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An innovative approach for compressive strength estimation of mortars having calcium inosilicate minerals

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ABSTRACT

There are several factors that can affect on the quality of construction and all of the using elements, such as mortars, as a basic component of the building industry, are effective in the ability and performance of the building. Therefore, determination of strength of mortar is an important property in construction and many studies have been done to identify the effective parameters and the predictive relationships to determine the strength of mortars. In this paper, the effect of two types of materials including micro-Silica and also Calcium Inosilicate minerals on the compressive strength of mortars has been investigated by artificial neural networks. Also, a suitable relationship to estimate the considered strength is proposed based on the selected neural network. The results of the relationships show that these equations with a high accuracy have a proper ability and acceptance performance to predict the compressive strength of considered mortars.

1. Introduction

One of the most important parameters that have an effective rule on the quality of construction is mortars. In order to increase the capacity of this basic member of the building, the effects of many factors, such as humid [1] and thermal environment [2], acid climate [3] and also curing should be considered, but today there is a special attention to the type of materials used in mortars. Researchers have shown that some materials such as carbon fiber [4] and metal fiber [3] have the ability to increase the compressive strength of mortars and thus improve the quality of construction. The evaluating of mortars is based on the using materials for their preparation, including mineral material types or Silica fume. There are also several models for predicting their compressive strength using statistical methods or soft computing approaches. In the next sections, these issues are discussed.

1.1. Evaluating of mortars

There are several scientific studies that investigated the compressive strength as one of the most important properties for evaluating the mortars. Chen et al. [5] used a model for porous materials to determine the capacity relationship of mortars. Their results indicated that the relationship between compressive strength and tensile strength is not constant. Sabdono et al. [6] presented a method which used Nano-cement particles and increased the compressive strength of mortar. Their results also indicated that more research is required to find behavior patterns of Nano cement and its effect on mortars [6]. Some of the scientific studies used palm oil fuel ash as a replacement material in fly ash based geopolymer mortar and studied the compressive strength of mortar in those conditions [7,8]. The importance of the curing factor related to the delay time and curing temperature was evaluated by Mijarsh et al. [9]. They studied the effect of time and Sodium silicate on compressive strength of geopolymer mortar. It was found that mixtures with high Sodium silicate created the highest development in compressive strength.

1.2. Mineral admixtures of mortars

Admixtures are materials that are added in small amounts to mortars. They are used to improve the behavior of mortars and they generally are mineral. Many studies have investigated the influence of admixtures on mortars. Demirboğa [10] added silica fume, fly ash and also blast furnace slag as a replacement material for cement and investigated the influence of this mineral admixtures on compressive strength. The relationship between porosity of the cement paste with mineral additives and compressive strength was determined by Li et al. [11]. Pozzolan is a mineral admixture that is widely used in mortars and Ezziane et al. [12] investigated the compressive strength of mortars admixed with this material under various curing temperatures. Itim et al. [13] studied the effect of various amounts of mineral admixtures on compressive strength of cement mortars. Filler effect of fine particle river sand as a non-pozzolanic material was studied by Jaturapitakkul

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Table 1
Summary of considered database (mix proportion by weight).

Parameter	Median	Minimum	Maximum	Standard deviation
Microsilica	0.00	0.00	12.50	3.92
HRWR dosage	0.67	0.32	2.00	0.44
OPC	85.00	70.00	97.50	8.02
CIM	10.00	0.00	30.00	9.43
Age (Day)	44.00	3.00	126.20	365.00
Compressive Strength (MPa)	44.05	13.20	66.20	13.17

et al. [14]. The results showed that the compressive strength of mortar with smaller filler particles is higher than that of the coarser ones. Wang et al. [15] used ground granulated blast-furnace slag, fly ash and also steel slag and studied the influence of this materials on strength of mortar. Tudjono [16] studied the effect of Nano fly ash and Nano lime on mortars. Tugrul et al. [17] used feldspar, clay and mica minerals on mortars and showed that addition of clay and mica minerals in the sand would reduce the strength of mortar. Their results also indicated that the detrimental effects of feldspar and mica minerals on strength of mortar are greater with crushed un-weathered mica and feldspars than naturally-weathered mica and feldspar minerals. The effect of co-fired biomass fly ashes in compressive strength of mortars was studied by Wang [18]. The research showed that biomass-containing fly ash could increase the strength. Rao and Rao [19] investigated the compressive strength of geo-polymer and fly ash mortars in their research.

1.2.1. Silica fume in mortars

Silica fume is a common material which is used in mortars and Toutanji and El-Korchi [20] investigated the effect of this material on compressive strength of mortars. Their results indicated that partial replacement of cement by silica fume and addition of superplasticizer would increase the strength of mortars. Kadri et al. [21] used metakaolin and silica fume in their mixtures of mortars with the aim of evaluating the effect of these materials on the compressive strength. Their results showed that metakaolin has a pozzolanic activity higher than silica fume. The effect of Nano-sized powders of main oxides of cement on the compressive strength of mortars containing silica fume [22] and Nano silica [23] was also studied by researchers.

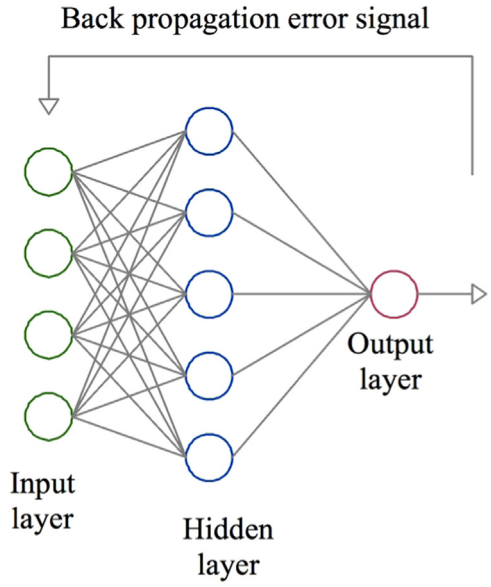

Fig. 2. Backpropagation neural network with 4 inputs and one output.

1.3. Prediction models

In civil engineering problems, estimation of the capacity of the elements is an important part of the design. In this section, the available models that are applied to determine the capacity of mortars are presented. These models are discussed under two categories includes theoretical and also soft computing approaches.

1.3.1. Theoretical approaches

There are conventional methods for predicting the compressive

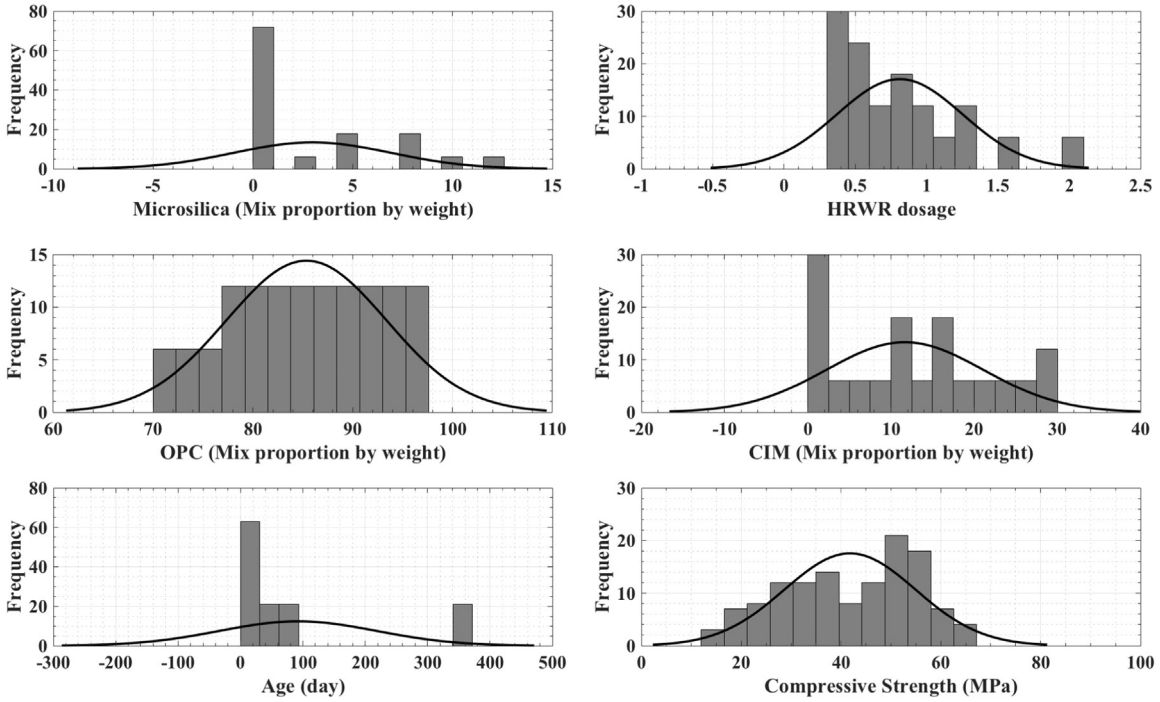

Fig. 1. The parameters Histograms of the considered database.

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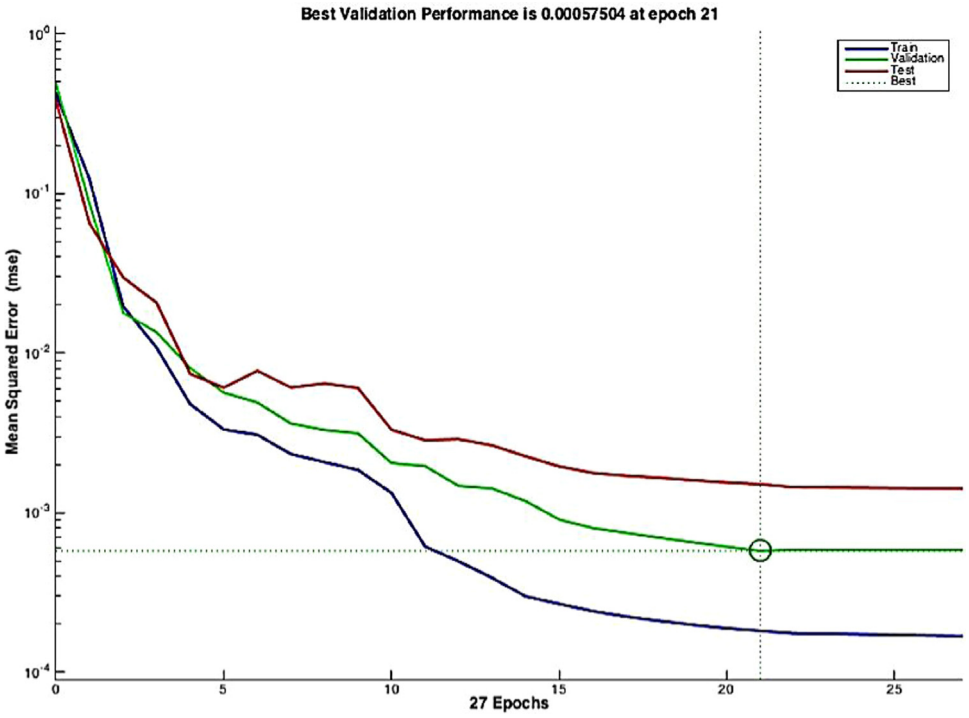

Fig. 3. Performance of ANN.

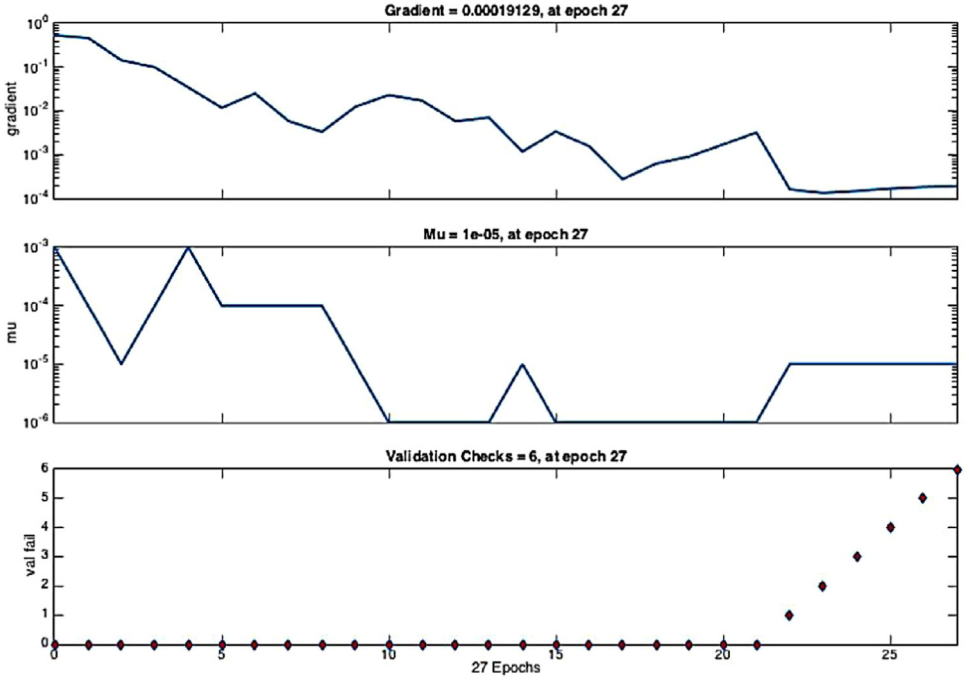

Fig. 4. Training state of ANN.

strength of mortars. Cho and Lin [24] evaluated a nondestructive assessment based on spectral analysis of surface waves for in-place cement mortars compressive strength. Voigt et al. [25] investigated ultrasonic wave reflection method compared with maturity method to determine early age compressive strength of mortars. Electromagnetic characterization was also used for evaluating compressive strength by Kwon et al. [26]. Alejandre et al. [27] considered shape and size for estimating the cement mortar compressive strength by micro-cores. Nazari and Sanjayan [28] used optimized support vector machine to create a model based on the compressive strength of geopolymer mortar.

1.3.2. Soft computing approaches

In the recent years, soft computing tools have been considered as powerful computational methods. They solve complex problems and can be used for simulating, evaluating and approximating with high accuracy. They can learn to present an answer based on their algorithm. Artificial neural networks (ANN) are a type of soft computing, which is applied to a lot of scientific fields, especially in structural engineering. There are a few research on strength prediction of mortars that have

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Table 2
Details of ANN.

Nodes	Input weights					Layer weights	Bias to	
	Input 1	Input 2	Input 3	Input 4	Input 5		Hidden layer	Output layer
Node 1	0.410	− 0.991	1.489	− 0.760	1.991	− 0.184	− 2.348	–
Node 2	− 1.132	0.083	0.025	1.266	0.984	− 0.179	2.789	–
Node 3	1.045	0.082	2.393	2.398	− 11.048	− 4.127	− 11.421	–
Node 4	2.987	− 1.870	− 2.827	1.691	− 1.298	− 0.882	0.140	–
Node 5	2.797	− 1.789	− 3.088	1.004	− 1.405	0.730	− 0.005	–
Node 6	− 0.232	− 0.663	− 1.082	− 0.522	− 1.109	− 0.380	− 0.931	–
Node 7	0.075	− 0.044	0.408	− 2.079	− 0.976	0.480	1.615	–
Node 8	− 3.835	− 1.300	− 0.602	2.486	− 0.272	− 0.130	− 2.470	–
Output	–	–	–	–	–	–	–	− 4.212

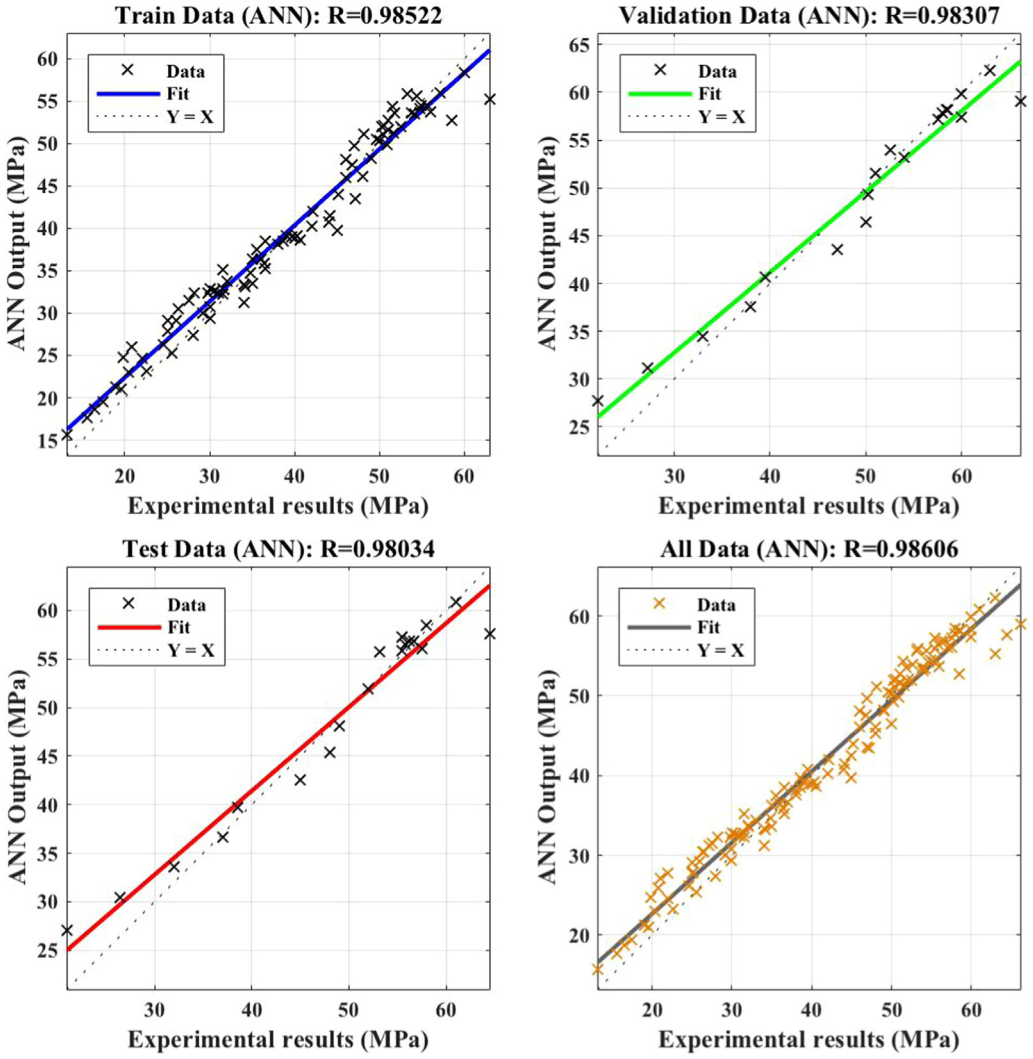

Fig. 5. Regressions of training, validation and test data simulated by ANN.

Table 3
Comparison between results of ANN.

Property	Inputs parameters				
	Microsilica	HRWR dosage	OPC	CIM	Age (day)
Reference value	3	0.8	85	12	90

been done based on artificial neural networks. Akkurt et al. [29] used a Genetic algorithm by feedforward neural network simulator algorithm in three layers for prediction of the cement mortars strength. They considered 100 data for training and 50 data for the test. Their network started with 20 neurons in the input layer and 20 neurons in hidden layer with the output of compressive strength of mortars. The results indicated that neural network could be a useful tool for the considered prediction. Onal and Ozturk [30] presented a relationship between microstructural properties of cement mortars, achieved by digital image processing techniques and compressive strength of mortars by artificial

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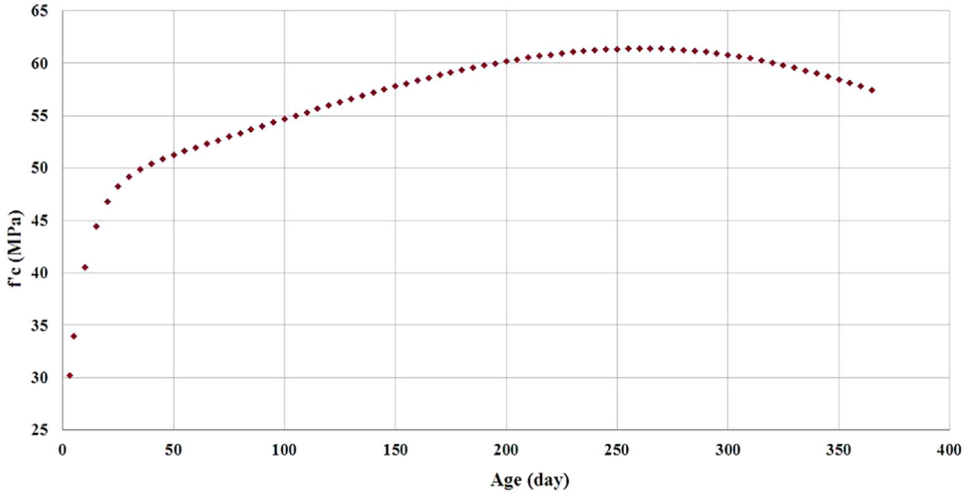

Fig. 6. Variation of f′c against age regarding other input parameters to be in their reference value.

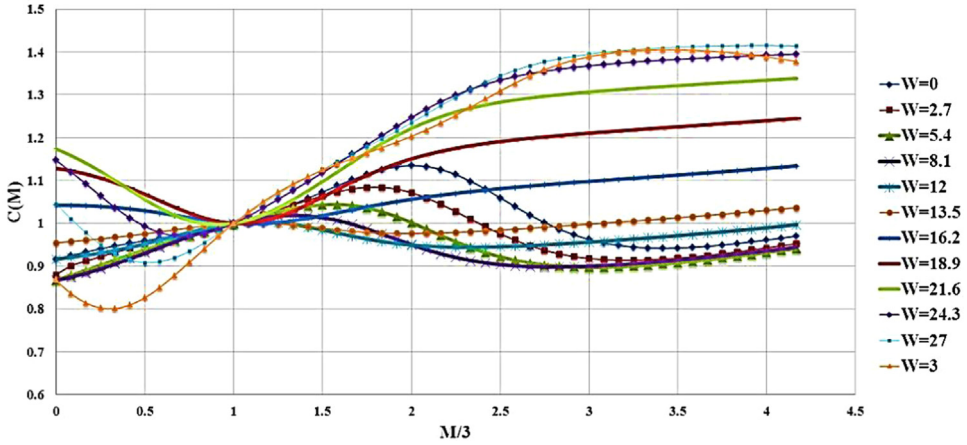

Fig. 7. Correction factor C(M) with various values of W.

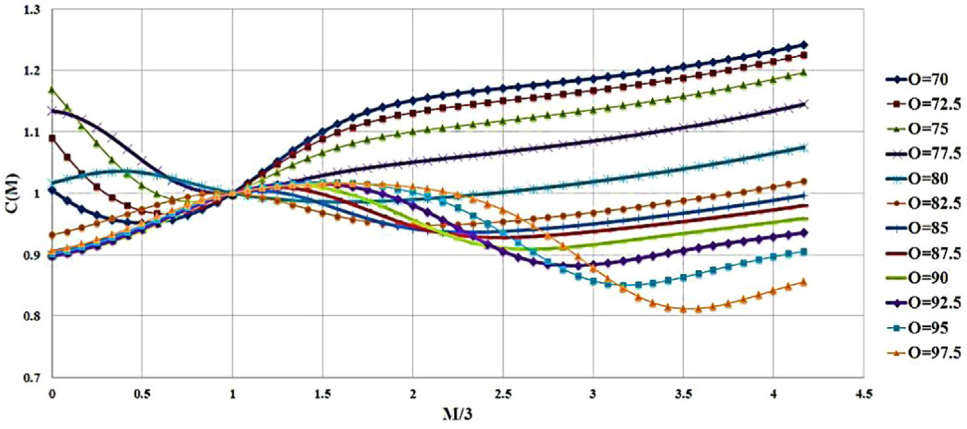

Fig. 8. Correction factor C(M) with various values of O.

neural networks. The results showed that the proposed model may be established between the parameters which are extracted by image analysis methods and compressive strengths.

There is a drawback of neural networks that can pose a problem because the solution that a network has learned cannot be expressed explicitly [31]. In this paper, an approach is used for predicting the compressive strength of mortars with the aim of applying the neural networks on the applicable interview. To training the ANNs, experimental data from mortars which were admixed with a mineral admixture namely calcium inosilicate mineral material was used. The final results of the simulation progress of the proposed ANN were used to determine a relationship which can be considered as a predicted equation with a high level of accuracy.

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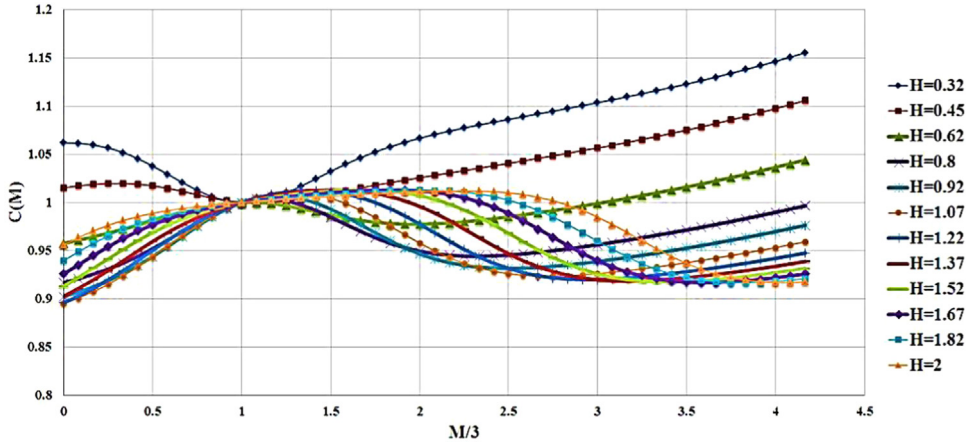

Fig. 9. Correction factor C(M) with various values of H.

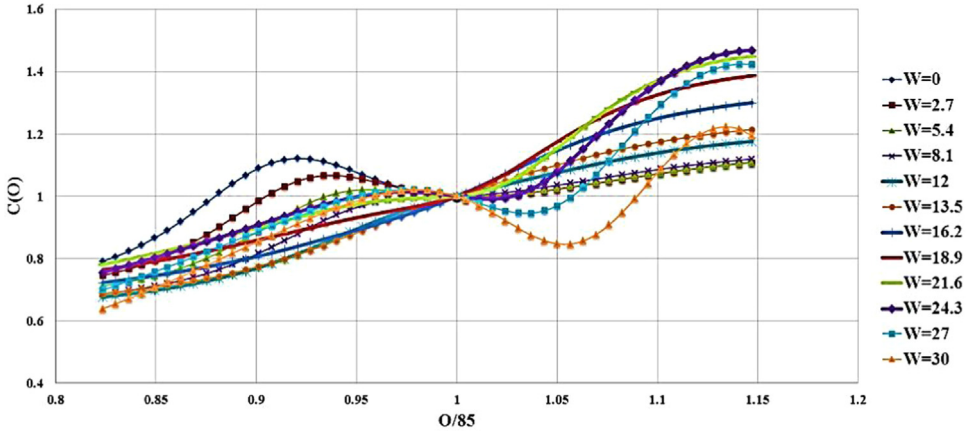

Fig. 10. Correction factor C(O) with various values of W.

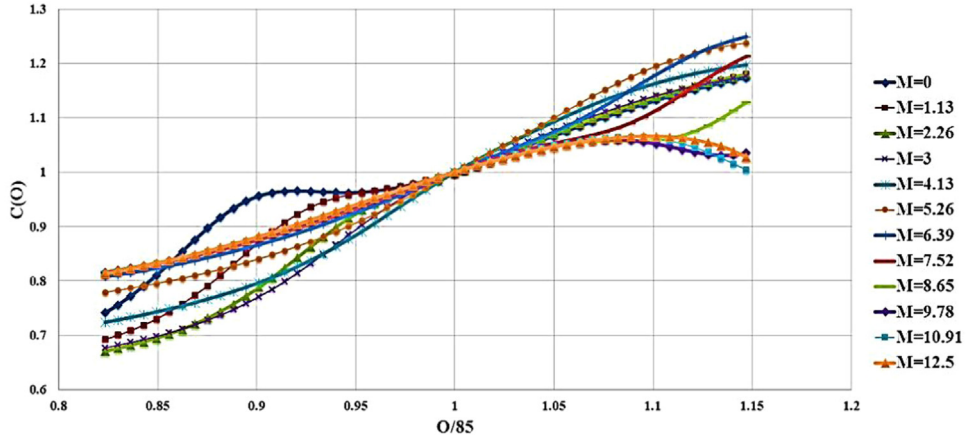

Fig. 11. Correction factor C(O) with various values of M.

2. Experimental data

In this paper, the compressive strength of mortars admixed with a calcium inosilicate mineral material (*CIM*) was investigated and predicted. This material contains several materials including SiO_3, CaO, Al_2O_3, Fe_2O_3, TiO_2, MnO, MgO, Na_2O and K_2O [32]. The dosage of each of these materials is different in each country and each mine. *CIM* also can be used in concrete as reinforcement [33]. It is a fibrous in the nature. Kalla et al. [32] presented a summary of mechanical and chemical properties of this mineral material in detail.

Artificial neural networks are structures which are trained by an experimental database. For this paper, the authors considered the 126 test results of Ransinchung and Kumar [34]. All of the mixtures in the selected database has a w/c = 0.5 and to compensate the loss in workability, a high range water reducer (HRWR) was also applied to all mortars. Table 1 shows a summary of considered data based on the mix proportions by weight. The parameter *OPC* is ordinary Portland cement in the table. Also, to have a better view of the database, the parameters histograms are presented in Fig. 1.

To increase the speed and accuracy of the proposed model, Eq. (1)

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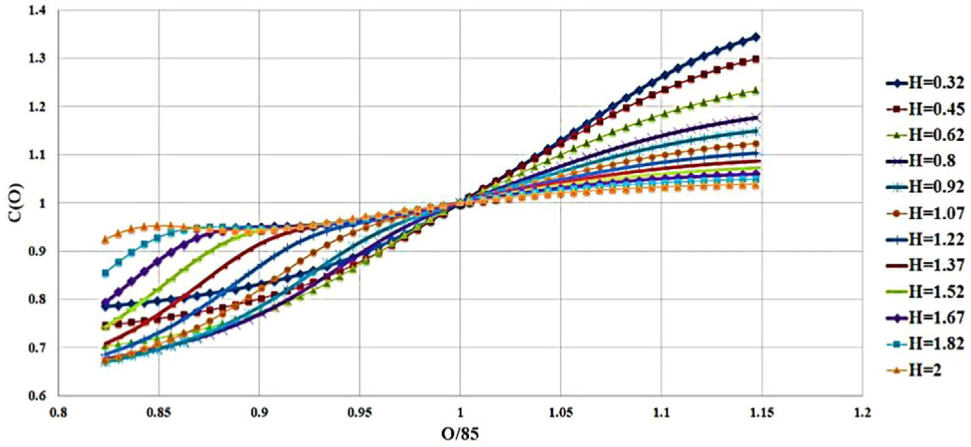

Fig. 12. Correction factor C(O) with various values of H.

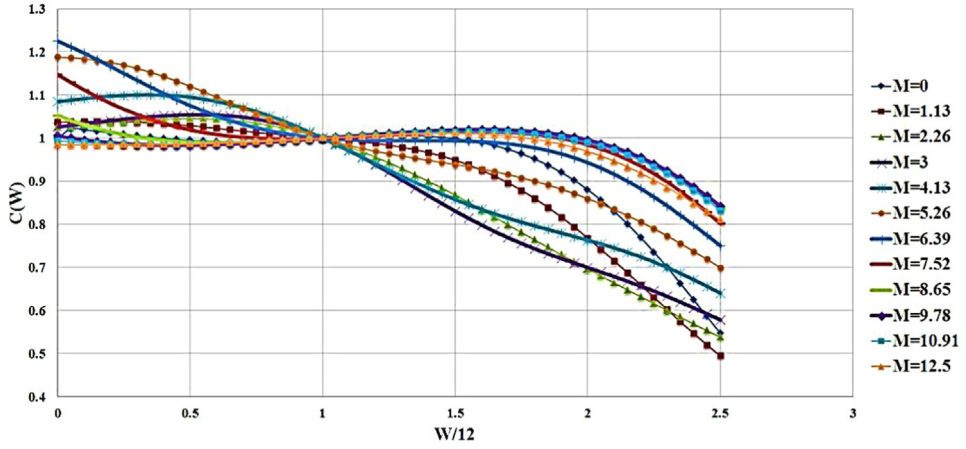

Fig. 13. Correction factor C(W) with various values of M.

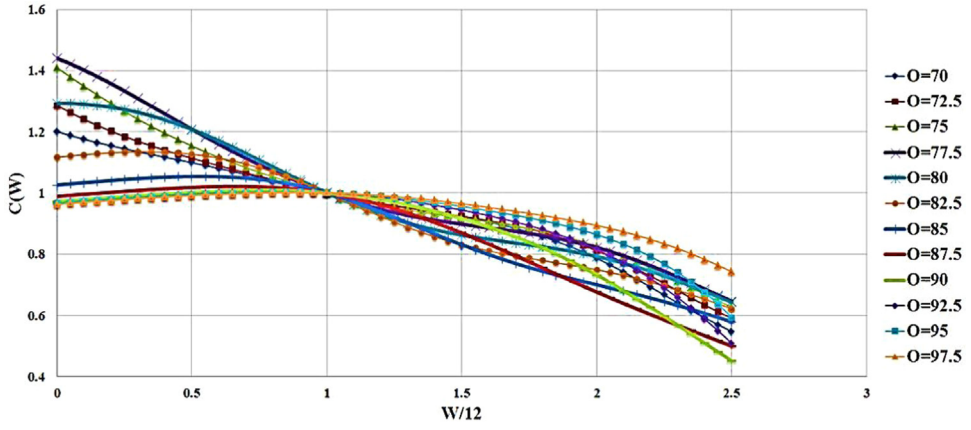

Fig. 14. Correction factor C(W) with various values of O.

which is considered the range of parameters between 0.1 and 0.9 was used as a normalization relationship. In this equation, x is the measured value for a parameter, x_i is the normalized value of x. The minimum and maximum values in the database for x are x_{min} and x_{max} respectively.

$$x_i = 0.8 \quad \frac{x - x_{min}}{x_{max} - x_{min}} + 0.1 \tag{1}$$

3. Artificial neural networks

Artificial neural networks (ANN) are models that approximate the operation of the human brain and are commonly used for estimating or approximating. A neural network consists of a number of independent variables as neurons. These neurons communicate with each other via weighted connections. These weights are modified based on data set during the network modeling using learning algorithms and this feature is their ability to learn from examples. ANNs solve problems by processing a set of training data and are organized in layers which are

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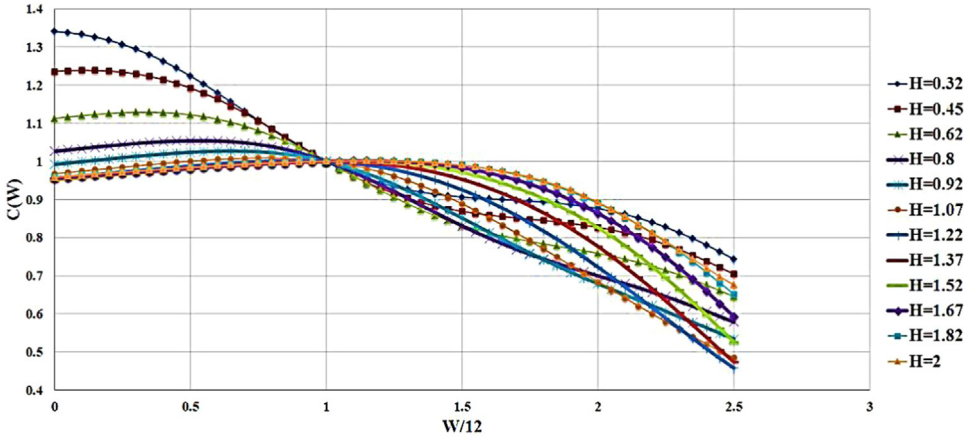

Fig. 15. Correction factor C(W) with various values of H.

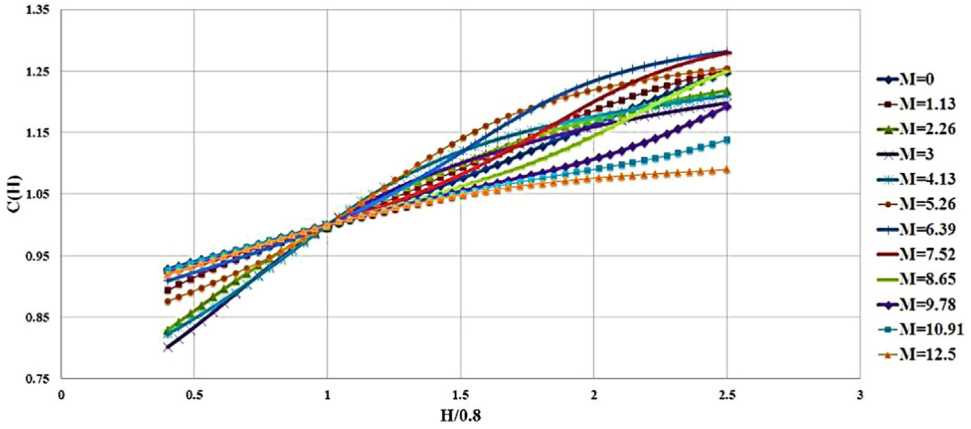

Fig. 16. Correction factor C(H) with various values of M.

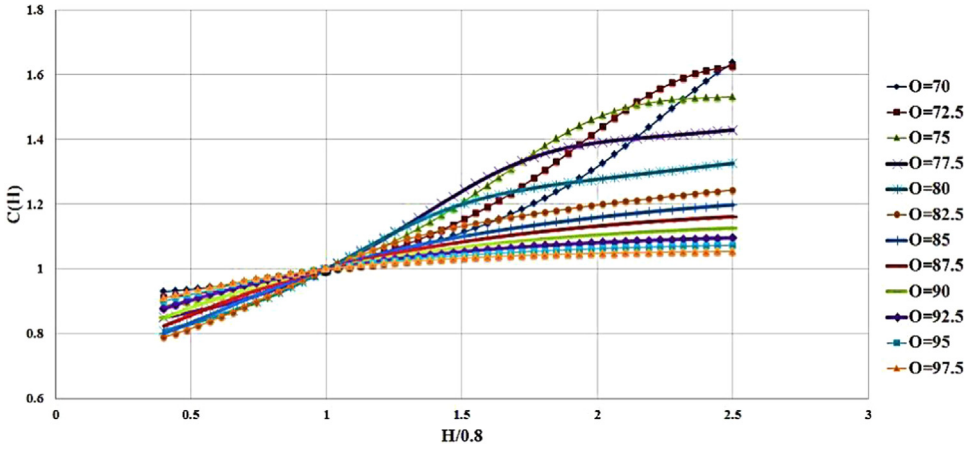

Fig. 17. Correction factor C(H) with various values of O.

made of a number of interconnected nodes. These nodes contain an activation function. In an ANN, patterns are presented to the network via the input layer. This layer communicates with one or more hidden layers. The output layer links to this hidden layer.

There are several types of ANNs and in this paper, the authors used feed-forward back-propagation type. The term back-propagation indicates the backward propagation of an error signal through the network. Based on the error signal, the hidden units are able to calculate their error to modify the weights. Fig. 2 shows a back propagation neural network.

4. Compressive strength prediction by ANN

4.1. ANNs modeling

The proposed neural network in this paper created by five parameters as inputs to predict the compressive strength of mortar as output. Age of mortar *A*, high-range water reducer *H*, micro-silica *M*, ordinary Portland cement *O* and calcium inosilicate mineral material *CIM* were the considered inputs, while the output was compressive strength *f'c*. It worth noting that the selected database was normalized based Eq. (1) and used randomly to apply in the ANN models. The

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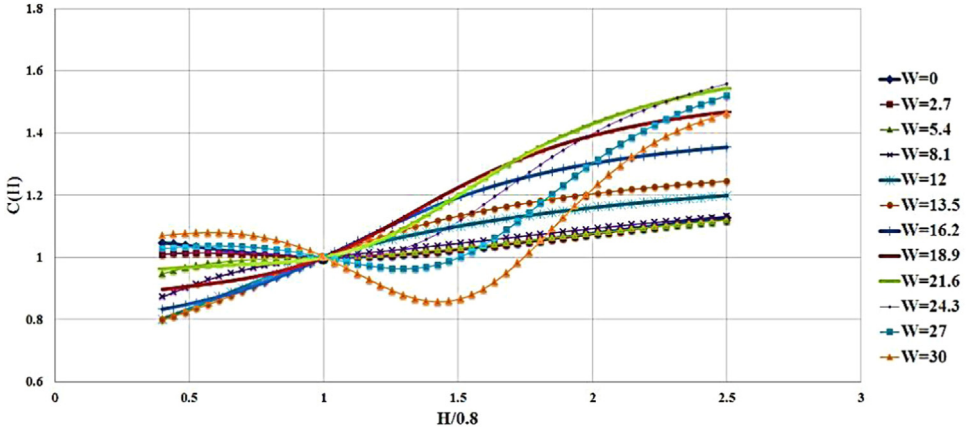

Fig. 18. Correction factor C(H) with various values of W.

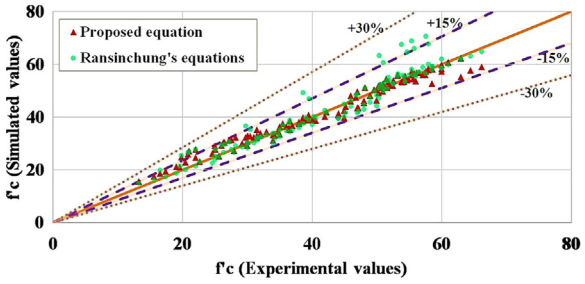

Fig. 19. Comparison between the proposed equation and Ransinchung's equations.

Table 4
Distribution of error for existing model versus proposed model based on ANN relative to experimental values.

Range of error (%)	Number of data in the range of models		Percentage of whole 126 data for models	
	Eq. (4)	Ransinchung and Kumar [32]	Eq. (4)	Ransinchung and Kumar [32]
± 5	80	78	63.5	61.9
± 10	101	95	80.1	75.4
± 15	118	108	93.6	85.7
± 20	121	115	96.0	91.3
± 25	122	118	96.8	93.6
± 30	126	126	100.0	100.0

database divided into three parts includes training data (88 datasets), validation data (19 datasets) and also testing data (19 datasets). The proposed structure of neural network as a predictor system to determine the compressive strength of mortar containing *CIM* were created by one hidden layer with eight nodes. The used training algorithm was Levenberg-Marquardt and the functions in the hidden and output layers were Tangent-sigmoid and Purelin respectively. Fig. 3 and also Fig. 4 show performance and training state of the proposed neural network. The details of Inputs weights and corresponding biases, also layer weight and its bias present in Table 2. Based on the results of the selected neural network with eight nodes, regression plots for train, validation, test and all data can be seen by Fig. 5 for real values of the database.

4.2. Relationship for prediction

Naderpour et al. [35] presented an approach to find a relationship based on ANNs for predicting the FRP-confined compressive strength of concrete and in this paper, the authors applied that method to extract a suitable relationship for the considered target. This section discussed and followed the method.

4.2.1. Relative importance between inputs and target

The method starts with selecting one of the inputs as a most effective parameter on the output. For this purpose, the authors used trial and error method to find the best parameter which has a direct relation with the output (compressive strength of mortar). The results showed that the parameter Age has better than the other parameters and with considering this parameter, the proposed ANN model, can be presented better results. Therefore, the parameter Age was selected as the relative important parameter in this paper.

4.2.2. Relationships between age and f'_c

The first step to find an equation for predicting the compressive strength of mortars is selecting one of the input parameters as the most effective parameter. Based on the previous section, the age of the mortar was selected. This parameter was directly considered to find the *f'c* by the relationship.

The next step is specifying a constant value for each of inputs that must be close to its mean value. Table 3 shows the reference values for all of the input parameters. It should be noted that the unit of the parameters microsilica, *OPC*, *HRWR* dosage and also *CIM* are based on mix proportion by weight.

After selecting age of mortar as the most effective parameter, ANN was utilized to simulate the *f'c* based on database with various values of age from 3 to 365 days while other four input parameters are kept constant at their reference values. Fig. 6 shows the fitting curve. Based on the fitting curve, the best regressions were obtained as (Eq. (2)):

$$\begin{aligned} f'c1 &= -0.0360\,(Age)^2 + 1.7577\,(Age) + 24.125 && \text{for } 3 \le Age \le 25 \text{ day} \\ f'c1 &= 0.0697\,(Age) + 44.015 && \text{for } 25 < Age \le 100 \text{ day} \\ f'c1 &= -0.000027\,(Age)^2 + 0.1362\,(Age) + 37.727 && \text{for } Age > 100 \text{ day} \end{aligned} \quad (2)$$

4.2.3. A relationship for predicting f'c based on ANN

Although the Eq. (2) cannot be used for predicting *f'c* directly, they can be corrected by the following equation (Eq. (3)) as correction function:

$$F(M, H, O, W) = C(M)*C(H)*C(O)*C(W) \quad (3)$$

where *C(M), C(H), C(O)* and *C(W)* are correction factors for microsilica, HRWR, OPC, and calcium inosilicate mineral material *CIM* respectively. These parameters can be calculated based on the following

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details and equations.

Finally, $f'c$ was obtained from Eq. (4):

$$f'c = f'c1*F(M, H, O, W) \quad (4)$$

The main neural network in this paper was ANN and the above correction factors were calculated by it. To derive the correction factors, for example, C(M), first, ANN should be applied for simulating $f'c$ based on 12 different values for each of input parameters in separate simulating. M was varying from minimum to maximum value in 51 data series while other parameters are in reference value. The 12 values which are used in the simulation, must be covered all range of the considered parameter. By dividing $f'c$ value that obtained from simulation of ANN by the value read off from the curves that determined from the network based on the reference value of M (Figs. 7–9), the correction factor $C(M)$ for each state can be obtained. Figs. 10–18 show master curves for other correction factors.

Based on average values of master curves for each of input parameters, the final equations (Eqs. (5)–(8)) are determined as follow:

$$C(M) = -0.0025\left(\frac{M}{3}\right)^5 + 0.0299\left(\frac{M}{3}\right)^4 - 0.126\left(\frac{M}{3}\right)^3 + 0.2081\left(\frac{M}{3}\right)^2 - 0.0798\left(\frac{M}{3}\right) + 0.972 \quad (5)$$

$$C(O)=1.3802\left(\frac{O}{85}\right)- 0.3815 \quad (6)$$

$$C(W)=-0.0719\left(\frac{W}{12}\right)^2+0.0133\left(\frac{W}{12}\right)+1.0664 \quad (7)$$

$$C(H)=0.1905\left(\frac{H}{0.8}\right)+0.8138 \quad (8)$$

Considering Eqs. (5)–(8) and by applying them to the proposed equation (Eq. (4)), the predicted values were calculated. The results with correlation factor 0.97 indicated that the proposed method has good results for prediction.

5. Comparison with existing equation

Ransinchung and Kumar [34] presented eighteen equations to find the compressive strength of mortars containing calcium inosilicate mineral material and micro-silica. Each of these equations must be used in special conditions and there is no unique equation for prediction. The results of the proposed equation in this paper which was obtained from ANN (Eq. (4)) is compared with Ransinchung's equations (Fig. 19).

It is clear from the Fig. 19 that although the calculated values are close to real amounts of $f'c$ in both models, the proposed equation had better performance than the other one. It is also worth to mention that the use of only one equation (Eq. (4)) is easier than using eighteen equations. The summary of the final comparison is presented in Table 4.

6. Conclusions

In this paper, an artificial neural network trained and validated based on 126 experimental data which were published in a literature. The model created by five input parameters to predict the compressive strength of the considered mortars. The results showed that the ANN model has an acceptance outputs in compared with the targets. To increase the workability of the proposed ANN model, the authors presented a mathematical form based on the model. The approach was determining several master curves based on simulated values of selected ANN. The results of the proposed equation indicated that it can be used for prediction with a high level of accuracy. The obtained values from the proposed equation were also compared with an existing equation and obtained better performance.

References

[1] Z. Berhane, Compressive strength of mortar in hot-humid environment, Cem. Concr. Res. 13 (2) (1983) 225–232.
[2] F. Sajedi, H.A. Razak, Effects of thermal and mechanical activation methods on compressive strength of ordinary Portland cement–slag mortar, Mater. Des. 32 (2) (2011) 984–995.
[3] A. Belferrag, A. Kriker, M.E. Khenfer, Improvement of the compressive strength of mortar in the arid climates by valorization of dune sand and pneumatic waste metal fibers, Constr. Build. Mater. 40 (2013) 847–853.
[4] P. Banfill, G. Starrs, G. Derruau, W. McCarter, T. Chrisp, Rheology of low carbon fibre content reinforced cement mortar, Cem. Concr. Compos. 28 (9) (2006) 773–780.
[5] X. Chen, S. Wu, J. Zhou, Influence of porosity on compressive and tensile strength of cement mortar, Constr. Build. Mater. 40 (2013) 869–874.
[6] P. Sabdono, F. Sustiawan, D.A. Fadlillah, The effect of nano-cement content to the compressive strength of mortar, Procedia Eng. 95 (2014) 386–395.
[7] N. Ranjbar, M. Mehrali, A. Behnia, U.J. Alengaram, M.Z. Jumaat, Compressive strength and microstructural analysis of fly ash/palm oil fuel ash based geopolymer mortar, Mater. Des. 59 (2014) 532–539.
[8] M. Mijarsh, M.M. Johari, Z.A. Ahmad, Compressive strength of treated palm oil fuel ash based geopolymer mortar containing calcium hydroxide, aluminum hydroxide and silica fume as mineral additives, Cem. Concr. Compos. 60 (2015) 65–81.
[9] M. Mijarsh, M.M. Johari, Z.A. Ahmad, Effect of delay time and Na_2SiO_3 concentrations on compressive strength development of geopolymer mortar synthesized from TPOFA, Constr. Build. Mater. 86 (2015) 64–74.
[10] R. Demirboğa, Influence of mineral admixtures on thermal conductivity and compressive strength of mortar, Energy Build. 35 (2) (2003) 189–192.
[11] Y.-X. Li, Y.-M. Chen, J.-X. Wei, X.-Y. He, H.-T. Zhang, W.-S. Zhang, A study on the relationship between porosity of the cement paste with mineral additives and compressive strength of mortar based on this paste, Cem. Concr. Res. 36 (9) (2006) 1740–1743.
[12] K. Ezziane, A. Bougara, A. Kadri, H. Khelafi, E. Kadri, Compressive strength of mortar containing natural pozzolan under various curing temperature, Cem. Concr. Compos. 29 (8) (2007) 587–593.
[13] A. Itim, K. Ezziane, E.-H. Kadri, Compressive strength and shrinkage of mortar containing various amounts of mineral additions, Constr. Build. Mater. 25 (8) (2011) 3603–3609.
[14] C. Jaturapitakkul, J. Tangpagasit, S. Songmue, K. Kiattikomol, Filler effect of fine particle sand on the compressive strength of mortar, Int. J. Miner. Metall. Mater. 18 (2) (2011) 240–246.
[15] Q.Y. Wang, Peiyu, Jianwen Feng, The influence of mineral admixtures on bending strength of mortar on the premise of equal compressive strength, J. Wuhan. Univ. Technol.-Mater. Sci. Ed. 27 (3) (2012) 586–589.
[16] S. Tudjono, X. Purwanto, K.T. Apsari, Study the effect of adding nano fly ash and nano lime to compressive strength of mortar, Procedia Eng. 95 (2014) 426–432.
[17] A. Tugrul, S. Hasdemir, M. Yılmaz, The effect of feldspar, mica and clay minerals on compressive strength of mortar, Engineering Geology for Society and Territory, 5 Springer, Switzerland, 2015, pp. 93–96.
[18] S. Wang, Cofired biomass fly ashes in mortar: reduction of alkali silica reaction (ASR) expansion, pore solution chemistry and the effects on compressive strength, Constr. Build. Mater. 82 (2015) 123–132.
[19] G.M. Rao, T.G. Rao, Final setting time and compressive strength of fly ash and GGBS-based geopolymer paste and mortar, Arab. J. Sci. Eng. 40 (2015) 3067–3074.
[20] H.A. Toutanji, T. El-Korchi, The influence of silica fume on the compressive strength of cement paste and mortar, Cem. Concr. Res. 25 (7) (1995) 1591–1602.
[21] E.-H. Kadri, S. Kenai, K. Ezziane, R. Siddique, G. De Schutter, Influence of metakaolin and silica fume on the heat of hydration and compressive strength development of mortar, Appl. Clay Sci. 53 (4) (2011) 704–708.
[22] M. Oltulu, R. Şahin, Single and combined effects of nano-SiO_2, nano-Al_2O_3 and nano-Fe_2O_3 powders on compressive strength and capillary permeability of cement mortar containing silica fume, Mater. Sci. Eng.: A 528 (22) (2011) 7012–7019.
[23] S. Haruehansapong, T. Pulngern, S. Chucheepsakul, Effect of the particle size of nanosilica on the compressive strength and the optimum replacement content of cement mortar containing nano-SiO_2, Constr. Build. Mater. 50 (2014) 471–477.
[24] Y.S. Cho, F.-B. Lin, Nondestructive evaluation of in-place cement mortar compressive strength using spectral analysis of surface waves, Constr. Build. Mater. 19 (10) (2005) 738–745.
[25] T. Voigt, Z. Sun, S.P. Shah, Comparison of ultrasonic wave reflection method and maturity method in evaluating early-age compressive strength of mortar, Cem. Concr. Compos. 28 (4) (2006) 307–316.
[26] S. Kwon, M. Feng, T. Park, J. Glassman, U. Na, An experimental evaluation of compressive strength in cement mortar using electromagnetic characterization, in: Proceedings of the ASCE, International Committee, Los Angeles Section, 5th International Engineering and Construction, Conference (IECC'5), 2008, pp. 433–441.
[27] F. Alejandre, V. Flores-Ales, R. Villegas, J. Garcia-Heras, E. Moron, Estimation of Portland cement mortar compressive strength using microcores. Influence of shape and size, Constr. Build. Mater. 55 (2014) 359–364.
[28] A. Nazari, J.G. Sanjayan, Modelling of compressive strength of geopolymer paste, mortar and concrete by optimized support vector machine, Ceram. Int. 41 (2015) 12164–12177.
[29] S. Akkurt, S. Ozdemir, G. Tayfur, B. Akyol, The use of GA–ANNs in the modelling of compressive strength of cement mortar, Cem. Concr. Res. 33 (7) (2003) 973–979.
[30] O. Onal, A.U. Ozturk, Artificial neural network application on

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microstructure–compressive strength relationship of cement mortar, Adv. Eng. Softw. 41 (2) (2010) 165–169.
[31] D. Nauck, F. Klawonn, R. Kruse, Foundations of Neuro-fuzzy Systems, John Wiley & Sons, Inc., New York, USA, 1997, p. 316.
[32] P. Kalla, A. Rana, Y.B. Chad, A. Misra, L. Csetenyi, Durability studies on concrete containing wollastonite, J. Clean. Prod. 87 (2015) 726–734.
[33] J. Beaudoin, P. Gu, N. Low, N. Mailvaganam, Durability of cement systems reinforced with wollastonite microfibers, Acids Spec. Publ. 185 (81–96) (2000).
[34] G. Ransinchung R.N., B. Kumar, Investigations on pastes and mortars of ordinary portland cement admixed with wollastonite and microsilica, J. Mater. Civ. Eng. 22 (4) (2009) 305–313.
[35] H. Naderpour, A. Kheyroddin, G.G. Amiri, Prediction of FRP-confined compressive strength of concrete using artificial neural networks, Compos. Struct. 92 (12) (2010) 2817–2829.