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An empirical model for shear capacity of RC deep beams using genetic-simulated annealing

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ABSTRACT

This paper presents an empirical model to predict the shear strength of RC deep beams. A hybrid search algorithm coupling genetic programming (GP) and simulated annealing (SA), called genetic simulated annealing (GSA), was utilized to develop mathematical relationship between the experimental data. Using this algorithm, a constitutive relationship was obtained to make pertinent the shear strength of deep beams to nine mechanical and geometrical parameters. The model was developed using an experimental database acquired from the literature. The results indicate that the proposed empirical model is properly capable of evaluating the shear strength of deep beams. The validity of the proposed model was examined by comparing its results with those obtained from American Concrete Institute (ACI) and Canadian Standard Association (CSA) codes. The derived equation is notably simple and includes several effective parameters.

1. Introduction

Reinforced concrete (RC) deep beams may be used in pile caps, bunkers, some shear walls, floor slabs under horizontal loads, and many different types of structures. In deep beams, the bending strain distribution through the depth of transverse sections of beam considerably deviates from the linear distribution, predicted by elementary bending theory of beams. Consequently, the transverse plane sections before bending do not remain plane after bending. As the ratio of depth to span of a beam becomes less than 2 for simply supported beams and 2.5 for continuous beams, the simple bending theory cannot be basically used for determination of the bending and shear stresses [29,39]. The failure mode of deep beams is usually dominated by the shear stresses; hence, shear in deep beams is a major consideration in their design. Many research efforts have been performed to formulate the shear strength of RC deep beams [28,32,34,40,45]. Some of the researchers have employed strut-and-tie model (STM) to determine the shear strength of RC deep beams [7,31,37,48]. STM has been also adopted by American Concrete Institute (ACI) [1] and the Canadian Standard Association (CSA) [13].

Empirical modeling by heuristic and modern search techniques such as artificial neural networks (ANNs) is a different approach to determine the shear strength of beams. ANNs have been widely applied to assess different characteristics

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of RC slender beams such as prediction of shear capacity [35], torsional strength [44], and deflection analysis [15]. Sanad and Saka [42] utilized ANNs to predict the shear strength of RC deep beam. Despite the acceptable performance of ANNs, they usually do not give a certain function to calculate the outcome using the input values. Fuzzy logic (FL) [47] is well suited to implementing control rules that can only be expressed verbally, or systems that cannot be modeled with linear differential equations. Recently, Choi et al. [11] used this method for the modeling of the shear strength of slender RC beams. Similar to ANNs, the FL approach is not basically able to provide the mathematical expression of the model. In addition, determination of the fuzzy rules is a difficult task in FL procedure. The ANN and FL approaches are mostly appropriate to be used as a part of a computer program [23].

Genetic programming (GP) [30] can be regarded as a new alternative approach for the modeling of concrete behavior. GP may generally be defined as a specialization of genetic algorithms (GA) where the solutions are computer programs rather than binary strings. The main advantage of the GP-based approaches is their ability to generate prediction equations without assuming prior form of the existing relationship [22]. The developed equations can be easily manipulated in practical circumstances. Pérez et al. [38], Gandomi et al. [21,24] and Ashour et al. [8] employed GP to derive complex relationships among the RC beam experimental data.

Simulated annealing (SA) is a general stochastic search algorithm, which introduces the concept of evolution into the annealing process. SA was first presented by Metropolis et al. [33] to mimic the natural process of metals annealing. This algorithm is independently applied to optimization problems by Kirkpatrick et al. [27]. SA is very useful for solving several types of optimization problems with nonlinear functions and multiple local optima. Deschaine et al. [14] and Folino et al. [16] combined GP and SA to make a hybrid algorithm with better efficiency. The SA strategy was used to decide the acceptance of a new individual. It was shown that introducing this strategy into the GP process improves the simple GP profitably [16]. This genetic-simulated annealing (GSA) method has rarely been applied to engineering problems [2,6,25].

In this study, the GSA approach was utilized to estimate the shear capacity of RC beams with stirrups. A generalized relationship was obtained between the load capacity and the amount of longitudinal and shear reinforcement, concrete compressive strength, effective depth, web width, beam span, and shear span to depth ratio. The proposed model was developed based on several shear test results of RC beams reported in the literature. A comparative study was performed between the obtained results and those of the ACI and CSA code models. A parametric study was further carried out to justify the results.

2. Method

2.1. *Genetic programming*

GP is a symbolic optimization technique that creates computer programs to solve a problem using the principle of Darwinian natural selection. GP was introduced by Koza [30] as an extension of GA. In GP, programs are represented as tree structures and expressed in the functional programming language [23]. The main difference between the GA and GP approaches is that in GP the evolving programs (individuals) are parse trees rather than fixed-length binary strings. The traditional optimization techniques, like GA, are generally used in parameter optimization to evolve the best values for a given set of model parameters. GP, on the other hand, gives the basic structure of the approximation model together with the values of its parameters. In fact, GP evolves population of computer programs according to their fitness determined by a program ability to perform a given computational task [3,46].

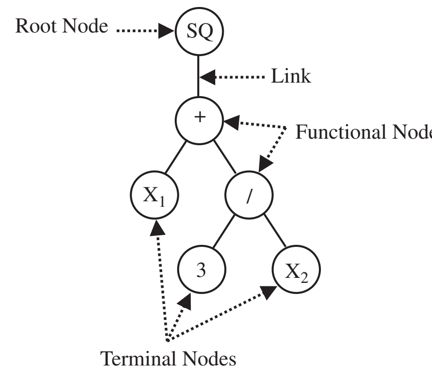

Fig. 1 – Typical tree representation for $(X_1+3/X_2)^2$ in GP.

A random population of individuals (trees) is created to achieve high diversity at the beginning of the GP procedure. The symbolic optimization algorithms present the potential solutions by structural ordering of several symbols. A population member in GP is a hierarchically structured tree comprising functions and terminals. The functions and terminals are selected from a set of functions and a set of terminals. For example, the function set, F, can contain the basic arithmetic operations (+, −, ×, /, etc.), Boolean logic functions (AND, OR, NOT, etc.), or any other mathematical functions. The terminal set, T, contains the arguments for the functions and can consist of numerical constants, logical constants, variables, etc. The functions and terminals are chosen at random and constructed together to form a computer model. The evolved model has a tree-like structure with a root point with branches extending from each function and ending in a terminal. An example of a simple tree representation of a GP model is illustrated in Fig. 1.

Once a population of individuals (models) has been created at random, the GP algorithm evaluates the fitness value of each computer program (individual), selects individuals for reproduction, and generates new individuals by reproduction, crossover and mutation [30]. The fitness value is usually calculated using a function named fitness function. This function is defined so that its value reflects how good the result of a computer program in the population can be matched with the experimental data. The reproduction operation gives a higher probability of selection to more successful individuals. They are copied into the matting pool without any change [2]. The crossover operation ensures the exchange of genetic material between the evolved programs. During the crossover procedure, a point on a branch of each solution (program) is selected at random and the set of