Construction and Building Materials 94 (2015) 371–379

Contents lists available at ScienceDirect

Construction and Building Materials

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

Explicit formulation of drying and autogenous shrinkage of concretes with binary and ternary blends of silica fume and fly ash

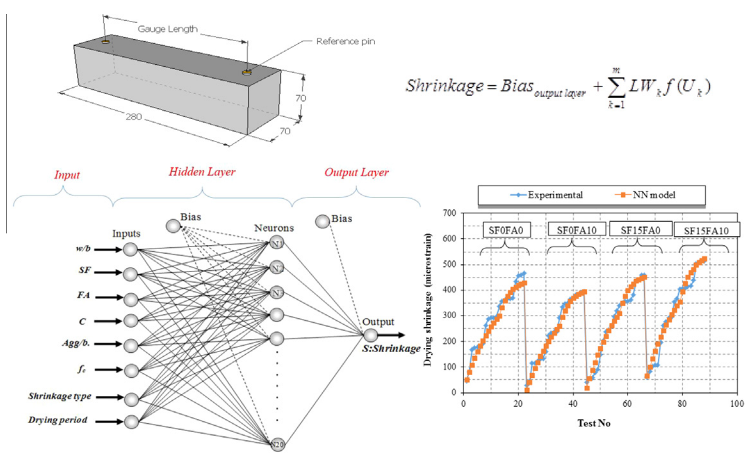
Kasım Mermerdaş *, Mohamed Moafak Arbili

Hasan Kalyoncu University, Faculty of Engineering, Civil Engineering Department, 27410 Gaziantep, Turkey

HIGHLIGHTS

- Explicit formulation of shrinkage of concretes with mineral admixtures was aimed.
- Experimental data from literature were collected to derive an analytical model.
- The utilized soft computing technique is artificial neural networks.
- The proposed models provided high accuracy prediction performance.
- An experimental study was conducted to verify the proposed model.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 25 April 2015
Received in revised form 1 June 2015
Accepted 12 July 2015
Available online 16 July 2015

Keywords:
Shrinkage
Modeling
Prediction
Experimental validation
Mineral admixtures

ABSTRACT

Shrinkage is generally considered as an important durability property of hardened concrete. During the drying process, free and absorbed water is lost from the concrete. When the drying shrinkage is restrained, cracks can occur depending on the internal stresses in the concrete. The ingress of deleterious materials through these cracks can cause decrease in the compressive strength and the durability of concrete. In the first stage of the study, a prediction model through the most popular soft computing method called neural network (NN) was derived. The data set used for training and testing of the prediction model covers the experimental data presented in the literature. In the second stage of the study, the findings of an experimental study on drying shrinkage behavior of concretes incorporated with silica fume (SF) and fly ash (FA) were reported. Free shrinkage strain measurements as well as corresponding weight loss were measured over 40 days of drying. The obtained experimental results were also used for the validation of the proposed prediction models. The highest amount of mineral admixture resulted in high shrinkage strain development. Moreover, the proposed NN model also accurately predicted the values obtained from experimental study.

1. Introduction

Concrete is the most widely used construction material in all over the world because of its serviceability performance. The more

* Corresponding author.
E-mail address: kasim.mermerdas@hku.edu.tr (K. Mermerdaş).

http://dx.doi.org/10.1016/j.conbuildmat.2015.07.074
0950-0618/

durable the concrete is, the longer the service life of the structure is. In some aspects shrinkage is of concern when it relates to durability of concrete structure. Excessive shrinkage may cause concrete cracking, even structural failure. Thus, cracking may lead to increased corrosion rate of steel reinforcement in concrete structure [1]. In the view of global sustainable development, therefore, researchers start to make use of blending of two or three supplementary cementing materials (SCMs) to optimize durability and cost of the concrete. The industrial by-products used as SCMs, such as fly ash and silica fume, have become more efficient admixtures to diminish the shrinkage effects and increase the durability of concrete. Usage of SCMs could substantially reduce the final cost of concrete mixtures since these materials are quite cheaper in comparison to Portland cement [2,3].

The problems encountered in the field of engineering are generally unstructured and imprecise influenced by intuitions and past experiences of a designer [4]. Complexity to mathematically model real world problems has compelled the human civilization to search for nature inspired computing tools. The evolution of such computing tools revolves around the information processing characteristics of biological systems. In contrast to conventional computing, these tools are rather "soft" as they lack the exactness and therefore placed under the umbrella of a multidisciplinary field called soft computing. Soft computing is an emerging collection of methodologies, which aim to exploit tolerance for imprecision, uncertainty and partial truth to achieve robustness, tractability and total low cost [5].

Soft Computing tools exploit the reasoning, intuition, consciousness, wisdom and adaptability to changing environments possessed by human beings for developing computing paradigms like fuzzy logic (FL), neural networks (NN) and genetic algorithms (GA). The integration of these techniques into the computing environment has given impetus to the development of intelligent and wiser machines possessing logical and intuitive information processing capabilities equivalent to human beings. These techniques whether complementing each other or working on their own, are able to model complex or unknown relationships which are either nonlinear or noisy. Soft computing techniques have a self-adapting characteristic paving a way for development of automated design systems. A synergistic partnership exploiting the strengths of these individual techniques can be harnessed for developing hybrid-computing tools [5]. In order to handle complex nonlinear relationships between various inputs and outputs, soft computing techniques are used to derive mathematical models obtained from soft computing methods such as neural network, genetic programming.

In the recent years, soft-computing techniques have been widely utilized to predict some critical properties of concrete and/or reinforced concrete [6–21]. For example, Vanluchene and Sun [6] presented an introduction to neural network by using back-propagation algorithm to solve three different structural engineering problems related to pattern recognition, decision making and problems that have numerically complex solutions. In the study of Ozcan et al. [10], compressive strength prediction was done by using NN and fuzzy logic. Shahin et al. [12] used neural networks for predicting settlement of shallow foundations on cohesion less soils. They compared predictive ability of NN with three of the most commonly used traditional methods. Tokar and Johnson [18] used ANN to forecast daily runoff as a function of daily precipitation, temperature and snowmelt. Lee and Han [21] developed efficient neural network models for generation of artificial earthquakes and response spectra.

Other than above mentioned studies, soft computing based explicit formulation of some design parameters of structural steel members and mechanical behavior of post installed anchors have also been reported in recent years [22–26]. This can be considered as an indication on how large the field of application of soft computing based modeling to handle the engineering problems.

In this study an explicit formulation of prediction model from NN was presented. For this purpose, experimental data were collected from the available test results presented in the previous studies. The prediction parameters were selected from mixture constituents of concrete and drying period. An experimental validation study was also conducted to evaluate the performance of the prediction model. In the study, SF and FA were used as a replacement for Portland cement (PC), ranging from 0% to 15% by weight, to evaluate its efficiency upon the concrete properties. Four different concrete mixtures with w/b ratio of 0.45 were designed. The focus of the experimental study is to evaluate the effectiveness of FA and SF on drying shrinkage of the concretes as well as assessment of the prediction capability of the proposed NN model.

2. Neural networks (NN)

An artificial neural network (NN) is an information-processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. NNs, like people, learn by example. An NN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons.

The training of NNs by back propagation have three stages [27]: (i) the feed forward of the input training pattern, (ii) the calculation and back propagation of the associated error, and (iii) the adjustment of the weights. This process can be used with a number of different optimization strategies. The error between the output of the network and the target value is propagated backward during the backward pass and used to update the weights of the previous layers as shown in Fig. 1 [28].

In this study, neural network fitting tool (nftool) provided as a soft-computing tool in MatlabV.R2012a was utilized to perform neural network modeling. In fitting problems, a neural network may be used to map between a data set of numeric inputs and a set of numeric targets. The nftool helps create and train a network, and evaluate its performance using mean square error and regression analysis.

A two-layer feed-forward network with sigmoid hidden neurons and linear output neurons can fit multi-dimensional mapping problems arbitrarily well, given consistent data and enough neurons in its hidden layer. The network was trained with Levenberg–Marquardt back propagation algorithm.

An artificial neuron consists of three main components namely weights, bias, and an activation function. Each neuron receives inputs $I_1, I_2, \ldots, I_n$ attached with a weight w_i which shows the connection strength for that input for each connection. Each input is then multiplied by the corresponding weight of the neuron connection. A bias can be defined as a type of connection weight with a constant nonzero value added to the summation of weighted inputs, as given in Eq. (1). Generalized algebraic matrix operation was also given in Eq. (2). to clarify the mathematical operations in an artificial neuron.

$$U_k = Bias_k + \sum_{j=1}^{n} w_{k,j} \times I_j \tag{1}$$