

Cost Optimization of Composite Beams using Genetic Algorithm and Artificial Neural Network

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Abstract. This paper aims to develop a Genetic Algorithm (GA) based model to minimize the cost of single span steel concrete composite bridges with precast decks. The model would also produce optimum design parameters in order to satisfy both strength and serviceability parameters.

Besides conventional design and deflection constraints, a new deflection constraint was imposed corresponding to the time delay for mobilization of composite action, which is known to control the increment in mid-span deflection to a significant degree without compromising the design parameters, between the precast concrete deck panels and the steel section. The time dependent effect on deflection has been estimated by employing Artificial Neural Network (ANN) to reduce the complexity in its evaluation.

The cross-sectional dimensions have been considered as decision variables in the present optimum design model along with the number of days for which the precast slabs should be placed in a casting yard. The model formulation accounts for the cost of concrete, steel beam and slab storage in the casting yard. The cost optimization problem has then been formulated and implemented using MATLAB by employing GA which is computationally efficient in solving such types of complex optimization problems.

Keywords: composite beam, genetic algorithm, artificial neural network, cost optimization.

1. Introduction

Traditionally, the optimum design of a composite beam involves an iterative trial-and-error process to correspond to minimum cost or minimum weight criterion. In past years, the cost based optimization of steel and concrete structures has been proposed and developed by several researchers. Jármai and Farkas [1] discussed the cost calculation and optimization of welded steel structures. Sarma and Adeli [2,3] published a review of articles dealing with the cost optimization of concrete and steel structures, respectively. Although initial models considered steel and concrete structures separately, but with time these models evolved and were applied to composite structures.

Bhatti [4] not only suggested the formulation of a non linear optimization problem but also that the conventional methods of solving such problems were computationally inefficient. His formulation included only the cost of the steel beams plus shear studs and not the cost of concrete. Long et al. [5] presented a non-linear programming based optimization of cable-stayed bridges with composite superstructures and proposed a cost objective function including the costs of concrete, structural steel, reinforcement, cables and formwork. Kravanja and Šilih [6] introduced a non-linear programming optimization models for composite I-beams. Kravanja and Šilih [7] also introduced a mixed-integer non-linear programming approach for cost optimization of composite I beams.

Recently, the conventional methods have been replaced by new evolutionary methods of optimization like Genetic Algorithms, Particle Swarm Optimization, etc. Adeli and Kin [8] proposed the use of neural

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dynamics model for cost optimization of composite beams. Govindaraj and Ramasamy [9] presented optimum detailed design of reinforced concrete continuous beams using Genetic Algorithms. Senouci and Ansari [10] developed a genetic algorithm model for the cost optimization of composite beams. The present formulation has been extended from this work. Lute et al. [11] analysed the cable stayed bridge model for optimization to result in efficient design by implementing Genetic Algorithms.

The long term deflection characteristics of steel concrete composite beams have also been studied in detail by some authors. Chaudhary et al.[12] studied the effect of concrete cracking and time-dependent effects of creep and shrinkage in composite beams through a hybrid numerical procedure. Chaudhary et al.[13] also established that midspan deflections could be reduced just by delaying the mobilization time of composite action between the precast deck panels and the steel section. This procedure has been integrated in the present formulation and a deflection constraint is imposed for the optimum design of composite bridges with precast decks.

The artificial neural networks (ANNs) have long been used for analysis prediction of various parameters in structural analysis of composite beams. Sakr and Sakla [14] studied the long-term deflection of cracked composite beams with nonlinear partial shear interaction by incorporating use of ANNs. Chaudhary et al. [15] employed an ANN based model to predict the bending moments in continuous composite beams which considers cracking and time effects in concrete.

2. Methodology

2.1. Optimization problem formulation

2.1.1 Decision variables

The present design formulation, which considers impact on the cost optimization of composite beams, includes the following decision variables:

x_1 = concrete slab thickness, x_2 = steel section shape, and x_3 = number of days for precast slab storage.

The different variables related to the steel section have been combined into a single decision variable (x_2). The compressive strength, f_{ck} ; unit weight Y_c of concrete slab and yield strength, f_y , of the steel section are assumed to be fixed in the beginning, and hence, are not considered as variables here.

2.1.2. Optimization objective

The present model is formulated to minimize the cost of composite beams while considering the impact of above mentioned decision variables. The following objective equation has been used in this model:

$$\text{Minimize composite beam cost } (C) = C_1 + C_2 + C_3 \quad \dots(1)$$

where, $C_1 \equiv$ cost of concrete, $C_2 \equiv$ cost of steel, and $C_3 \equiv$ cost of casting yard storage.

The individual cost functions are evaluated as follows:

$$C_1 = A_c \times L \times c_1 \quad \dots(2)$$

$$C_2 = \rho \times A_s \times L \times c_2 \quad \dots(3)$$

$$C_3 = \text{days} \times c_3 \quad \dots(4)$$

where, $A_c \equiv$ concrete slab area; $L \equiv$ beam span; $\rho \equiv$ unit weight of steel section; $A_s \equiv$ area of steel section;

$c_1 \equiv$ cost of concrete per unit volume (Rs. 3700/ m^3 for M-25);

$c_2 \equiv$ cost of steel per unit weight (Rs. 48/kg);

$c_3 \equiv$ cost of placing the slab in casting yard (Rs. 600/month/slab)

2.1.3 Optimization constraints

The minimization of the objective function is subjected to the following constraints:

a) Bending stress (σ)

$$\sigma = M/Z \leq \sigma_{\max} = 0.66 \times f_y = 165 \text{ N/mm}^2 \quad \dots(5)$$

where,

$M \equiv$ moment due to uniformly distributed load $= wL^2/8$

$Z \equiv$ section modulus of the transformed section $= I/y$

and, $w \equiv$ load per unit length of the beam,

$I \equiv$ moment of inertia of the transformed section

$$I = I_s + A_s(D/2 + d - y)^2 + I_c/m + A_c(y - d/2)^2 \quad \dots(6)$$

where, y represents the distance from the top of transformed section to the neutral axis of the section:

$$y = [A_s(D/2 + d) + A_c/m(d/2)] / [A_s + A_c/m] \quad \dots(7)$$

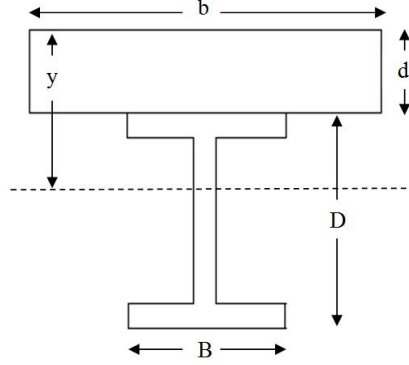


Fig. 1 : Composite beam section

b) Deflection due to applied loads (Δ_L)

For unshored composite beams, the deflection of the composite beam due to applied loads is given by:

$$\Delta_L = 5wL^4/384EI \leq \Delta_{max} = kL \quad \dots(8)$$

where, $w \equiv$ load per unit length of the beam,

$E \equiv$ modulus of elasticity of steel section

$I \equiv$ moment of inertia, and

$k \equiv$ coefficient ranging from 1/500 to 1/900 for highway bridges.

c) Deflection due to time delay (ψ)

The time dependent effect on deflection is also taken into account as a factor ψ which can be computed from the instantaneous deflection (d_{it}) and final deflection (d_t) according to the following equation:

$$\psi(t, I_r) = 100 \times [(d_t - d_{it})/d_{it}] \quad \dots(9)$$

The time dependent variations of the midspan deflection were determined by using the available procedure [12]. The d_{it} and d_t values were obtained for corresponding values of number of days (t) and the ratio of cracked to uncracked moment of inertia, $I_r = I_{cr}/I_{un}$, to compute ψ as given by Eqn (9). The factor ψ is constrained to vary below 50% for the present study.

A total of 48 datasets were generated out of which 36 were used for training and 12 for testing the *feed-forward backpropagation* neural network for 35 epochs in *MATLAB*. The generated set was normalized to vary between 0 and 1 before being fed to the neural network. The mean squared error (MSE) obtained for training and testing datasets are 0.0000027917 and 0.000010393, respectively.

To summarize, our optimization problem has following constraints on stress (σ) and deflection (Δ):

$$c_1 = \sigma - \sigma_{max} \leq 0 \quad \dots(10)$$

$$c_2 = \Delta_L - \Delta_{max} \leq 0 \quad \dots(11)$$

$$c_3 = \psi - 50 \leq 0 \quad \dots(12)$$

where the maximum allowable values (for 20m span) are taken as:

$$\sigma_{max} = 165 \text{ N/mm}^2 \quad \dots(13)$$

$$\Delta_{max} = \frac{L}{900} mm = 22.22 mm \quad \dots(14)$$

The constraints in the normalized form can be written as:

$$c_1 = \sigma/\sigma_{max} - 1 \leq 0 \quad \dots(15)$$

$$c_2 = \Delta_L/\Delta_{max} - 1 \leq 0 \quad \dots(16)$$

$$c_3 = \psi/50 - 1 \leq 0 \quad \dots(17)$$

2.2. Optimization procedure and results

Genetic algorithms, which are used for the implementation of the proposed model, are search and optimization tools which adopt the survival of the fittest and genetic evolution among populations of chromosomes over successive generations as basic mechanism for the search process. Successive generations evolve by applying the operators of reproduction, crossover, and mutation on a population of chromosomes whose patterns depend upon the problem under consideration. The chromosome size is determined by the model, considering the total number of decision variables included in the design problem.

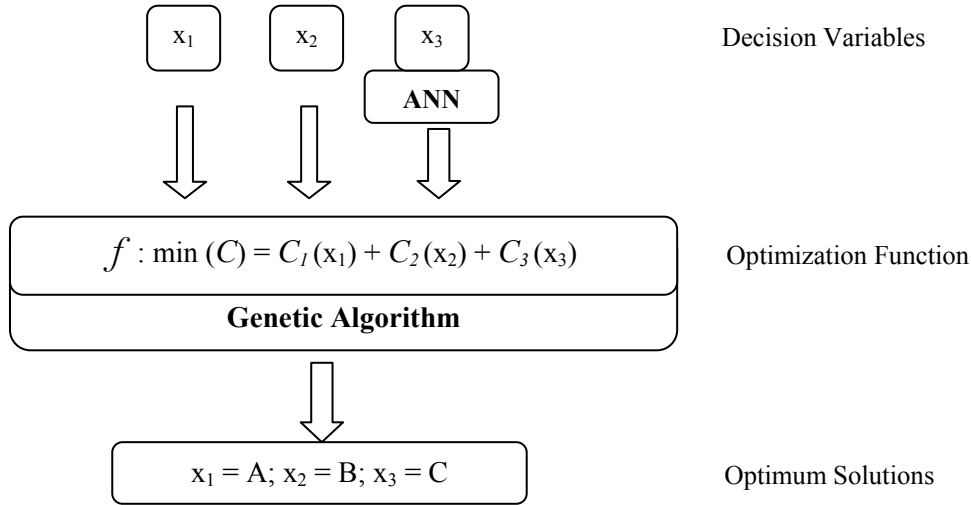


Fig. 2 : Optimization Procedure

The optimization process is started by assuming random values for the involved decision variables from their respective range sets which are given below:

Decision variable	Values	Number of values
x_1	75;100;125;150;175;200;225;250	8
x_2	from Steel Table [17] (ISJB150 – ISMC400)	63
x_3	7;21;30;60;90;120;180;270;360	9

The steps for GA fitness are evaluated using a *MATLAB* computer program for a population size of 20 over 50 generations. The crossover and mutation fractions assumed for consecutive generations are 0.8 and 0.2, respectively. The optimum parameters obtained with this model for two different loading conditions are:

Loading (kN/m)	20	30
Concrete slab thickness, d (mm)	100	150
Steel section	ISMB 600	ISWB 600
Number of days	60	120
Cost (INR)	17,177	21,093

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