KSCE Journal of Civil Engineering (2021) 25(3):891-905
DOI 10.1007/s12205-021-0431-0

pISSN 1226-7988, eISSN 1976-3808
www.springer.com/12205

Structural Engineering

Prediction of Catenary Action Capacity of RC Beam-Column Substructures under a Missing Column Scenario Using Evolutionary Algorithm

Iftikhar Azim[a,e], Jian Yang[a,e], Muhammad Farjad Iqbal[b], Zafar Mahmood[c], Muhammad Faisal Javed[d], Feiliang Wang[a,e], and Qing-feng Liu[a,e]

[a]Shanghai Key Laboratory for Digital Maintenance of Buildings and Infrastructure, School of Naval Architecture, Ocean and Civil Engineering, Shanghai Jiao Tong University, Shanghai 200240, China
[b]Dept. of Civil Engineering, GIK Institute of Engineering Sciences and Technology, Topi 23460, Pakistan
[c]Dept. of Maths, Stats & Computer Science, The University of Agriculture, Peshawar 25000, Pakistan
[d]Dept. of Civil Engineering, COMSATS University Islamabad, Abbottabad 22060, Pakistan
[e]State Key Laboratory of Ocean Engineering, Shanghai Jiao Tong University, Shanghai 200240, China

ARTICLE HISTORY

Received 17 March, 2020
Revised 31 August 2020
Accepted 12 October 2020
Published Online 8 January 2021

KEYWORDS

Progressive collapse
Catenary action
Gene expression programming
RC beam-column substructure
Regression analysis

ABSTRACT

Catenary action plays crucial role in resisting the applied vertical load at large deformations stage in reinforced concrete (RC) structures. This paper aims to predict the catenary action capacity of RC beam-column substructures by utilizing the distinctive properties of gene expression programming (GEP). The input parameters selected for the modelling are: double-beam span-to-depth ratio, relative axial restraints stiffness, relative rotational restraints stiffness, bottom and top longitudinal reinforcement ratios, and yield strength of longitudinal rebars. A comprehensive and reliable database was collated from internationally published research articles to develop and verify the model. The GEP-based model was assessed by comparing its performance with regression based model. Various statistical indicators and external validation criteria suggested in literature proved that the model is accurate and possess high prediction and generalization capacity. Sensitivity analysis was carried out to show the contributions of the input parameters, while parametric analysis was performed to show that the proposed model is not merely a combination of the input parameters but can accurately represent the given physical system. The proposed formulation from GEP is found to be simple, robust, and easy to utilize for pre-design purposes.

1. Introduction

When an initial local failure caused by the removal of a major load bearing element (e.g., a column) in a structure, is not sustained and it spreads in sequence throughout the structure can trigger progressive collapse (Azim et al., 2020a). Current studies on progressive collapse of RC frame-only structures conclude that a structure can resist progressive collapse by flexural action, Vierendeel frame action, compressive arch action (CAA), catenary action (CA) with and without support from infill walls (Sasani et al., 2007; Yu and Tan, 2013a; Qian et al., 2015; Fu, 2016; Ren et al., 2016; Yu et al., 2019; Nyunn et al., 2020; Wang et al., 2020b). Progressive collapse can be activated by abnormal loadings such as bomb blasts, vehicle collision, and fire (Wang et al., 2020a). In such scenario, RC beams in the presence of proper axial restraints can produce arching action by developing axial compression, which can enhance the resisting capacity of beams beyond flexural capacity at small deformations stage (vid. Fig. 1(a)) (Sasani et al., 2011; Azim et al., 2020b). At large deformations stage, the axial restraints start to apply tension forces and overtake the compressive forces. This tensile force allows the beam to develop additional load resisting mechanism known as catenary resistance, which is the last line of defense in mitigating progressive collapse (Xiao and Hedegaard, 2018) (vid. Fig. 1(b)). The development of CA depends on various parameters such as adequate rotational and axial restraints, geometrical, and material properties of the beam (Yu and Tan, 2013a; Elsanadedy, 2019; Wang et al., 2020c).

CORRESPONDENCE Jian Yang j.yang.1@sjtu.edu.cn School of Naval Architecture, Ocean and Civil Engineering, Shanghai Jiao Tong University, Shanghai 200240, China

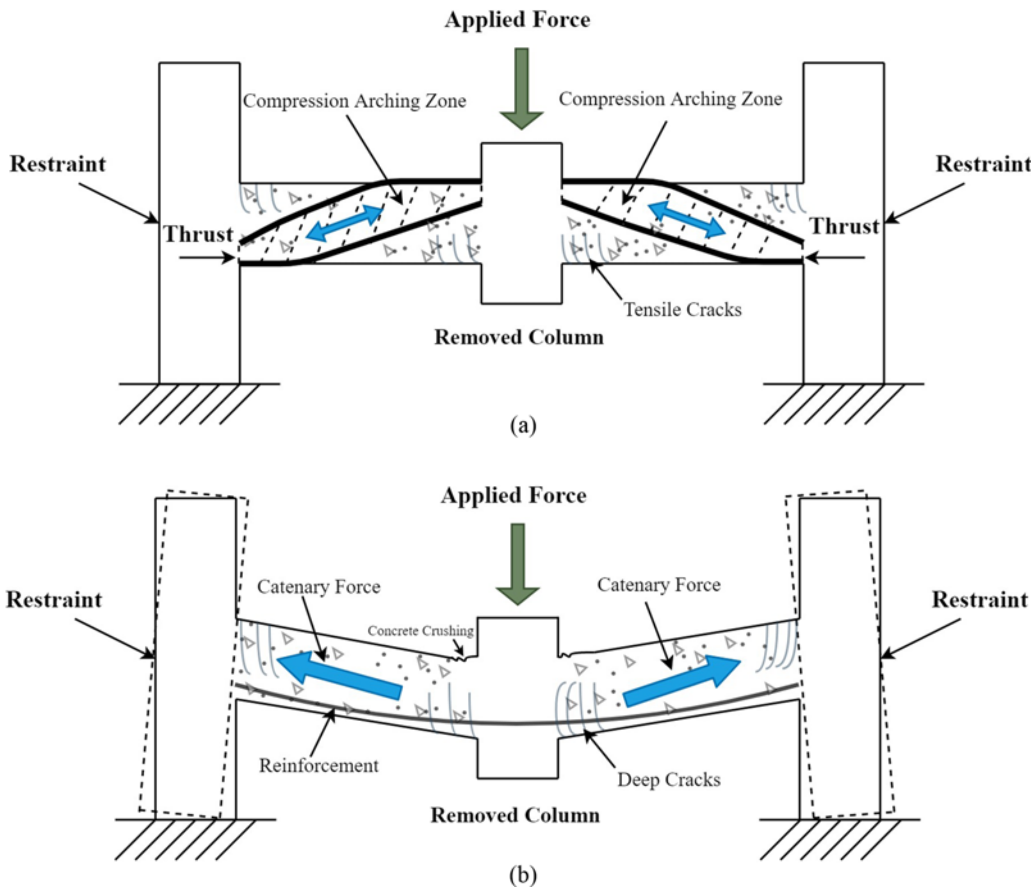

Fig. 1. Development of (a): Compressive Arch Action in RC Beam-Column Substructures, (b) CA in RC Beam-Column Substructures (Azim et al., 2020a)

Previous studies proposed numerous analytical models to formulate the CA capacity (f_c) of restrained RC beams (Jian and Zheng, 2014; Li et al., 2014; Nav et al., 2016; Pham and Tan, 2017; Harry and Lu, 2019; Wang and Kang, 2019). However, they are subject to assumptions and restrictions, which can also affect the accuracy. They are also restricted to a very limited database. Moreover, other techniques such as numerical modelling require good modelling skills, deep understanding of the finite element method and huge computing resources. Therefore, there is a need to develop simple models by using the soft computing techniques to solve complex structural problems, which involve geometrical and material non-linearities. This paper presents a prediction model by utilizing the distinctive properties of GEP to accurately predict f_c. To the best knowledge of the authors, no prediction models exist in literature to formulate f_c of RC beam-column substructures. Recently, Azim et al. (2020c) predicted the CAA capacity of such substructures. Hence, this study is dedicated to fill this research gap and employ soft computing techniques to formulate simplified empirical relations to predict f_c. The results produced by the GEP are compared with those attained from the regression analysis to prove the supremacy of the evolutionary algorithms. The GEP based model performance is evaluated through statistical errors and external validation criteria available in literature. The established GEP model correlates f_c of RC beam-column substructures with six influencing factors i.e. double-beam span-to-depth ratio ($\frac{L}{d}$), axial restraints stiffness normalized by the beam axial stiffness (α), rotational restraints stiffness normalized by the rotational stiffness of beam ends (β), bottom and top longitudinal reinforcement ratios (ρ_t, ρ_b), and yield strength of longitudinal steel rebars (f_y). A comprehensive database of RC frame substructures subjected to loading (quasi-static) is collated based on internationally published experimental studies results.

2. Gene Expression Programming

In 1960, John Holland (1975) proposed genetic algorithm (GA). The algorithm was based on the genetic operators of Darwin's theory of evolution such as reproduction, mutation, and crossover that were applied to computer systems. The solutions in GA are presented in chromosomes of fixed length. In 1985, Cramer (1985) invented genetic programming (GP) by applying GAs to evolve programs and presented the solutions in non-linear tree-like structures as opposed to the fixed length binary strings of GA. A fitness function is utilized by GP to evaluate every program, which also functions as the objective function which the algorithm targets to optimize (Gandomi et al., 2011b). GP is a variant of GA as the initial random population of individuals

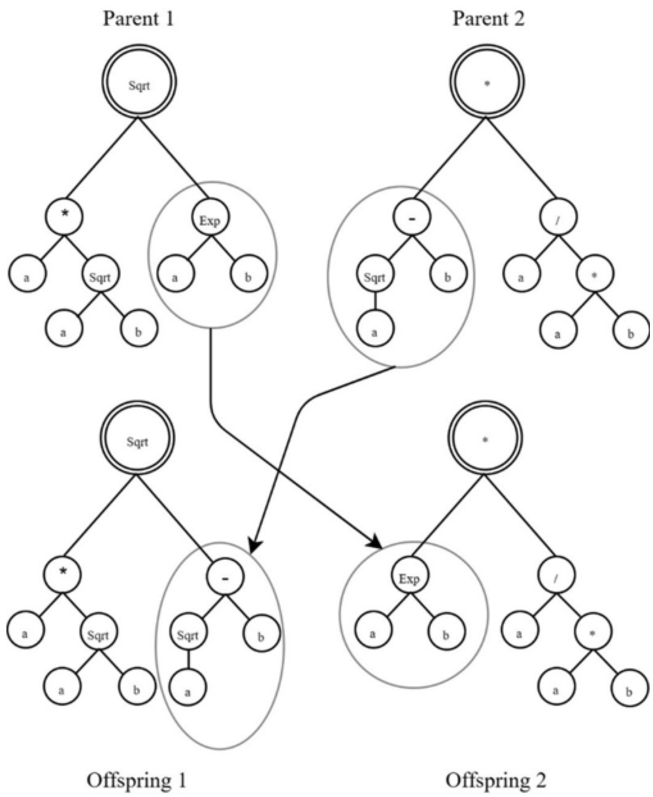

Fig. 2. A Typical Example of Crossover Operation in GP

is first generated by choosing them according to a specified fitness function. The genetic variations are introduced with the help of genetic operators at the end (Ferreira, 2006). GP was further developed by Koza (1994) by experimenting on symbolic regression. During the reproduction stage, a strategy is defined to kill the worst fitness trees during the reproduction stage and the surviving population is combined (Saridemir, 2010). The crossover operation produces offspring population by replacing the branches of two parent trees. By this operation, a mix is created to create fitness of the next level by mixing different parts of the trees (vid. Fig. 2). The mutation operation inhibits the premature convergence of the model by substituting a randomly selected node with another one from the same set (Saridemir, 2010), excluding itself as shown in Fig. 3. In GP, only the crossover operation is used to

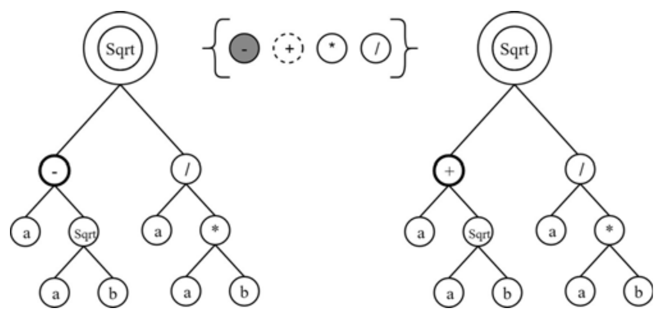

Fig. 3. Process of Mutation in GP

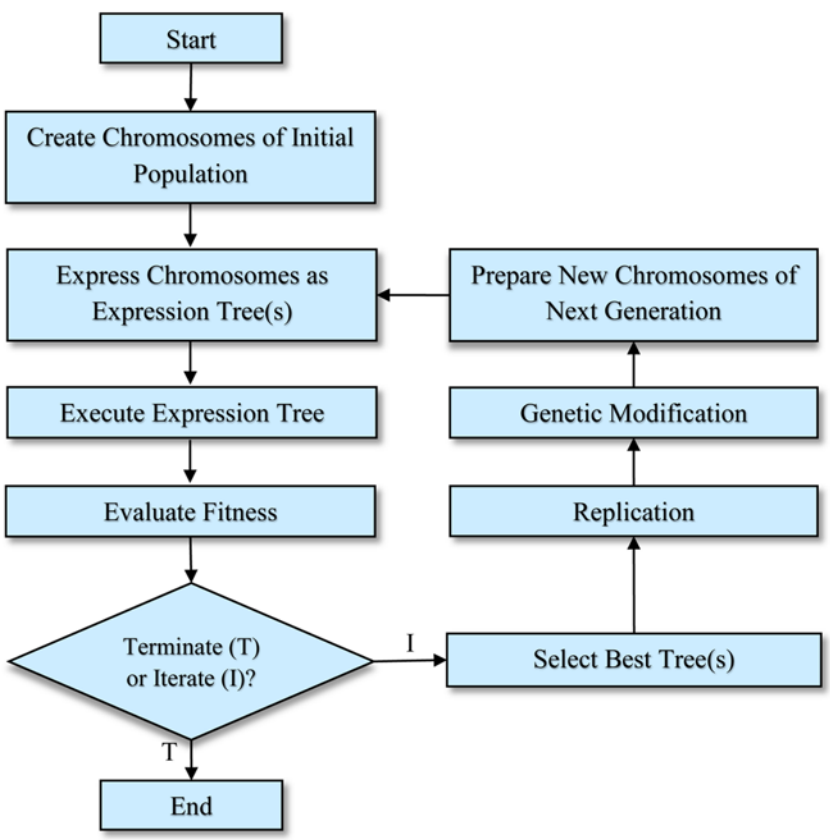

Fig. 4. Flow Diagram of the GEP Algorithm

make enormous population of parse trees. This is one of the drawbacks of this technique. Similarly, GP does not have simple and autonomous genome.

GEP is a modified version of GP proposed by Ferreira (2001) based on evolutionary algorithms. It inherits linear chromosomes from GA and trees-like structures from GP (Iqbal et al., 2020). GEP consists of five key components that are usually specified to solve practical problems: the function set, terminal set (which consists of pre-selected constants and problem related variables), fitness function, control parameters, and termination condition (Gandomi and Roke, 2015; Javed et al., 2020a; Murad, 2020). It utilizes the fixed length strings as its genotypes whose linearity, shape, and size are changed at later phases and expressed as phenotypes i.e., parse trees (also termed as expression trees (ETs)) with distinct shapes and sizes which represents chromosomes (Gandomi et al., 2013). Hence, this algorithm separates the genotype from phenotype and thus the programming can receive all the evolutionary advantages. The ETs are composed by single chromosome that consists of one or multiple genes (Murad et al., 2019). The genes are further divided into head and tail. To generate new individuals, ETs go through the selection procedure directed according to their fitness by roulette wheel selection, which assures the survival and replication of the finest individual to the subsequent generation (Gandomi and Roke, 2015). During the reproduction stage, genetic operators (crossover, mutation, and rotation) are used by the algorithm to introduce variations in the population by modifying the chromosomes (Javed et al., 2020b). Fig. 4 shows a sketch of the GEP evolutionary algorithm.

GEP technique needs two languages: the language of genes and the language of ETs. The main benefit of GEP is that it can produce chromosomes. The chromosomes are used to present any parse tree. To achieve this objective, *Karva* language is introduced, which is used to read and express the programmed information in the chromosomes (Ferreira, 2003). The *K*-expressions, from the *Karva*, are converted to ETs. The ETs are decoded to attain a mathematical formulation able to forecast the dependent variable in terms of the selected independent variables (Ferreira, 2006).

3. Data Collection

The data used in the model development is collected after extensive literature review of internationally published documents. The data is collected from 30 various studies (Bazan, 2008; He and Yi, 2008; Su et al., 2009; Tsai et al., 2013; Yu and Tan, 2013a; Ren et al., 2014; Yu and Tan, 2014; Kim and Choi, 2015; Tsai and Chang, 2015; Qian et al., 2015; Ahmadi et al., 2016; Alogla et al., 2016; Rashidian et al., 2016; Ren et al., 2016; Smith, 2016; Lu et al., 2017; Yu and Tan, 2017; Weng et al., 2017; Lim et al., 2017a; Lim et al., 2017b; Elsayed et al., 2019; Pham and Tan,

Table 1. Sample Datasets from Collated Database (Yu and Tan, 2013a; Lim et al., 2017b; Su et al., 2009)

Ref.	Depth of beam (d) (mm)	Width of beam (b) (mm)	Cylindrical compressive strength of concrete (f'_c) (MPa)	Total net span (L) (mm)	Double beam span-to-depth ratio (L/d)	Top rebars ratio ρ_t (%)	Bottom rebars ratio ρ_b (%)	Axial restraint stiffness (K_a) (kN/m)	Ratio of axial restraint stiffness to beam axial stiffness (α)	Rotational restraint stiffness (K_r) (kN-m/rad)	Ratio of rotational restraint stiffness to rotational stiffness of beam ends (β)	Yield strength of longitudinal rebars (f_y) (MPa)	Actual CA capacity (f_c) (kN)	Predicted CA capacity (kN)
Yu and Tan, 2013a	250	150	31.2	5,750	23	0.9	0.49	1.06E+05	0.59	1.00E+04	2.66	511	68.91	69.65
	250	150	31.2	5,750	23	0.73	0.49	1.06E+05	0.59	1.00E+04	2.66	511	67.63	64.27
	250	150	38.2	5,750	23	1.24	0.82	4.29E+05	2.22	3.00E+04	7.46	494	103.68	102.01
	250	150	38.2	5,750	23	1.24	1.24	4.29E+05	2.22	3.00E+04	7.46	494	105.07	109.22
	250	150	38.2	5,750	23	1.87	0.82	4.29E+05	2.22	3.00E+04	7.46	494 (ϕ13), 513 (ϕ16)	143.28	144.68
	250	150	38.2	4,550	18.2	1.24	0.82	4.29E+05	1.76	3.00E+04	5.90	494	105.99	91.96
	250	150	38.2	3,350	13.4	1.24	0.82	4.29E+05	1.29	3.00E+04	4.35	494	91.83	80
Lim et al., 2017b	180	100	25.6	4,620	25.67	1.52	1.01	1.00E+06	9.65	2.00E+04	17.87	507	70.90	61.85
	180	100	25.6	4,620	25.67	1.52	1.01	1.00E+06	9.65	2.00E+04	17.87	507	68.50	61.85
	180	100	25.6	4,620	25.67	2.02	1.33	1.00E+06	9.65	2.50E+04	22.34	400	76.00	79.27
	180	100	25.6	4,620	25.67	1.52	1.01	1.00E+05	1.45	1.00E+04	8.93	507	34.10	36.31
	180	100	25.6	4,620	25.67	1.52	1.01	1.00E+05	0.96	1.00E+04	8.93	507	67.00	61.25
Su et al., 2009	300	150	25.84	2,700	9	0.55	0.55	1.00E+06	2.51	1.75E+04	1.46	350	93.1	88.42
	300	150	28.24	2,700	9	0.83	0.83	1.00E+06	2.40	1.75E+04	1.40	350	140	139.15
	300	150	31.2	2,700	9	1.13	1.13	1.00E+06	2.29	1.75E+04	1.33	340	178	165.14
	300	150	23.04	2,700	9	0.55	0.38	1.00E+06	2.66	1.75E+04	1.55	350 (ϕ12), 340 (ϕ14)	45.9	57.10
	300	150	26.48	2,700	9	0.83	0.55	1.00E+06	2.48	1.75E+04	1.45	350	58.1	65.94
	300	150	28.64	2,700	9	1.13	0.75	1.00E+06	2.39	1.75E+04	1.39	340	144	136.01
	300	150	21.12	5,700	19	1.13	0.75	1.00E+06	5.86	1.75E+04	3.42	340	90.2	82.06
	200	100	15.92	2,700	13.5	1.3	1.3	1.00E+06	7.20	1.75E+04	9.45	350	65.7	71.31
	200	100	16.8	2,700	13.5	1.3	1.3	1.00E+06	7.01	1.75E+04	9.20	350	77.6	71.87
	200	100	16.32	2,700	13.5	1.3	1.3	1.00E+06	7.11	1.75E+04	9.33	350	54.4	71.56

2019; Deng et al., 2020; Diao et al., 2020; Qian et al., 2020; Qiu et al., 2020; Qiang et al., 2020; Vieira et al., 2020; Yang et al., 2020; Zhang et al., 2020) dedicated to study planar substructures subjected to static loading. Though, many studies are carried out on the contributions of neighboring structural elements, for instance slabs (Qian and Li, 2012; Qian and Li, 2015a; Qian and Li, 2015b; Qian et al., 2016; Qian and Li, 2017; Nyunn et al., 2019; Weng et al., 2020) and transverse beams (Weng et al., 2017; Shah et al., 2019). Table 1 shows the data of some of the specimens used in the development of the model in this study.

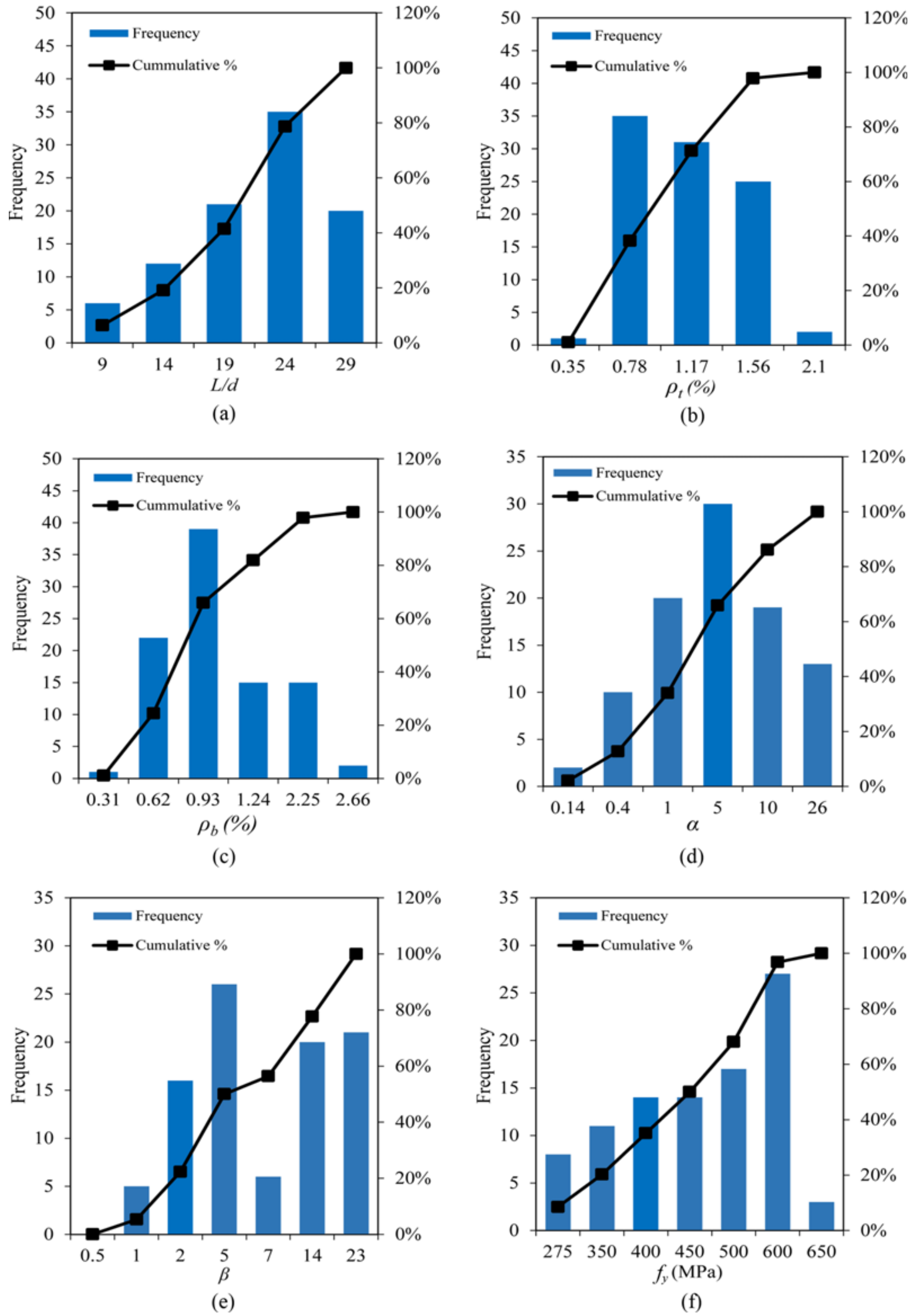

Fig. 5. Distribution Histograms of the Input Variables Used in Development of the Model: (a) Span-to-Depth Ratio, (b) Top Reinforcement Ratio, (c) Bottom Reinforcement Ratio, (d) Normalized Axial Restraints Stiffness, (e) Normalized Rotational Restraints Stiffness, (f) Yield Strength of Rebars

The collected data consists of the width (b) & depth (d) of the beam, double beam span length (L), span-to-depth ratio (L/d), axial restraints stiffness (K_a), rotational restraints stiffness (K_r), normalized axial restraints stiffness (α), normalized rotational restraints stiffness (β), bottom and top reinforcement ratios at the beam-column joints (ρ_t & ρ_b), and yield strength of rebars (f_y). α and β were calculated by using the relationships given below:

$$\alpha = \frac{K_a}{\frac{E_c A}{L}}, \tag{1}$$

$$\beta = \frac{K_r}{\frac{4E_c I}{L}}, \tag{2}$$

where $\frac{E_c A}{L}$ is the beam axial stiffness; $\frac{4E_c I}{L}$ is the rotational stiffness of the beam ends; E_c represent the modulus of elasticity concrete; I represent the second moment of inertia of an uncracked concrete section of the beam; A represent the cross-sectional area of the beam.

Some of the studies used concrete cubes to test the concrete compressive strength. Cylindrical compressive strengths of the concrete specimens were taken to be 80% of the cubes strength as suggested in (Elwell and Fu, 1995). Also, E_c was not provided in some of the experimental studies. The below relationship was used to calculate E_c as provided in ACI 318-14 (2014) as given below:

$$E_c = 4700\sqrt{f_c'}. \tag{3}$$

The visual representation of the independent variables considered in the development of the model is represented by the frequency histograms as shown in Fig. 5. Various statistical measures of the input variables considered in the model development are summarized in Table 2.

One of the primary objectives of machine learning techniques is to provide solutions that not only do well on the learning data set but on the unseen data as well (Shahrara et al., 2017). This ability of a model is called 'generalization capacity', while failure in showing this ability is known as the 'overfitting of data'. Overfitting is one of the main issues in these techniques (Kalfat et al., 2016). It is typically the outcome of an overly trained algorithm, which gives higher testing error as compared to learning stage. In order to counter overfitting and consequently enhance the generalization capacity, it is suggested to test the established model on a validation set. In this study, the same technique was applied to avoid overfitting of the model (Shahrara et al., 2017). The datasets were classified into learning, validation, and testing sets. The learning and validation sets are sometimes collectively called training set, and the testing set is called validation set. The model was first trained on the training set (genetic evolution) and validation set was used to validate the robustness of the model. The validated model which performed well in the training stage was then tested on the unseen data. The datasets in the testing set were carefully curated in which the input parameters spanned over various ranges. The uniform division of the datasets was achieved by finding the consistent various statistical properties such as mean, range, standard deviation etc. in the learning and validation sets of the involved input parameters (Gandomi et al., 2012). The collected data contains 94 specimens out of which 66% were used in the learning phase of the model, and 34% datasets were utilized for the validation and testing of the developed model on unseen data.

Various input parameters which are used in the model development might be interdependent. Interdependency is required to be checked prior to the model development as it makes the model difficult to interpret. Smith (1989) suggested that if the

Table 3. Correlation Coefficients between the Selected Input Parameters

	L/d	ρ_t (%)	ρ_b (%)	α	β	f_y
L/d	1	0.42	-0.05	0.16	0.50	0.45
ρ_t (%)	0.42	1	0.33	0.23	0.42	0.20
ρ_b (%)	-0.05	0.33	1	0.35	0.31	-0.05
α	0.16	0.23	0.35	1	0.64	-0.06
β	0.50	0.42	0.31	0.64	1	-0.005
f_y	0.45	0.20	-0.05	-0.06	-0.005	1

Table 2. Statistical Parameters of the Input Variables Used in the GEP Model

Parameter	L/d	ρ_t (%)	ρ_b (%)	α	β	f_y
Mean	19.89	0.965	0.897	4.25	7.59	442.57
Standard error	0.57	0.035	0.046	0.448	0.698	9.37
Median	22.95	1.01	0.82	2.46	5.05	451
Mode	23	1.24	0.82	10.03	20.82	275
Standard deviation	5.48	0.343	0.451	4.34	6.76	90.83
Sample variance	30.01	0.118	0.203	18.86	45.75	8,250.22
Kurtosis	-0.98	0.046	3.22	4.68	-0.51	-0.64
Skewness	-0.47	0.398	1.57	1.60	0.93	-0.13
Range	19.57	1.67	2.35	25.55	21.76	368.20
Minimum	9	0.350	0.31	0.14	0.58	275.00
Maximum	28.57	2.02	2.66	25.69	22.34	643.20

value of correlation coefficients between two input parameters is >0.80, then there exists a strong correlation. The coefficients are checked for all the likely combinations between the input variables (vid. Table 3). The table shows that the values of correlation coefficients are well below 0.80 (both negative and positive), hence showing no problem of ‘interdependency’.

4. Development of Model Using GEP

The choice of the parameters involved in the modelling affect the model’s generalization ability. The fitting parameters for the model were chosen on the basis of the recommendations in literature (Gandomi et al., 2011a; Gandomi et al., 2011b). The number of chromosomes govern the running time of the model. The architecture of the evolved models depends on its number of genes and the head size. The latter controls the complexity of every mathematical term, while the former dictates the number of terms in the evolved models. In a model with number of genes > 1, a linking function such as addition, multiplication, subtraction or division is utilized to link sub-ETs (Murad et al., 2020). In the model development, several combinations of parameters settings for the GEP algorithm were tried. Three different number of chromosomes (30, 50, and 100), four optimal head size levels (7, 8, 10, and 12), four optimal levels for number of genes (3, 4, 5, and 6), and two linking functions such as multiplication and addition were considered. The model was developed by using GeneXproTools v5.0.

The model with the optimal parameters was selected by minimizing the fitness function and statistical parameters described in Section 5. The settings of the parameters for the final GEP-based model are shown in Table 4. Thus, the basic form of f_c could be presented as

$$f_c = f\left(\frac{L}{d}, \rho_t, \rho_b, \alpha, \beta, f_y\right). \tag{4}$$

5. Performance Measures

In this study, the models’ performance is measured by calculating correlation coefficient (R), root mean square error (RMSE), root square error (RSE), mean absolute error (MAE), and performance index (ρ). ρ can be calculated by Eq. (5)

$$\rho = \frac{RRMSE}{1+R}, \tag{5}$$

where RRMSE stands for relative root mean square error.

It should be noted that due to the sensitivity of R to division and multiplication, it cannot be considered as the only measure of a model’s accuracy (Iqbal et al., 2020). A value of $R > 0.8$ is considered to be acceptable (Gandomi et al., 2011a). A model can make prediction with high accuracy if the value of R is greater, while those of the RMSE, MAE, RSE, and ρ are minimum.

The ρ ranges from 0 to +∞ with a value near to zero designating better performance of a model and vice versa. If the value of $\rho <$ 0.2, it shows better agreement between the predicted and the experimental/actual values (Gandomi and Roke, 2015). In order to address the issue of over-fitting, a function called objective function (OBJ), is evaluated as proposed in the literature (Gandomi and Roke, 2015; Iqbal et al., 2020). Eq. (6) is used to calculate OBJ and is termed as the fitness function. It simultaneously considers the effect of the relative percentages of datasets in the two datasets and statistical errors (R and RRMSE). Therefore, the value of OBJ (0 for perfect fitting) can be an effective parameter to judge the overall performance of the trained model.

$$OBJ = \left(\frac{n_T - n_V}{n}\right)\rho_T + 2\left(\frac{n_V}{n}\right)\rho_V \tag{6}$$

where n_T and n_V are the number of datasets in the training and validation sets, respectively; ρ_T and ρ_V are the performance indexes of the training and validation set, respectively; n is the total number of datasets in the training set.

Table 4. Parameter Settings for the Final GEP Model

Parameter		Setting
Chromosomes		50
	Genes	6
General	Head size	12
	Tail size	13
	Linking function	Addition
	Fitness function	RMSE
	Function set*	+, −, ×, ÷, 1/x, √, exp, pow, ³√, x³

Note: In the functions set, ‘exp’ and ‘pow’ refers to exponential and power functions, respectively.

6. Results and Discussion

A simplified relationship for forecasting the CA resistance of RC beam-column substructures based on the GEP algorithm is shown in Eq. (7). The model was finalized after numerous trials for the minimum OBJ value of 0.074.

$$\begin{aligned} f_c = {} & \frac{2.29}{\beta}\left[7.18^{\rho_t}(\rho_t + 2.86) + \rho_b^{(8.93-\alpha)}\right] + \frac{1}{1.53^{\rho_b}}\left(\beta - \frac{3.82}{\alpha} - 34.47\right) + \\ & \frac{1}{\left(8.5\times 10^{-5}\rho_t\alpha^{\beta} - \frac{\rho_t - \rho_b}{98.33\alpha}\right)^{1/3}} - \frac{15}{\left[2.3^{(\rho_t f_y - L/d)\left(\frac{-0.28}{L/d}\right)} - \rho_t\right]\beta} + \\ & \frac{1}{\left[\frac{L/d - 0.744 L/d\alpha^{1/3}}{f_y}\right]^{1/3}} + \frac{1}{\beta - 7.4} + 2.29e^{\rho_b} - \beta + 75.47. \end{aligned} \tag{7}$$

The above expression contains mathematical operators, constants, and variables, is derived from the sub-ETs shown in Fig. 6. In the figure, the 6 sub-ETs (from the 6 genes considered in the model development) encode the various portions of the complicated solution of the problem modeled, and are linked by the arithmetic operator addition. The sub-ETs are read from left to right and from top to bottom. The variables in the figure are

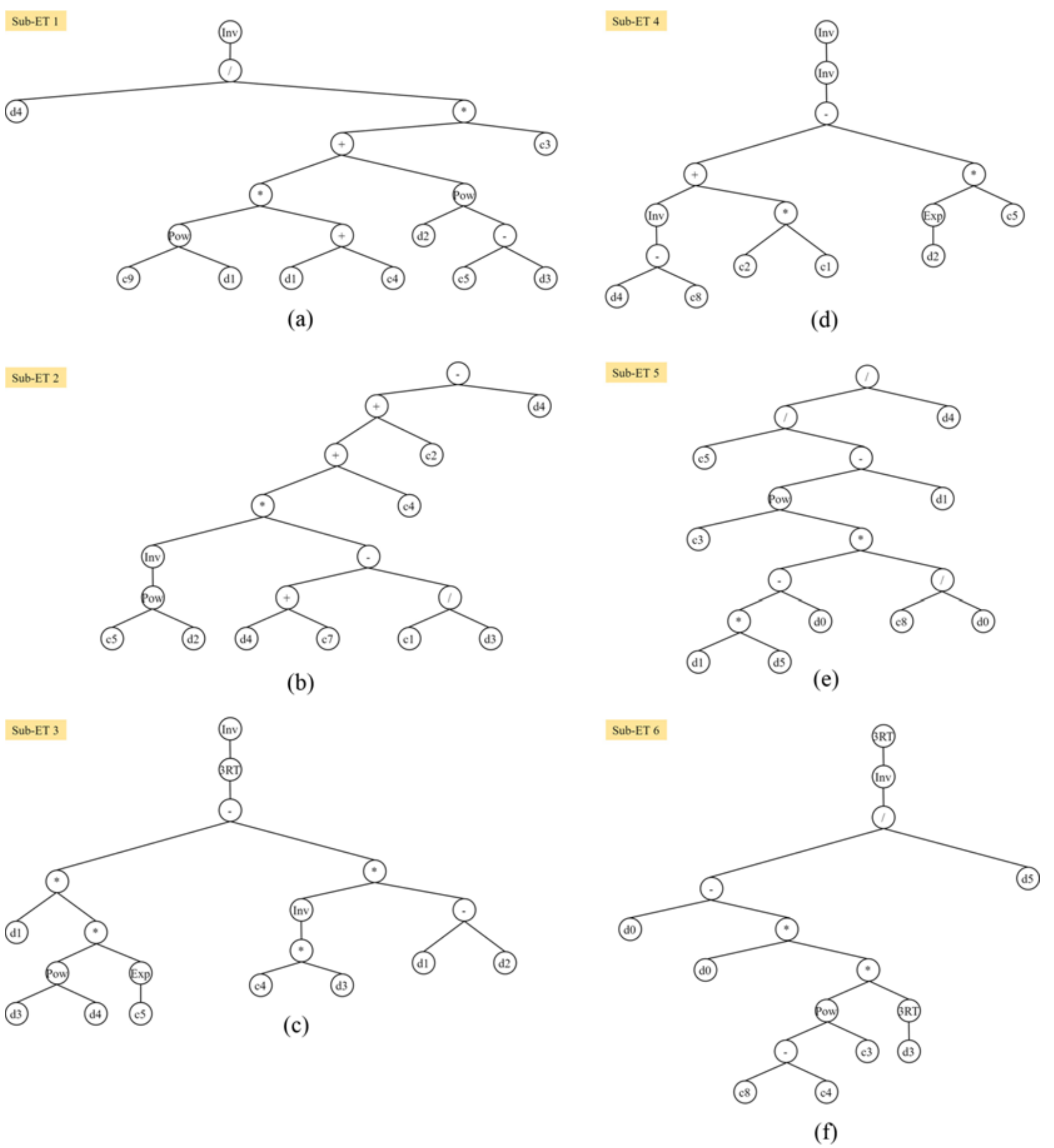

Fig. 6. Expression Tree of the Final GEP Model with Addition as the Linking Function for f_c: (a) Sub-ET 1, (b) Sub-ET 2, (c) Sub-ET 3, (d) Sub-ET 4, (e) Sub-ET 5, (f) Sub-ET 6

Table 5. Variables Notations and Constants Values in the ET of the Developed Model

Variables		Constants											
		Sub-ET1		Sub-ET2		Sub-ET3		Sub-ET4		Sub-ET5		Sub-ET6	
d0	L/d	c3	2.29	c1	3.83	c4	98.33	c1	-7.69	c3	2.30	c3	-1.23
d1	ρ_t	c4	2.86	c2	8.49	c5	-9.37	c2	-7.96	c5	-15.02	c4	-3.21
d2	ρ_b	c5	8.94	c4	5.98			c5	-2.29	c8	-0.28	c8	-1.94
d3	α	c9	7.18	c5	1.53			c8	7.41				
d4	β			c7	-34.47								
d5	f_y												

represented by the letter 'd', while the constants are represented by 'c'. Both the letters are followed by a number. The notations for the input variables and constants in the sub-ETs are shown in Table 5. After the derivation of equation, it is then simplified by using MatchCad software. Each sub-ET represents an individual feature of the problem under consideration to develop a meaningful

Table 6. Statistical Indicators of the Developed GEP Model for the Training Phase

Statistical parameter	R	MAE	RMSE	RSE	RRMSE		GEP predicted/actual		
							Average	SD	COV
GEP	0.96	9.06	11.34	0.06	0.13	0.069	1.05	0.204	0.195

solution. It is recommended to start from basic functions set (+, −, ×, ÷), single gene chromosomes and small head size (usually from 7). The algorithm begins by creating an initial population of suitable solutions, and iteratively evolves from generation to generation towards the best solution (Azim et al., 2020b). On the basis of the fitness function (RMSE in this study), selection inside the population of solutions takes place in GEP algorithm. The algorithm was run until the values of R and the fitness function do not change significantly. Other statistical measures such as RMSE, MAE, RSE etc. are calculated, and the OBJ function is also calculated for the trained model after the algorithm is stopped. In the next iterations, number of genes, head size, and mathematical functions in the functions set are increased, while a linking function is also selected (addition in this study).

The summary of the optimal parameters used in the modelling the GEP based model is shown in Table 4. The final model was selected after comparing the performance of the models with various combinations of GEP algorithm's parameters in the training and testing sets. The evolutionary number of generations also play a vital role in the success of a model. The model was stopped after 56305 generations, and the algorithm was stopped when no noteworthy changes were observed.

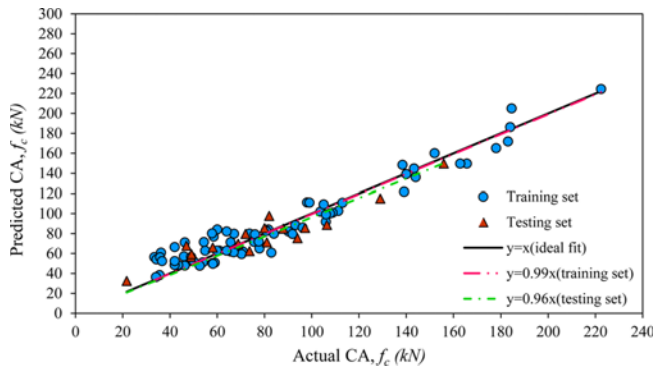

Fig. 7. Actual vs. Predicted f_c Using the GEP Model

Table 7. External Validation of the Developed GEP Model

S. No.	Equation	Condition	GEP	Reference
1	$R_{testing} = \dfrac{\sum_{i=1}^{n}(x_i-\bar{x}_i)(y_i-\bar{y}_i)}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x}_i)^2\sum_{i=1}^{n}(y_i-\bar{y}_i)^2}}$	$R > 0.8$	0.94	(Frank and Todeschini, 1994)
2	$q^2 = 1-\dfrac{\sum_{i=1}^{test}(x_{i_{testing}}-y_{i_{testing}})^2}{\sum_{i=1}^{test}(x_{i_{testing}}-\bar{x}_{i_{training}})^2}$	$q^2 > 0.5$	0.861	(Tropsha et al., 2003)
3	$k_{testing} = \dfrac{\sum_{i=1}^{n}(x_i\times y_i)}{y_i^2}$	$0.85 < k < 1.15$	0.963	(Golbraikh and Tropsha, 2002)
4	$k'_{testing} = \dfrac{\sum_{i=1}^{n}(x_i\times y_i)}{y_i^2}$	$0.85 < k' < 1.15$	1.02	
5	$n = \dfrac{R_{testing}^2-R_{o_{testing}}^2}{R_{testing}^2}$	$n < 0.10$	-0.098	(Tropsha et al., 2003)
6	$m = \dfrac{R_{testing}^2-R_{o_{testing}}'^2}{R_{testing}^2}$	$m < 0.10$	-0.125	
	where	$R_o^2 \cong 1$	0.985	
	$R_{o_{testing}}^2 = 1-\dfrac{\sum_{i=1}^{n}(y_i-x_i^o)^2}{\sum_{i=1}^{n}(y_i-\overline{y_i^o})^2},\ x_i^o = k\times y_i$			
	$R_{o_{testing}}'^2 = 1-\dfrac{\sum_{i=1}^{n}(x_i-y_i^o)^2}{\sum_{i=1}^{n}(x_i-\overline{x_i^o})^2},\ y_i^o = k'\times y_i$	$R_o'^2 \cong 1$	0.997	

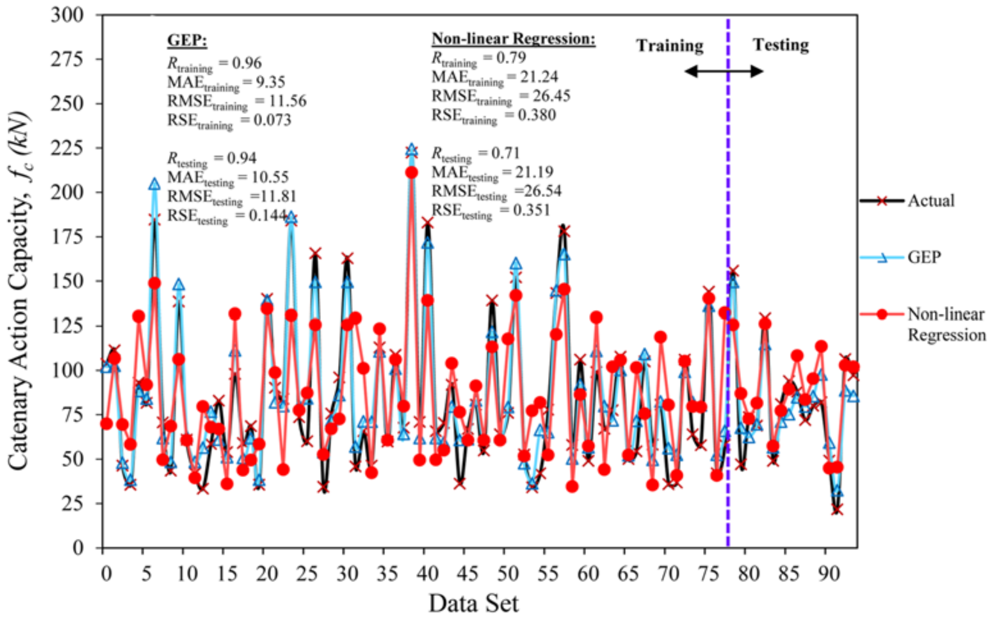

Fig. 8. Graphical Comparison of f_c Predicted by Using GEP Algorithm and Non-linear Regression Method

6.1 Validity and Performance Analysis of GEP Model

The number of datasets used in the model development are also important as the final model rely on them. Numerous researchers have recommended that the least ratio of the total number of datasets to the number of input parameters must be ≥5 (Frank and Todeschini, 1994). In this paper, it is approximately 94/6 ≈ 16, which is higher than the recommended threshold. Fig. 7 compare the predicted and actual values for the training and testing sets. The figure also shows the regression lines and its slopes for both the datasets. For an ideal fit case, the slope of the regression line is taken as 1. The values of the slopes for the training and testing sets are 0.99 and 0.96, respectively. This indicates a strong correlation between the actual and the predicted values in both the sets.

Various statistical measures such as RMSE, MAE, RSE, and ρ are calculated to further highlight the performance of the GEP-based model in the training stage (vid. Table 6). Considering Table 6, the value of R is >0.80, suggesting a strong correlation between the actual/experimental and the predicted values. Similarly, other indicators; for example: RMSE, MAE, RSE, RRMSE, and ρ are low which indicate the high predictive capability of the model with high precision.

In order to evaluate the true predictive ability of the proposed GEP model, Golbraikh and Tropsha (2002) and Tropsha et al. (2003) suggested external validation criteria on the testing set. The selected criteria for the GEP model and the related results are shown in Table 7. The table shows that all the criteria are satisfied, which suggest that the developed model hold the prediction ability and not just a correlation.

The comparison of the GEP model with the actual data and also with the non-linear regression model is shown in Fig. 8. For the sake of comparison, the statistical parameters are shown separately for the regression model, although there is no such concept of training and testing of data in regression analysis. The formulations obtained on the basis of the non-linear regression analysis are presented below in Eq. (8):

$$f_c = -2.5L/d^{0.97} + 4.62\rho_t^{4.16} + 3.98\rho_b^{3.16} - 2.85\alpha^{0.7} - 53.44\beta^{0.25} - 0.29f_y^{0.83} + 252. \quad (8)$$

Figure 8 clearly shows that the GEP model exhibits the highest accuracy compared to the non-linear regression technique. The GEP model also have a better generalization performance due to similar MAE and RMSE values (Pan et al., 2009). This is owing to the fact that the regression techniques are based on the assumptions of linearity or non-linearity and normality of the residuals (Gandomi et al., 2011a). Contrarily, the GEP based models do not have such limitations and are capable of efficiently learning the complex behavior among the input and output.

7. Sensitivity Analysis

Sensitivity analysis is carried out to check the importance of each independent variable in the learning algorithms such as GEP. The analysis was performed by attaining the frequency values of each input variable for the generated models by evaluating how many times each variable contributes to the fitness. A value of 1 shows that the respective input parameter appeared in all of the best thirty programs generated by the GEP algorithm. This is a common method to conduct sensitivity analysis in GEP based studies and has been successfully used by many researchers (Gandomi et al., 2011b; Gandomi et al., 2012). The frequencies of the input parameters are shown in Fig. 9. It can also be noted from the figure that CA capacity is more sensitive to α and ρ_t than the remaining variables, which is also true from structure engineering viewpoint (Pham and

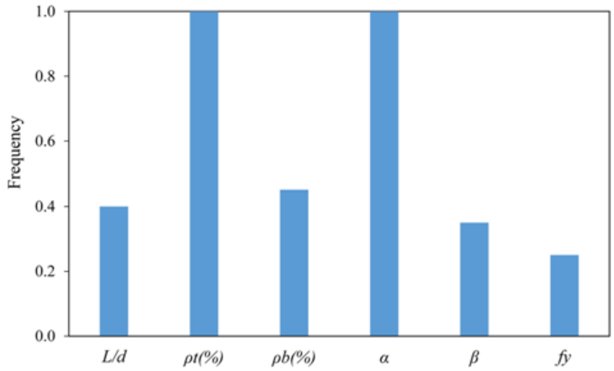

Fig. 9. Contributions of the Input Variables in the GEP-Based Model

Tan, 2017; Wang and Kang, 2019).

8. Parametric Analysis

Parametric analysis is carried out for the proposed GEP model on the basis of engineering rules and physics of the problem considered to show that the GEP formulation is not merely a combination of the independent variables which best fit the values of the response variable. Parametric analysis is another way to avoid overfitting of the model. Furthermore, better performance of a model on the training set and its validation on unseen data does not assure its robustness (Shahin et al., 2005).

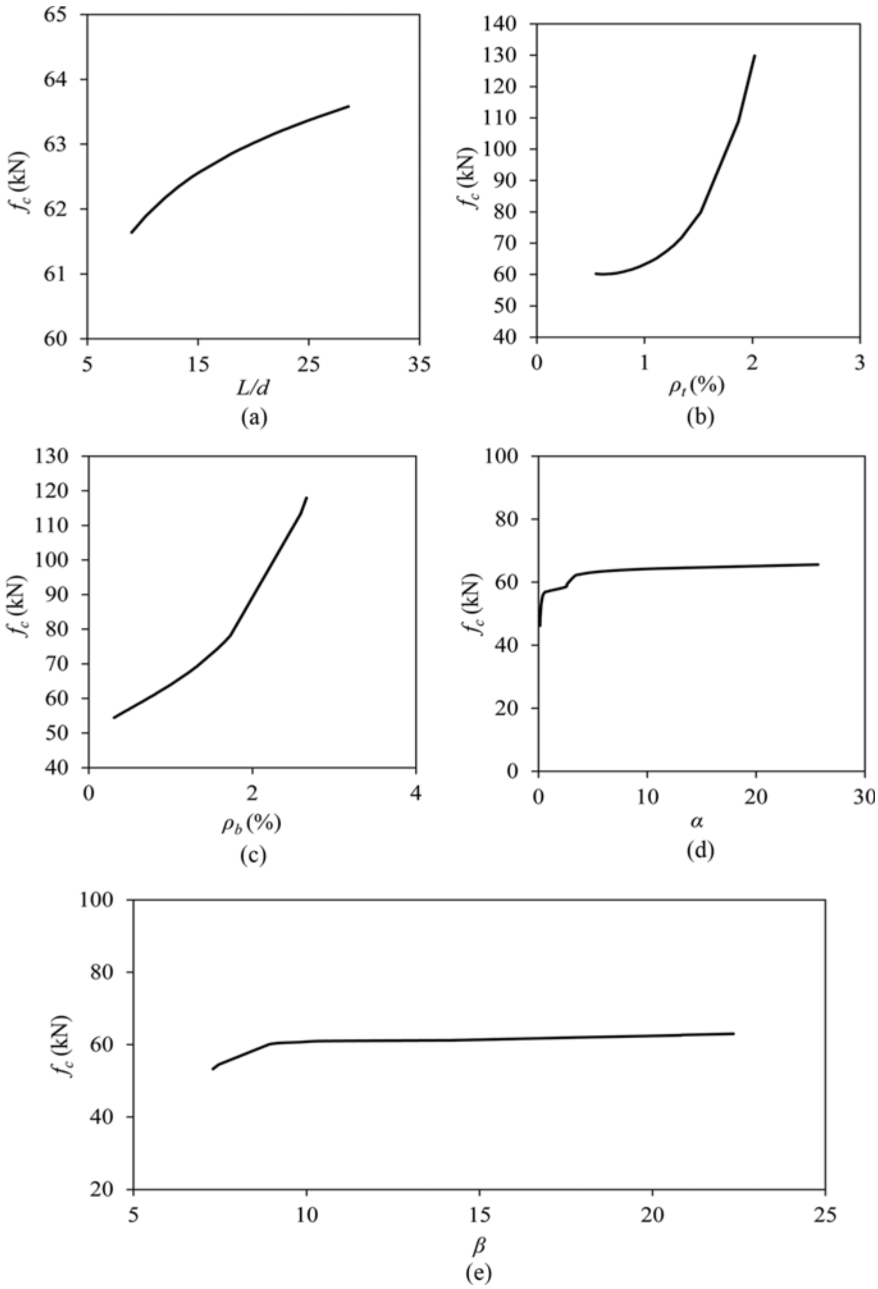

Fig. 10. Parametric Analysis Results Based on the Established GEP Model: (a) Span-to-Depth Ratio, (b) Top Reinforcement Ratio, (c) Bottom Reinforcement Ratio, (d) Normalized Axial Restraints Stiffness, (e) Normalized Rotational Restraints Stiffness

The method proposed for carrying out parametric studies in Shahin et al. (2005) is also implemented in this paper, which is to vary a single input parameter at a time while the remaining parameters are constant at the average values of their datasets. Thus, a synthetic data is generated by varying the value of a single input parameter in increments. Fig. 10 shows the parametric study results. The study is performed for the following ranges of the input parameters: L/d (9-28.57), ρ_t (0.55-2.02), ρ_b (0.31-2.66), α (0.14-25.69), and β (7.30-22.34).

Figure 10(a) shows that the value of f_c increases when the value of L/d is increased. L/d is an important structural parameter which determines the behavior of RC frame substructures. Flexure and axial are the prominent behaviors in higher L/d specimens, while the behavior of lower L/d test specimens is governed by shear and flexure. Higher L/d tests specimens mitigate progressive collapse by developing catenary resistance due to the fact that such specimens can develop sufficient deformation, a mandatory condition for establishing sufficient CA (Azim et al., 2020a). On the other hand, lower L/d specimens exhibit higher CAA capacities and lower f_c. Lower L/d specimens do exhibit CA but cannot overcome the loss in shear due to their shear dominant behavior (Tsai and Chang, 2015; Azim et al., 2020a). This parametric study is in close agreement with the studies conducted by Yu and Tan (2013a), Pham and Tan (2017), Tsai and Chang (2015) and Su et al. (2009).

Figures 10(b) and 10(c) show the effects of ρ_t and ρ_b on f_c. Generally, if the reinforcement ratio is increased at the beam-column joints, structural resistance in all the stages of the load resistance mechanisms will increase. A higher ρ_t is not only beneficial to the overall structural resistance before and after the fracture of bottom rebars but can also increase the structural resistance, especially during the CA stage. After the bottom rebars fracture, the axial forces in the beam and the applied load almost become equal due to the fact that all the resistance at this stage is offered by the top rebars. In other words, the top rebars act as a last line of defense to increase the structural resistance, and they determine the structural capacity during the CA stage. Similarly, a higher ρ_b is useful to the specimens' overall load-carrying capacity, and can provide higher progressive collapse resistance especially at the CAA stage (i.e., at small deformations) by delaying the fracture of the bottom rebars. However, this causes sudden decrease in the load resisting capacity afterwards. Thus, it can be concluded from this parametric study that by increasing ρ_t, a significant increase in f_c can be achieved. While ρ_b has minor effect on the catenary resistance of RC beam-column substructures. Similar observations were reported by Yu and Tan (2013a) and Pham and Tan (2017).

Similarly, the effects of different boundary conditions on f_c at the ends of the substructures specimens are also shown in Figs. 10(d) and 10(e). As discussed above, the axial and rotational restraints values are normalized by the respective beam axial stiffness and rotational stiffness of the beam ends. It can be noted from Fig. 10(d) that f_c is more sensitive to α when the axial restraints are weaker. CAA and CA cannot be mobilized when the axial restraints are weaker as there is no alternate path to transfer the beam's axial force. In such a scenario, the beam deflect more towards the middle joint, which results in high local rotations at both sides of the joint. Consequently, the bottom rebar near the middle joint fractures to accommodate such large deformations. However, f_c is marginally affected when the axial restraints are stronger for the synthetic data produced during this parametric study. Fig. 10(e) demonstrates the effects of rotational restraints on f_c. It can be seen from the figure, f_c is sensitive to weaker rotational restraints while the catenary resistance is marginally affected when the restraints are stronger. Therefore, it can be concluded that strong axial and rotational restraints have minor effects on f_c. The observations agree well with Pham and Tan (2017), Pham and Tan (2016), Yu and Tan (2010), and Yu and Tan (2013b). The above parametric study results certify that the proposed GEP model is accurate. In addition, it can be confidently utilized for the estimation of f_c.

9. Conclusions

The paper adopts a new method to formulate the catenary capacity of RC beam-column substructures under a missing column scenario based on the GEP algorithm. An extensive database is collated from existing literature, which consists of various input parameters considered in the modelling. The GEP model's performance is assessed by calculating various statistical measures (MAE, RMSE, RSE, RRMSE, and ρ) and several external validation criteria recommended in literature. The model not only satisfied the statistical and external validation criteria but also performed well on the unseen data, which clearly show the accuracy, prediction power and generalization capability of the model. Additional verifications are performed by comparing the GEP model with non-linear regression model. Due to the presence of non-linearity in the data, the GEP model gave better results as compared to regression models, and could be reliably use in the pre-design of RC beam-column substructures subjected to a missing column scenario. The GEP model also represented the physical relationships in the considered system very well verified by the parametric study. The inclusion of more data points in the training stage can further improve the performance of the developed model.

Acknowledgments

The corresponding author would like to thank the supports from the National Key Research and Development Program of China (Grant No. 2016YFC0701400), Science and Technology Program of Guangzhou, China (Grant No. 201704030057) and the Opening Project of State Key Laboratory of Green Building Materials.

ORCID

Iftikhar Azim https://orcid.org/0000-0001-6082-5643
Muhammad Farjad Iqbal https://orcid.org/0000-0002-5985-0902

References

ACI 318-14 (2014) Building code requirements for structural concrete. ACI 318-14, American Concrete Institute, Farmington Hills, MI, USA

Ahmadi R, Rashidian O, Abbasnia R, Mohajeri FN, Usefi N (2016) Experimental and numerical evaluation of progressive collapse behavior in scaled RC beam-column subassemblage. *Shock and Vibration* 2016:1-17, DOI: 10.1155/2016/3748435

Alogla K, Weekes L, Augusthus-Nelson L (2016) A new mitigation scheme to resist progressive collapse of RC structures. *Construction and Building Materials* 125:533-545, DOI: 10.1016/j.conbuildmat.2016.08.084

Azim I, Yang J, Bhatta S, Wang F, Liu QF (2020a) Factors influencing the progressive collapse resistance of RC frame structures. *Journal of Building Engineering* 27:100986, DOI: 10.1016/j.jobe.2019.100986

Azim I, Yang J, Iqbal MF, Javed MF, Nazar S, Wang F, Liu QF (2020b) Semi-analytical model for compressive arch action capacity of RC frame structures. *Structures* 27:1231-1245, DOI: 10.1016/j.istruc.2020.06.011

Azim I, Yang J, Javed MF, Iqbal MF, Mahmood Z, Wang F, Liu QF (2020c) Prediction model for compressive arch action capacity of RC frame structures under column removal scenario using gene expression programming. *Structures* 25:212-228, DOI: 10.1016/j.istruc.2020.02.028

Bazan ML (2008) Response of reinforced concrete elements and structures following loss of load bearing elements. PhD Thesis, Northeastern University, Boston, MA, USA

Cramer NL (1985) A representation for the adaptive generation of simple sequential programs. In: Grefenstette JJ (ed), Proceedings of the 1st international conference on genetic algorithm, 183-187

Deng X-F, Liang S-L, Fu F, Qian K (2020) Effects of high-strength concrete on progressive collapse resistance of reinforced concrete frame. *Journal of Structural Engineering* 146:4020078, DOI: 10.1061/(ASCE)ST.1943-541X.0002628

Diao M, Li Y, Guan H, Lu XZ, Gilbert PB (2020) Influence of horizontal restraints on the behaviour of vertical disproportionate collapse of RC moment frames. *Engineering Failure Analysis* 109:104324, DOI: 10.1016/j.engfailanal.2019.104324

Elsanadedy HM (2019) Residual compressive strength of high-strength concrete exposed to elevated temperatures. *Advances in Materials Science and Engineering* 2019:1-12, DOI: 10.1155/2019/6039571

Elsayed WM, Moaty M, Issa ME (2019) Effect of reinforcing steel debonding on RC frame performance in resisting progressive collapse. *HBRC Journal* 12:242-254, DOI: 10.1016/j.hbrcj.2015.02.005

Elwell DJ, Fu G (1995) Compression testing of concrete: Cylinders vs. cubes. New York State Department of Transportation and Federal Highway Administration, Albany, NY, USA

Ferreira C (2001) Gene expression programming: A new adaptive algorithm for solving problems. *Complex Systems* 13:87-129

Ferreira C (2003) Function finding and the creation of numerical constants in gene expression programming. In: Benitez J, Cordon O, Hoffman F, Roy R (eds) Advances in soft computing. Springer, London, UK, 257-265

Ferreira C (2006) Gene expression programming: Mathematical modeling by an artificial intelligence. Springer, Berlin, Germany

Frank IE, Todeschini R (1994) The data analysis handbook. Elsevier, Amsterdam, The Netherlands

Fu F (2016) Structural analysis and design to prevent disproportionate collapse. Taylor & Francis Group, London, UK

Gandomi AH, Alavi AH, Mirzahosseini MR, Nejad FM (2011a) Nonlinear genetic-based models for prediction of flow number of asphalt mixtures. *Journal of Materials in Civil Engineering* 23:248-263, DOI: 10.1061/(ASCE)MT.1943-5533.0000154

Gandomi AH, Alavi AH, Mousavi M, Tabatabaei SM (2011b) A hybrid computational approach to derive new ground-motion prediction equations. *Engineering Applications of Artificial Intelligence* 24:717-732, DOI: 10.1016/j.engappai.2011.01.005

Gandomi AH, Babanajad SK, Alavi AH, Farnam Y (2012) Novel approach to strength modeling of concrete under triaxial compression. *Journal of Materials in Civil Engineering* 24:1132-1143, DOI: 10.1061/(ASCE)MT.1943-5533.0000494

Gandomi AH, Roke DA (2015) Assessment of artificial neural network and genetic programming as predictive tools. *Advances in Engineering Software* 88:63-72, DOI: 10.1016/j.advengsoft.2015.05.007

Golbraikh A, Tropsha A (2002) Beware of q^2! *Journal of Molecular Graphics and Modelling* 20:269-276, DOI: 10.1016/S1093-3263(01)00123-1

Gandomi AH, Yun GJ, Alavi AH (2013) An evolutionary approach for modeling of shear strength of RC deep beams. *Materials and Structures* 46:2109-2119, DOI: 10.1617/s11527-013-0039-z

Harry OA, Lu Y (2019) Simplified theoretical model for prediction of catenary action incorporating strength degradation in axially restrained beams. *Engineering Structures* 191:219-228, DOI: 10.1016/j.engstruct.2019.04.043

He Q, Yi W (2008) Experimental study on collapse-resistant behavior of RC beam-column sub-structure considering catenary action. The 14th world conference on earthquake engineering, October 12-17, Beijing, China

Holland JH (1975) Adaptation in natural and artificial systems. University of Michigan Press, Ann Arbor, MI, USA

Iqbal MF, Liu Q, Azim I, Zhu X, Yang J, Javed MF, Rauf M (2020) Prediction of mechanical properties of green concrete incorporating waste foundry sand based on gene expression programming. *Journal of Hazardous Materials* 384:121322, DOI: 10.1016/j.jhazmat.2019.121322

Javed MF, Amin MN, Shah MI, Khan K, Iftikhar B, Farooq F, Fahid A, Allyousef R, Alabduljabbar H (2020a) Applications of gene expression programming and regression techniques for estimating compressive strength of bagasse ash based concrete. *Crystals* 10(9):737, DOI: 10.3390/cryst10090737

Javed MF, Farooq F, Memon SA, Akbar A, Khan MA, Fahid A, Allyousef R, Alabduljabbar H, Rehman SKU (2020b) New prediction model for the ultimate axial capacity of concrete-filled steel tubes: An evolutionary approach. *Crystals* 10:741, DOI: 10.3390/cryst10090741

Jian H, Zheng Y (2014) Simplified models of progressive collapse response and progressive collapse-resisting capacity curve of RC beam-column substructures. *Journal of Performance of Constructed Facilities* 28:04014008, DOI: 10.1061/(ASCE)CF.1943-5509.0000492

Kalfat R, Nazari A, Al-Mahaidi R, Sanjayan J (2016) Genetic programming in the simulation of Frp-to-concrete patch-anchored joints. *Composite Structures* 138:305-312, DOI: 10.1016/j.compstruct.2015.12.005

Kim J, Choi H (2015) Monotonic loading tests of RC beam-column subassemblage strengthened to prevent progressive collapse. *International Journal of Concrete Structures and Materials* 9:401-413, DOI: 10.1007/s40069-015-0119-2

Koza JR (1994) Genetic programming as a means for programming computers by natural selection. *Statistics and Computing* 4:87-112, DOI: 10.1007/BF00175355

Li Y, Lu XZ, Guan H, Ye L (2014) Progressive collapse resistance demand of reinforced concrete frames under catenary mechanism.

ACI Structural Journal 111:1225-1234

Lim NS, Tan KH, Lee CK (2017a) Experimental studies of 3D RC substructures under exterior and corner column removal scenarios. *Engineering Structures* 150:409-427, DOI: 10.1016/j.engstruct.2017.07.041

Lim NS, Tan KH, Lee CK (2017b) Effects of rotational capacity and horizontal restraint on development of catenary action in 2-D RC frames. *Engineering Structures* 153:613-627, DOI: 10.1016/j.engstruct.2017.09.059

Lu XZ, Lin K, Li Y, Guan H, Ren P, Zhou Y (2017) Experimental investigation of RC beam-slab substructures against progressive collapse subject to an edge-column-removal scenario. *Engineering Structures* 149:91-103, DOI: 10.1016/j.engstruct.2016.07.039

Murad Y (2020) Joint shear strength models for exterior RC beam-column connections exposed to biaxial and uniaxial cyclic loading. *Journal of Building Engineering* 30:101225, DOI: 10.1016/j.jobe.2020.101225

Murad YZ, Hunifat R, Wassel A-B (2020) Interior reinforced concrete beam-to-column joints subjected to cyclic loading: Shear strength prediction using gene expression programming. *Case Studies in Construction Materials* 13:e00432, DOI: 10.1016/j.cscm.2020.e00432

Murad Y, Imam R, Hajar HA, Hammad A, Shawash Z (2019) Predictive compressive strength models for green concrete. *International Journal of Structural Integrity* 11:169-184, DOI: 10.1108/IJSI-05-2019-0044

Nav FM, Abbasnia R, Rashidian O, Usefi N (2016) Theoretical resistance of RC frames under the column removal scenario considering high strain rates. *Journal of Performance of Constructed Facilities* 30:04016025, DOI: 10.1061/(ASCE)CF.1943-5509.0000867

Nyunn S, Wang F, Yang J, Liu QF, Azim I, Bhatta S (2020) Numerical studies on the progressive collapse resistance of multi-story RC buildings with and without exterior masonry walls. *Structures* 28:1050-1059, DOI: 10.1016/j.istruc.2020.07.049

Nyunn S, Yang J, Wang FL, Liu Q (2019) Nonlinear dynamic analysis on progressive collapse resistance of a multi-story reinforced concrete building with slab. In: Proceedings of the 2nd international conference in sutainable buildings and structures (ICSBS 2019). October 25-27, Suzhou, China, 121

Pan Y, Jiang J, Wang R, Cao H, Cui Y (2009) A novel QSPR model for prediction of lower flammability limits of organic compounds based on support vector machine. *Journal of Hazardous Materials* 168:962-969, DOI: 10.1016/j.jhazmat.2009.02.122

Pham AT, Tan KH (2016) Numerical and analytical studies on load-carrying mechanism of reinforced concrete beam-column structures against progressive collapse. Proceedings of the 11th fib international PhD symposium in civil engineering, August 29-31, Tokyo, Japan, 857-864

Pham AT, Tan KH (2017) A simplified model of catenary action in reinforced concrete frames under axially restrained conditions. *Magazine of Concrete Research* 69:1115-11134, DOI: 10.1680/jmacr.17.00009

Pham AT, Tan KH (2019) Static and dynamic responses of reinforced concrete structures under sudden column removal scenario subjected to distributed loading. *Journal of Structural Engineering* 145:04018235, DOI: 10.1061/(ASCE)ST.1943-541X.0002214

Qian K, Li B (2012) Slab effects on response of reinforced concrete substructures after loss of corner column. *ACI Structural Journal* 109:845-856

Qian K, Li B (2015a) Quantification of slab influences on the dynamic performance of rc frames against progressive collapse. *Journal of Performance of Constructed Facilities* 29:1-11, DOI: 10.1061/(ASCE)CF.1943-5509.0000488

Qian K, Li B (2015b) Strengthening of multibay reinforced concrete flat slabs to mitigate progressive collapse. *Journal of Structural Engineering* 141:04014154, DOI: 10.1061/(ASCE)ST.1943-541X.0001125

Qian K, Li B (2017) Dynamic and residual behavior of reinforced concrete floors following instantaneous removal of a column. *Engineering Structures* 148:175-184, DOI: 10.1016/j.engstruct.2017.06.059

Qian L, Li Y, Diao M, Guan H, Lu XZ (2020) Experimental and computational assessments of progressive collapse resistance of reinforced concrete planar frames subjected to penultimate column removal scenario. *Journal of Performance of Constructed Facilities* 34:04020019, DOI: 10.1061/(ASCE)CF.1943-5509.0001420

Qian K, Li B, Ma J (2015) Load-carrying mechanism to resist progressive collapse of RC buildings. *Journal of Structural Engineering* 141:04014107, DOI: 10.1061/(ASCE)ST.1943-541X.0001046

Qian K, Li B, Zhang Z (2016) Influence of multicolumn removal on the behavior of RC floors. *Journal of Structural Engineering* 142:04016006, DOI: 10.1061/(ASCE)ST.1943-541X.0001461

Qiang H, Yang J, Feng P, Qin W (2020) Kinked rebar configurations for improving the progressive collapse behaviours of RC frames under middle column removal scenarios. *Engineering Structures* 211:110425, DOI: 10.1016/j.engstruct.2020.110425

Qiu L, Lin F, Wu K (2020) Improving progressive collapse resistance of rc beam-column subassemblages using external steel cables. *Journal of Performance of Constructed Facilities* 34:04019079, DOI: 10.1061/(ASCE)CF.1943-5509.0001360

Rashidian O, Abbasnia R, Ahmadi R, Mohajeri Nav F (2016) Progressive collapse of exterior reinforced concrete beam–column sub-assemblages: Considering the effects of a transverse frame. *International Journal of Concrete Structures and Materials* 10:479-497, DOI: 10.1007/s40069-016-0167-2

Ren P, Li Y, Lu XZ, Guan H, Zhou Y (2016) Experimental investigation of progressive collapse resistance of one-way reinforced concrete beam-slab substructures under a middle-column-removal scenario. *Engineering Structures* 118:28-40, DOI: 10.1016/j.engstruct.2016.03.051

Ren P, Li Y, Zhou Y, Lu XZ, Guan H (2014) Experimental study on the progressive collapse resistance of RC slabs. Structure congress 2014, April 3-5, Boston, MA, USA, 868-879

Saridemir M (2010) Genetic programming approach for prediction of compressive strength of concretes containing rice husk ash. *Construction and Building Materials* 24:1911-1919, DOI: 10.1016/j.conbuildmat.2010.04.011

Sasani M, Bazan M, Sagiroglu S (2007) Experimental and analytical progressive collapse evaluation of actual reinforced concrete structure. *ACI Structural Journal* 104:731-739

Sasani M, Kazemi A, Sagiroglu S, Forest S (2011) Progressive collapse resistance of an actual 11-story structure subjected to severe initial damage. *Journal of Structural Engineering* 137:893-902, DOI: 10.1061/(ASCE)ST.1943-541X.0000418

Shah S, Wang F, Yang J (2019) Numerical modelling of structural behaviour of transverse beam under interior column removal scenario. Proceedings of the 2nd international conference in sustainable buildings and structures, October 25-27, Suzhou, China, 127

Shahin MA, Maier HR, Jaksa MB (2005) Investigation into the robustness of artificial neural networks for a case study in civil engineering. MODSIM 2005 International Congress on Modelling and Simulation: Modelling and Simulation Society of Australia and New Zealand, 7983

Shahrara N, Çelik T, Gandomi AH (2017) Gene expression programming approach to cost estimation formulation for utility projects. *Journal of Civil Engineering and Management* 23:85-95, DOI: 10.3846/13923730.2016.1210214

Smith GN (1989) Probability and statistics in civil engineering. Collins Professional and Technical Books, London, UK

Smith PP (2016) An investigation into tensile membrane action as a means of emergency load redistribution. PhD Thesis, University of Southampton, Southampton, UK

Su Y, Tian Y, Song X (2009) Progressive collapse resistance of axially-restrained frame beams. *ACI Structural Journal* 106:600-607

Tropsha A, Gramatica P, Gombar VK (2003) The importance of being earnest: Validation is the absolute essential for successful application and interpretation of QSPR models. *QSAR and Combinatorial Science* 22:69-77, DOI: 10.1002/qsar.200390007

Tsai M-H, Chang Y-T (2015) Collapse-resistant performance of RC beam–column sub-assemblages with varied section depth and stirrup spacing. *The Structural Design of Tall and Special Buildings* 24:555-570, DOI: 10.1002/tal.1199

Tsai M-H, Lu J-K, Huang B-H (2013) Effect of bar cutoff on the arch and catenary actions of RC beams under gravitational loadings. Proceedings of the thirteenth East Asia-Pacific conference on structural engineering and construction (EASEC-13), September 11-13, Sapporo, Japan

Vieira A de A, Triantafyllou SP, Bournas DA (2020) Strengthening of RC frame subassemblies against progressive collapse using TRM and NSM reinforcement. *Engineering Structures* 207:110002, DOI: 10.1016/j.engstruct.2019.110002

Wang S, Kang S-B (2019) Analytical investigation on catenary action in axially-restrained reinforced concrete beams. *Engineering Structures* 192:145-155, DOI: 10.1016/j.engstruct.2019.05.008

Wang F, Yang J, Nyunn S, Azim I (2020a) Effect of concrete infill walls on the progressive collapse performance of precast concrete framed substructures. *Journal of Building Engineering* 32:101461, DOI: 10.1016/j.jobe.2020.101461

Wang F, Yang J, Pan Z (2020b) Progressive collapse behaviour of steel framed substructures with various beam-column connections. *Engineering Failure Analysis* 109:104399, DOI: 10.1016/j.engfailanal.2020.104399

Wang F, Yang J, Shah S (2020c) Effect of horizontal restraints on progressive collapse resistance of precast concrete beam-column framed substructures. *KSCE Journal of Civil Engineering* 24(3): 879-889, DOI: 10.1007/s12205-020-1035-9

Weng J, Lee CK, Tan KH, Lim NS (2017) Damage assessment for reinforced concrete frames subject to progressive collapse. *Engineering Structures* 149:147-160, DOI: 10.1016/j.engstruct.2016.07.038

Weng YH, Qian K, Fu F, Fang Q (2020) Numerical investigation on load redistribution capacity of flat slab substructures to resist progressive collapse. *Journal of Building Engineering* 29:101109, DOI: 10.1016/j.jobe.2019.101109

Xiao H, Hedegaard B (2018) Flexural, compressive arch, and catenary mechanisms in pseudostatic progressive collapse analysis. *Journal of Performance of Constructed Facilities* 32:04017115, DOI: 10.1061/(ASCE)CF.1943-5509.0001110

Yang T, Chen W, Han Z (2020) Experimental investigation of progressive collapse of prestressed concrete frames after the loss of middle column. *Advances in Civil Engineering*, DOI: 10.1155/2020/8219712

Yu J, Gan Y-P, Wu J, Wu H (2019) Effect of concrete masonry infill walls on progressive collapse performance of reinforced concrete infilled frames. *Engineering Structures* 191:179-193, DOI: 10.1016/j.engstruct.2019.04.048

Yu J, Tan KH (2010) Macromodel-based simulation of catenary action of RC beam-column sub-assemblages. In: Proceedings of the 3rd fib international congress 2010, Washington DC, USA

Yu J, Tan KH (2013a) Structural behavior of RC beam-column subassemblages under a middle column removal scenario. *Journal of Structural Engineering* 139:233-250, DOI: 10.1061/(ASCE)ST.1943-541X.0000658

Yu J, Tan KH (2013b) Experimental and numerical investigation on progressive collapse resistance of reinforced concrete beam column sub-assemblages. *Engineering Structures* 55:90-106, DOI: 10.1016/j.engstruct.2011.08.040

Yu J, Tan KH (2014) Special detailing techniques to improve structural resistance against progressive collapse. *Journal of Structural Engineering* 140:04013077, DOI: 10.1061/(ASCE)ST.1943-541X.0000886

Yu J, Tan KH (2017) Structural behavior of reinforced concrete frames subjected to progressive collapse. *ACI Structural Journal* 114:63-74

Zhang WX, Wu H, Zhang JY, Hwang HJ, Yi WJ (2020) Progressive collapse test of assembled monolithic concrete frame spatial substructures with different anchorage methods in the beam–column joint. *Advances in Structural Engineering* 23:1785-1799, DOI: 10.1177/1369433219900679