Prediction of sulfate resistance of cements produced with GBFS and SS additives using artificial neural network

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Abstract: Concrete structures built on sulfate rich soil or wetland, or directly exposed to seawater are subjected to sulfate attack, which might be critical, as the durability of concrete is highly dependent on its resistance against sulfate compounds. The objective of this study is to develop a methodology for the prediction sulfate resistance capabilities of sulfate resistance of mortars prepared with cements incorporating granulated blast-furnace slag (GBFS) and steel slag (SS) as partial replacement of Portland cement clinker in different ratios. Three different combinations of GBFS and SS were utilised to partially replace Portland cement clinker at various proportions from 20% to 80%. Parameters such as specific surface, specific gravity, volumetric expansion, Vicat setting time, compressive strength, sulfate resistance and durability against high temperature were investigated on the produced cement samples. Furthermore, experimental results were also obtained by building models in accordance with the artificial neural network (ANN) technique to predict the sulfate resistance of cements. The results showed that ANNs can be successfully used to model the relationship between the sulfate resistance and each of the observed parameters.

Keywords: granulated blast-furnace slag; GBFS; steel slag; durability; sulfate resistance; artificial neural network; ANN.

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1 Introduction

Industrial wastes are generally considered to pose a major source of environmental concerns worldwide. Land disposal, merely a partial solution, creates secondary pollution issues and bears additional costs. The environmental regulations, requiring the minimisation of waste disposal, mandate the reuse of waste materials. For this reason, more efficient solutions such as alternative recovery options need to be investigated as well. In this respect, the cement and concrete industry stand out as an important consumer of industrial by-products or solid wastes. It is estimated that granulated blast-furnace slag (GBFS) accounts for approximately 250 million tons of slag production, while steel slag (SS) production reaches about 160 million tons worldwide. Solid wastes should be reused in order to improve the efficiency of natural resource consumption and also for the purpose of sustainable development. The possibility of being able to recycle or process materials to be utilised as a partial replacement for cement promises a great deal of potential economic benefits in all areas of the construction industry (Özkan and Yüksel, 2008). From this perspective, it could be proposed that the utilisation potential of iron containing solid wastes produced as a byproduct in steel factories as a raw material in cement and concrete sectors is significant. Various studies were conducted using such types of waste materials in cement production (Özkan and Yüksel, 2008; Özkan, 2008; Binici et al., 2007; Shih et al., 2011).

SS contains calcium silicates and ferrite along with oxides of aluminum, manganese, calcium and magnesium (Reddy et al., 2006). The mineralogical composition of SS changes with its chemical composition. Olivine, merwinite, calcium silicates (C_2S, C_3S), C_4AF, C_2F, salts such as CaO-FeO-MnO-MgO in solid solution and free CaO are commonly found minerals in SS (Shih et al., 2004). The presence of C_3S, C_2S, C_4AF and C_2F ensures that SS possesses cementitious properties. The free CaO content increases basicity of the SS, which in turn improves reactivity of the slag (Ghodousi et al., 2009). However, a high content of free CaO in SS leads to volume expansion problems (Özkan, 2008).

GBFS is currently being used in cement and concrete industry. GBFS is used as an admixture in concrete or as an additive in the production process of Portland slag cements in countries where GBFS is abundant. Although some properties of concretes containing GBFS, such as creep, shrinkage, strength and freeze-thaw resistance are still under review, the entrainment of GBFS into cement and concrete is proven to display many advantages (Escalante-Garcia et al., 2009; Yuksel et al., 2007). Calcium silicate hydrate (CSH) is obtained by the addition of GBFS into cement to react with the Portland (CH) compound, which is released by cement hydration. Alkali silica facilitates this step by increasing the reaction rate.

Concrete durability is one of the most important parameters in structural design, which heavily depends on the material specifications, design process, environmental effects, workmanship, as well as past breakdowns and reparations. Deterioration is generally caused by a combination of external factors or internal dynamics of the particular concrete, as these influential forces can be mechanical, physical or chemical (Siddique and Kadri, 2011). Sulfate attack culminates in a particularly dangerous type of deterioration and constitutes one of the aforementioned external factors influencing concrete structures. Structures located on sulfate bearing soil or exposed to marine environments are vulnerable to sulfate attack. A highly crucial aspect of concrete durability is the resistance to sulfate attack in such situations (Al-Dulaijan, 2007).

Sulfate attack on concrete is a complex process, influenced by many factors such as cement type, sulfate cation type, sulfate concentration and exposure period, all of which may affect the resistance against sulfate (Cohen and Mather, 1991). In case cement-based materials are exposed to sodium sulfate attack, byproducts like gypsum and ettringite are produced in a way that they might lead to volumetric expansion in concrete. Formation of gypsum plays an important role in the overall damage incurred by the concrete due to inducing a softening of the material. There is also close relationship between the $Ca(OH)_2$ content and gypsum formation (Torii and Kawamura, 1994). On the other hand, ettringite formation results in cracking and expansion of the material, where the latter event is related to the water absorption of crystalline ettringite (Planel et al., 2006; Biricik et al., 2000). The presences of pozzolanic materials give rise to an increase in the resistance to sodium sulfate attack. Additionally, the effectiveness of pozzolanic materials against sulfate attack is dependent on the maximum temperature reached during their production stage. Wild et al. (1997) concluded that a calcination temperature for clay below 900°C produces a marked drop in sulfate resistance when the pozzolanic product partially replaces the cement in mortar (Wild et al., 1997). Pozzolanic materials also prevent other undesired effects by binding to $Ca(OH)_2$. Some observations supporting this dynamic were obtained in our study, which demonstrated that all substitution materials increased durability of the concrete exposed to a Na_2SO_4 solution (Özkan, 2008; Wild et al., 1997).

The aim of this study is to construct an artificial neural network (ANN) model to predict the sulfate resistance of composite cements containing GBFS and SS. For this purpose, the required data for developing the ANN model were collected from the experiments conducted. This paper is organised as follows: the next section is a description of the employed materials, grinding and mixing processes, the experimental test and ANN. Section 3 presents the experimental results obtained from the study; Section 4 proposes a prediction of ANN models, finally followed by the conclusion in Section 5.

2 Experimental work

2.1 Material

Materials like clinker, gypsum, SS and GBFS were used in the investigation, and were obtained in non-ground form. The chemical compositions of these materials are shown in Table 1.

Table 1 Chemical compositions of GBFS and SS, clinker and gypsum (wt. %)

Materials	*CaO*	*SiO_2*	*Fe_2O_3*	*Al_2O_3*	*MgO*	*SO_3*
Clinker	66.11	21.57	3.17	5.09	1.74	1.35
Gypsum	32.57	0.67	0.24	0.21	2.20	46.56
GBFS	37.80	35.10	0.70	17.54	5.50	0.70
SS	58.53	10.72	15.30	1.71	4.27	0.04

A magnetic separation process was applied to the SS at the steel plant to reduce its iron content. CEN standard sand was used to manufacture mortar specimens (EN 196-1, 2005). The chemical composition and particle size distribution of standard sand were presented in Table 2.

Table 2 Chemical compositions and particle size of standard sand

Chemical composition (%)		*Sieve size (mm)*	*Residue (%)*
SiO_2	93.05	2	-
Al_2O_3	3.11	1.6	5.23
Fe_2O_3	0.37	1	33.02
CaO	0.17	0.5	65.74
MgO	0.03	0.16	86.21
SO_3	0.07	0.08	99.12
K_2O	1.50	Humidity	0.11
Na_2O	0.57		
Lost on ignition			

2.2 Grinding and mixture

The materials used in this study were supplied in granular size as they were originally obtained in granular form from the factory. Each material was then ground for different time durations. Next, the materials were mixed with each other at the amounts specified previously and then ground again to attain the desired specific surface area, thus yielding the cements used in the tests.

SS and GBFS were first substituted together with the clinker-gypsum mixture and then separately, and hence two main groups of cement were established on the basis of these substitutions. Clinker-gypsum mixture was substituted with three different GBFS-SS compositions with proportions of 50% GBFS and 50% SS; 60% GBFS and 40% SS; and lastly 70% GBFS and 30% SS. Table 2 illustrates the composition proportions of the mixtures used in our study. All of the main groups were further divided into sub-groups and symbolised by suffixes (a, b, c and d) with respect to their varying ratios in compositions.

2.3 Experimental test

The physical properties of the produced cements, including weight percentages, specific surface values and specific gravities were examined in conformity with the European Standards (EN 196-6, 2000). The initial and final cement setting times and expansion ratios of the cements were determined according to European Standards (EN 196-3, 2005).

Dimensions of the specimens were 40 × 40 × 160 mm. The ratios of cement, sand, and water were chosen to be 1:3:0.5, respectively. After the specimens were preserved in their moulds for 24 hours at a room temperature of 20°C, they were removed from the moulds and immersed in water at 20 ± 2°C until being taken out for testing purposes (EN 196-1, 2005).

Compression tests at 7, 28 and 90 days were conducted with the mortar specimens, which were removed from the water bath on the specific test day for measuring the 7-day and 28-day compressive strengths and three sample was used for each experiment.

Mortar specimens produced for high temperature resistance tests were taken from the water tank on the 28th day. High temperature tests were conducted on the 90th day. Specimens, which were used for each experiment, were then exposed to 800°C. When the inner temperature of the furnace reached the target temperature, the heating was halted. The specimens were then taken out and placed in a room for cooling where the relative humidity ranged from 60% to 70% for 24 hours.

Resistance to sulfate was evaluated by comparing the residual compressive strengths of the specimens in each group exposed to these solutions against each other as well as with the compressive strength of a reference group of the same age. For this purpose, three samples was immersed in a 4% Na_2SO4 solution at the end of 7th day, while another was placed in a 4% $MgSO_4$ solution. Both of these samples were kept in these solutions until the end of 90th day. Meanwhile, the reference group was continuously cured in water until the end of the 90th day. Additionally, each solution was stirred twice a day and their concentrations were checked once a week.

2.4 Artificial neural network

The organisation and functioning mechanisms of biological neurons inspired the mathematical models called the ANNs. ANNs can exhibit a surprising number of human brain characteristics (Öztas et al., 2006; Demir et al., 2011). The fundamental concept of neural networks is the structure of the information processing system (Adhikary and Mutsuyoshi, 2006; Sarıdemir, 2009), which consists of a large number of simple processing elements named as neurons. The ANN architecture is commonly referred to as a fully interconnected feed forward multilayer perceptron. In addition, a bias is also built in that is only connected to neurons in the hidden and output layers with modifiable weighted connections. The number of neurons in each layer may vary depending on the problem being evaluated. ANNs can automatically approximate which functional form would best characterise the data. ANNs are also inherently non-linear, which means that not only do they estimate non-linear functions well but they can also extract any residual non-linear elements from the data after the linear terms are removed (Rumelhart and McClelland, 1986; Wasserman, 1989; Arulmozhi and Sheelarani, 2012).

The inputs and outputs of training and testing sets must be initialised in advance of the training of the feed work network. In the forward phase, the weighted sum of input components is calculated as given below:

$$net_j = \sum_{i=1}^{n} w_{ij} x_i + bias_j \tag{1}$$

where net_j is the weighted sum of the j^{th} neuron for the input received from the preceding layer with n neurons, w_{ij} is the weight between the j^{th} neuron and the ith neuron in the preceding layer, and finally x_i is the output of the i^{th} neuron in the preceding layer. The output of the jth neuron out_j is calculated with a sigmoid function that is symbolised by $\psi(\gamma_I' w_t)$ and defined as follows:

$$\psi\left(\gamma_I' w_t\right) = \frac{1}{1 + e^{-\gamma_I' w_t}} \tag{2}$$

The training of the network is achieved by adjusting the assigned weights and is repeated for a large number of training sets and training cycles. The goal of the training procedure is to determine the optimal set of weights, which would ideally produce the right output for any input. Training the weights of the network is performed iteratively to capture the relationship between the input and output patterns.

3 Experimental result

In this study, the physical, mechanical and durability characteristics of composite cements prepared by the substitution of GBFS and SS with the clinker were investigated. Initially, GBFS and SS replaced the clinker entirely on their own and then by forming mixtures with each other at proportions of 50% GBFS and 50% SS; 60% GBFS and 40% SS; and lastly 70% GBFS and 30% SS. Furthermore, the obtained cements were ground at varying fineness levels in order to evaluate the impact of grain size. Overall, 48 different sets of cements were produced. For starters, in order to analyse the physical properties of the cements, specific surface, specific gravity, volume expansion and the initial and final setting time tests were conducted. Next, mortar samples were prepared using the produced cement types and the 7, 28 and 90-day compressive strengths of these samples were tested. Finally, their resistance against temperature levels up to 800°C, in addition to various sulfate solutions, was tested in order to investigate their durability characteristics.

The physical properties and compositions of produced cements are shown in Table 3. The initial and final setting times, expansion ratios, specific surface and specific gravity of the analysed cements are listed.

Table 3 Composition and physical properties of cement

Code	*Composition*			*Physical properties*				
	SS (%)	*GBFS (%)*	*Clin.-Gyps. (%)*	*Sp. surf. cm^2/g*	*Sp. grav. g/cm^3*	*Initial T. sa*	*Final T. sa*	*Vol. exp. mm*
M1a	0	20	80	3,115	3.05	4:10	5:40	1.00
M1b	0	40	60	3,108	3.01	4:20	5:30	1.00
M1c	0	60	40	3,090	2.95	4:30	5:60	1.00
M1d	0	80	20	3,100	2.92	4:30	6:00	1.00
M2a	20	0	80	3,214	3.06	4:00	4:50	1.00
M2b	40	0	60	3,213	3.02	4:20	5:30	1.00
M2c	60	0	40	3,152	2.97	4:30	5:40	2.00
M2d	80	0	20	3,124	2.95	4:40	5:60	2.00
M3a	8	12	80	3,138	3.05	4:10	5:30	0.50
M3b	16	24	60	3,028	3.01	4:30	5:20	1.00
M3c	24	36	40	3,055	2.96	4:40	5:40	1.50
M3d	32	48	20	3,077	2.93	4:20	5:40	1.50
M4a	10	10	80	3,450	3.12	4:20	5:50	1.50
M4b	20	20	60	3,550	3.15	4:20	5:50	2.00
M4c	30	30	40	3,650	3.12	4:30	6:10	2.00
M4d	40	40	20	3,700	3.11	4:35	6:10	2.00
M5a	8	12	80	3,400	3.06	4:10	4:50	1.00
M5b	16	24	60	3,450	3.04	4:30	5:20	1.50
M5c	24	36	40	3,500	3.03	4:40	5:30	1.50
M5d	32	48	20	3,600	3.02	4:50	5:20	1.50
M6a	6	14	80	3,300	3.12	4:20	5:40	1.00
M6b	12	28	60	3,350	3.11	4:20	5:10	1.00
M6c	18	42	40	3,450	3.08	4:20	5:30	1.50
M6d	24	56	20	3,600	3.07	4:30	5:40	1.50

Table 3 Composition and physical properties of cement (continued)

Code	Composition			Physical properties				
	SS (%)	GBFS (%)	Clin.-Gyps. (%)	Sp. surf. cm^2/g	Sp. grav. g/cm^3	Initial T. sa	Final T. sa	Vol. exp. mm
M7a	6	14	80	3,800	3.12	4:20	5:40	1.00
M7b	12	28	60	3,800	3.11	4:20	5:10	1.00
M7c	18	42	40	3,800	3.08	4:20	5:30	1.50
M7d	24	56	20	3,800	3.07	4:30	5:40	1.50
M8a	6	14	80	4,200	3.12	4:20	5:40	1.00
M8b	12	28	60	4,200	3.11	4:20	5:10	1.00
M8c	18	42	40	4,200	3.08	4:20	5:30	1.50
M8d	24	56	20	4,200	3.07	4:30	5:40	1.50
M9a	6	14	80	4,600	3.12	4:20	5:40	1.00
M9b	12	28	60	4,600	3.11	4:20	5:10	1.00
M9c	18	42	40	4,600	3.08	4:20	5:30	1.50
M9d	24	56	20	4,600	3.07	4:30	5:40	1.50
M10a	10	10	80	4,180	3.09	4:20	5:50	1.00
M10b	20	20	60	4,220	3.08	4:20	5:50	1.50
M10c	30	30	40	4,240	3.07	4:30	6:10	2.00
M10d	40	40	20	4,210	3.07	4:35	6:10	2.00
M11a	8	12	80	4,200	3.08	4:10	4:50	1.00
M11b	16	24	60	4,240	3.08	4:30	5:20	1.50
M11c	24	36	40	4,220	3.07	4:40	5:30	2.00
M11d	32	48	20	4,230	3.06	4:50	5:20	2.00
M12a	6	14	80	4,150	3.06	4:20	5:40	0.50
M12b	12	28	60	4,200	3.05	4:20	5:10	1.00
M12c	18	42	40	4210	3.03	4:20	5:30	1.50
M12d	24	56	20	4,220	3.03	4:30	5:40	2.00

7, 28, and 90-day compressive strength values of the mortar specimens and a comparison of the residual compressive strength at high temperatures and against sulfate attack are presented in Table 4.

Table 4 Compressive strength and residual resistance of mortars

Code	*Compressive strength*			*Residual compressive strength*		
	7 days	*28 days*	*90 days*	*High temp.*	Na_2SO_4	$MgSO_4$
	(MPa)			(F_T/F_{20})	(F_S/F_w)	
M1a	24.25	37.67	51.75	0.19	0.99	0.93
M1b	19.05	32.35	51.31	0.16	1.05	0.94
M1c	15.31	29.94	41.85	0.13	1.07	0.98
M1d	14.20	27.82	38.90	0.13	1.06	1.00
M2a	22.13	28.58	43.40	0.15	0.98	0.96
M2b	21.60	27.88	42.30	0.16	1.03	0.97
M2c	19.98	24.31	38.40	0.13	1.05	0.98
M2d	18.87	22.54	36.78	0.14	1.04	0.98
M3a	20.04	31.58	53.27	0.17	1.01	0.96
M3b	18.52	31.29	51.69	0.16	0.97	0.98
M3c	14.48	30.65	43.70	0.11	1.06	0.96
M3d	13.92	29.90	38.96	0.15	1.07	0.94
M4a	20.95	34.86	49.90	0.23	1.05	0.94
M4b	17.92	30.43	48.34	0.23	1.06	0.95
M4c	10.94	23.30	36.30	0.18	1.08	0.96
M4d	6.21	18.12	25.17	0.20	1.07	0.96
M5a	23.01	35.67	54.60	0.23	1.06	0.97
M5b	16.92	31.23	50.80	0.25	1.08	1.02
M5c	11.65	24.50	38.67	0.21	1.09	1.00
M5d	5.81	21.25	33.45	0.20	1.11	1.00
M6a	23.75	37.78	57.80	0.28	1.09	0.95
M6b	19.23	35.12	53.70	0.24	1.10	0.95
M6c	14.81	26.76	44.23	0.15	1.14	0.96
M6d	9.67	23.45	33.54	0.16	1.14	0.98
M7a	30.56	46.22	68.84	0.24	1.03	0.97
M7b	29.78	37.91	65.33	0.24	1.04	0.98
M7c	21.41	49.91	54.87	0.22	1.17	1.12
M7d	8.90	28.90	40.45	0.22	1.08	0.98

Table 4 Compressive strength and residual resistance of mortars (continued)

Code	*Compressive strength*			*Residual compressive strength*		
	7 days	*28 days*	*90 days*	*High temp.*	*Na_2SO_4*	*$MgSO_4$*
		(MPa)		*(F_T/F_{20})*	*(F_S/F_w)*	
M8a	31.66	47.67	70.45	0.25	1.03	0.97
M8b	30.31	42.13	69.98	0.27	1.05	0.98
M8c	25.22	38.67	55.61	0.23	1.05	0.99
M8d	20.66	35.81	54.14	0.21	1.07	0.96
M9a	36.23	49.23	72.34	0.29	1.05	0.98
M9b	34.38	44.19	66.26	0.26	1.06	0.98
M9c	24.84	45.38	65.53	0.15	1.09	0.98
M9d	18.25	47.00	61.20	0.17	1.14	1.00
M10a	27.57	43.04	59.40	0.26	1.01	0.94
M10b	26.35	35.38	61.19	0.26	1.02	0.95
M10c	18.23	32.36	45.95	0.18	1.03	0.96
M10d	14.95	26.86	38.60	0.20	1.02	0.95
M11a	30.28	44.04	65.00	0.23	1.04	0.96
M11b	24.88	36.31	64.30	0.25	1.04	0.97
M11c	19.42	34.03	48.95	0.21	1.05	0.98
M11d	15.92	28.58	41.61	0.19	1.04	0.97
M12a	31.66	47.67	70.45	0.39	1.07	1.06
M12b	30.31	42.13	69.98	0.32	1.08	1.07
M12c	25.22	38.67	55.61	0.20	1.09	1.05
M12d	20.66	35.81	54.11	0.21	1.04	0.98

Residual compressive strengths for high temperature levels are examined in consideration of the temperature and the replacement ratio. The residual compressive strength after heating at different temperatures (T) is expressed as a ratio of $F_{T/}F_{20}$ where F_T is the strength after heating at a temperature of 800ºC and F_{20} is the initial strength of concrete at 20ºC. The residual compressive strength for sulfate is derived from the ratio of $F_{S/}F_w$ where F_S is the compressive strength of specimens exposed to sulfate attack, and F_w represents the strength of control specimens.

4 ANN model prediction

The ANN model is employed for the purpose of estimating the sulfate resistance. The connections in generalised feed forward networks, which are a generalisation of the MLP, can overlap individual or multiple layers. A two-layer feed forward neural network model was implemented to predict the residual compressive strength with the assistance of an optimised back propagation training algorithm. In addition, this study deliberately utilised the scaled conjugated gradient algorithm as the optimised training method, in which the data is divided into two sets as the training set and testing set. A total of 35 data values were specified as the training set that was used to train the neural network-based model. The remaining 11 data pieces that were not utilised by the training process were chosen to be the testing set and then used to verify the generalisation capability of the model based on the ANN. The pre-processing operation consists in the data normalisation in such a way that the inputs and outputs values will be within the range of 0 to 1. In the ANN modelling process, the input and the output exchange rate datasets for each parameter are normalised in following formulation [0, 1].

$$D = 0.1 + 0.8 \frac{\left(D_t - D_{\min}\right)}{\left(D_{\max} - D_{\min}\right)} \tag{3}$$

where D is the normalised value, D_t is the value to normalise, D_{min} and D_{max} are minimum and maximum variable values, respectively. The ANN model was analysed with one, two or three layers and number of epochs at 1,000, 2,000 or 3,000. Primarily, the ANN model's training performance was investigated and the obtained results are given in Table 5.

Table 5 Training performance of ANN models

Hidden number	*Epoch number*	*Minimum MSE*	*Final MSE*
3	3,000	0.001191	0.001191
2	*3,000*	*0.001158*	*0.001158*
1	3,000	0.001967	0.001967
3	2,000	0.002245	0.002245
2	2,000	0.002066	0.002066
1	2,000	0.002986	0.002986
3	1,000	0.009113	0.009113
2	1,000	0.008911	0.008911
1	1,000	0.007081	0.007081

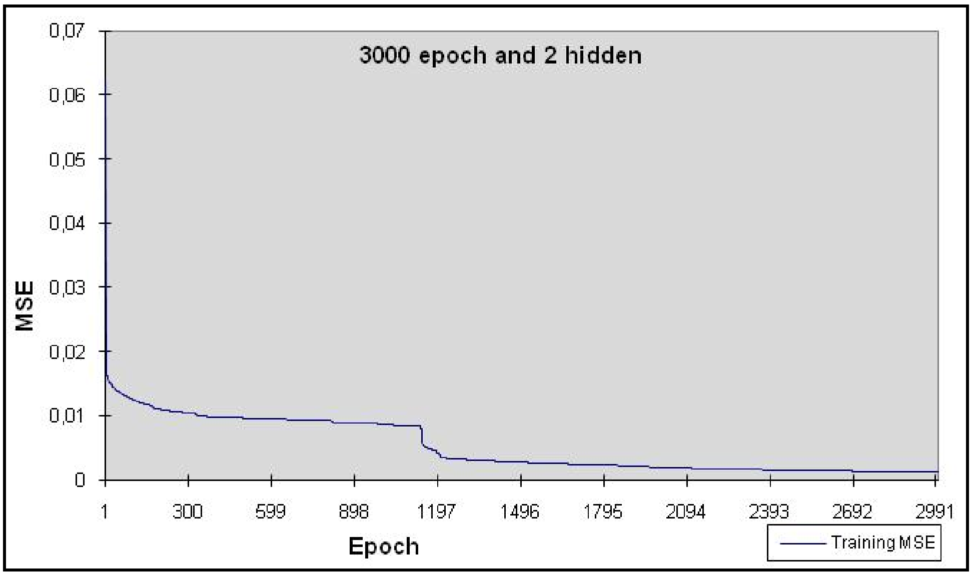
In view of the training mean square error (MSE) for the ANN model, it is seen that the model with two hidden layers and 3,000 epochs displayed the best training performance. Figure 1 depicts the best ANN model's training performance with respect to residual compressive strength.

The evaluation and comparison of the prediction performance necessitates the introduction of an appropriate evaluation criterion. In this context, three different consistency measures are employed in the literature to compare the predictive power of ANN models with each other. In order, these criteria are the MSE, the mean absolute error (MAE), and the mean absolute percentage error (MAPE). Even though these stated criteria are reliable measures of the prediction errors relative to the actual values, they are incapable of reflecting a model's ability to forecast inflection points. The aforementioned values are obtained by the following procedure:

The first measurement is the MSE,

$$MSE = \sum\nolimits_{t=1}^{T} \frac{\left(P_t - Z_t\right)^2}{T} \tag{4}$$

Figure 1 ANN model's training performance (see online version for colours)



The second criterion is the MAE,

$$MSE = \sum_{t=1}^{T} \frac{|P_t - Z_t|}{T} \tag{5}$$

The third criterion is the MAPE,

$$MAPE = \frac{1}{T} \sum_{t=1}^{T} \frac{P_t - Z_t}{Z_t} \tag{6}$$

where P_t is the predicted value at time t; Z_t is the actual value at time t; and T is the number of predictions.

The forecasting results of ANN models are summarised in Table 6.

Gypsum and ettringite are produced from cement-based materials under exposure to sulfate attack, which often leads to volumetric expansion in the concrete. Gypsum formation significantly influences the damage to the material as it results in softening. Also, the $Ca(OH)_2$ content and gypsum formation are highly correlated (Torii and Kawamura, 1994). Formation of ettringite leads to cracking and expansion of the material, where the latter phenomenon is related to the water absorption by crystalline ettringite. The presence of a pozzolanic material in cements improves the resistance to sodium sulfate attack. In addition to the effectiveness of pozzolanic material in providing additional strength against sulfate attack depends on the maximum temperature reached during the production stage of pozzolan. Wild et al. observed that clay calcination temperatures below 900°C lead to marked deterioration in sulfate resistance if the cement in mortar is partially replaced by the pozzolanic product. Pozzolanic materials also hinder other undesired effects by binding to $Ca(OH)_2$. Several observations supporting this dynamic were obtained in our study, indicating that all substitution materials increased durability of the concrete exposed to a Na_2SO_4 solution (Özkan, 2008; Planel et al., 2006; Biricik et al., 2000; Wild et al., 1997; Binici et al., 2012).

Table 6 Comparison of observed and predicted data from ANN models

	Epoch N.	*Hidden N.*	*MSE*	*NMSE*	*MAE*	*Min abs error*	*Max abs error*	r^2	*% Correct*
Na_2SO_4	3,000	3	0.00092	0.09148	0.02352	0.00563	0.07429	0.95073	90
$MgSO_4$	3,000	3	0.00746	0.18007	0.06879	0.00394	0.19675	0.94022	100
Na_2SO_4	*3,000*	*2*	*0.00089*	*0.08810*	*0.02255*	*0.00007*	*0.06886*	*0.96835*	*100*
$MgSO_4$	*3,000*	*2*	*0.00516*	*0.12459*	*0.05265*	*0.00181*	*0.18815*	*0.96992*	*100*
Na_2SO_4	3,000	1	0.00193	0.19166	0.03016	0.00418	0.11314	0.90783	100
$MgSO_4$	3,000	1	0.00522	0.12554	0.05464	0.00919	0.19245	0.96237	100
Na_2SO_4	2,000	3	0.00482	0.47754	0.06262	0.01497	0.13760	0.72947	100
$MgSO_4$	2,000	3	0.00266	0.06414	0.04770	0.00593	0.08020	0.95996	100
Na_2SO_4	2,000	2	0.00091	0.09989	0.02521	0.00616	0.07050	0.96165	100
$MgSO_4$	2000	2	0.00855	0.20649	0.08246	0.03318	0.20433	0.96439	100
Na_2SO_4	2,000	1	0.00302	0.29921	0.04756	0.00576	0.08262	0.84307	90
$MgSO_4$	2,000	1	0.00417	0.10062	0.05485	0.00646	0.13205	0.96713	100
Na_2SO_4	1,000	3	0.00434	0.43018	0.04880	0.00257	0.17515	0.79565	100
$MgSO_4$	1,000	3	0.00576	0.13913	0.06355	0.01289	0.19210	0.96082	100
Na_2SO_4	1,000	2	0.00391	0.38751	0.05290	0.00280	0.14126	0.79052	100
$MgSO_4$	1,000	2	0.00522	0.17778	0.05640	0.00376	0.19204	0.96183	100
Na_2SO_4	1,000	1	0.00591	0.38751	0.05290	0.00280	0.14126	0.79052	100
$MgSO_4$	1,000	1	0.00622	0.19778	0.05640	0.00376	0.19204	0.96183	100

A comparison between the entire ANN alternatives demonstrates that the model with two hidden layers and 3,000 epochs displayed the best performance with respect to prediction accuracy similar to the situation in training tests. The amount of pozzolanic material used in sulfate-resistant cement production was predicted with an accuracy of 97% in this study. Hence, estimation of the strength against sulfate will be reliably carried out by taking into account the GBFS and SS contents of the cements as well as their physical and mechanical properties. The tests that aim to measure the sulfate resistance of cements and concretes generally take a long period. As a virtue of this prediction model, valuable insight into the sulfate resistance will be gained without having to wait for such long durations.

The estimated and realised values for residual compressive strengths of mortars samples against Na_2SO_4 and $MgSO_4$ are displayed in Figures 2 and 3, respectively.

5 Conclusions

GBFS and SS containing composite cements with altered compositions were prepared in the laboratory. In this study, five different cement mixtures were used to replace the clinker. The pozzolanic materials in cement were substituted for the clinker at the following proportions: 50% GBFS vs. 50% SS, 60% GBFS vs. 40% SS, 70% GBFS vs. 30% SS

In addition, the influence of fineness was investigated by grinding the cements at various degrees. The cements were also evaluated with respect to their physical and mechanical characteristics, as well as resistance against high temperature levels and sulfate. All of the obtained results were compiled in a single table and a total of 46 different types of cement were utilised in the analyses. The data obtained from the tests conducted on the cement samples were analysed in terms of their effect on the sulfate-resistance of cement. The cement content and the physical and mechanical properties were processed as ANN model inputs and henceforth the resistance of these cements against sulfate compounds was successfully predicted.

As a result of the performed tests, it was demonstrated that entrainment of GBFS and SS improved the resistance of cement against sulfate attack. The increase in resistance was positively correlated with the substitute ratio of slag, but the achieved enhancement differed for exposure to sodium sulfate and magnesium sulfate, as the resistance against the former compound is higher compared to the latter. In addition to this, it was observed that the cement fineness had no discernible impact on the sulfate resistance. The ANN model that employed the cement content and the physical and mechanicals properties as inputs predicts the actual resistance against sulfate with an accuracy of 97%. As a virtue of gaining the capability to estimate the sulfate resistance of cements simply by taking account of the slag content used in the production and the relevant physical and mechanical properties, a significant deal of time loss in cement production will be eliminated. Furthermore, since the proportions of slag and clinker as well as the fineness ratio needed to attain the desired level of sulfate resistance in cement production will be known beforehand, the actual production will be carried out in accordance with these findings. In turn, this will induce a notable shortening in several stages of cement production.

Figure 2 The estimated and realised values for residual compressive strength of Na_2SO_4 (see online version for colours)

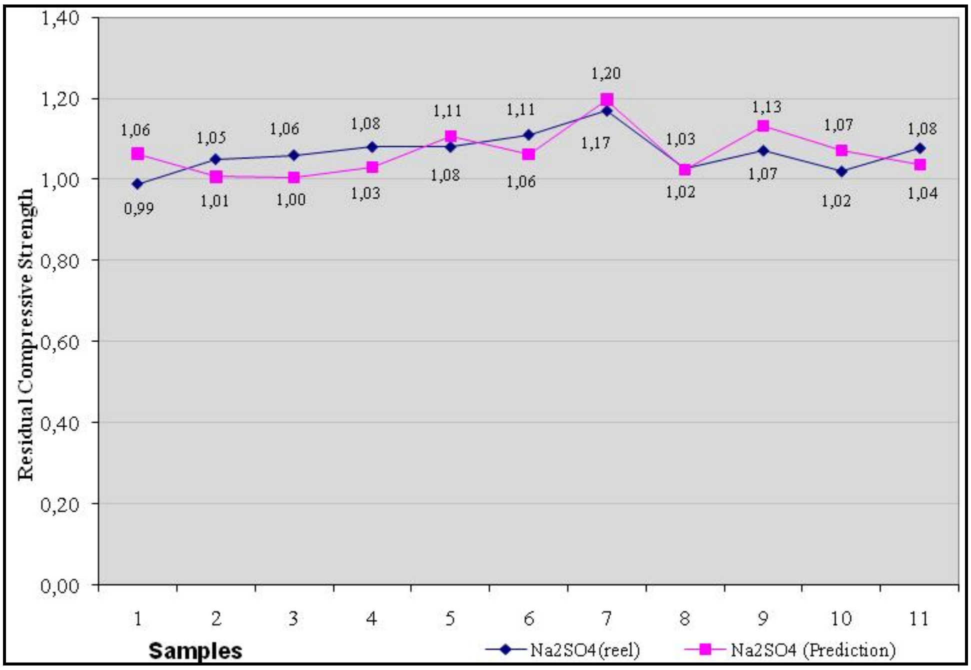
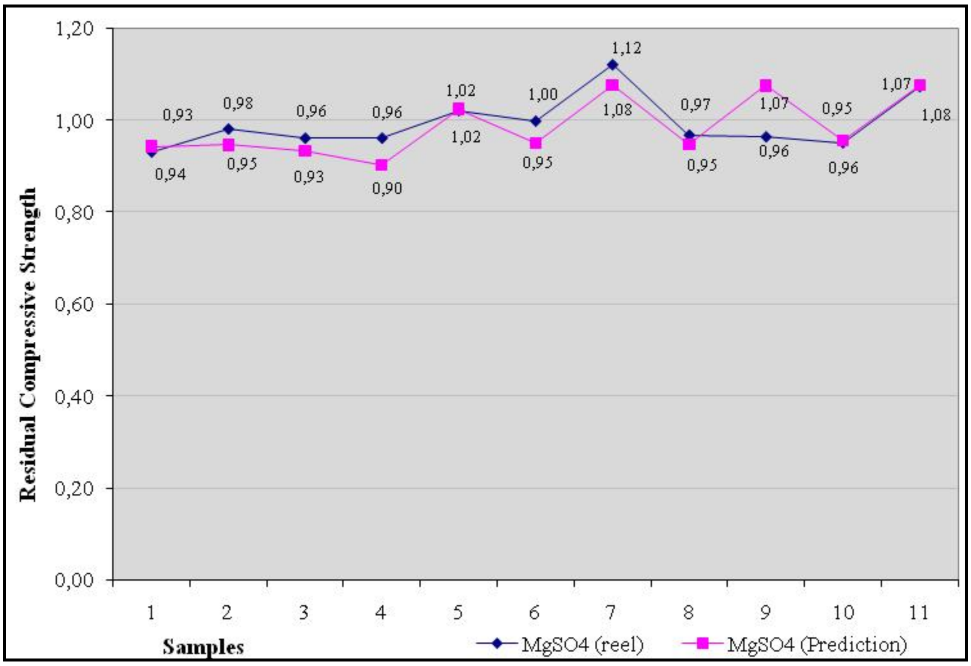


Figure 3 The estimated and realised values for residual compressive strength of $MgSO_4$ (see online version for colours)



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