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Prediction of compressive strength of lightweight mortar exposed to sulfate attack

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Abstract. This paper summarizes the results of experimental research, and artificial intelligence methods focused on determination of compressive strength of lightweight cement mortar with silica fume and fly ash after sulfate attack. The artificial neural network and the support vector machine were selected as artificial intelligence methods. Lightweight cement mortar mixtures containing silica fume and fly ash were prepared in this study. After specimens were cured in 20±2℃ waters for 28 days, the specimens were cured in different sulfate concentrations (0%, 1% $\mathrm{MgSO_4^{-2}}$, 2% $\mathrm{MgSO_4^{-2}}$, and 4% $\mathrm{MgSO_4^{-2}}$ for 28, 60, 90, 120, 150, 180, 210 and 365 days. At the end of these curing periods, the compressive strengths of lightweight cement mortars were tested. The input variables for the artificial neural network and the support vector machine were selected as the amount of cement, the amount of fly ash, the amount of silica fumes, the amount of aggregates, the sulfate percentage, and the curing time. The compressive strength of the lightweight cement mortar was the output variable. The model results were compared with the experimental results. The best prediction results were obtained from the artificial neural network model with the Powell-Beale conjugate gradient backpropagation training algorithm.

Keywords: cement mortar; silica fume; fly ash; compressive strength; modeling; sulfates/sulfate resistance

1. Introduction

Lightweight aggregates have a density lower than conventional aggregates. The densities are varied between 560 and 2000 kg/m^3 (Kostmatka *et al*. 2002). The water absorption is generally between 5% and 30% (Payam *et al*. 2013, FIP 1983). Lightweight aggregates are divided into the natural and artificial. Lightweight concrete can easily produce by using natural or artificial lightweight aggregate (Kılıç *et al.* 2003). The earliest application was produced the cement mortar ships during First World War in North America (Wilson 1954). The lightweight cement mortars with high compressive strength have produced during these years (Spratt 1974). Al-Noury said that the compressive strength of the lightweight mortar might be estimated with an empirical formula, if the densities of the lightweight mortar are known (Al-Noury *et al*. 1990, Yu 2013). Yu and Gjørv reported that the cement paste enters in to lightweight aggregates in mixing (Yu *et al.* 2013, Zhang and Gjørv 1991).

The sulfate ion causes deterioration of concrete structural parts exposed to sulfate salts (Brown 1981, Ouyang *et al.* 1988, Mehta 1983, Stark 1980, Wee *et al.* 2000, Hossain and Lachemi 2006). Sulfate attack is a slowly process on cement-based materials. Some properties of material may be increased an early stage of the sulfate attack (Aköz *et al.* 1999, 1995, 1997, Cohen and Mather 1991). The sulfate resistance of concrete can be improved by controlling sulfate permeation into concrete. Furthermore, the sulfate attack can prevent by using such as fly ash, silica fume (Hossain 1999, Kalousek *et al.* 1972, Al-amoudi *et al.* 1994, 1995, Naik *et al.* 1996, Wong and Poole 1987, Dunstan 1980). The dissolved chloride in water increases the rate of portlandite. Hence, it causes to loss of stiffness and strength of concrete. The sulfates are increasing the harmful effect to concrete as they are causing to the expansion, cracking, spalling and the loss of strength (Wee *et al*. 2000, Shannag and Shaia 2003). Sahmaran (Sahmaran *et al.* 2007) showed that the repetitive crystallization of sulfates might affect the performance of cements against sulfate attack. Felekoglu *et al*. showed (Felekoğlu *et al.* 2006) that the expansions of cement mortar increased by the amount of mineral additions. They said that the test method couldn’t be an appropriate method for determination of sulfate resistance of blended cements. Binici *et al.* showed (Binici *et al.* 2007) that pumice aggregates were a suitable material for blended cement production for the sulfate resistance.

Artificial neural network models (ANN) for concrete strength have applied by investigators (Zarandi *et al.* 2008, Topcu and Sarıdemir 2007a, 2008a, b, Yeh 2007, Demir 2008, Altun *et al.* 2008). Zarandi (Zarandi *et al.* 2008) used a fuzzy-neural network model for the prediction of compressive strength of concrete. Topcu presented an artificial neural network model for prediction of the concrete strength (Topçu *et al.* 2007, 2008a, b). Yeh presented an ANN model and second-order regressions for prediction of slump flow of concrete (Yeh 2007). Demir presented an artificial neural network model for estimation of elastic modulus of concrete (Demir 2008). Altun presented ANN model for compressive strength of

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Table 1 The chemical properties of cement, fly ash and silica fume

Bulk Oxide	% by mass		
	Portland Cement	Fly Ash	Silica Fume
SiO_2	21.12	48.53	91
Al_2O_3	5.62	24.61	0.58
Fe_2O_3	3.24	7.59	0.24
CaO	62.94	9.48	0.71
MgO	2.73	2.28	0.33
LOI	1.42	0.93	1.84
Specific surface area (cm^2/g)	3430	2836	--
Particle size	--	87.5%<125 m	96.5%<45 m
Specific gravity	3.10	2.27	2.2

lightweight concrete containing steel fiber (Altun *et al*. 2008). Inan used to the neuro fuzzy model for estimation of sulfate expansion of concrete (Inan *et al*. 2007). Zhou was used to predict compressive strength of hollow concrete block masonry prisms using ANN and ANFIS (Zhou *et al.* 2016).

The support vector machine (SVM) has been generally determined the classification or function-approximation problems (Ranković *et al.* 2014). The SVMs uses training and testing of data instances. Furthermore, the SVMs minimize the generalization error (Wang *et al.* 2012). Recently, the SVMs have been successfully used in the civil engineering. Lee successfully applied the support vector model for the concrete strength using the mix proportion data (Lee *et al.* 2007). Chen devised an SVM model for the fire-damaged concrete. He said that the ability to predict of the SVM model increases by the increase of the parameters (Chen 2008). Shi and Dong estimated the strength properties of cement samples with SVM. They indicated that SVM could be used for prediction strength of cement (Shi and Dong 2011). Sonebi *et al*. was investigated the feasibility using SVM for the prediction of the fresh properties of self-compacting concrete. They said that the proposed SVM model can gain a high precision (Sonebi *et al.* 2016).

The prediction of the strength properties of lightweight concrete containing mineral admixtures exposed to sulfate attack has not been investigated. Because of this, the ANN models with the different learning algorithms, and the support vector machine was devised to predict of strength properties of lightweight concrete containing mineral admixtures exposed to sulfate attack.

2. Materials and methods

2.1 Materials

CEM I 42.5 N was selected in this study. Fly ash and Silica fume were obtained from Turkey. The chemical analysis properties of the materials were shown in Table 1. The fly ash is a class C fly ash as per ASTM C618 (ASTM C618 2012). Pumice aggregate was used in the production of cement mortars. The specific gravity of lightweight aggregate was 2.

Table 2 Mixture proportion of concretes

Mix	Cement, kg/m^3	Fly Ash, kg/m^3	Silica fume, kg/m^3	W/B	Pumice Aggregates, kg/m^3	SP, ltr/m^3
H	400	--	--	0.77	1038	4.8
U	340	60	--	0.77	1024	4.8
S	360	--	40	0.77	1028	4.8

2.2 Preparation of specimens

The maximum size of pumice aggregates was used 4 mm for this study. The mix proportions are shown in Table 2. The super plasticizer was used to improve the workability. The produced mortar was placed in the standard cube (50 mm×50 mm×50mm) molds. Three samples were prepared for each mixture and curing time. Total number of samples was 288. The specimens were removed after 24 hours. They were kept in a water tank at 20±2℃ for 28 days.

2.3 Exposure to magnesium sulfate of samples

The specimens were separated into two groups after the curing. The first group of specimens was continuously kept under a water tank at 20±2℃. The other group was kept in three tanks with the following sulfate concentrations:

- 1% $MgSO_4^{-2}$ (10.000 mg/l),
- 2% $MgSO_4^{-2}$ (20.000 mg/l),
- 4% $MgSO_4^{-2}$ (40.000 mg/l).

ACI-225R-85 and ACI-201.2R-77 (ACI-225R-85 1985, ACI-201.2R-77 1977) standards, any sulfate water in which the sulfate ion concentration is within: 1500 *ppm*<SO_4=< 10000 *ppm* were determined as “severe” sulfate environment, and those for which the sulfate ion concentration is greater than 10000 *ppm* were determined as “very severe” sulfate water environment. The sulfate water tanks had three different ranges of SO_4=concentration: 10000 *ppm*, 20000 *ppm* and 40000 *ppm*, which are both in “very severe” condition according to ACI (ACI 225R-85 1985, ACI 201.2R-77 1977). The samples were taken out of the sulfate solutions at the end of one year exactly, left in the laboratory environment without washing for a couple of days to attain air-dry forms. The measurements were made at 4, 6, 9, and 12 months according to ASTM C 1012 (ASTM C1012 2004). Due to this, the max exposure time to sulfate attack was selected 12 months.

3. Results

3.1 Residual mechanical results after sulfate attacks

Sulfate attack has been investigated in the reaction between the cement hydrates and dissolved compounds in the attacking solution (Taylor 1997). Furthermore, there have been many works with sulfate deterioration. They

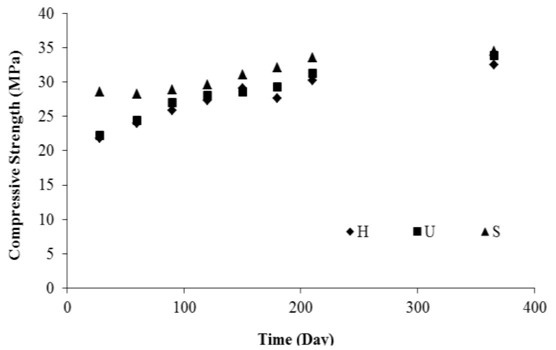

Fig. 1 Compressive results of lightweight cement mortar exposed 0% sulfate attack

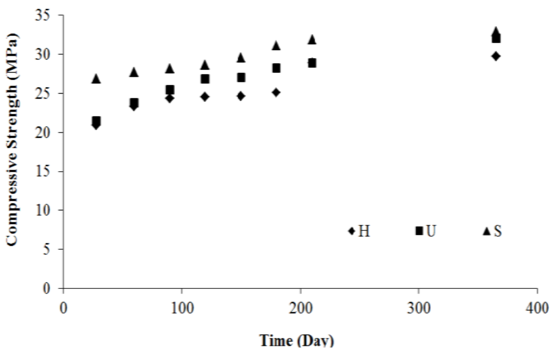

Fig. 2 Compressive results of lightweight cement mortar exposed 1% sulfate attack

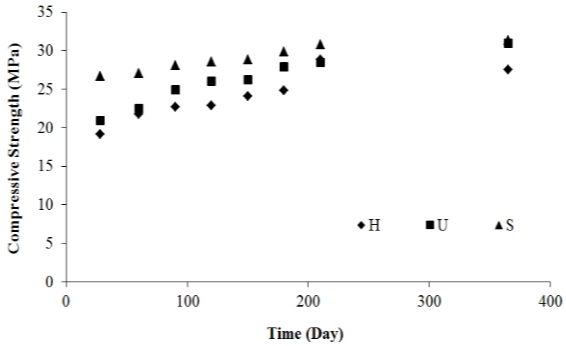

Fig. 3 Compressive results of lightweight cement mortar exposed 2% sulfate attack

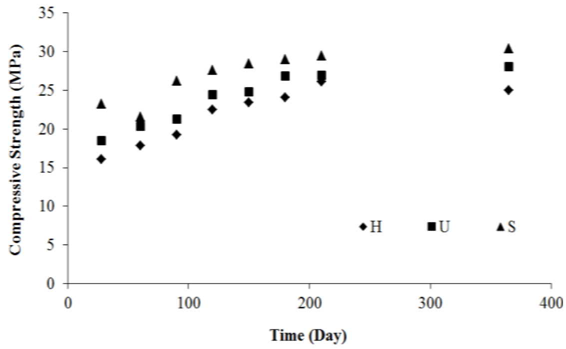

Fig. 4 Compressive results of lightweight cement mortar exposed 4% sulfate attack

have occurred the ettringite, gypsum, M-S-H and brucite after sulfate attack (Taylor 1997, Moon *et al.* 2003, Rasheeduzzafar *et al.* 1994, Seung *et al.* 2008). Besides, many researchers (Tsivilis *et al.* 2003, Vuk *et al.* 2002, Irassar *et al.* 2005, 2003, Hartshorn *et al.* 2001) have studied that the sulfate deterioration in cement system containing significant levels of limestone filler at the certain temperature.

The compressive strength results of lightweight cement mortars incorporating fly ash and silica fume exposed to different magnesium sulfate concentration during 365 days can be seen in Figs. 1-4. It can be shown from Figs. 1-4 that the compressive strength of lightweight cement mortars decreases with the increase of sulfate concentration. The compressive strength of specimens without mineral admixtures has decreased 3.90%, 2.92%, 6.06%, 10.04%, 15.31%, 9.05%, 4.30%, and 8.78% compared to that the compressive strength of mortars exposed to 1% sulfate attack at 28, 60, 90, 120, 150, 180, 210, and 365 days, respectively. The compressive strength of mortars without mineral admixtures has decreased 12.29%, 9.38%, 12.46%, 16.31%, 17.43%, 10.07%, 4.76%, and 15.51% compared to that mortars without mineral admixtures exposed to 2% sulfate attack at 28, 60, 90, 120, 150, 180, 210, and 365 days, respectively. The compressive strength of mortars without mineral admixtures has obtained as 26.24%, 25.51%, 25.66%, 17.45%, 19.63%, 12.93%, 13.52%, and 23.12% decrease compared to that compressive strength of lightweight cement mortars without mineral admixtures exposed to 4% sulfate attack at curing days, respectively. The decrease of compressive strength of lightweight cement mortars containing fly ash has occurred 3.28%, 2.38%, 5.74%, 4.18%, 5.33%, 3.35%, 7.54%, and 5.40% compared to that compressive strength of lightweight cement mortars containing fly ash exposed to 1% sulfate attack at curing days, respectively. The change of compressive strength of lightweight cement mortars containing fly ash has obtained 6.07%, 7.91%, 7.71%, 7%, 8.13%, 4.55%, 9.20%, and 8.73% decrease compared to that compressive strength of lightweight cement mortars containing fly ash exposed to 2% sulfate attack at curing days, respectively. The compressive strength of lightweight cement mortars containing fly ash has decreased 16.73%, 16.56%, 21.04%, 12.63%, 12.89%, 8.24%, 13.83%, and 17.23% compared to that compressive strength of lightweight cement mortars containing fly ash exposed to 4% sulfate attack at curing days, respectively. The decrease of compressive strength of lightweight cement mortars containing silica fume has obtained 5.98%, 1.81%, 2.49%, 3.48%, 4.96%, 2.84%, 4.98%, and 4.78% compared to that compressive strength of lightweight cement mortars incorporating silica fume exposed to 1% sulfate attack at curing days, respectively.

The change of compressive strength of lightweight cement mortars incorporating silica fume has found 6.75%, 3.97%, 2.77%, 3.75%, 7.27%, 7.07%, 8.19%, and 9.13% decrease compared to that compressive strength of lightweight cement mortars incorporating silica fume exposed to 2% sulfate attack at curing days, respectively. The compressive strength of lightweight cement mortars incorporating silica fume has decreased 18.74%, 23.40%, 9.32%, 6.78%, 8.56%, 9.60%, 12.4%, and 12.05% compared to that compressive strength of lightweight

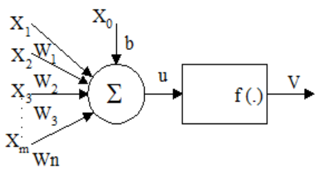

Fig. 5 Artificial neuron model

cement mortars incorporating silica fume exposed to 4% sulfate attack at curing days, respectively. The effect of chemical composition of mineral admixtures (fly ash, silica fume, etc.) is a significant factor affecting its sulfate resistance performance (Assem *et al.* 2014). Lightweight cement mortars containing silica fume were given the best results among mineral additives. Wee et al. said that the samples containing 5% and 10% silica fume were played a major role in resisting sodium (Wee *et al.* 2000). The mortar samples with the silica fume decrease calcium hydroxide because of the pozzolanic reaction. Furthermore, it allows the magnesium sulfate to more easily attack the C-S-H because the cement bond is destruction.

The gypsum would tend to form due to locally reduce pH and the limited local of aluminums Rasheeduzzafar *et al.* 1994, Al-Amoudi 1998, Lee and Moon 2005). The lightweight cement mortars containing fly ash were given a better performance than lightweight cement mortars without mineral admixture. The fly ash has the major roles in resistance to sulfate attack. They are given below.

• The mortars containing fly ash have shown that the sulphate-containing hydrate has the long-term stability.

• The formation of the monosulphate phase occurs the less volume change when compared to the formation of ettringite.

• There is no recrystallisation as the case with ettringite formation (Plowman and Cabrera 1996).

3.2 Application of artificial neural network

Artificial neural network is both the mathematical and computational model.

It uses to simulate the functions of biological neural networks (Duan *et al.* 2013, Hanbay *et al.* 2008, Haykin 1994, Hanbay *et al.* 2008b, Bilim *et al.* 2009). Although it seems simple and small in size, ANN has incredible capability in modeling the human brain (Haykin 1994). A diagram of an artificial neuron model is seen from Fig. 5.

Let

$$X=(X_1, X_2, X_3, X_4, X_4 \ldots X_n) \tag{1}$$

Eq. (1) shows the n input applied to the neuron. W_j shows the weight for X_j. B is a bias. Eq. (2) shows the output of the neuron. The neurons are connected to the connection link. There is a weight of each link. Furthermore, there is an activation function of each neuron. The nonlinear activation function is usually used sigmoid (Hanbay *et al*. 2008a, b Haykin 1994, Hanbay *et al*. 2008b, Bilim *et al*. 2009).

$$u = \sum_{j=0}^{m} x_j w_j - b \quad \text{and } V=f(u) \tag{2}$$

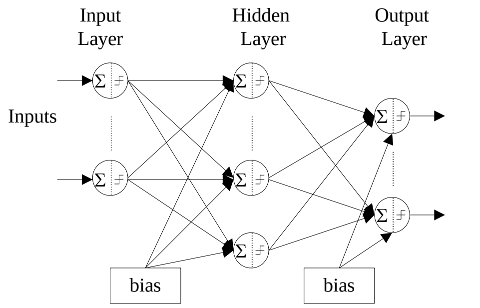

Fig. 6 Multilayer feed forward neural network structure

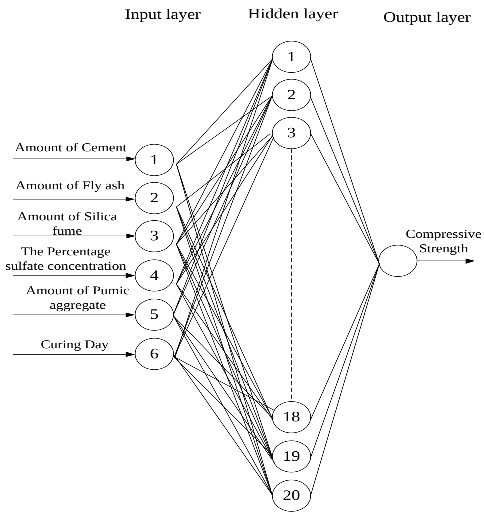

Fig. 7 ANN architecture

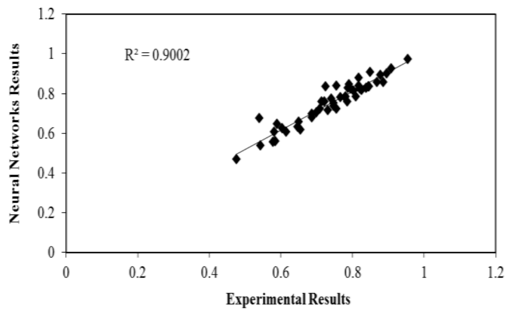

Fig. 8 Linear relationship between measured and predicted compressive strengths for the BFGS quasi-Newton backpropagation of ANN

If an ANN model designed, some things must be taken considered. Firstly, the appropriate structure of the ANN model must be determined. Secondly, the activation function needs to be identified. Thirdly, the numbers of layers and units in each layer must be determined. The most general model supposes complete interconnections between all units. They may be bidirectional or unidirectional (Hanbay *et al.* 2008a, Haykin 1994, Hanbay *et al.* 2008b, Bilim *et al.* 2009). There are many kinds of ANN structure. The multilayer feed forward of ANN is one of these. It is shown in Fig. 6.

In this study, the network model was devised using six inputs and one output parameter. The amount of cement, the amount of fly ash, the amount of silica fumes, the amount

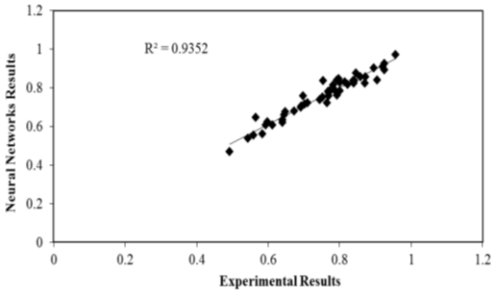

Fig. 9 Linear relationship between measured and predicted compressive strengths for the Powell-Beale conjugate gradient backpropagation of ANN

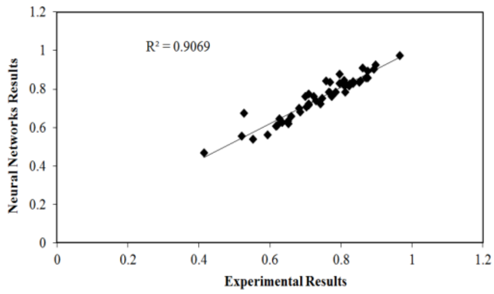

Fig. 10 Linear relationship between measured and predicted compressive strengths for the Fletcher-Powell conjugate gradient backpropagation of ANN

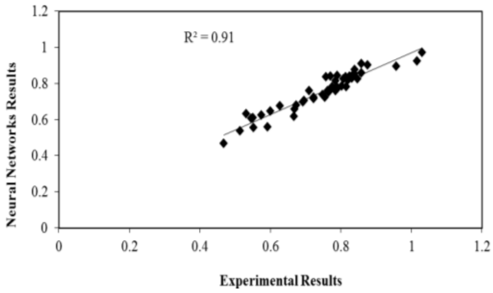

Fig. 11 Linear relationship between measured and predicted compressive strengths for the Polak-Ribiere conjugate gradient backpropagation of ANN

of pumice aggregates, the percentage sulfate concentrations and days were used as input variables. The compressive strength was selected as the output variable of the model. The average of 288 samples was taken. The 96 data samples were used for ANN. The data were divided with max values to normalize. The ANN architecture is shown in Fig. 7. All algorithms of ANN were used. The BFGS quasi-Newton, the Powell-Beale conjugate gradient, the Fletcher-Powell conjugate gradient, the Polak-Ribiere conjugategradient, the Levenberg-Marquardt, the One-step secant, the Resilient, the Scaled conjugate gradient back-propagation algorithms were only learned. The number of neurons in the hidden layer was changed to the better results in the training.

The best result for the BFGS quasi-Newton back-propagation was achieved from the fifteen neurons. The best result for the Powell-Beale conjugate gradient back-propagation algorithm was found from the twenty neurons. The best result for the Fletcher-Powell conjugate gradient back-propagation was achieved from the twelve neurons.

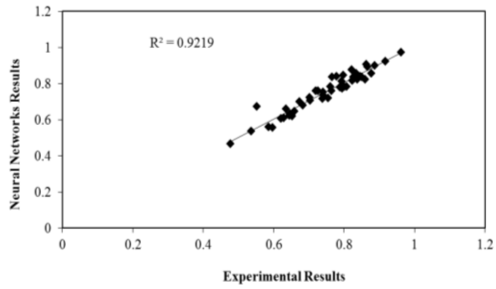

Fig. 12 Linear relationship between measured and predicted compressive strengths for the Levenberg-Marquardt backpropagation of ANN

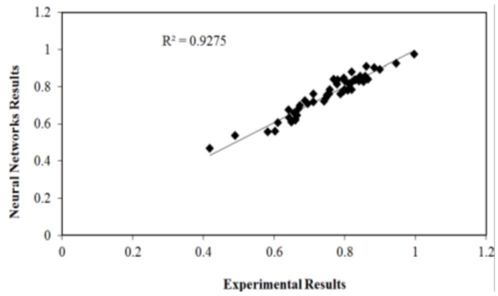

Fig. 13 Linear relationship between measured and predicted compressive strengths for the one step secant backpropagation of ANN

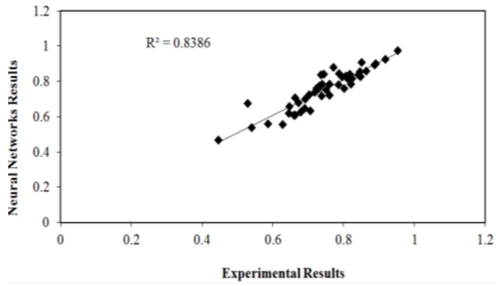

Fig. 14 Linear relationship between measured and predicted compressive strengths for the Resilient backpropagation of ANN

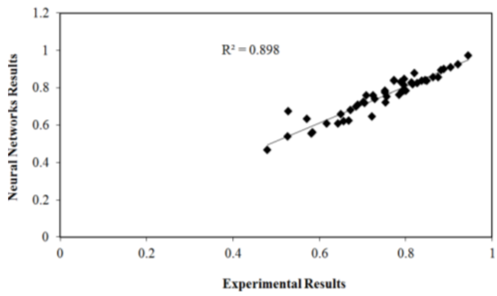

Fig. 15 Linear relationship between measured and predicted compressive strengths for the scaled conjugate gradient backpropagation of ANN

The best result for the Polak-Ribiere conjugate gradient back-propagation was achieved from the nineteen neurons. The best result for the Levenberg-Marquardt back-propagation was achieved from the five neurons.

The best result for the One-step secant back-propagation was achieved from the ten neurons. The best result for the

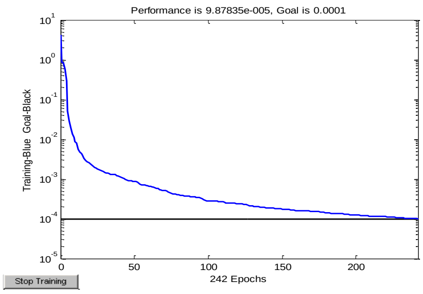

Fig. 16 Training performance for the BFGS quasi-Newton backpropagation of ANN

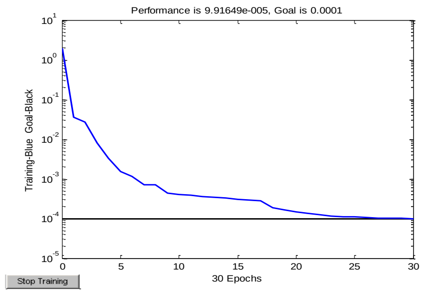

Fig. 20 Training performance for the Levenberg-Marquardt backpropagation of ANN

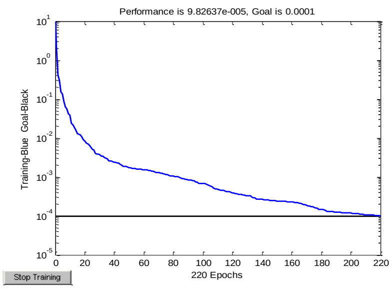

Fig. 17 Training performance for the Powell-Beale conjugate gradient backpropagation of ANN

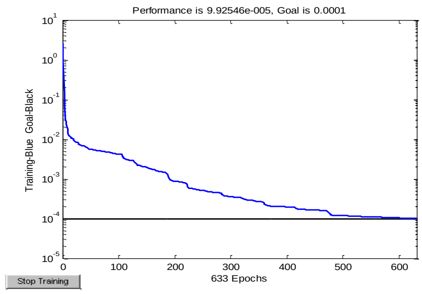

Fig. 21 Training performance for the one step secant backpropagation of ANN

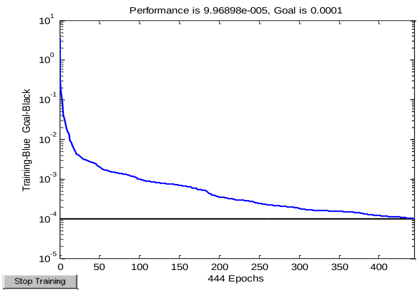

Fig. 18 Training performance for the Fletcher-Powell conjugate gradient backpropagation of ANN

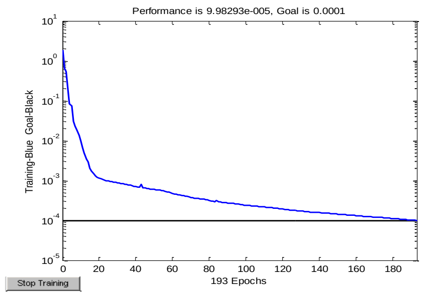

Fig. 22 Training performance for the resilient backpropagation of ANN

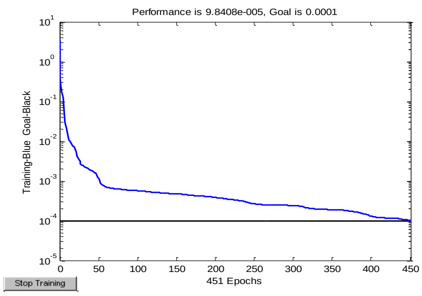

Fig. 19 Training performance for the Polak-Ribiere conjugate gradient backpropagation of ANN

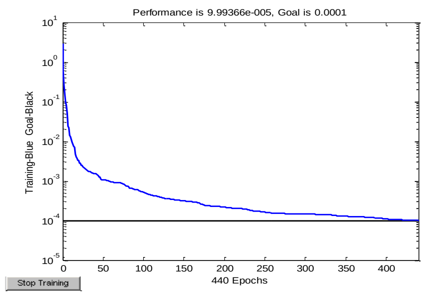

Fig. 23 Training performance for the scaled conjugate gradient backpropagation of ANN

Resilient back-propagation was achieved from the seventeen neurons. The best result for the scaled conjugate gradient back-propagation was achieved from the seventeen neurons. 96 data samples were used for artificial neural networks. 48 data were used for training the network, and the other 48 data were randomly determined. They were selected for the test data. Figs. 8-15 present the measured compressive strength and the predicted compressive strength of ANN model with R^2 coefficients. As it is visible in Figs. 8-15, the values obtained from the ANN results are very close to the experimental results.

Furthermore, All of R^2 values show that the proposed ANN models are suitable and can predict the compressive strength results of lightweight concrete exposed to sulfate attack. This can be also observed in the other articles related to predicting concrete properties (Nazari and Riahi 2011, Özcan 2012, Sobhani *et al*. 2010, Erdem 2010, Uysal and Tanyildizi 2011, Gulbadilar and Kocal 2016). Fig. 7 shows that the best algorithm for the compressive strength results of lightweight concrete exposed to sulfate attack is the

Powell-Beale conjugate gradient back-propagation with an R^2 of 0.93516. The training performance is shown in Figs. 16-23. Artificial neural networks have the capacity of learning and modeling using the data obtained from experiments. The artificial neural network can be a powerful tool for solving the civil engineering problems (Sarıdemir *et al*. 2009).

3.3 Application of support vector machine

Support Vector Machine (SVM) is learning machines implementing the structural risk minimization principle because of good generalization on a limited number of learning patterns. SVM minimizes the generalization error bound to achieve generalized performance (Yuvaraj *et al*. 2013). Support Vector Machine was used by Vladimir Vapnik for the first-time (Vapnik 1995). The fundamental theory of SVM can be shortly explained as follows. Consider a binary classification problem with its training set of N sample points shown by Eq. (3).

$$((x_1, y_1), \dots, (x_i, y_i), \dots (x_N, y_N)), x_i \epsilon R^d \quad y_i \epsilon [-1, 1] \tag{3}$$

The x_i is a sample value of the input vector $\mathbf{x}$ consisting of N training patterns. y_i is the corresponding value of the desired model output. The $\hat{y}$ is represented as a linear function. The function is shown by Eq. (4).

$$\hat{y_i} = f(x) = w^T \phi(x) + b \tag{4}$$

The coefficient's w and b are the adjustable model parameters. w is a one-dimensional array, and the superscript "T" denotes "transposed". $\phi(x)$ is a non-linear transformation function to map the input space to a higher-dimension feature. The SVM minimizes the empirical risk. R_{emp} is found as an Eq. (5).

$$R_{emp} = \frac{1}{N} \sum_{i=1}^{N} |y_i - \hat{y}_i|_\varepsilon \tag{5}$$

$|y_i - \hat{y}_i|_\varepsilon$ is the Vapnik's ε-insensitive loss function defined as Eq. (6)

$$|y_i - \hat{y}_i|_\varepsilon = \begin{cases} 0 & if\ |y_i - \hat{y}_i| \le \varepsilon \\ |y_i - \hat{y}_i| - \varepsilon & otherwise \end{cases} \tag{6}$$

The parameters w and b in Eq. (2) are then estimated by minimizing the cost function $J_\varepsilon(w, \xi, \xi^*)$ defined by the Eq. (7).

$$J(w,\xi,\xi_i^*) = \frac{1}{2} w^T w + C \sum_{i=1}^{N} (\xi + \xi_i^*) \tag{7}$$

The constraints

$$y_i - \hat{y}_i \le \varepsilon + \xi_i \qquad i = 1,2, \dots, N \tag{8}$$

$$-y_i + \hat{y}_i \le \varepsilon + \xi_i^* \qquad i = 1,2, \dots, N \tag{9}$$

$$\xi_i \ge 0 \quad i = 1,2, \dots, N \tag{10}$$

$$\xi_i^* \ge 0 \quad i = 1,2, \dots, N \tag{11}$$

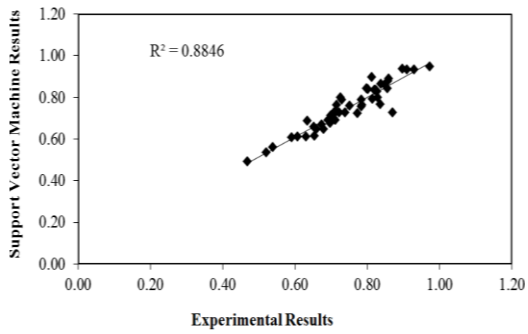

Fig. 24 Linear relationship between measured and predicted compressive strengths of support vector machine model

The ξ_i and ξ_i^* are positive slack variables and C is a positive real constant (Yuvaraj *et al.* 2013, Vapnik 1995, Kecman 2001, Cover 1965, Chen *et al.* 2009).

A support vector model was designed by the seven inputs and output parameters. The input variables were determined as the amount of cement, the amount of fly ash, the amount of silica fumes, the amount of pumice aggregates, the percentage sulfate concentrations and days. The compressive strength of the lightweight concrete was selected as the output variable. The several parameters need to know for applying the SVM algorithm. Primarily, it should be determined three parameters. These parameters are namely, C, error insensitive zone (ε), and kernel specific parameters (γ) (Yuvaraj *et al.* 2013). The optimal values of parameters were obtained with several trials for this data. The values of C, ε and γ were used as 100, 1.1×10^{-6} and 0.19, respectively.

Furthermore, the data were divided with max values to normalize. From these data, 48 data were used for training, and the other 48 data were randomly determined. They used as the test data. The results were shown in Fig. 24. It can be seen from Fig. 24 that the support vector model has predicted the compressive strength results of lightweight concrete exposed to sulfate attack with an R^2 of 0.88456. The SVM model contains three parameters (Kezhen and Caijun 2010). These parameters are C, ε and γ. It can be said that few parameters are easier to identify. Although the ANN model shown a good performance to estimate the compressive strength results of lightweight concrete exposed to sulfate attack, it has a large number of controlling parameters, the number of hidden layers, learning rate, the number of training epochs and transfer functions. An optimum combination of these parameters is obtained much more difficult.

4. Conclusions

In this study, the prediction performances of the ANN and SVM models were investigated for the compressive strength of lightweight cement mortar with fly ash and silica fume exposed to sulfate attack. The following results could be drawn from this study:

• When analyzed experimental data, the compressive strength of lightweight cement mortars decreases with the increase of sulfate concentration. The compressive strength results of lightweight cement mortars showed that lightweight cement mortars containing silica fume was given the best results among mineral additives.

• SVM model was predicted the compressive strength of lightweight cement mortar with fly ash and silica fume exposed to sulfate attack with R^2 value of 0.890. This correlation coefficient showed that the SVM model used in this paper was a good performance in the estimation of compressive strength of lightweight cement mortar with fly ash and silica fume exposed to sulfate attack.

• The eight ANN algorithms were tested in this study. The ANN models were compared each other. The Powell-Beale conjugate gradient back-propagation was found as the best learning algorithm. The ANN model showed a very good statistical performance because the correlation coefficients (R^2) between measured and predicted results were 0.9352 for the compressive strength of lightweight cement mortar with fly ash and silica fume exposed to sulfate attack.

Finally, the results indicated that the ANN model with the Powell-Beale conjugate gradient backpropagation training algorithm has the ability to predict the compressive strength results of lightweight cement mortars showed that lightweight cement mortars containing fly ash and silica fume with a high degree of accuracy.

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