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Artificial neural network based mechanical and electrical property prediction of engineered cementitious composites

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HIGHLIGHTS

- Properties of ECCs were predicted by artificial neural network technique.
- Datasets for neural network training were collected by a literature review.
- Experimental testing was conducted to verify the neural network training.
- Parameters affecting the performance of artificial neural network were discussed.

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ABSTRACT

Engineered cementitious composite (ECC) is a type of cement-based material fabricated with a variety of add-in functional fillers, featuring superior properties of strain-hardening, ductility and energy absorption. Proper composition is essential for designing ECC material, which may lead to different mechanical and electrical properties. However the design for ECC is still a complex process on the basis of micro-mechanism followed by numerical and experimental analyses, and there is no simple model yet for practical engineering application. This study presents the prediction of mechanical and electrical properties of ECC based on the artificial neural network (ANN) technique with the aim of providing a gateway for a more efficient and effective approach in ECC design. Specifically, neural network models were developed for ECCs reinforced with polyvinyl alcohol (PVA) fibre or steel fibre (SF) with experimental data collected from other researchers for training. The development, training and validation of the proposed models were discussed. To assess the capability of well-trained ANN models for property prediction, experimental studies were conducted, including compression test, four-point bending test, tensile test and electrical resistance measurement for ECCs of various composition. Excellent consistency between the predicted and tested results is obtained, demonstrating the feasibility of ANN models for property prediction of ECCs.

1. Introduction

Cementitious materials are widely used in the construction of many key engineering structures. However, cement-based concrete is a quasi-brittle material with an inherent weakness in resisting tensile stress and an inclination to exhibit extensive cracking with potential brittle failure, in particular under dynamic loading such as impact loading. Engineered cementitious composite (ECC), which is a special class of high-performance fibre-reinforced cement composite (HPFRCC), has been developed by reinforcing the matrix using short high-performance fibres or functional particles (equal to or less than 2%), such as steel fibre (SF), polypropylene (PP), polyethylene (PE), polyvinyl alcohol (PVA) fibres, carbon fibre (CF), carbon black (CB). It offers significantly improved mechanical properties over regular fibre-reinforced concrete (FRC) [35] and is a promising engineering material due to its excellent mechanical properties such as high tensile strength, large pseudo-strain-hardening capacity to resist microcracking, and high energy absorption [9,18]. Meanwhile, ECC also features a strong potential for self-sensing applications when fabricated with fibres of high conductivity in proper proportion [11]. The significant low fibre content in ECC compared with regular FRC reduces not only the material cost but also the intensive labour cost incurred in the fabrication of FRC.

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It is understood that the superior mechanical and electrical performance of ECCs are highly dependent on the proportion of add-in fibres and many other constituents. If the properties of an ECC could be predicted based on its composition, for example, the design of a particular type of ECC reaching a specific level of strength as well as excellent conductivity, it would be beneficial to engineers in terms of planning, design, cost and time management. However, researchers have not yet developed a simple method for determining properties based on the composition of the ECC. The design for ECC can be based on the micromechanics related to the interaction between fibres and matrix [13]. However from the theoretical material design to practical application, it requires a complex process starting with microstructure tailoring and optimisation, followed by time-consuming experimental and finite element analyses [15,14].

Artificial neural network (ANN) technique is a time saving, efficient and, more importantly, accurate computational method for solving complex nonlinear problems. ANNs are inspired by the sophisticated functionality of human brains, where many billions of interconnected neurons process data in parallel [34]. This approach is an enthralling mathematical tool for solving complicated problems which are difficult to approach linearly. The neural network technique has been adopted and used to simulate a wide variety of complex problems in both science and engineering fields [27,37]. In particular, the technique has been successfully used to model the confined compressive strength and strain of concrete columns [24]. Some researchers have modified the multi-layer ANN model to predict concrete strength and elastic modulus [7,12]. The ANN technique has also been applied to many other types of concrete, such as autoclaved aerated concrete [32], self-compacting concrete [22] and granulated blast furnace slag concrete [6].

In this study, several ANN models are developed correspondingly in order to predict the electrical and mechanical properties, such as resistivity, compressive strength, flexural strength and tensile strength, of some typical ECCs fabricated with PVA and SF. The datasets for ANN training are based on a comprehensive literature review of previous studies. A set of experiments including compression test, four-point bending test, tensile test and electrical resistance measurement for ECCs with various proportions of PVA and SF were conducted to demonstrate the capability of ANN models in predicting the mechanical and electrical properties of ECCs.

The paper is structured as follows. Section 2 introduces the ANN techniques, the ANN models developed for ECCs and the predicted results of the properties for PVA and SF reinforced ECCs. Section 3 presents the experimental studies elaborating material selection, specimen preparation, test set-up and results. Section 4 gives a discussion on the results and conclusions are drawn in Section 5 finally.

2. Artificial neural network

Artificial neural networks are a group of models inspired by biological central nervous systems to achieve estimation functions that depend on a large number of inputs. ANNs have been well acknowledged as useful and cost-effective tools to solve complex tasks [10]. Commonly, an ANN model consists of one input layer, two hidden layers (where the training occurs) and one output layer. Different numbers of neurons are required for the input and hidden layers for training and all layers are assigned to different transfer functions, e.g. tan-sigmoid, log-sigmoid and pure linear. The ANN model is then validated using an appropriate validation method such as k-fold validation or cross-validation.

2.1. Feedforward ANN model and backpropagation training

An ANN model consisting of two hidden layers has been demonstrated to be adequate in most structural-related analysis [19]. The feedforward network consists of a series of layers where each layer has a connection from the preceding one and the information passes through the network in the forward direction utilising the neuron connections within the layers [29]. In general, ANN models feature one input layer with a known value $i_p(p = 1, 2, \ldots m)$, two processing layers containing j and k neurons respectively, and one output layer with related parameters $o_s(s = 1, \ldots, n)$. The neurons are connected via the weight matrix and a set of biases. Mathematically, the s^{th} output variable, depicted in Fig. 1, in the designed ANN model is calculated by [5]

$$\bar{o}_s = F_3\left(\left(\sum_{q=1}^{k}\bar{w}^3_{q-i}\cdot F_2\left(\left(\sum_{r=1}^{j}\bar{w}^2_{r-q}\cdot F_1\left(\left(\sum_{p=1}^{m}\bar{w}^1_{p-r}\cdot\bar{i}_p\right)+\bar{b}^1_r\right)\right)+\bar{b}^2_q\right)\right)+\bar{b}^3_i\right) \tag{1}$$

where $\bar{w}^l_{u-v}(l = 1, 2, 3)$ represents the weight connecting the u^{th} neuron in the l^{th} layer and the v^{th} neuron in the $(l+1)^{\text{th}}$ layer, while $\bar{b}^l_v$ and $n\bar{i}^l_v$ are the added bias and the net input in the l^{th} layer for the v^{th} neuron in the $(l+1)^{\text{th}}$ layer. $F_l(l = 1, 2, 3)$ is the transfer function for activating neurons in different layers [5].

The neural network can learn its weights and biases using the gradient descent algorithm, i.e. by repeatedly computing the gradient function ∇C, where C is a general function used in the neural network, and then moving in the opposite direction. The process is carried out until the descent algorithm reaches the desired value, e.g. a minimum. However, there is a gap where the gradient of the function can be difficult to obtain [23]. As a result, an algorithm known as backpropagation is used to provide a fast algorithm for computing such a gradient. Backpropagation is associated with a stochastic steepest descent algorithm for ANN training within a required error tolerance [19]. The mean square error function (MSE) E_r is defined as [5]

$$E_r = \frac{1}{n}\sum_{s=1}^{n}(\bar{t}_s - \bar{o}_s)^2 \tag{2}$$

where $\bar{t}_s$ is the s^{th} target vector and n is the total number of output vectors. In the training process, the weight and bias values are modified based on the steepest descent method in order to minimise the MSE, E_r [31]. Before the training proceeds, the selection of neuron numbers should be appropriately decided. The criterion for the numbers of neurons was suggested by Su and Ye [30] as:

$$i = \sqrt{p+q} + B \tag{3}$$

where i, p and q are the numbers of neurons, input components and output components for each processing layer, respectively. B is an empirical constant ranging from 4 to 8, depending on various applications of the model.

In the present study, the neural network training was accomplished utilising the "Neural Network Toolbox – MATLAB" (R2016b). The transfer functions were selected to be Tan-sigmoid and Log-sigmoid for the processing layers 1 and 2 respectively. The transfer function was set to be pure linear for the output layer so as to avoid limiting the output values to a small range.

2.2. Artificial neural network set-up

In order to achieve property prediction, the neural network model needs to be trained first using the available datasets where different constituents of ECCs are considered as input and corresponding electrical and mechanical properties are considered as output. In this study, datasets for PVA-ECCs were based on a com-