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Soft computing for modeling punching shear of reinforced concrete flat slabs

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Abstract This paper presents applying gene expression programming (GEP) approach for predicting the punching shear strength of normal and high strength reinforced concrete flat slabs. The GEP model was developed and verified using 58 case histories that involve measured punching shear strength. The modeling was carried out by dividing the data into two sets: a training set for model calibration, and a validation set for verifying the generalization capability of the model. It is shown that the model is able to learn with high accuracy the complex relationship between the punching shear and the factors affecting it and produces this knowledge in the form of a function. The results have demonstrated that the GEP model performs very well with coefficient of determination, mean, standard deviation and probability density at 50% equivalent to 0.98, 0.99, 0.10 and 0.99, respectively. Moreover, the GEP predicts punching shear strength more accurately than the traditional methods.

1. Introduction

Punching shear is considered to be one of the major criteria that control the design of concrete members such as flat slabs, spread footing or raft footings. This type of shear usually exists in the vicinity of slab column connections due to the high concentration of stress. The brittle nature of punching shear failure in structures made it very dangerous; when shear failure occurs, the resistance of the structure tremendously reduced and consequently collapse takes place because of separation of column and slab. Therefore, design methods and codes of practice have paid great interest to account for such kind of failure.

Determining the punching shear strength is a complex design problem owing to the influence of numerous factors involved. Because of the complexity of the problem many researchers have attempted to model the punching shear phenomenon using different assumptions (*e.g.* [1–3]). As a result, different methods have been proposed to predict the punching shear strength of concrete members. However, considering the results obtained from applying these methods on same problem reveals different results depending on the method employed. Moreover, in several instances comparing these results with experimental data shows over-prediction by 20–50%. Consequently, more

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accurate methods are needed for better prediction of punching shear strength. Artificial intelligence techniques can represent a potential option to be explored.

The main concept behind the use of these techniques is that they learn adaptively from experience and extract various functions each appropriate for its purpose. Artificial intelligence systems have the ability to operate on large quantities of data and learn complex model functions from examples by training on set of input and corresponding output. The greatest advantage of the artificial intelligence over the traditional modeling techniques is their ability to capture a nonlinear and complex interaction between variables of a system without having to assume the form of the relationship between the input and the output variables. Artificial intelligence techniques have been applied to solve many problems in the field of engineering (*e.g.* [4–7]).

In this paper, the punching shear strength of flat slabs is modelled using a developed form of artificial intelligence techniques that is gene expression programming (GEP). Recently, GEP has been applied with success in solving engineering problems (*e.g.* [8–10]). The paper aimed to investigate feasibility of using GEP to determine a model relating punching shear strength with its significant factors; evaluate the performance of the model in training and validation sets and via sensitivity analysis; compare the predictions of the model with predictions of number of commonly adopted methods.

2. Overview of gene expression programming

GEP is an instance of an evolutionary algorithm from the field of evolutionary computation, invented by Ferreira [11] as a global optimization algorithm. It has similarities to other evolutionary algorithms such as the genetic algorithms (GAs), as well as other evolutionary automatic programming techniques such as genetic programming (GP). Similar to the GAs, GEP uses the evolution of computer programs (individuals or chromosomes) that are encoded linearly in chromosomes of fixed length, and likewise the GP the evolved programs are expressed nonlinearly in the form of expression trees (ETs) of different sizes and shapes. However, GEP implements different evolutionary computational method. The GEP distinguishes itself from GAs in that the evolved solutions are expressed in the form of parse trees of different sizes and structures and unlike the GP, genetic variations are performed on chromosomes before they are translated into ETs.

The GEPs chromosomes can be composed of single or multiple genes; each gene is encoded in a smaller sub-program. Every gene has a constant length and includes a head that contains functions (*e.g.* $+, -$) and terminals (*e.g.* d1, d2, which are the symbolic representation of the input variables), and a tail composed of terminals only. The genetic code represents a one-to-one relationship between the symbols of the chromosome, the functions or terminals. The process of information decoding from chromosomes to ETs is called translation, which is based on sets of rules that determine the spatial organization of the functions and terminals in the ETs and the type of interaction (link) between the sub-ETs [12]. The principal terms of the GEP are described in the following subsections.

2.1. Initial population

In GEP, the search for a solution begins when a number of computer programs (individuals or chromosomes), referred to as the initial population, are randomly created from the set of functions and terminals defined by the user. Each program is expressed, evaluated and assigned fitness according to how well it performs towards the desired objective.

2.2. Chromosome gene and expression trees

The chromosome is a linear symbolic string of fixed length composed of one or multiple genes of equal size. A typical GEP chromosome is presented in Fig. 1.

The gene is a sub-program encoded in the chromosome and it consists of a head and a tail. The length of the head is usually predefined by the user during data setting, while the length of the tail is determined by the following:

$$t = h(n - 1) + 1 \tag{1}$$

where t is the tail length; h is the head length and n is the number of function's arguments.

Although the genes of the GEP have all the same size, they code for different expression trees of different sizes. The trees represent a spatial illustration demonstrating the interactions among the gene's components on the map of solution. Fig. 2 shows expression trees of the genes of the chromosome in Fig. 1.

2.3. Mutation

In GEP, mutation means randomly selecting any component of the gene's head or tail and replacing it with any other randomly selected component from the function or terminal set. In the heads, any component can change into another (function or terminal), whereas in the tails terminals can only change into terminals. The mutation may take place at one or two points within the chromosome and there are no constraints, neither in the kind of mutation nor in the number of mutations. In all cases, the newly created individuals are syntactically correct programs.

2.4. Recombination

The last significant step during each cycle of program evolution includes introducing genetic variation by recombination. The variations take place when two chromosomes are paired

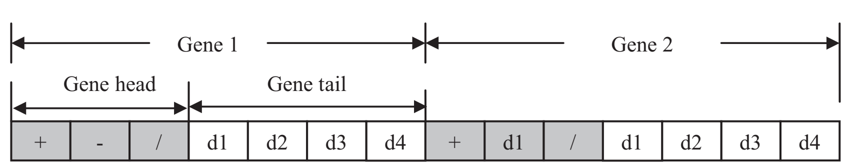

Figure 1 GEP chromosome.

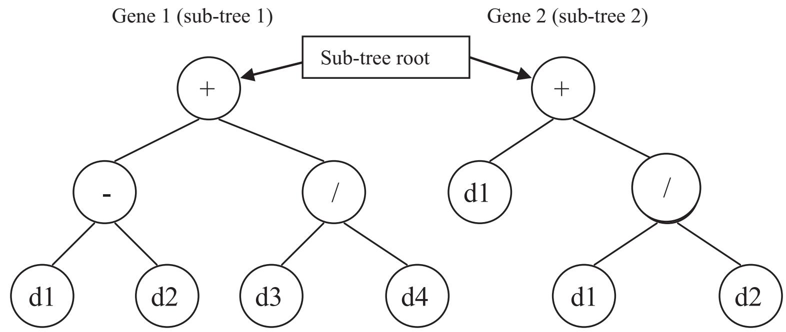

Figure 2 Expression trees of chromosome in Fig. 1.

and split exactly at the same point to exchange their components downwards to the merging point. The following steps explain how recombination is performed.

- Two chromosomes are selected randomly from the population;
- one part of each chromosome is selected randomly;
- the two chromosomes pair and trade in the selected parts; and
- two offspring belonging to the new population are obtained.

2.5. Modeling process

As illustrated in Fig. 3, the process that the GEP implements for developing the problem's solution begins with creating an initial population of computer programs chosen randomly from the sets of functions and terminals. The functions can contain basic mathematical operators (*e.g.* $+$, $-$, $\times$, /) or any other user-defined functions, whereas the terminals can consist of numerical constants, logical constants or variables. Each program (chromosome) is executed and its fitness is evaluated through the fitness function, which measures how good the chromosome is in competition with the rest of population. Chromosomes are then selected for further development based on their fitness. The ones that have higher fitness are given a higher chance of being selected, whereas the low fitness chromosomes are deleted or given a slim chance for selection. The selected programs are then subjected to further developments, which are performed through genetic variations such as mutation and recombination. New offspring of chromosomes with new traits are generated and used to replace the existing population. The chromosomes of the new generation are then subjected to the same developmental process, which is repeated until the stopping criteria are satisfied.

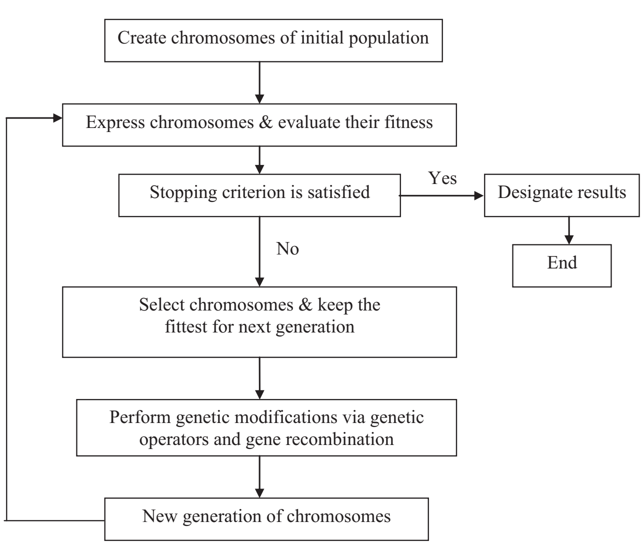

Figure 3 Flow chart of gene expression algorithm.

3. Proposed GEP model development

The GEP model developed in this study is based on experimental results collected from the literature and comprises a total of 58 case histories: 6 cases reported by Hallgern and Kinnunen [13], 16 cases reported by Marzouk and Hussein [14], 9 cases reported by Tomaszewicz [15], 8 cases reported by Metwally et al. [16], 6 cases reported by Ramdane [17] and 13 cases reported by Abdel Hafez [18]. The tested slabs have different thickness ranging between 100 and 300 mm and supported by columns of circular or square cross section. The slabs were made of normal and high strength concrete which its compressive strength was determined from cylinder test. The tensile reinforcement ratio of the slabs was ranging between 0.0049 and 0.0428. The slabs were tested by applying a compressive load until failure. The failure load was determined as the plunging load beyond which further increase in strain corresponds to no increase in resistance. No further details were available about the procedure of the tests.

3.1. Model input and output

Extensive search was carried out in the literature to identify the factors that affect the punching shear strength of normal and high strength reinforced concrete members. It was concluded that the punching shear resistance is influenced by the perimeter of punching shear block, b_0, which is calculated based on ACI-318 [19], depth of concrete member, d, concrete cylindrical compressive strength, f_{cu}, and tension reinforcement ratio of slab at the critical section, ρ_t, [19–21]. Thus, the GEP model was presented with these input variables. The single output was the measured shear resistance, F_s, which is taken as the failure load measured from the compression test of the slabs. The effect of column diameter or width is not considered in this study because they are included in the calculations of perimeter of the shear block.

3.2. Data division

Dividing the available data into subsets (a training set and a validation set) is a necessary step in modeling with GEP. Usually GEP models involve a large number of programs, so they have a high tendency towards over-fitting, particularly if the training data are noisy. Thus, the main aim of this step is to prevent the model from over-fitting which may take place during the training phase. Over-fitting refers to the ability of the model to memorize rather than generalize the form of the relationship between input and output data.

In the literature, there is no definite ratio of the used data to be assigned to each subset, but in general 10–20% of the available data is suggested to be used as a validation set, and 80–90% as a training set [12].

In order to develop a robust model, researchers suggest that all of the patterns contained in the available data should be contained in the calibration set. Likewise, all of the patterns in the available data should also be contained in the validation data. This provides the toughest evaluation of the generalization ability of the model [22]. To achieve this, several researchers [12,23] suggest that data subsets should be statistically consistent; training and validation sets should possess similar statistical properties including mean, standard deviation, maximum and minimum.

In this work, the data were randomly divided into two statistically consistent sets as recommended by Master [23] and detailed by Shahin et al. [24]. In total, 48 case records (83%) of the available 58 cases were used for training and 10 cases (17%) for validation. The statistics of the data used for the training and validation sets are presented in Table 1, which include the mean, standard deviation, minimum, maximum and range. It should be noted that, like all empirical models, GEP performs best in interpolation rather than extrapolation, thus the extreme values of the data used were included in the training set.

3.3. Modeling process and determination of GEP model

The success of the modeling process using GEP depends significantly on the design of the model structure. In this, the optimal model parameters were determined to ensure that the best performing model was achieved. In the search for a model using the GEP, the number of chromosomes, chromosome structure, functional set, fitness function, linking function and rates of genetic operators play important roles during the modeling process, and choosing suitable rates of these parameters can considerably reduce modeling time and effort and produce a robust solution.

In this work, the search to determine the values of setting parameters was carried out in steps. During each step, runs were carried out and the value of one of the above parameters was varied, whereas the values of the other parameters were set constant (*i.e.* number of chromosomes = 30, number of genes = 3, gene's head size = 8, functions set = $+$, $-$, $\times$, and $/$, fitness function = mean squared error (MSE), linking function = $+$, mutation rate = 0.04, and gene recombination rate = 0.1). The runs were stopped after 25,000 generations, which were found sufficient to evaluate the fitness of the output. At the end of each run, the MSE for both training and validation sets was determined. The optimal value of each parameter was obtained from the plot of variations of MES in training and validation sets with each setting parameter as presented in Fig. 4.

After finding the optimal values of setting parameters, the GEP model was determined by conducting new runs using these parameters. The outputs of the runs involved chromosomes (models) which represent potential solutions to the problem. The best model was determined by analysing these solutions to determine an expression that conformed as closely as possible to the engineering understanding of the punching shear strength. Moreover, selection criteria were adopted for screening the best model; the model has to achieve the best possible correlation between predicted and experimental values (coefficient of determination $R^2 \geqslant 0.80$), for both of the training and validation sets; and it has to have average error of measured to predicted values within 10%. A desirable criterion of the model is also to be a short and simple expression.

Table 1 Statistics of parameters for the training and validation subsets used in the development of the GEP model.

Statistical parameters	Subset	Input and output variables				
		b_0 (mm)	D (mm)	ρ_t	f_{cu} (MPa)	F_s (kN)
Mean	Training	1117	154	1	70	527
	Validation	1104	149	2	73	565
Standard deviation	Training	385	48	1	27	531
	Validation	456	47	1	24	659
Maximum	Training	2080	300	4.24	128	2450
	Validation	2080	250	2.81	99.7	2250
Minimum	Training	640	100	0.58	29.89	70
	Validation	640	100	0.49	29.89	92.5
Range	Training	1440	200	3.66	98.11	2380
	Validation	1440	150	2.32	69.11	2157.5

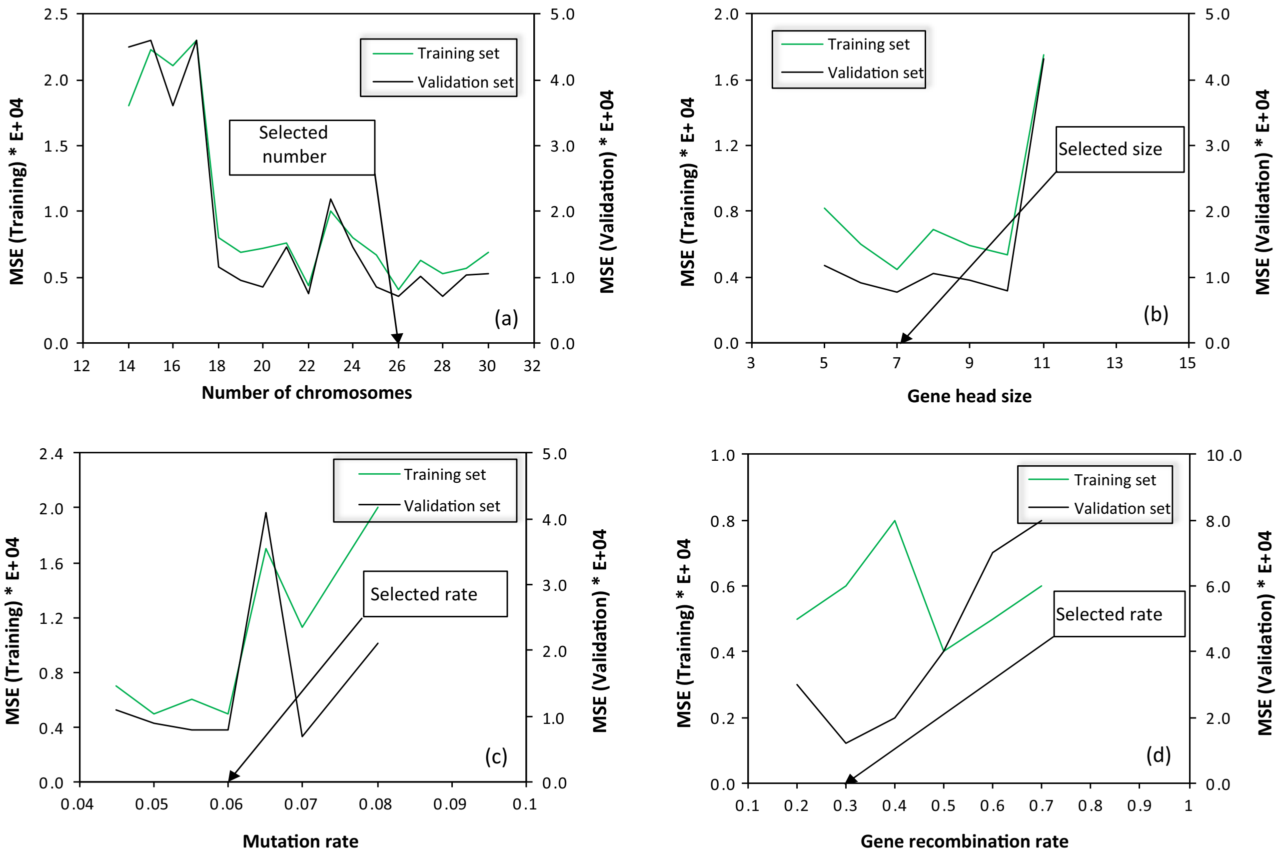

Figure 4 Effect of setting parameters on the performance of the GEP model: (a) number of chromosomes; (b) gene head size; (c) mutation rate; and (d) gene recombination rate.

Table 2 Input parameters used for the GEP models.

Parameter	Used input
Number of chromosomes	27
Number of genes	3
Head size	10
Functions set	$+, -, \times, /\ \sqrt[2]{x},\ \sqrt[3]{x},\ x^2,\ x^3$
Fitness function	Mean squared error
Linking function	$+$
Mutation rate	0.05
Recombination rate	0.3

The model that satisfied the selection criteria was further developed with the optimization and simplification procedures available in the program. Table 2 presents the optimum setting parameters used during the search for the GEP model.

4. Results and model evaluation

4.1. Expression trees and model formulation

The output of the modeling process was dispatched in a form of expression trees as shown in Fig. 5. The figure illustrates mathematical operations and the interaction among the input variables. This can give an insight into the nature of the relationship between the input and the output.

The ETs can be easily translated into a mathematical expression which can be simplified and rearranged to be as follows:

$$F_s = \frac{b_0 - d + d^2}{45.29 - 0.86\rho_t} + \left(\frac{9.70\rho_t - f_{cu}}{8.49 - \rho_t}\right)^2 + \frac{2d^2}{(b_0 - d)(-0.27\rho_t)} + 3.63 \quad (2)$$

where F_s = predicted punching shear, b_0 = perimeter of shear block, d = depth of concrete member, ρ_t = ratio of tension reinforcement multiplied by 100, f_{cu} = cylinder compressive strength in 28 day.

4.2. Evaluation the performance of the model in training and validation sets

The performance of the GEP model is shown numerically in Table 3 and depicted graphically in Fig. 6. Table 3 indicates that the model performs well with high coefficient of determination, R^2, of 0.98 and 0.99 for the training and validation sets, respectively. The propinquity of R^2 for both data sets also indicates that the model has a good ability to generalize. The table also shows that the mean values are very close to unity. Fig. 6 illustrates that the model has minimum scatter around the line equality between the measured and the predicted shear strength for the training and validation sets. This is an additional conformation to robust performance of the model. The results demonstrate that the developed GEP model performs well.

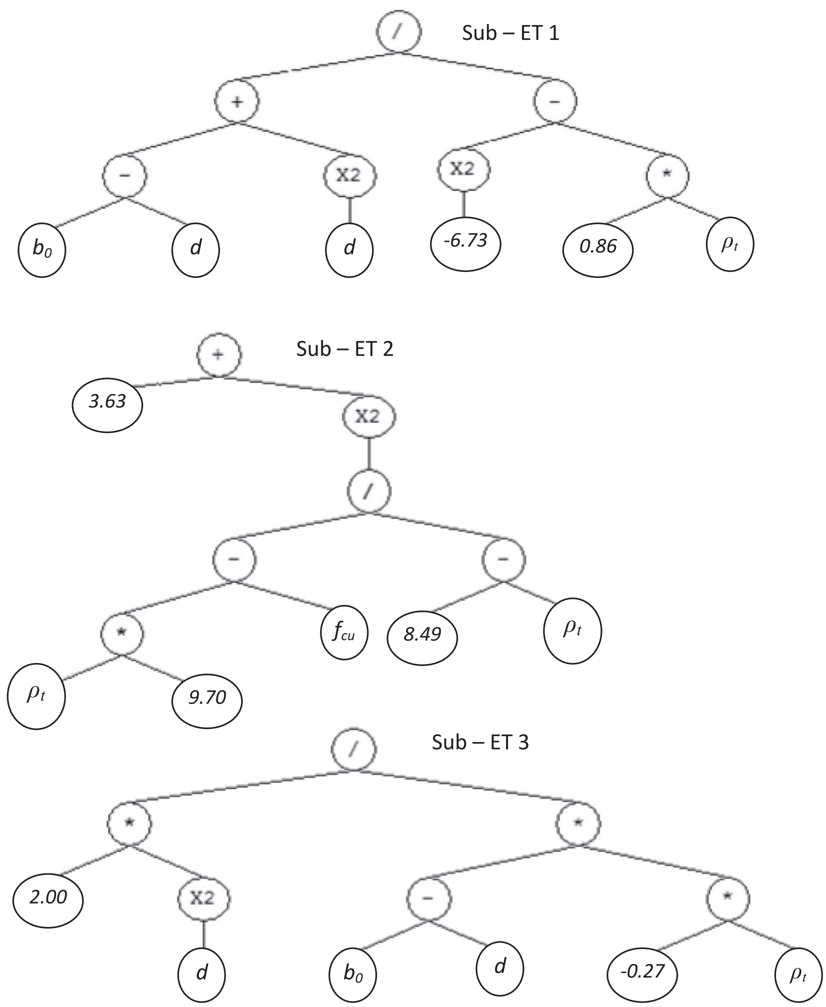

Figure 5 Expression trees of the developed model.

Table 3 Performance of the GEP model in training and validation sets.

Performance measure	Data set	
	Training	Validation
Mean	1.01	0.96
Coefficient of determination, R^2	0.98	0.99

4.3. Comparing GEP model with number of commonly used methods

To evaluate the performance of the GEP model further, the predictions of the model were compared with those obtained from three of currently adopted methods including ACI-318 [19], BS-8110 [20] and CEP-FIP MC [21]. A brief description of the compared methods is provided in Table 4. The coefficient of determination, R^2, the mean and the cumulative probability at 50% (P_{50}) from the GEP model and the compared methods, in relation to the available case records, were carried out and the results are presented numerically in Table 5 and graphically in Fig. 7. The cumulative probability, P_{50}, is

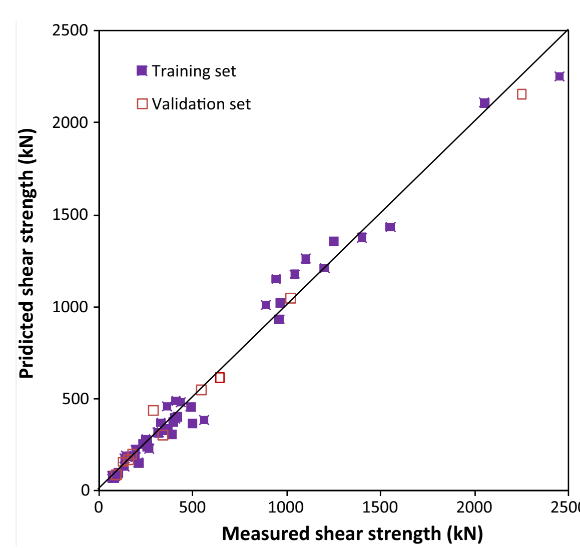

Figure 6 Performance of the GEP model in training and validation sets.

Table 4 A brief description of the common methods used for predicting punching shear.

Method	Description
The American Building Code [19]	The critical perimeter is assumed at $0.5d$ from the perimeter of the loaded area, and v_C is the smallest of the following: $v_c = 0.17\left(1+\frac{2}{\beta}\right)\lambda\sqrt{f_c'}b_0 d \quad (\mathrm{N/mm^2}) \qquad (4)$ $v_c = 0.083(\frac{\alpha_s d}{b_0}+2)\lambda\sqrt{f_c'}b_0 d \quad (\mathrm{N/mm^2}) \qquad (5)$ $v_c = 0.33\lambda\sqrt{f_c'}b_0 d \quad (\mathrm{N/mm^2}) \qquad (6)$ where: v_c = concrete shear resistance; β = long side/short side of the column and should be taken greater than or equal to2 ($\beta \geq 2$); λ = modification factor for lightweight concrete; f_c' = concrete cylinder compressive strength = 0.85 f_{cu} for cube strength; a_s 40, 30, and 20 for interior, exterior, corner columns respectively. The requirement of the ACI code that f_c' does not exceed 68 MPa was disregarded in computations
The British Standard [20]	The critical section adopted by the British Standard is at $1.5d$ from the column face, and v_c is calculated as follows: $v_c = \frac{0.79}{\gamma_m}\left\{\frac{100A_s}{b_v d}\right\}^{\frac{1}{3}}\left\{\frac{400}{d}\right\}^{\frac{1}{4}} \quad (\mathrm{N/mm^2}) \qquad (7)$ for strength > 25 MPa the value in the table may be multiplied by $\left(\frac{f_{cu}}{25}\right)^{\frac{1}{3}}$ where: f_{cu} = concrete compressive strength; d = effective depth; b_v = breadth of section; A_s = area of tension reinforcement; γ_m = 1.25 for shear strength without reinforcement $f_{cu} \leq 40$ MPa, $\frac{A_s}{b_v d} \leq 3\%$ and $.400/d \geq 1$
CEP-FIP [21]	In MC-90 the punching shear resistance, F_{sd}, is expressed as: $F_{sd} = 0.12\xi(100\rho f_{ck})^{\frac{1}{3}}u_1 d \qquad (8)$ where f_{ck} = the characteristic compressive strength of concrete ξ = size-effect coefficient calculated from $\xi = 1+\sqrt{\frac{200}{d}} \qquad (9)$
CEP-FIP [21]	u_1 = the length of the control perimeter at $2d$ from the column face; and ρ = reinforcement ratio calculated as $\rho = \sqrt{\rho_x \rho_y} \qquad (10)$ ρ_x, ρ_y = reinforcement ratios in x and y directions In the ultimate limit state the partial safety factor is 1.5. For the calculation of punching load capacity, F_{sd} is multiplied by 1.5, which gives the following equation $F_{sd} = 0.18\xi(100\rho f_{ck})^{\frac{1}{3}}u_1 d \qquad (11)$ The highest concrete grade considered in MC90 is C80, which corresponds to f_{ck} = 80 MPa. Influences of reinforcement and slab depth are also considered in this design code

Table 5 Statistical evaluation of the predictions of the GEP model in comparison with commonly used methods.

Statistical measure	Data set	Prediction method			
		GEP (proposed)	ACI-318	BS-8110	ECP-FIP
R^2	All data	0.98	0.90	0.98	0.88
	Validation	0.99	0.88	0.98	0.86
Mean, μ	All data	0.99	1.44	1.09	1.36
	Validation	0.96	0.74	0.89	0.89
Standard deviation, σ	All data	0.10	0.40	0.10	0.40
	Validation	0.10	0.30	0.20	0.40
Probability density, P_{50}	All data	0.99	0.74	0.93	0.81
	Validation	1.01	0.70	0.85	0.80

calculated from Eq. (3) by sorting the values of predicted capacity by measured capacity (Q_p/Q_m) in an ascending order for each method. The smallest Q_p/Q_m is given number i = 1 and the largest is given $i = n$. The value of Q_p/Q_m that corresponds to P = 50 is considered as P_{50}.

$$P = \frac{1}{n+1} \qquad (3)$$

Visual inspection of Fig. 7 may conclude that the model has minimum scatter around the line of equality between measured and predicted shear strength. The figure also illustrates that the majority of the points lay below the line of equality. Table 5 shows that the model performs well in comparison with the other methods. The consistency of the results for all the data set and validations sets indicates to strong capability to

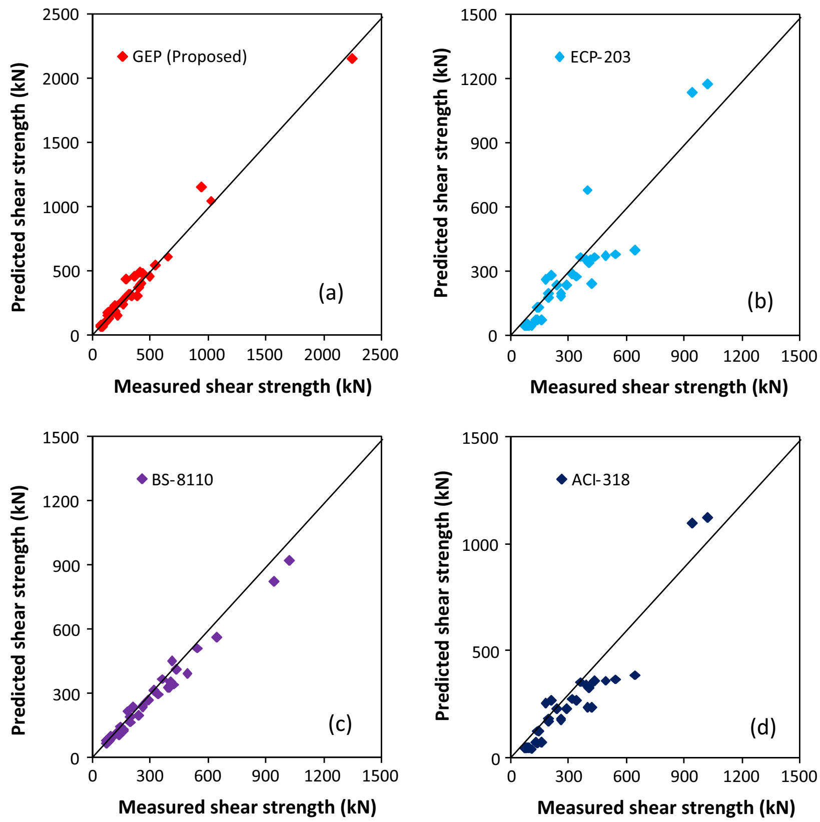

Figure 7 Comparison the accuracy of GEP model with traditional methods: (a) GEP model; (b) ECP-203; (c) BS-8110; and (d) ACI-318-11.

generalize and high accuracy. The overall results in Table 5 and Fig. 7 may suggest that the GEP model tends to underpredict the measured shear strength. Comparing the results obtained by the GEP model with results of the other methods shows that the model performs better.

4.4. Parametric study

A parametric study was carried out to assess the performance of the proposed model further and determine the effects of varying the input variables on the output. The effect of using different ratios of tension reinforcement on the output was also investigated. A set of hypothetical input that lies within the range of the training data was used to verify the response of the GEP model to the variations of the input variables. The effect of each input variable was investigated by allowing it to change within its minimum and maximum values whereas all other input variables remained constant to their mean values. For example, the effect of slab depth, d, on shear strength was determined by allowing d to change but all other input variables were set constant. This procedure was repeated consecutively for all input variables and the results are shown in Fig. 8. A visual inspection of the figure may conclude as follows:

i. Shear strength increases with increasing values of input variables.
ii. Slab depth and concrete strength are the major factors that effect the shear strength.
iii. Using different ratios of tension reinforcement lead to significant increase in the shear strength. The largest increase in shear strength exists when tension reinforcement ratio is between 0.01 and 0.02. Afterwards, the increase in strength with increase of tension reinforcement continues in decreasing rate.
iv. A ratio of tension reinforcement of 0.02 may be suggested for design.
v. The results are consistent with published experimental results in sense that the shear strength increases with increase of shear block perimeter, depth of slab, ratio of tension reinforcement and concrete compressive strength.

5. Conclusion

The results of this study have shown that the gene expression programming technique is successful in correlating between the punching shear strength and the significant factors affecting it. The GEP model has achieved high coefficient of determination and low mean values in training and validation sets indicating high accuracy and great capability for generalization. Parametric study has revealed that the punching shear strength increases with increase of shear block perimeter, depth of slab, ratio of tension reinforcement and concrete compressive strength. The analysis also shows that slab depth is the most influencing factor on the punching shear strength. The

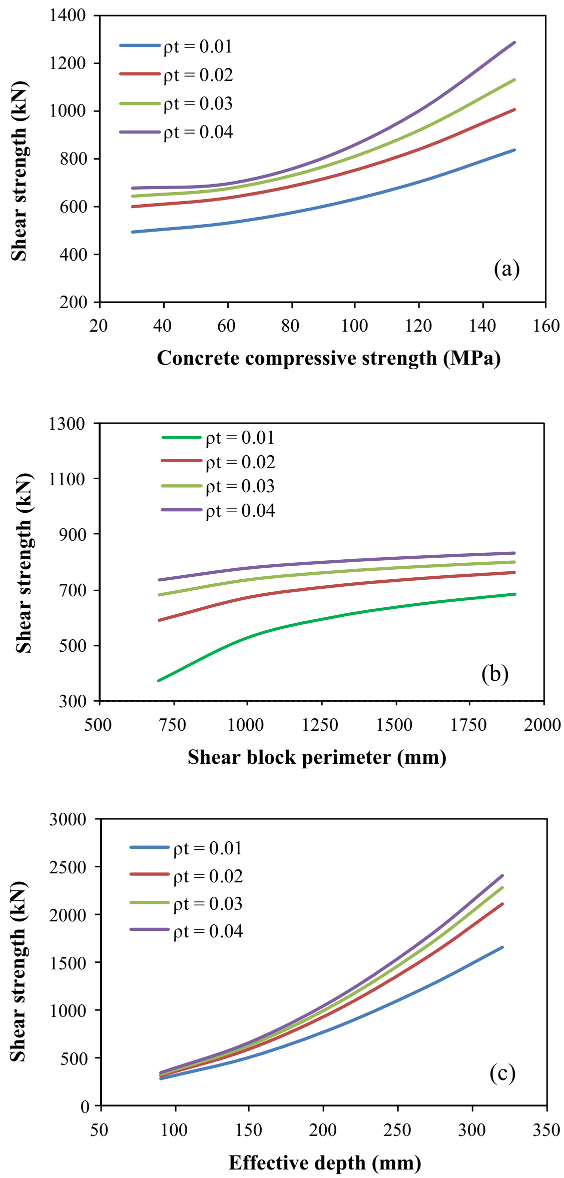

Figure 8 Parametric analyses to verify performance of the GEP model: (a) concrete compressive strength versus shear strength; (b) shear block perimeter versus shear strength; and (c) effective depth versus shear strength.

ratio of tension reinforcement has significant influence on punching shear; a ratio of 0.02 appears to be appropriate for design. The results also demonstrate that the GEP model performs well in comparison with the commonly used traditional methods. Over all, the output of this study indicates that the developed GEP model can be used as alternative for predicting the punching shear strength of normal and high strength concrete.

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