as target

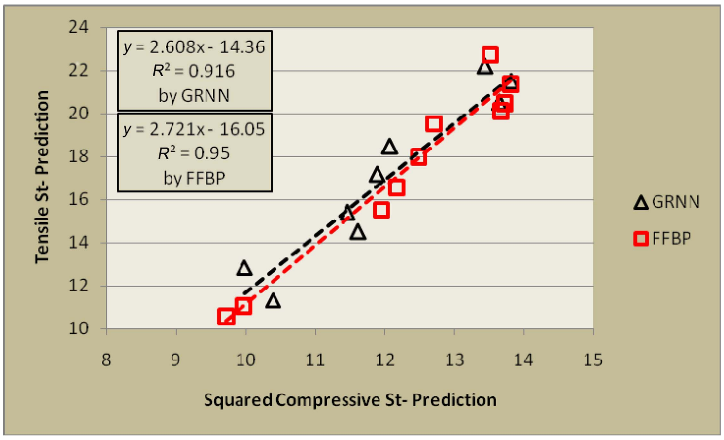

Fig. 14 Relationship between squared compressive strength and tensile strength in both GRNN and FFBP

The predicted tensile strength from generated GRNN is in good agreement with the experimental results. The relationship between the squared compressive strength and the tensile strength of the network output by GRNN and FFBP are given in Fig. 14. The result of the predicted relationship by GRNN is compared with the FFBP output produced by the current researchers in another study (Razavi *et al.* 2011) The accurate squared correlation coefficient is close to 1 and in good agreement with the FFBP output. The results present the effective relation between the squared compressive strength and the tensile strength predicted by both networks GRNN and FFBP.

4. Conclusions

(1) Mixtures made with 60% or more of scoria instead of sand were categorized as lightweight mortar according to the BS code.

(2) By increasing the percentage of scoria instead of sand in the mortar from 0 to 100%, the mortar 28-days density, compressive strength, and tensile strength decreased by 49, 7.5 and 16.7%, respectively.

(3) The training performance function for the compressive and tensile strength was 0.69 and 0. 57%, respectively.

(4) The training coefficient for the determination of the compressive and tensile strength was 0.905 and 0.934, respectively.

(5) The ratio between the network outputs and the experimental results for the compressive and tensile strength was between 0.9 to 1.12 and 0.88 to 1.22, respectively.

(6) The relationship between squared compressive strength and tensile strength predicted by GRNN presented an effective coefficient of determination equal to 0.916.

References

Aydin, A.C., Karakoç, M.B., Düzgün, O.A. and Bayraktutan, M.S. (2010), "Effect of low quality aggregates on the mechanical properties of lightweight concrete", *Sci. Res. Essays,* **5**(10), 1133-1140.

BS EN 992 (1996), *Determination of the dry density of lightweight aggregate concrete with open structure*, British Standards Institution.

Donald F. Specht (1990), "Probabilistic neural networks", *Neural Networks*, **3**(1), 109-118.

Famili, H. (1997), "A project about lightweight concrete", *Published by University of Elmo sanat, Iran, Tehran*.

Gadea, J., Rodríguez, A., Campos, P., Garabito, J. and Calderón, V. (2010), "Lightweight mortar made with recycled polyurethane foam", *Cement Concrete Comp.,* **32**(9), 672-677.

Kendrick, R., Acton, D. and Duncan, A. (1994), "Phase-diversity wave-front sensor for imaging systems", *Appl. Optics,* **33**(27), 6533-6547.

Lanzóna, M. and García-Ruiz, P.A. (2008), "Lightweight cement mortars: Advantages and inconveniences of expanded perlite and its influence on fresh and hardened state and durability", *Constr. Build. Mater.,* **22**(8), 1798-1806.

Lo, T.Y. and Cui, H.Z. (2004), "Effect of porous lightweight aggregate on strength of concrete", *Mater. Lett.,* **58**(6), 916-919.

Mahesh, P. and Surinder, D. (2008), "Modeling pile capacity using support vector machines and generalized regression neural network", *J. Geotech. Geoenviron.,* **134**(7), 1021.

Mahmut, F. and Gungor, M. (2007), "Generalized regression neural networks and feed forward neural networks for prediction of scour depth around bridge piers", *Adv. Eng. Softw.,* **40**(8), 731-737.

Mannan, M.A., Alexander, J., Ganapathy, C. and Teo, D. (2006), "Quality improvement of oil palm shell (OPS) as coarse aggregate in lightweight concrete", *Build. Environ.,* **41**(9), 1239-1242.

Merikallio, T. and Mannonen, R. (1996), "Drying of lightweight concrete produced from crushed expended clay aggregates", *Comput. Concrete Res.,* **26**(9), 1423-1433.

Mukesh, D. (1996), "Introduction to neural networks: Application of neural computing for process chemists, part 1", *J. Chem. Educ.,* **73**(5), 431-434.

Rajamane, N.P., Peter, J.A. and Ambily, P.S. (2007), "Prediction of compressive strength of concrete with fly ash as sand replacement material", *Cement Concrete Comp.,* **29**(3), 218-223.

Razavi, S.V., Jumaat, M.Z., EI-Shafie, A.H. and Mohammadi, P. (2011), "Artificial neural network for mechanical strength prediction of lightweight mortar", *Sci. Res. Essays,* **6**(16), 3406-3417.

Sanahi, G. (1998), *Application of perlit in construction process*, University of Tabriz, Iran.

Sari, D. and Pasamehmetoglu, A. (2004), *The effect of grading and admixture on the pumice lightweight aggregate concrete*, *Depart. Civil Eng.,* Atilim University. Ankara. Turkey.

Shideler, J. (1975), "Lightweight aggregate concrete for structural use", *ACI J.,* **54**(4), 299-328.

Shorabi, M. and Rigi, A. (2005), "Application of lightweight concrete properties with lightweight grain of taftan in construction method", *2nd International Conferences on Concrete & Development,* Tehran, Iran, 109.

Short, M. and Kinniburgh, W. (1978), *Lightweight concrete*, Galliard, 464.
Topcu, I.B. and Odler, I. (1996), "Semi lightweight concretes produced by volcanic slags", *Cement Concrete Res.*, **27**(1), 15-21.
Unal, O., Uygunog, T. and Yildiz, A. (2007), "Investigation of properties of low strength lightweight concrete for thermal insulation", *Build. Environ.,* **42**(2), 584-590.
Wehenkel, L. (1996), "Contingency severity assessment for voltage security using non-parametric regression techniques", *IEEE T. Power Syst.,* **11**(1), 101-111.
Wei, Y., Yang, J., Lin, Y., Chuang, S. and Wang, H. (2008), "Recycling of harbor sediment as lightweight aggregate", *Mar. Pollut. Bull.,* **57**(6-12), 867-872.
Williams, T. and Gucunski, N. (1995), "Neural networks for backcalculation of modula from SASW test", *J. Comput. Civil Eng.,* **9**(1), 1-9.

CM