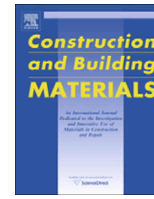
Construction and Building Materials 25 (2011) 4105–4111

Contents lists available at ScienceDirect

Construction and Building Materials

journal homepage: www.elsevier.com/locate/conbuildmat



Predicting the core compressive strength of self-compacting concrete (SCC) mixtures with mineral additives using artificial neural network

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A R T I C L E I N F O

Article history:
Received 24 August 2010
Received in revised form 19 October 2010
Accepted 13 November 2010
Available online 2 June 2011

Keywords:
Self-compacting concrete (SCC)
The core compressive strength
Mineral admixture
Artificial neural network

A B S T R A C T

In this study, an artificial neural networks study was carried out to predict the core compressive strength of self-compacting concrete (SCC) mixtures with mineral additives. This study is based on the determination of the variation of core compressive strength, water absorption and unit weight in curtain wall elements. One conventional concrete (vibrated concrete) and six different self-compacting concrete (SCC) mixtures with mineral additives were prepared. SCC mixtures were produced as control concrete (without mineral additives), moreover fly ash and limestone powder were used with two different replacement ratios (15% and 30%) of cement and marble powder was used with 15% replacement ratio of cement. SCC mixtures were compared to conventional concrete according to the variation of compressive strength, water absorption and unit weight. It can be seen from this study, self-compacting concretes consolidated by its own weight homogeneously in the narrow reinforcement construction elements. Experimental results were also obtained by building models according to artificial neural network (ANN) to predict the core compressive strength. ANN model is constructed, trained and tested using these data. The results showed that ANN can be an alternative approach for the predicting the core compressive strength of self-compacting concrete (SCC) mixtures with mineral additives.

1. Introduction

Self-compacting concrete (SCC) has emerged in Japan in the late 1980s as a material that can flow under its own weight, so that it can be easily placed, without need for additional mechanical compaction, in complicated formwork, congested reinforced structural elements and hard to reach areas [1–3]. This concrete has gained wide use in many countries for different applications and structural configurations [4–8]. The key performance criterion of this technology is attaining a highly fluid behavior while preventing bleeding and segregation of the mixture components [9].

Self-compacting concrete (SCC) removes the need for compaction when placing fresh concrete. This saves time, reduces overall cost, improves working environment and opens the way for the automation of the concrete construction. Because of these significant benefits, SCC is expected to gradually replace most of the ordinary concrete currently produced [10,11]. Especially the developments in the superplasticizer technology have contributed considerably to formation and progression of the self-compacting concrete [12,13]. Different from the classical concrete design, the self-compacting concrete needs the superplasticizers, viscosity increasing addition and inert or pozzolanic mineral additions in big quantity all together or partly.

The artificial neural networks solve very complex problems with the help of interconnected computing elements. Basically, the processing elements of a neural network are similar to the neurons in the brain, which consist of many simple computational elements arranged in layers [14]. In recent years, the ANNs have been extended extensively and applied to many civil engineering applications [15] such as concrete durability [16], drying shrinkage [17], ready mixed concrete delivery [18], slump model [19], workability of concrete with metakaolin and fly ash [20,21], concrete structures [22–25], mechanical behavior of concrete at high temperatures [26], construction smoothness specification pay factor limits [27], cost analysis of HPC in tall building construction [28], asphalt concrete permeability [29] and long term effect of fly ash and silica fume on compressive strength [30]. The concrete mix proportion thus obtained is expected to result with the lesser number of trials, cost and time. Further the concrete designed by ANN is expected to have optimum cement and water contents, thus leading to higher durability and relatively better economical and ecological effects [31].

In this study large-sized (300 × 150 × 20 cm), L-shaped and double-sided reinforcement mesh equipment which was designed often combined with a special pre-screen in the form of equipment and placed in molds and curtain wall specimens were produced. The aim of this paper is to construct an ANN model to predict the com-

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0950-0618/$ - see front matter
doi:10.1016/j.conbuildmat.2010.11.108

Table 1
Properties of portland cement and mineral additives.

	Cement	Fly ash	Limestone powder	Marble powder
Chemical composition (%)				
SiO_2	19.10	47.09	4.93	0.70
Al_2O_3	4.85	17.41	0.82	0.29
Fe_2O_3	3.24	8.34	0.58	0.12
CaO	61.86	13.98	51.97	55.49
MgO	2.02	1.85	0.58	0.23
SO_3	2.63	4.65	–	–
Loss ignition	2.90	1.79	40.40	42.83
Cl^-	0.00	–	–	–
Na_2O	–	2.44	–	2.44
K_2O	–	1.80	–	1.80
Physical properties				
Specific gravity	3.08	2.17	2,79	2,71
Blaine (cm^2/g)	3996	2469	2500	8889

Table 2
Mix proportions of SCC and vibrated concrete for 1 m^3.

Materials (kg/m^3)	Vibrated concrete	Control	FA15 SCC	FA30 SCC	LP15 SCC	LP30 SCC	MP15 SCC
Cement	550	550	467	385	467	385	467
Limestone powder	–	–	–	–	83	165	–
Marble powder	–	–	–	–	–	–	83
Fly ash	–	–	83	165	–	–	–
Water	182	182	182	182	182	182	182
w/c ratio	0.33	0.33	0.39	0.51	0.37	0.47	0.39
w/p ratio	0.33	0.33	0.33	0.33	0.33	0.33	0.33
Sand	865	869	865	878	866	860	863
CSI	466	467	457	445	464	461	463
CSII	320	311	305	297	311	307	312

pressive strength. For this purpose, a computer program was developed in MATLAB. Furthermore, the results obtained from the ANN model were compared with the average results of the experiments.

2. Experimental procedure

2.1. Materials

The Portland cement used in this study was produced according to the European Standards EN-197/1 and labeled as CEM I/42.5 R. The physical and chemical properties of the Portland cement is listed in Table 1. The maximum size of coarse aggregate was selected as 16 mm in order to avoid the blocking effect of SCC. Besides, fly ash, marble powder and limestone powder were used as mineral and filler additives in SCC to utilize it. Specific surface area by Blaine and 28th day compressive strength of cement were 399.6 m^2/kg, and 48.3 MPa, respectively.

Marble powder (MP) was provided from a marble managing plant in Bilecik directly used in SCC without any processes. The specific surface area by Blaine of MP is 889 m^2/kg. Limestone powder was a by-product of quarry crushers and collected from the filtration system of a quarry crushers. The characteristic properties, mineralogical composition and particle size distribution of filler materials are given Table 1.

Polycarboxylate based and high range water reducing superplasticizer was also used in the mixtures at the ratio of 1.6% of binder materials by weight for reducing the water/binder ratio of SCC. The solid content and pH of superplasticizer were 21% and 8%, respectively. Tap water used was obtained from the city waterworks of Sakarya for the production of concrete mixtures during the experimental procedure.

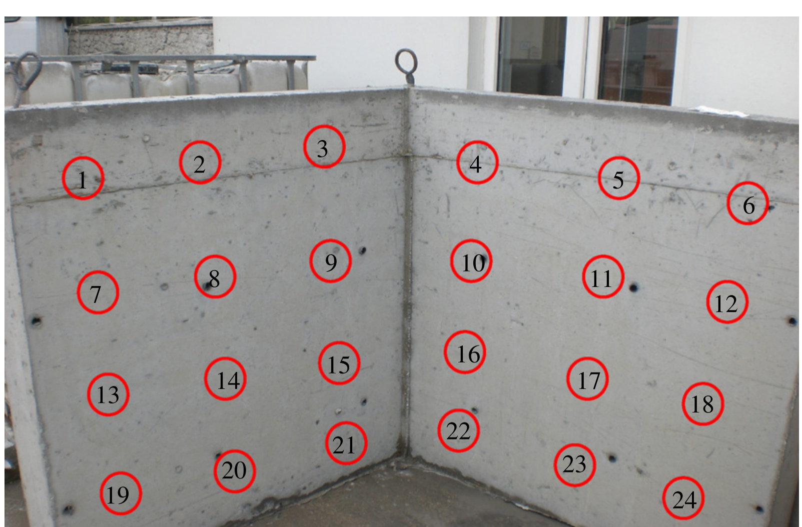

Fig. 1. Core points on curtain wall.