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Modeling shear capacity of RC slender beams without stirrups using genetic algorithms

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Abstract. High-strength concrete (HSC) is becoming increasingly attractive for various construction projects since it offers a multitude of benefits over normal-strength concrete (NSC). Unfortunately, current design provisions for shear capacity of RC slender beams are generally based on data developed for NSC members having a compressive strength of up to 50 MPa, with limited recommendations on the use of HSC. The failure of HSC beams is noticeably different than that of NSC beams since the transition zone between the cement paste and aggregates is much denser in HSC. Thus, unlike NSC beams in which micro-cracks propagate around aggregates, providing significant aggregate interlock, micro-cracks in HSC are trans-granular, resulting in relatively smoother fracture surfaces, thereby inhibiting aggregate interlock as a shear transfer mechanism and reducing the influence of compressive strength on the ultimate shear strength of HSC beams. In this study, a new approach based on genetic algorithms (GAs) was used to predict the shear capacity of both NSC and HSC slender beams without shear reinforcement. Shear capacity predictions of the GA model were compared to calculations of four other commonly used methods: the ACI method, CSA method, Eurocode-2, and Zsutty's equation. A parametric study was conducted to evaluate the ability of the GA model to capture the effect of basic shear design parameters on the behaviour of reinforced concrete (RC) beams under shear loading. The parameters investigated include compressive strength, amount of longitudinal reinforcement, and beam's depth. It was found that the GA model provided more accurate evaluation of shear capacity compared to that of the other common methods and better captured the influence of the significant shear design parameters. Therefore, the GA model offers an attractive user-friendly alternative to conventional shear design methods.

Keywords: genetic algorithms; analysis; high-strength; concrete; beams; prediction; shear.

1. Introduction

Slender reinforced concrete beams without web reinforcement can undergo diagonal tensile failure. This failure mode is sudden since it occurs almost immediately after the formation of the first diagonal crack (Rebeiz 2001). This problem is even more critical for high-strength concrete (HSC) which exhibits a more brittle failure than that of normal strength concrete (NSC). Hence, several design codes limit the compressive strength of concrete to less than 70 MPa. The use of a very low water/cement ratio along with pozzolonic materials has enabled concrete to reach compressive strengths exceeding 70 MPa. The use of HSC in construction projects has been steadily increasing since it offers a multitude of benefits over NSC, including reducing the cross-section of columns in high-rise reinforced concrete

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buildings providing relatively more floor space, reducing dead loads, offering more clear space, reducing elastic deflections and wind sway (higher elastic modulus), and achieving higher durability.

Unlike NSC beams in which cracks propagate around aggregates providing significant aggregate interlock as a shear resisting mechanism and indication of imminent failure, cracks in HSC generally propagate through aggregates (trans-granular) providing little or no warning of failure since the transition zone between the cement paste and aggregates has been densified by the inclusion of pozzolonic materials and the use of low w/c ratio. Therefore, there is need to critically examine the validity of using design provisions that have traditionally been developed for NSC for developing HSC members. Table 1 presents some commonly used shear calculation methods:

1.1. ACI code

The ACI 318-95 code considers the shear capacity of slender reinforced concrete beams without stirrups as the shear stress at which diagonal cracking begins. The shear capacity can be calculated using one of two equations. The first one, ACI 11-3, only considers the compressive strength of concrete and the beam dimensions, while the second, ACI 11-6, also includes the influence of the longitudinal reinforcement. The compressive strength of concrete for both equations is limited to less than 70 MPa (Table 1).

1.2. CSA simplified method

The CSA simplified design method is similar to the ACI method except that it neglects the influence of the longitudinal reinforcement and the shear span to depth ratio. It does, however, include a term to account for the size effect for beam depths greater than 300 mm (Table 1).

Table 1 Shear design calculation methods considered in this study

Method	Shear strength[1]
ACI 11-3	$V_c = \left(\frac{\sqrt{f_c'}}{6}\right) b_w d$
ACI 11-6	$V_c = \left(0.16\sqrt{f_c'} + 17\rho_L \frac{V \cdot d}{M}\right) b_w d$
CSA (simplified)	$V_c = 0.2\sqrt{f_c'} b_w d$ when $d \leq 300$ mm $V_c = \left(\frac{260}{1000 + d}\right)\sqrt{f_c'} b_w d$ when $d > 300$ mm
Zsutty	$V_c = 2.32\left(\frac{f_c' \rho_L d}{a}\right)^{\frac{1}{3}} b_w d$
EC -2	$V_c = 0.18k(100\rho_L f_c')^{1/3} b_w d \geq 0.035 k^{3/2} f_c'^{1/2} b_w d$ where $k = 1 + \sqrt{\frac{200}{d}} \leq 2.0 \rho_l = \frac{A_l}{b_w d} \leq 0.02$

1. f_c' = concrete compressive strength, b_w = beam width, d = beam depth, ρ_l = percent of longitudinal reinforcement, a/d = shear span to depth ratio

1.3. Zsutty's equation

Zsutty's equation was developed in the 1970's using regression analysis of experimental data. It has proven to be relatively accurate in predicting the shear strength of NSC beams. Hence, this equation has become widely used in the literature. The equation takes into account the compressive strength of concrete, longitudinal reinforcement ratio, and shear span to depth ratio (Table 1).

1.4. Eurocode-2 method

The European code calculates the shear capacity of reinforced concrete beams without web reinforcement accounting for the influence of the concrete compressive strength, longitudinal reinforcement ratio, and the size effect. Its main equation is also shown in Table 1.

1.5. Cope and research significance

Extrapolations of current shear design provisions for NSC to calculate the shear capacity of HSC beams may result in unreliable results since such provisions were generally based on experimental data obtained on beams made of NSC. Recently, there have been several attempts to develop shear design equations which perform better than current standard methods and predict the shear capacity of NSC and HSC beams more accurately. For instance, some researchers have used artificial neural networks (ANNs) to predict the shear strength of reinforced concrete beams (Oreta 2004, Mansour, *et al*. 2004, Cladera and Mari 2004, El Chabib, *et al*. 2005). ANNs are modeled on artificial intelligence and are composed of interconnected processing elements that have the ability to be trained to map between a given input and the desired output. Although ANN can accurately predict the shear capacity of beams, they do not offer simple design equations that can be used in practice. Predicting the shear strength of reinforced concrete beams using nonlinear finite element analysis has also been attempted and it was found to be able to accurately predict the lower bound strength of RC beams (Bhatt and Kader 1998).

In this study, a new approach based on genetic algorithms (GAs) was used to predict the shear capacity of both NSC and HSC slender beams without shear reinforcement. Genetic algorithms are modeled on the basis of Darwinian evolution and natural selection. They have the ability to traverse highly nonlinear and noisy search spaces and reach global maxima or minima without getting trapped at local extreme values such as several other search and optimization methods (Goldberg 1989). This makes GAs widely applicable to many highly constrained problems in various civil engineering applications.

Genetic algorithms have been used for the mixture proportioning of high-performance concrete (Lim and Yoon 2004), design of reinforced concrete (RC) beams (Coello, *et al*. 1997), and the detailed design of reinforced concrete members for multi-storey buildings (Koumousis and Arsenis 1998). They have also been used in calibrating models for river flow simulation and forecast (Wang 1997). A conceptual rainfall-runoff model was developed using a genetic algorithm to solve for various parameters. It was shown that GAs are a useful search technique in calibrating models with a high number of parameters, and are consistently capable to find an objective function value very close to the global minimum (Wang 1997).

Since the shear capacity of slender RC beams is influenced by various complex parameters, design codes do not agree on how to quantify the effect of each parameter, while experimental data is scattered and at times conflicting. Thus, genetic algorithms may offer a promising effective tool to predict the shear capacity of RC beams. In this study, a genetic algorithm is developed to create an equation that can accurately predict the shear strength of normal and high-strength reinforced concrete beams without stirrups. A parametric study is then carried out to determine the ability of the model to capture the effect of basic shear design parameters on the behaviour of normal and high-strength reinforced concrete slender beams under shear loads. Finally, two GA models are developed in order to design slender beams for shear loading given: 1) the desired ultimate shear capacity, and 2) the beam's dimensions (width and depth).

2. Genetic algorithms

Genetic algorithms are a powerful and broadly applicable stochastic search and optimization technique. In the past, much attention has been given to GAs as an optimization tool, but they are also widely applicable in developing models to fit data. GAs are search procedures based on the mechanisms of natural selection and natural genetics. They are different from standard optimization and search procedures in the following essential ways (Goldberg 1989):

- GAs work with a coded set of variables, not the variables themselves
- GAs search from a population of solutions, not a single solution
- GAs use payoff information (fitness function) not derivatives or other auxiliary knowledge
- GAs use probabilistic transition rules, not deterministic rules

Genetic algorithms work with a coded set of randomly generated solutions called *population*. Each individual in the population is called a *chromosome*, and represents a potential solution to the problem at hand. A chromosome is a string of symbols, which represent the *genes* (features) of each chromosome; it is usually, but not necessarily, a binary bit string consisting of ones and zeros (e.g. 1010011011). The chromosomes evolve through successive iterations, called *generations*. During each generation, the chromosomes are evaluated using some measure of fitness. The potential solutions to the problem at hand are then ranked according to their fitness and subsequently undergo selection, recombination and mutation. A brief description of selection, recombination and mutation is provided below, while more thorough explanations can be found in the literature (Michalewicz 1992, Cen and Cheng 1997).

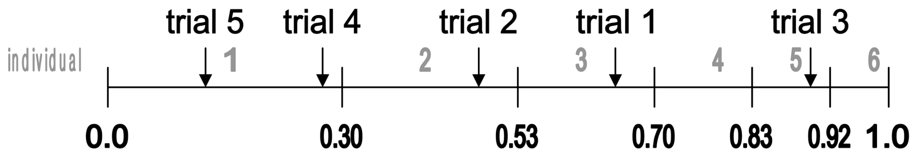


Fig. 1 Roulette wheel selection

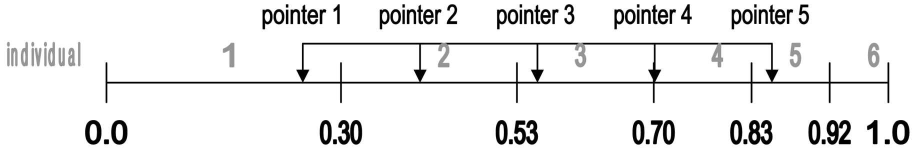


Fig. 2 Stochastic universal sampling

2.1. Selection

The chromosomes can be selected using a variety of different selection methods such as the roulette wheel selection (Fig. 1), stochastic universal sampling (Fig. 2), or tournament selection. The selection process provides the driving force in a genetic algorithm, directing the search towards promising regions in the search space (Michalewica 1992). The intensity of the driving force depends on the selection pressure.

For roulette wheel selection the individuals in the population are mapped continuously around a disc or on a line whereby each individual segment is equal in size to its fitness. A random number is generated and the individual whose segment spans the random number is selected. This process is continued until the desired number of individuals is obtained. In the case of stochastic universal sampling the individuals are mapped continuously on a line with each individual segment equal in size to its fitness. Equally spaced pointers are placed over the line with their number being equal to that of the desired individuals. In tournament selection a number of individuals are randomly selected from the population and the best individual is selected from the group to be the parent. This process is repeated until the desired number of individuals has been selected. The size of the tournament can range from 2 to the number of individuals present in the population.

2.2. Recombination

Recombination, also known as *crossover*, is preformed on pairs of selected chromosomes in the form of single point crossover (Fig. 3), two-point crossover, or uniform crossover in the case of binary values. The crossover operator combines some features of two parent chromosomes to form two new offspring. A higher crossover rate allows exploration in the large solution space and reduces the chances of settling for a false optimum. However, if this rate is too high, it results in the wastage of a lot of computation time

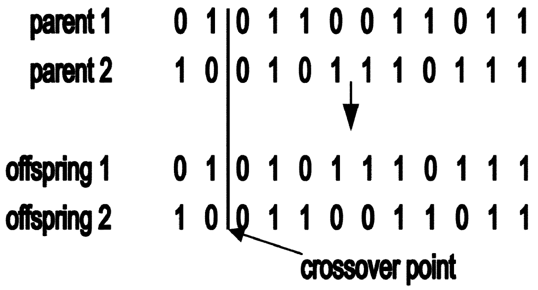


Fig. 3 Single point crossover

Fig. 4 Area of possible offspring using intermediate recombination

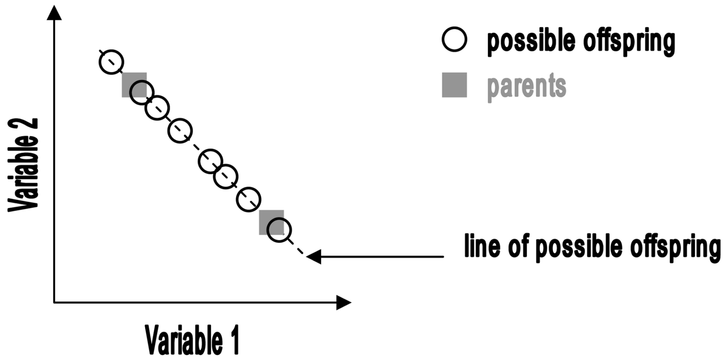


Fig. 5 Possible values of offspring after extended line recombination

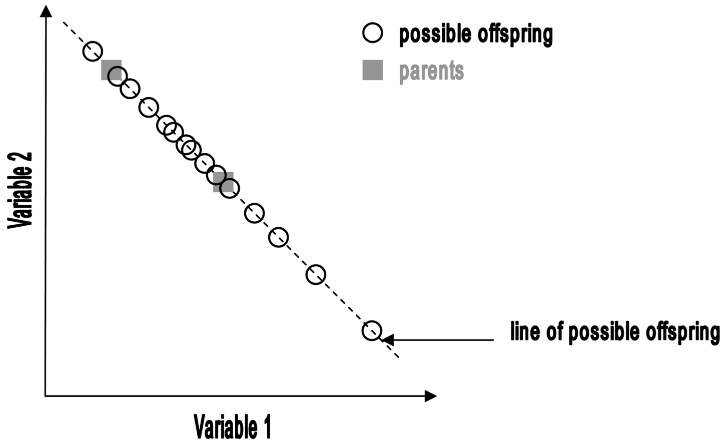


Fig. 6 Possible values of offspring after extended line recombination according to parent positions and variable boundaries

in exploring unpromising regions of the solution space. For real values, the recombination methods are slightly more complex but are based on the same principles. These include intermediate recombination (Fig. 4), line recombination (Fig. 5), and extended line recombination (Fig. 6).

In intermediate recombination, the offspring are chosen somewhere around and between the variable values of the parents. The interval for selection is [$-d$, $1+d$] where $d = 0.25$, which ensures that the variable area of the offspring does not shrink over the generations. In line recombination, the offspring are chosen at any point on the line defined by the parents. Extended line recombination is not restricted to the line between the parents and a small area outside it. Rather, the parents just define the line where possible offspring may be created. The area for possible offspring is defined by the domain of the variables, although the probability of creating offspring near the parents is higher. The offspring are more often created in the direction from the worse to the better parent.

2.3. Mutation

Mutation is a secondary genetic operator, which randomly changes the genes (features) of a chromosome. This allows genes that were not present in the initial population to help guide the search.

If the mutation rate is too low, many genes that would have been useful are never tried out. But if it is too high, there will be much random perturbation, and the offspring will start losing their resemblance to the parents (Michalewica 1992).

Although GAs are randomized, they do not simply walk the solution space in hopes of finding the global optimum. In fact, they efficiently incorporate information from previous stages to create new search points in the design space resulting in improved performance (Koumousis and Arsenis 1998). GAs are robust in that they can rapidly transverse a complex multi-dimensional search space to obtain a solution (Goldberg 1989). Such a search requires balancing two apparently conflicting objectives: exploiting the best solution and exploring the search space.

3. Genetic algorithm model for shear capacity of RC beams

A total of 263 NSC and 117 HSC slender beams collected from the literature were used in this study, among which 122 NSC and 45 HSC slender beams were used to develop and train the model. The number of beams used for training the model was increased until it was determined that any additional beams did not significantly improve the GA solution. The remaining beams were used to test and verify the GA model. A commercial genetic algorithms program was used for determining the unknown coefficients for the model equation.

To build a genetic algorithm, the form of the empirical equation defining the problem at hand must first be developed. The input parameters considered in this study are the beam depth (d), beam width (b_w), the shear span-to-depth ratio (a/d), the percent of longitudinal reinforcement (p_l), and the concrete compressive strength (f_c'). The ranges of input parameters for data used in the study are presented in Table 2. The final form of the shear strength equation used in the model is as follows:

$$V_c = \left(\alpha\left(1 + \sqrt{\frac{\beta}{d_v}}\right)(f_c')^q(\rho_L)^r\left(\frac{d}{a}\right)^s\right)b_w d \tag{1}$$

where α, β, q, r, s: represent the unknown coefficients, and $d_v = 0.9d$ is the effective beam depth which accounts for the lever arm between the resultant tensile and compressive forces at a beam section.

Table 2 Range of experimental database parameters

Parameter	Minimum	Maximum	Average
d (mm)	40.60	1097.28	568.94
b_w (mm)	38.10	400.00	219.10
p_l (%)	0.48	5.04	2.76
f_c' (MPa)	10.5	99.0	54.8
a/d	2.40	6.05	4.23
V_{fail} (kN)	2.69	368.10	185.40

Table 3 Range for model coefficients

Bound	α	β	q	r	s
Lower	0	0	0	0	-1
Upper	10	400	1	1	1

Table 4 Genetic algorithm settings

Number of Individuals	70
Variable Format	Real values
Maximum Generations	10000
Selection Method	Roulette wheel selection
Selection Pressure	1.7
Recombination Name	Extended line
Recombination Rate	0.74
Mutation Rate	0.01

An objective function was constructed as a measure of how well the model predicted output agrees with the experimentally measured output, and then a search was conducted to find the coefficients that minimize this function. The ranges of the coefficients in which the search was conducted are shown in Table 3. The selection of the GA settings requires careful consideration since it is problem-dependent and tends to ultimately control the performance of the genetic algorithm. Although some rules of thumb do exist, such as high levels of mutation tend to disorganize the convergence on the solution; it is the responsibility of the experimenter to decide on appropriate values for the selective pressure, recombination rate, and mutation rate. The appropriate selection of these parameters along with the population size is essential for the successful performance of a genetic algorithm. The final settings used in the present genetic algorithm are presented in Table 4.

4. Results and discussion

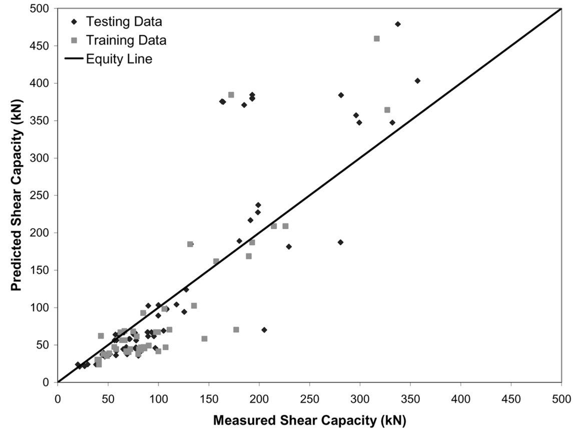
Once the appropriate settings of the GA were established, the genetic algorithm model was run five times. The results from the five trials along with the corresponding objective function value (OBJ) and generation in which the results were obtained are presented in Table 5. The final optimized equation accounting for both normal and high-strength reinforced concrete slender beams without stirrups is:

$$V_c = \left(0.35\left(1+\sqrt{\frac{362}{d_v}}\right)(f_c')^{0.18}(\rho_L)^{0.40}\left(\frac{d}{a}\right)^{0.34}\right)b_w d \qquad (2)$$

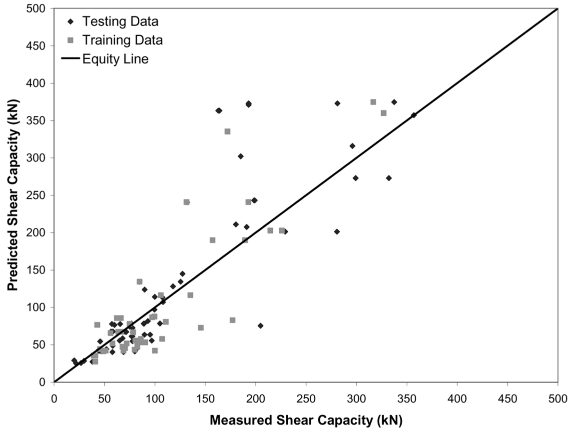
The calculation of the shear capacity of reinforced concrete slender beams (both NSC and HSC) using the GA model along with that of the ACI equation, the CSA simplified method, the Eurocode-2,

Table 5 Results of model using genetic algorithm

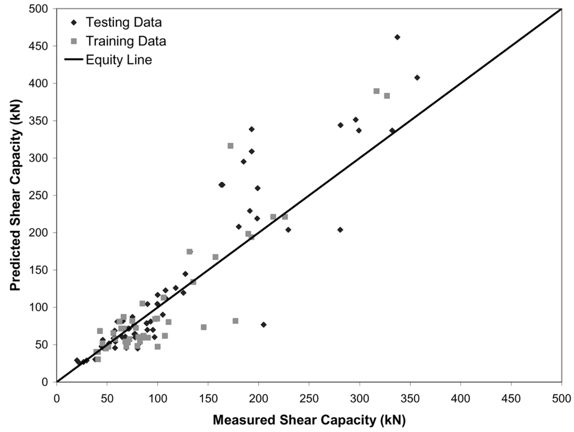
Run	α	β	q	r	s	OBJ	Generation
1	0.3542	361.80	0.4043	0.1831	-0.3380	1652.4	9716
2	0.3867	349.41	0.4098	0.1708	-0.3712	1653.9	9429
3	0.3534	358.32	0.4045	0.1851	-0.3405	1652.4	8354
4	0.3629	372.47	0.4054	0.1758	-0.3409	1652.4	8451
5	0.3847	349.33	0.4099	0.1717	-0.3693	1653.8	9652



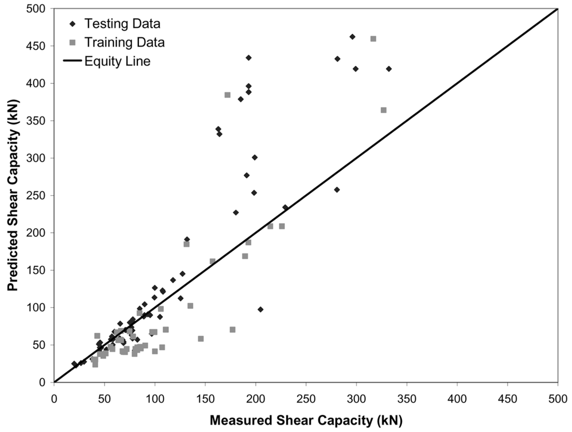
(a) – ACI



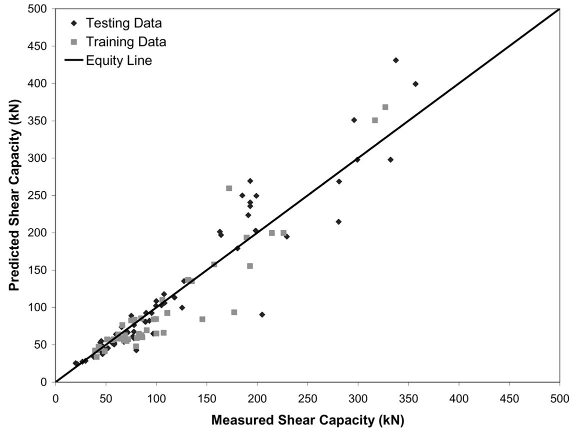
(b) – CSA



(c) – EC-2

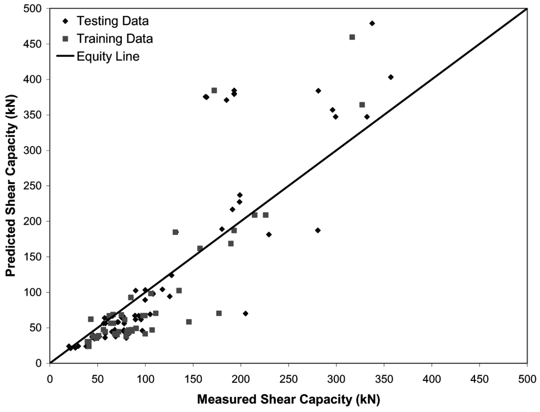


(d) – Zsutty

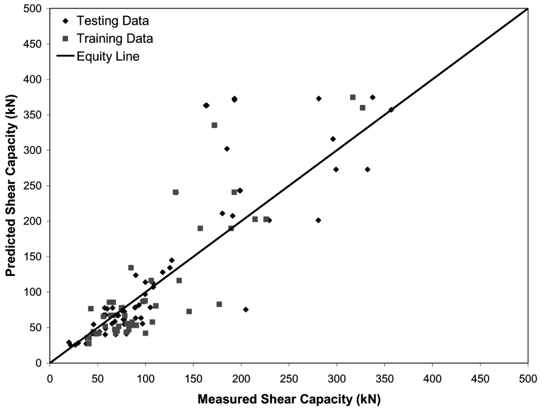


(e) – GA

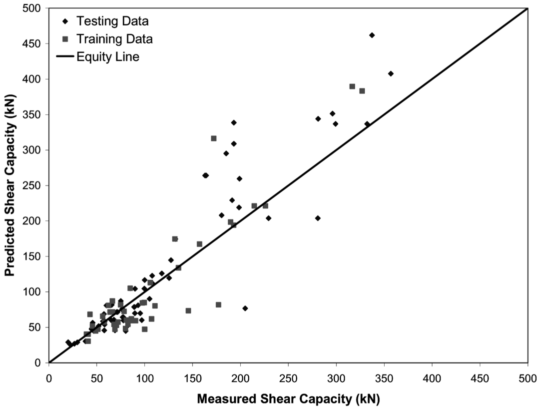
Fig. 7 Measured versus predicated shear capacity for normal strength concrete slender beams



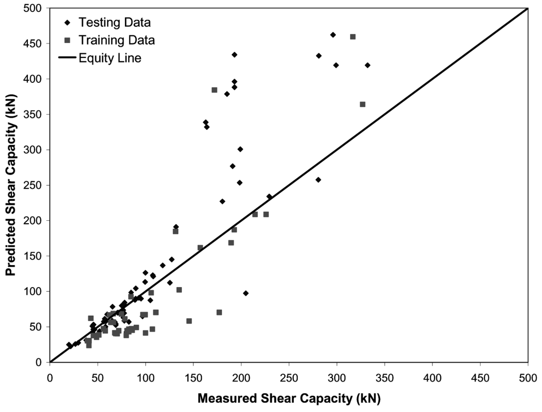
(a) – ACI



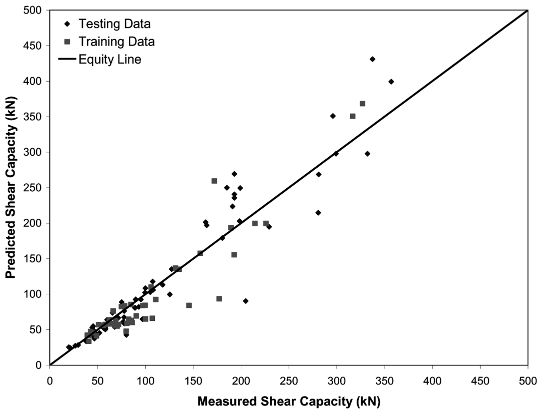
(b) – CSA



(c) – EC-2



(d) – Zsutty



(e) – GA

Fig. 8 Measured versus predicated shear capacity for high-strength concrete slender beams

Table 6 Performance of shear calculation methods

Prediction method	Normal strength concrete (NSC)				High strength concrete (HSC)			
	AAE (%)	Vmeasured/Vpredicted			AAE (%)	Vmeasured/Vpredicted		
		Average	STDV	COV		Average	STDV	COV
GA	10.5	0.99	0.15	14.59	14.6	1.09	0.25	25.91
ACI 11-6	24.7	1.30	0.31	23.64	34.0	1.24	0.47	38.02
CSA	21.8	1.22	0.30	24.42	28.0	1.12	0.42	37.11
EC-2	13.2	1.08	0.20	18.74	21.0	1.07	0.35	32.54
Zsutty	14.2	1.04	0.20	19.44	25.5	1.02	0.31	30.25

and Zsutty's equation is presented in Figs. 7 and 8, respectively versus the experimentally measured shear capacity values. It can be observed that the data points predicted by the GA model are located on or within a small range around the equity line for both NSC and HSC beams (Figs. 7e and 8e), whereas those calculated by the other methods lie over a much wider range away from the equity line. The ACI (11-6) and CSA simplified methods tended to underestimate the shear capacity of normal and high-strength reinforced concrete slender beams for shear capacity values of up to 200 kN, while the EC-2 and Zsutty's equation provided relatively more accurate results.

For beams exceeding 200 kN in shear capacity, only the GA model provided accurate predictions, while the remaining four methods demonstrated poor results particularly for HSC beams. The ACI (11-6) code and Zsutty's equation in particular tended to overestimate the shear capacity for normal strength concrete beams in this high shear capacity range. All methods other than the genetic algorithm model overestimated the shear capacity of high-strength concrete beams, likely because they could not capture the effect that smooth fracture surfaces due to trans-granular failures have on reducing the aggregate interlock shear resisting mechanism.

The ability of each of the shear design/calculation methods considered in this study to accurately estimate the shear capacity of slender beams was measured using the average absolute error (*AAE*) as per Eq. (3) along with the ratio of measured to predicted shear strength (V_m/V_p).

$$AAE = \frac{|V_m - V_p|}{V_m} \times 100 \tag{3}$$

where V_m and V_p are the measured and predicted shear capacity, respectively. The average, standard deviation (*STDV*), and coefficient of variation (*COV*) of measured to predicted shear strength ratio and average absolute error (*AAE*) for all shear design/calculation methods investigated are presented in Table 6. The results indicate that the GA was successful in learning the relationship between the different shear design parameters and the shear strength of reinforced concrete slender beams. The GA model outperformed all other methods in predicting the shear strength of both NSC and HSC beams. EC-2 had satisfactory performance for both NSC and HSC beams but was un-conservative for high shear capacity HSC beams. Zsutty's equation achieved satisfactory performance for both NSC and HSC beams but had inadequate results over the high shear capacity range. ACI 11-6 and CSA both underestimated the shear capacity of NSC and HSC slender beam without stirrups having low shear capacity, which is expected since they are design tools with reduction factors. However, they achieved highly un-conservative calculations for high shear capacity HSC beams. In all cases the *AAE* and *COV* were higher for HSC than NSC, therefore reinforcing the idea of a loss in ultimate shear capacity of HSC beams, due to the effect of smooth fracture surfaces and the inability of current design provisions to capture this phenomenon.

5. Parametric study

Sets of new beams were created from randomly selected beams in the database to study the influence of various shear design parameters on the shear strength of reinforced concrete slender beams without stirrups. The findings of this parametric study are described below.

5.1. Size effect

There is substantial evidence (Zararis and Papadakis 2001, Collins and Kuchma 1999, Kani 1967) that the depth of slender RC beams has a significant influence on their shear capacity. It has been shown that as the beam's depth increases, the shear stress at failure decreases. To investigate this size effect on the shear capacity of reinforced concrete slender beams without stirrups, a set of beams was generated from a beam randomly selected from the database, keeping all design parameters constant except for the beam's depth, which was varied between 219 and 466 mm. It can be noted from Fig. 9 that the GA model, EC-2 and to a lower extent the CSA simplified method were able to capture the effect of the beam depth on its shear strength. However, both ACI (11-6) and Zsutty's equation ignore the effect of the beam depth on the ultimate shear strength. Experimental results for two beams with comparable design parameters to the randomly selected beam were used for comparison. The GA and the EC-2 Code had results closest to the experimental values.

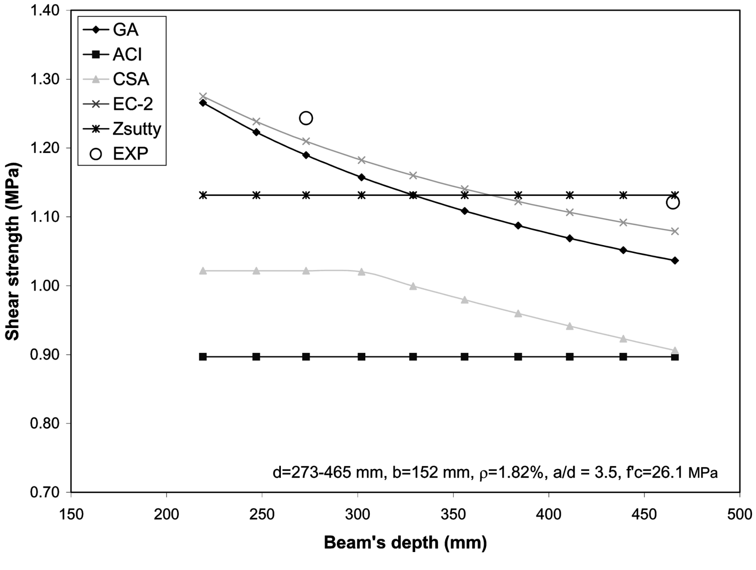


Fig. 9 Effect of d on shear strength of RC beams without shear reinforcement

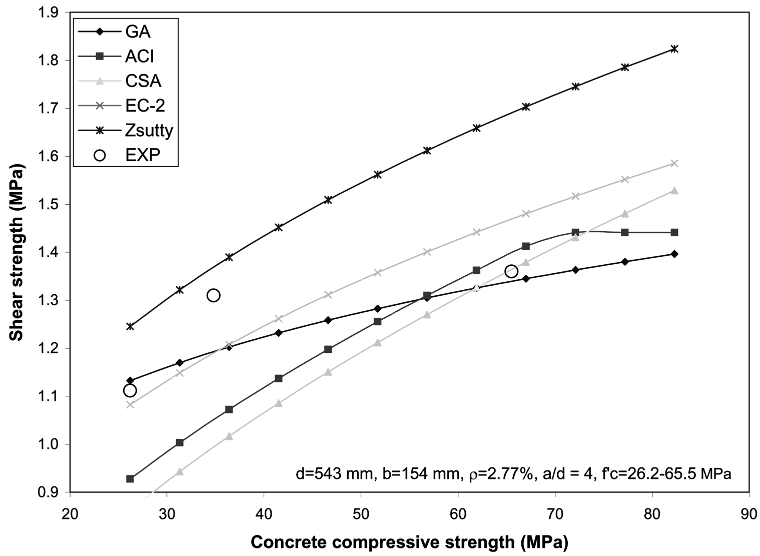


Fig. 10 Effect of f_c' on shear strength of RC beams without shear reinforcement

5.2. Influence of concrete compressive strength

To examine the influence of concrete compressive strength on the shear capacity of slender RC beams without stirrups, a set of new beams was also generated from one beam randomly selected from the database. The design parameters of the original beam were maintained constant, except that the compressive strength varied between 26 and 82 MPa. Fig. 10 shows the influence of concrete compressive strength on the shear capacity of RC slender beams as predicted by the GA model compared to calculations of the other methods used in the study. It can be seen from Fig. 10 that for GA predictions, the rate of increase of shear strength up to a compressive strength of 70 MPa is greater than that beyond 70 MPa, indicating that the GA has captured the effect of loss in shear friction provided by aggregate interlock at high compressive strength. It can also be observed in Fig. 10 that shear capacity calculations of the GA model were closer to experimentally measured data, followed by the EC-2 code. The rate of increase in shear capacity versus compressive strength for HSC beams is 60% of that for NSC beams. The CSA simplified method ignores this phenomenon, while the ACI code recognizes the loss in shear friction but makes no attempt to capture it accurately in the design equation and maintains the shear capacity constant beyond f_c' of 70 MPa. Since 33-50% of the ultimate shear capacity of slender concrete beams without stirrups is provided by aggregate interlock along the fracture surface (Rebeiz 2001), which tends to be smoother for HSC than NSC, it is expected that the rate of increase in shear capacity will decrease with concrete compressive strength above 70 MPa (Kim and Park 1996, Taylor 1970).

5.3. Influence of longitudinal steel reinforcement

To evaluate the influence of the longitudinal steel reinforcement, ρ_l on the ultimate shear capacity of reinforced concrete slender beams without shear reinforcement, two new sets of beams were generated. The first set representing NSC shares the same design parameters, except that the longitudinal

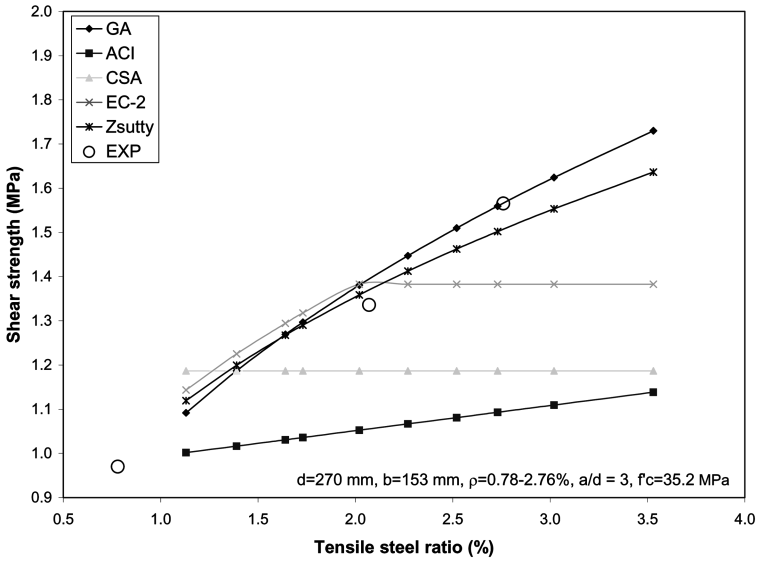


Fig. 11 Effect of ρ_l on shear strength of NSC beams without shear reinforcement

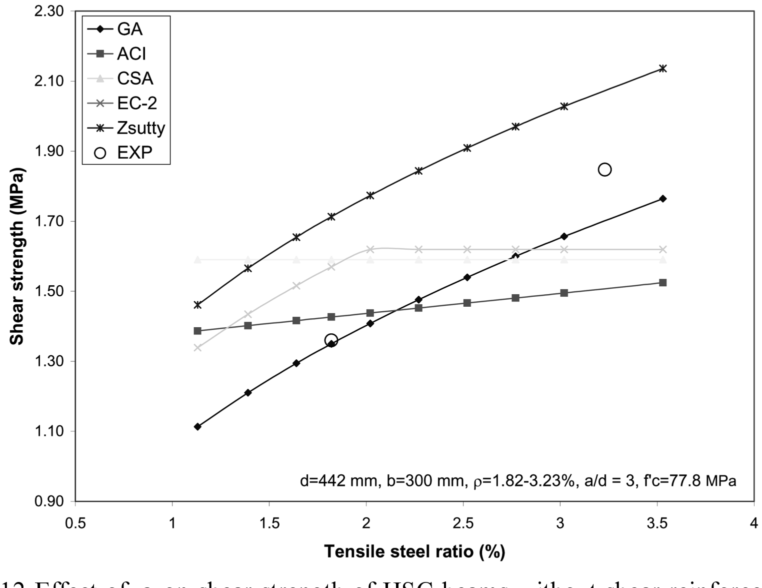


Fig. 12 Effect of ρ_l on shear strength of HSC beams without shear reinforcement

reinforcement ratio was varied between 1.13% and 3.53%. The beams in the second set represent HSC and share the same design parameters, but the longitudinal reinforcement ratio also ranged from 1.13% to 3.53%. Fig. 11 illustrates the effect of the longitudinal reinforcement ratio on the shear strength of NSC slender beams. It can be seen that the ACI (11-6) code underestimates the influence of the longitudinal reinforcement, while the CSA simplified method ignore its contribution. Fig. 11 shows the ability of the GA model to accurately capture the influence of the longitudinal reinforcement on the shear capacity of NSC beams. Zsutty's equation also captures the effect of longitudinal reinforcement fairly accurately although it tends to underestimate its contribution for high tensile steel ratios. Similarly, EC-2 can accurately evaluate the shear capacity of NSC beams with tensile steel ratios less than 2.0%. Unfortunately the equation limits the tensile steel ratio to 2.0% and hence it fails to capture its influence at higher reinforcement levels.

Fig. 12 shows the influence of the longitudinal reinforcement ratio on the shear strength of HSC slender beams. It can be noted that all methods except the GA model tended to overestimate the effect of the tensile steel ratio on the shear capacity of RC slender beams having a reinforcement ratio below 2%. Above 2%, with the exception of Zsutty's equation, which overestimated this effect, all methods provided conservative results. The GA model provided the best shear capacity predictions amongst all other methods for slender HSC beams at all reinforcement ratios. Experimental results for three NSC and two HSC beams with comparable properties to the randomly selected beams were used for comparison and it can be seen that results of the GA model followed the experimental trend the closest in both cases.

6. Optimization of beam design using genetic algorithms

The ability to accurately predict the shear strength of RC beams is important, but the capability to design beams to meet specific design criteria in a rapid, easy, and accurate manner is even more critical. A second genetic algorithm program was developed in this study in order to design RC slender beams based on the new shear strength equation optimized in the first part of this paper. The genetic algorithm settings used for the optimization are presented in Table 7. The first design model requires only to input

Table 7 Genetic algorithm settings for beam optimization

Number of Individuals	75
Variable Format	Real values
Maximum Generations	500
Selection Method	Stochastic universal sampling
Selection Pressure	1.7
Recombination Name	Extended line
Recombination Rate	0.54
Mutation Rate	0.001

Table 8 Results of beam optimization model 1

		GA Optimization				GA Optimization				GA Optimization		
		1	2	3		1	2	3		1	2	3
Beam	D-3				D1				78			
d (mm)	359	295	376	499	139	138	167	81	465	449	393	480
b_w (mm)	229	298	382	288	60	88	42	103	200	256	234	128
p_l (%)	4.32	3.56	1.44	1.39	1.35	0.54	4.08	1.46	1.35	0.88	1.64	2.98
f_c' (MPa)	36.1	33.2	17.8	21.5	34.0	48.9	30.4	37.7	24.9	19.8	19.2	47.8
a/d	3.5				3				3			
Shear (kN)	129	129	129	129	11.6	11.6	11.6	11.6	87.3	87.3	87.3	87.3

Table 9 Results of beam optimization model 2

		GA Optimization				GA Optimization				GA Optimization		
		1	2	3		1	2	3		1	2	3
Beam	D-3				D1				78			
d (mm)	359				139				465			
b_w (mm)	229				60				200			
p_l (%)	4.32	4.21	4.01	4.28	1.35	1.43	2.00	1.87	1.35	1.34	1.28	1.17
f_c' (MPa)	36.1	38.3	41.1	37.5	34	59.5	36.6	45.6	24.9	26.3	28.1	32.0
a/d	3.5				3				3			
Shear (kN)	129	129	129	129	11.6	11.6	11.6	11.6	87.3	87.3	87.3	87.3

the desired ultimate shear capacity and the GA is responsible for specifying the appropriate beam depth, width, percent of longitudinal reinforcement and the compressive strength of concrete to meet the design intent. Three beams were randomly selected from the database to test the ability of the GA to design RC slender beams without stirrups. The results from the optimization are presented in Table 8. It can be seen that the GA was able to accurately predict the design parameters and was ultimately able to provide multiple solutions that satisfied the design criteria.

The second design model requires inputting the desired ultimate shear capacity along with the beam dimensions, and the GA is responsible for determining an appropriate concrete compressive strength and percent of longitudinal reinforcement. The same three beams used for the first model were used in the second model and the results are presented in Table 9. Results from the optimization of the second model were in better agreement with the randomly selected experimental beam than the first model since more variables of the beam have been fixed.

It should also be noted that the GA model can carry out multi-objective optimization so that it designs optimal beams to meet specific design criteria, but also optimizes the design so that it is the most economical beam to meet the shear capacity requirements. Since the GA model is a predictive tool with optimization capacity, its predictions can be multiplied by a reduction factor to achieve reasonably conservative results for design purposes. Other existing methods, even though used for design, can have highly un-conservative predictions of shear capacity as shown earlier in the paper.

7. Conclusions

This study demonstrates the advantages of using genetic algorithms to develop models for predicting the shear strength of reinforced concrete beams. A GA model was trained using 122 NSC and 45 HSC beams from the literature. A shear design equation was developed and proved to be more accurate in estimating the shear strength of both normal and high-strength reinforced concrete slender beams than the ACI 11-6, CSA simplified method, Eurocode-2, and Zsutty's equation. A parametric study on the sensitivity of each of the methods to various shear design parameters was carried out and the following conclusions can be made:

- The GA model better captured the beam size effect on the shear capacity of reinforced concrete slender beams without shear reinforcement compared to all other methods considered in this study.
- The GA model predicted that the rate of increase in shear strength decreases with increasing

concrete compressive strength above 70 MPa, which is consistent with experimental data in the literature.

- The amount of longitudinal reinforcement influences the ultimate shear capacity of RC slender beams. The GA model captured such an influence for both NSC and HSC beams. Both EC-2 and Zsutty's method captured this influence but only over a limited range. Conversely, the ACI (11-6) underestimates this influence, while the CSA simplified method simply ignores its contribution. For low tensile reinforcement ratios, both the ACI code (11-6) and the CSA simplified method overestimate the impact of the reinforcement particularly for HSC beams.

Two optimization models were created and the GAs proved reasonably accurate in predicting the design parameters for various beams under stipulated design criteria. Thus, GAs can be used to optimize structural members meeting specific criteria. They can also be used to optimize the most economic shear design, and could be used for design purposes provided that a reduction factor is added for safer design.

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