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Application of artificial neural networks to predict the bond strength of FRP-to-concrete joints

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HIGHLIGHTS

- ▶ A BPNN model for predicting the bond strength of FRP-to-concrete joints is proposed.
- ▶ The results of the BPNN compared with experimental results and those from five existing analytical models.
- ▶ BPNN is a convenient tool for developing a parametric study.
- ▶ The application of BPNN techniques provide a reliable and simple model for predicting the bond strength.

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ABSTRACT

A Back-Propagation Neural Network (BPNN) model for predicting the bond strength of FRP-to-concrete joints is proposed. Published single-lap shear test specimens were used to predict the bond strength of externally bonded FRP systems adhered to concrete prisms. A database of one hundred and fifty experimental data points from several sources was used for training and testing the BPNN. The data used in the BPNN are arranged in a format of six input parameters including: width of concrete prism; concrete cylinder compressive strength; FRP thickness; bond length; bond width (i.e. FRP width); and FRP modulus of elasticity. The one corresponding output parameter is the bond strength. A parametric study was carried out using BPNN to study the influence of each parameter on the bond strength and to compare results with common existing analytical models. The results of this study indicate that the BPNN provides an efficient alternative method for predicting the bond strength of FRP-to-concrete joints when compared to experimental results and those from existing analytical models.

1. Introduction

A common form of retrofit of existing reinforced concrete (RC) infrastructure is to adhesively bond fiber reinforced polymers (FRPs) to the concrete surfaces [1,2]. During the last few decades, FRP materials have been used in a variety of configurations in the retrofit of existing civil engineering infrastructure, and as an alternative reinforcement for new concrete construction. The attractiveness of the material lies mainly in its corrosion resistance, high strength and stiffness to weight ratio, and fatigue resistance. Further, the high versatility and constructability of the external retrofit techniques using FRP systems results in many advantages in civil and transportation infrastructure applications, since the FRP can be bonded to structures with any cross-section [3].

The strength and ductility of an RC flexural member retrofitted with longitudinal externally bonded (EB) FRP is typically controlled by the intermediate crack (IC) debonding failure mechanism. Because of its relative simplicity, and the similarity of the stress state at the FRP-to-concrete interface, the single-lap shear test [4] shown in Fig. 1 is often used to idealize the critical IC debonding mechanism [5,6]. From the single-lap shear test the debonding mechanism may be better understood, the bond strength quantified, and the fundamental interface bond stress–slip relationship determined, which is required in analytical and numerical simulation [7].

Many experimental studies have been conducted to investigate the bond strength using the single-lap shear tests [4,5,8–12]. Also, many theoretical studies have been published using various methods such as fracture mechanics, the finite element method, and empirically derived equations [4,6–8,13–18] to study the bond strength of FRP-to-concrete joints. Conventional modeling often tends to become quite intractable and difficult. Many of the models used to estimate the bond strength of FRP-to-concrete joints are highly empirical and their predictive abilities are limited by the

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Nomenclature

b_c	width of concrete prism	P_u	bond strength
b_f	width of FRP	s_f	local slip when bond stress reduces to zero
E_f	elastic modulus of FRP	s_o	local slip at maximum bond stress
E_c	elastic modulus of concrete	t_a	thickness of adhesive layer
f_c'	concrete cylinder compressive strength	t_d	thickness of debonded concrete
f_t	concrete tensile strength	t_f	thickness of FRP
G_f	interfacial fracture energy	α	reduction factor
G_{cf}	fracture energy of concrete	β_l	bond length factor
K_G	factor of the debonding capacity model	β_w	width ratio factor
k_c	concrete compaction factor	τ_{max}	maximum local bond stress
L	bond length	τ'	thickness ratio of debonded concrete cover and FRP
L_e	effective bond length	Σ	Young's modulus ratio of FRP and concrete

corresponding data sets from which they were derived. In some cases, the models do not provide reliable predictions for use in practice. In recent years, alternative approaches to modeling have emerged under soft computing, such as neural networks (NNs). NNs are an observational model developed on the basis of available data representing a mapping between input and output variables. The main advantage of NNs is that one does not have to explicitly assume a model form, which is a prerequisite in the conventional approaches [19]. In other words, when the information available for constructing the model is only available in the form of data derived from observations or measurements, neural network models, based on the input/output variables system, have been successfully used to generate the relationships between these variables.

NNs are a system of interconnected computational neurons arranged in an organized fashion to carry out an extensive computing to perform a mathematical mapping [20]. First interest in NNs (or parallel distributed processing) emerged after the introduction of simplified neurons by McCulloch and Pitts in 1943 [21]. These neurons were presented as models of biological neurons and as conceptual components for circuits that could perform computational works. NNs can be most adequately characterized as a computational model with particular properties such as the ability to adapt or learn, to generalize, and to cluster or organize data, in which operation is based on parallel processing.

NN models have a large number of highly interconnected processing elements (nodes or units) that usually operate in parallel and are configured in regular architectures. The collective behavior of an NN, like a human brain, demonstrates the ability to learn, recall, and generalize from training patterns or data. NNs are inspired by modeling networks of biological neurons in the brain. Hence, the processing elements in NNs are also called artificial neurons [20,22]. More information on the use of NNs in engineering applications may be found in [22]. The NN used in this paper is typically applied to solve many civil engineering applications such as structural analysis and design [23–25], structural damage assessment [26,27], structural dynamics and control, seismic liquefaction prediction, constitutive modeling [28,29] and pavement condition-rating modeling [30].

The purpose of this paper is to investigate the ability of an NN to predict the bond strength of FRP-to-concrete joints. The performance of the NN model is compared with experimental data and other published analytical models. The study is based on an available database including 150 test specimens.

2. Fundamental aspects of artificial neural networks

Unlike conventional problem solving algorithms, neural networks can be trained to perform a particular task. This is done by presenting the system with a representative set of examples describing the problem, namely pairs of input and output samples; the neural network will then extrapolate the mapping between input and output data. After training, the neural network can be used to recognize data that is similar to any of the examples shown during the training phase [22]. The neural network can even recognize incomplete or noisy data, an important feature that is often used for prediction, diagnosis or control purposes. Further, neural

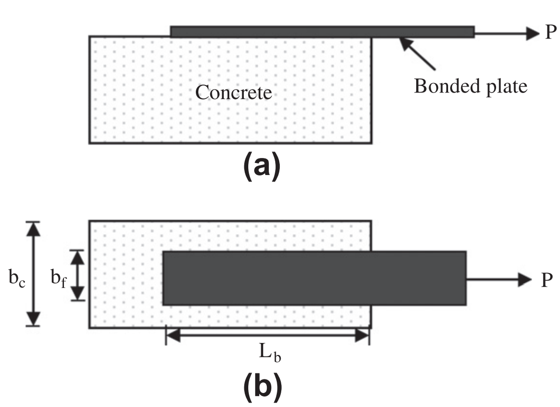

Fig. 1. Single-lap shear test specimen (a) side view (b) top view.

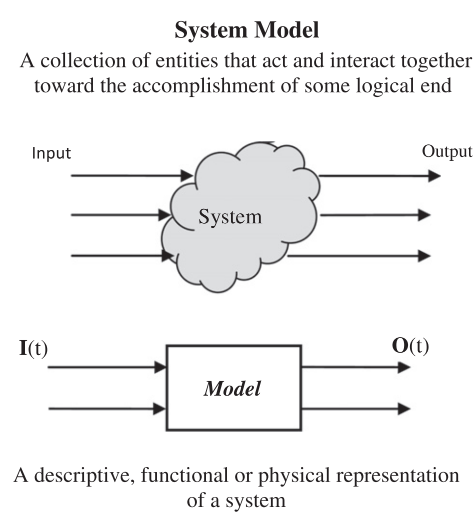

Fig. 2. Schematic diagram of a system model [31].