Journal of Soft Computing in Civil Engineering 9-3 (2025) 97-116

Contents lists available at SCCE

Journal of Soft Computing in Civil Engineering

Journal homepage: www.jsoftcivil.com

Efficient Behavior Factor Estimation in Moment-Resisting Reinforced Concrete Frames through Gene Expression Programming

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https://doi.org/10.22115/scce.2024.444559.1808

ARTICLE INFO

Article history:
Received: 18 February 2024
Revised: 21 May 2024
Accepted: 11 August 2024

Keywords:
Gene expression programming (GEP);
Artificial intelligence;
Reinforced concrete frames;
Behavior factor;
Seismic behavior.

ABSTRACT

This study presents a novel approach for estimating the behavior factor of moment-resisting reinforced concrete (RC) frames using a gene expression programming (GEP) method, which involves designing and analyzing over three hundred RC frames. A comprehensive database detailing the specifications of moment-resistant RC frames has been established. This database has several influential parameters as the input parameters. The performance of the developed models was evaluated using statistical indicators, and the best model was determined. The chosen model demonstrated values of 0.0061, 0.049, and 0.0037 for root mean squared error (RMSE), mean absolute error (MAE), and mean squared error (MSE), respectively. Additionally, the R^2 values for the training and test data were 0.93 and 0.82, respectively. Finally, a highly accurate mathematical equation was obtained to predict the behavior factor of the RC frames using GeneXpro Tools software. After sensitivity analysis of the behavior factor predicted to the investigated parameters, the results indicated that seismic conditions have minimal impact on the behavior factor of moment-resisting RC frames. The number of stories has an inverse relationship with the behavior factor, while the impact of changing the span length ratio to story height on the behavior factor is not uniform. The study's findings indicated that the GEP method effectively predicted the behavior coefficient of RC frames.

How to cite this article: Azhdari N, Hashemi S. S, Javidi S, Fazeli A. Efficient behavior factor estimation in moment-resisting reinforced concrete frames through gene expression programming. J Soft Comput Civ Eng 2025;9(3):97–116. https://doi.org/10.22115/scce.2024.444559.1808

1. Introduction

According to the seismic design principle, the structures in earthquakes need energy dissipation, stiffness, and strength to resist forces and prevent collapse. This is achieved through appropriate materials, proper detailing of structural elements, and seismic-resistant systems like beams, walls, frames, and dampers. Moderate earthquakes require elastic structures, while severe earthquakes need ductile behavior to absorb energy and prevent failure. So applying the nonlinear analysis will provide a comprehensive understanding of the structures' behavior and guarantee their safety and functionality during earthquakes. While linear analysis only provides an estimate of a structure's response to seismic activity, the linear earthquake spectrum enables professionals to calculate seismic forces and visualize potential damage. Accurate estimation of ground motion can be achieved through the use of the spectrum, which facilitates the calculation of seismic forces that a structure may experience. By considering a structure's seismic response, engineers can make informed decisions regarding design and construction, which ultimately contribute to the safety of our built environment. The behavior factor or response modification factor (RMF) reduces the earthquake loads obtained from the linear spectrum to account for nonlinear effects such as material yielding and deformation capacity. Therefore, the behavior factor represents the reduction of design loads due to the overstrength and ductility of the structure [1].

The importance of accurately determining the behavior factor in seismic design cannot be overstated, as it affects the estimated seismic loads and the structure's design. Considering the interplay between the type of lateral load-resisting system used, the structural geometric properties, and the behavior factor in seismic design is essential. In this regard, extensive studies have been conducted on the behavior factor, focusing on various aspects such as determination and evaluation methods for different structural systems.

Hashemi et al. [2], investigated the RMF of RC structures utilizing bubble deck systems. The study found that the lateral strength of buildings increases with the increase in the span length to story height ratio. The results indicate that the changes in the span length and number of stories have a more significant impact on RMF compared to the variation in the usage category of buildings. Studying the seismic vulnerability of existing prefabricated RC structures indicated the importance of friction-based connections between beams and columns. The study focused on the effectiveness of dissipative connectors composed of carbon-wrapped steel tubes and proposed a simplified formula for computing the behavior factor [3]. The evaluation of the RMF value based on the Indian seismic standard has been undertaken by Mondal et al. [4], indicating an overestimation for RC moment frame buildings. Habibi et al. [5] have presented a new relation to estimating the behavior factor of irregularly RC moment resisting frames. Another study has compared the performance-based seismic evaluation of RC frames designed using direct displacement-based design (DDBD) and conventional force-based design (FBD) approaches. The DDBD approach resulted in higher energy dissipation and a higher response reduction factor than FBD. The building height was found to be a crucial factor affecting behavior factor [6]. Shandilya et al. [7] studied RC buildings with open ground stories comprising 3, 4, 5, and 6 stories, incorporating structures with and without haunches. This study used the adaptive pushover technique within Seismostruct software for analysis. The findings showed that the seismic response relies on the geometric features of the structure, so structures with haunches demonstrated higher behavior factor, overstrength factors, and peak base shear than those without haunches. Oumenour et al. [8] studied the influence of structure height and bay numbers on the seismic behavior factor of RC moment frames. They designed multiple RC frames with varying stories, based on the Algerian seismic code RPA 99/Version 2003. The behavior factor component was determined through pushover analyses conducted on the models. Results show a decrease in the behavior factor as structure height increases, while bay numbers do not significantly influence this factor.

Researchers have discovered that the structural system's geometry can affect structural performance. By factoring in these considerations during design, engineers can enhance the structural system for better performance and safety. So it is essential to find a method to estimate essential factors of structural performance based on geometric parameters. In this regard, the use of artificial intelligence can help accurately predict outcomes and facilitate informed decision-making. Artificial intelligence methods like artificial neural networks (ANN), genetic algorithms (GA), and genetic programming (GP) use natural tools to enhance decision-making processes in research [9–11].

GEP is a computational approach that uses GA to evolve mathematical models for data prediction, which has been employed by several scholars to address research problems. Diverse domains in civil engineering have leveraged this method. For instance, the compressive strength of steel fiber reinforced concrete (SFRC) has been explored using the GEP approach, considering various factors such as fine aggregate to cement ratio, coarse aggregate to cement ratio, water to cement ratio, fiber percentage, superplasticizer to cement percentage, and fiber length to diameter ratio. An accurate mathematical relationship was extracted from a comprehensive database of 115 assorted designs of SFRC, with 80% of the database used for training and the rest for testing [12]. Also, Iqbal et al. [13] conducted a study predicting the mechanical properties of green concrete with waste foundry sand. They estimated compressive strength and elastic modulus. The models proposed in their research show high predictive accuracy, based on influential parameters from existing experimental studies. The study by Azim et al. [14] demonstrates the effectiveness of using GEP to estimate the compressive arch action capacity of RC beam-column substructures. The findings from Kontoni's research indicate that the GEP provides more straightforward models compared to ANN. Additionally Choosing different complexity and fitness functions can improve the performance of the approach [15]. The assessment of the developed models for forecasting the critical buckling loads of steel plates using GEP, ANN, and EPR shows that the ANN model, with an R^2 value of 98.6%, outperforms the other models. This result highlights the higher accuracy and lower error of the ANN model. Therefore, artificial intelligence methods can be utilized as a successful approach to tackle real-world problems [16]. In addition, the GEP has been utilized in various fields of science, such as predicting mechanical properties and behavior of materials like soil, rock, and concrete. This technique can predict reconstructed strain in soil collapse treatment samples using the nano-silica effect [17,18], redistribute moments in RC structures [19], scour around bridge piers [20], shear strength for RC columns under seismic loads [21] and the modulus of elasticity for rocks under triaxial stress conditions [22]. The GEP predictions in these studies are based on data-driven models utilizing datasets gathered from laboratory tests and field data measurements. The analysis results demonstrate a high level of performance and accuracy. The studies' findings highlight the exceptional performance and accuracy of the GEP approach, showcasing outstanding results.

Several prior studies have explored the structural behavior during earthquakes and estimated the behavior factor of RC frames using artificial intelligence. For example, in EBF steel frames, Razavi et al. [23] used a genetic algorithm to study behavior during near-fault quakes. They gathered 12960 data points for steel EBF frames (3-20 stories) and established a correlation to calculate the behavior factor. Correlation coefficients for testing and training datasets were 0.84 and 0.83, indicating agreement between predicted and actual values. Another research study analyzed intermediate RC moment resistance frames using GEP. A model was created to predict behavior factor. The correlation coefficients for the training and testing datasets were found to be 0.92 and 0.90, respectively, indicating the efficacy of the methodology employed. Additionally, parameters like span length and number of stories had the most impact [24].

Previous studies have demonstrated that the behavior factor depends on the structural system's geometry and is influenced by a range of significant parameters. A thorough review indicates that limited research is available on the seismic behavior of structures and the prediction of behavior factor based on geometric features using artificial intelligence. Additionally, studies on estimating the behavior factor of RC frames using GEP have a small database and have explored fewer parameters. Therefore to further investigate the study of behavior factor and expand on previous research, this study aims to propose a mathematical equation to evaluate the behavior factor using the structural system's geometric characteristics. To achieve this goal, creating a wide database of research studies that concentrate on the RC frames system is crucial, utilizing nonlinear static analysis. This database encompasses a range of parameters that impact the behavior factor, including the number of stories, the ratio of span length to story height, design base acceleration, site class of soil, and the ratio of concrete compressive strength to yield stress of longitudinal reinforcements. So, multiple models of RC frames were designed, and nonlinear static analysis was conducted to estimate the behavior factor. The GEP method and GeneXpro Tools software were employed to generate and evaluate the results. Overall, this approach successfully evaluated the behavior factor of moment-resistant RC frames, providing valuable insights into the effects of various parameters on their performance.

2. Methods

This research has employed the nonlinear static pushover approach for computing seismic parameters such as over-strength and behavior factors as well as buildings' ductility. The pushover analysis method entails applying a static and incremental lateral load, which simulates the effects of earthquake loads, to the structure until it experiences collapse [25]. As illustrated in Fig. 1, The pushover curve is represented as a bilinear envelope and characterizes the actual response of structures. The pushover curve's horizontal axis denotes the top story's lateral displacement, while the vertical axis represents the structure's base shear or lateral capacity.

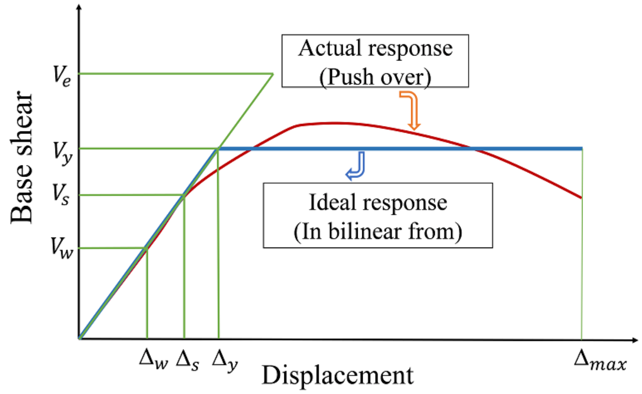

Fig. 1. Base shear versus overall structural drift [2].

During the analysis, the structures under investigation were subjected to gravitational loading, including full dead load, reduced live load, and lateral loads, to ensure consistency with the actual earthquake state. The lateral loads employed were proportional to the first mode shape. One of the methods employed to model the nonlinear response of RC frame members involves assigning the response of plastic hinges while considering their specific lengths. Plastic hinges are classified into two categories: either by analyzing the entire cross-section or by segmenting it into sub-components for a comprehensive evaluation. The fiber theory method scrutinizes the individual reactions of sub-components to ascertain the collective structural performance. The research employs the fiber theory, which considers the combination of concrete and steel behaviors and uses fiber plastic hinges. Various researchers have investigated the plastic hinge length, resulting in different outcomes. The proposed equations exhibit significant variations and dispersions [2]. The plastic hinge length was considered equal to the height of the cross-section, as shown in Eq. (1) [26].

$$L_p = h \tag{1}$$

L_p denotes the plastic hinge length and h denotes the cross-section height.

In this paper, a three-phase stress-strain model is used to simulate the behavior of the reinforcements. The model includes linear elastic, perfectly plastic region, and strain hardening phases. The simulation of the concrete behavior is carried out using the model proposed by Mander et al. [27].

2.1. Employed method to calculate the behavior factor

Uang [28], presented a straightforward method for determining the behavior factor, a critical parameter accounting for structures' nonlinear behavior under seismic loading. The method involves obtaining the structures' behavior factor utilizing Eq. (2) and considering three significant parameters of the structures.

$$\mathrm{R} = \mathrm{R_s R_\mu Y} \tag{2}$$

The over-strength factor, denoted as R_S, represents the ratio of the lateral strength (V_y) to the lateral design strength (V_S) of a structure. The strength factor is impressed by various factors, such as the degree of indeterminacy, material properties, and non-structural components' effects. On the other hand, the ductility coefficient, R_{μ}, represents the ratio of V_e to V_y, as defined in Fig. 1. Researchers, including [29–31] have conducted various studies on the ductility coefficient.

The allowable stress factor, Y, plays a vital role in determining the strength of the structure. For the allowable stress design method, Y is defined as the ratio of V_S to V_w, while for the ultimate design method, the value of Y equals 1. Based on these considerations, Eq. (2) is rewritten as Eq. (3), as depicted in Fig. 1. More details on the calculation of the seismic parameters can be found in Fig. 1.

$$R = \frac{V_e}{V_y} \times \frac{V_y}{V_s} \times 1 = \frac{V_e}{V_s} \tag{3}$$

Researchers have employed various definitions for the ultimate and yield displacements and an appropriate method for determining these displacements is crucial in seismic design [32]. The present study's yield and ultimate displacements are computed based on equivalent elasto-plastic yield and fracture or buckling, respectively.

2.2. Numerical nonlinear modeling of the structures and validation process

The present study employed the SAP2000 software for the numerical modeling, analysis, and design of structures due to its capabilities for nonlinear modeling through forming plastic hinges based on the Fiber theory. The accuracy of the employed nonlinear modeling method was evaluated and validated through the analysis of the experiment conducted by Anil and Altin [33]. This experimental investigation involved the evaluation of an RC frame subjected to lateral loading, which was selected for comparison to the results obtained from the numerical model. The compressive strength of the concrete materials used in the studied frame is 21.8 MPa. The yield stress of the longitudinal reinforcements for column sections is 475 MPa, and that for beam sections is 592 MPa. The geometric properties of the tested frame are presented in Fig. 2.

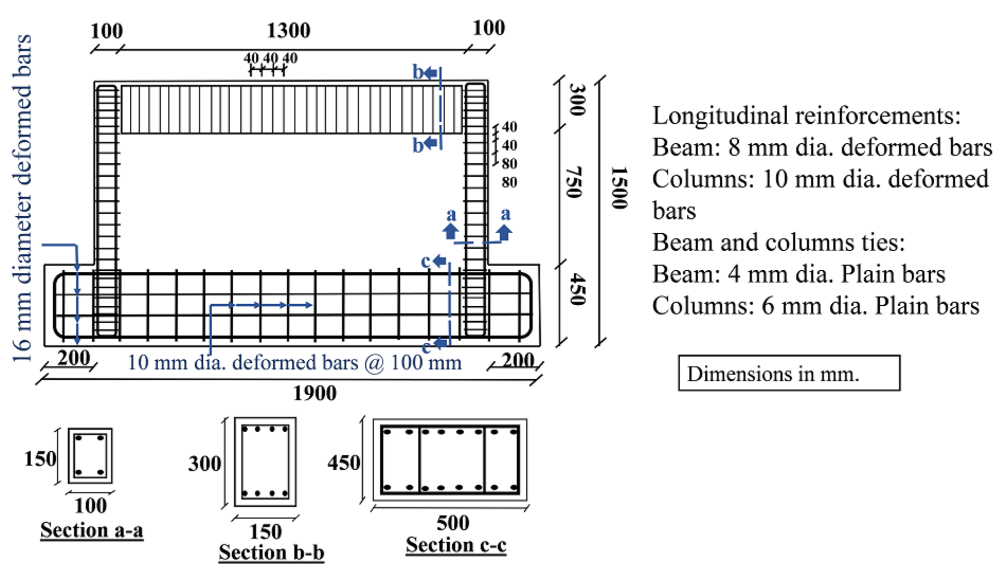

Fig. 2. Geometric details of the tested RC frame by Anil and Altin (dimensions in mm) [33].

After the numerical modeling and nonlinear analysis based on the assumptions of the selected numerical method, the results of the nonlinear analysis in the form of a pushover envelope curve were compared to the experimental results. As shown in Fig. 3, the numerical method used to estimate both strength and stiffness was found to have an acceptable level of accuracy compared to experimental results. The deviation in capacity estimation was less than 4%, indicating that the numerical method was reliable in estimating the required parameters. Therefore, the application can be extended to analyzing different structures by developing other models.

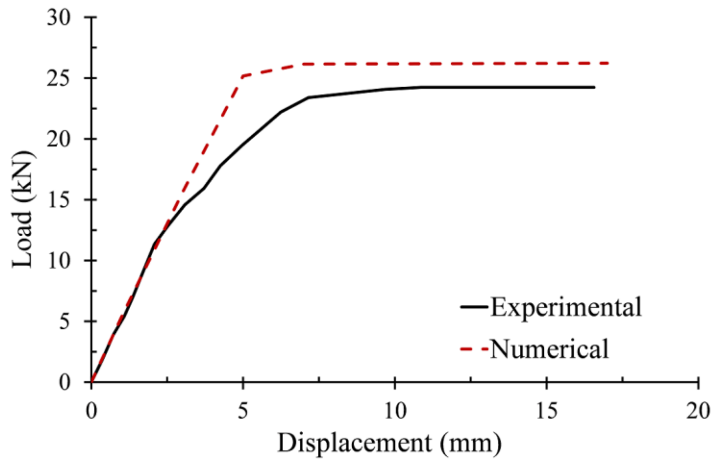

Fig. 3. Comparison of the numerical and experimental response of the Anil and Altin model [33].

2.3. Structural modeling

The primary objective is to investigate various moment-resisting RC frame models subjected to analysis and design. The theoretical principles described have been applied to extract the behavior factor for more than three hundred RC frames modeled and analyzed using SAP2000 software. Subsequently, the geometric specifications of the RC frames and the derived behavior factor were transferred to GeneXpro Tools software to establish a relationship between different geometric parameters and behavior factor. Nonlinear statistical modeling was performed using the GEP approach to accomplish this task. The investigation focused on a two-dimensional frame that consisted of 4 equal-sized spans (See Fig. 4). The structures were subjected to loading based on the ASCE/SEI-7-22 code.

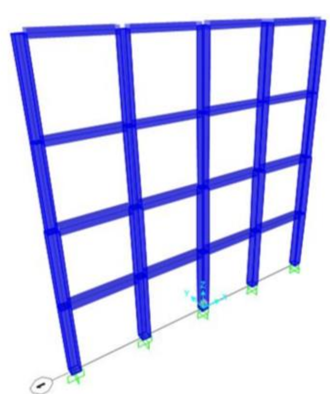

Fig. 4. Display of one of the analyzed frame.

various parameters that impact the design and behavior of structures were selected for investigation. The chosen parameters include the number of stories (N), the ratio of span length to story height (L/H), the ratio of concrete compressive strength to yield stress of longitudinal reinforcements (F), design base acceleration (A), and the site class of soil (S). The design base acceleration was assumed to be 0.35g, 0.3g, and 0.25g, where g represents gravitational acceleration. The soil types under the foundations were assumed to be C and D according to ASCE/SEI-7-22. The number of stories considered for the RC frames were 2, 4, 6, 8, 10, 12, and 15, and the length span to story height ratio was set at 1, 1.5, 2, and 2.5. The structures were designed assuming residential application, with an importance factor (I) of one, and the height of all stories was set at 3.3 meters.

The RC frames were designed with a concrete compressive strength of 30 MPa and yield stress of longitudinal reinforcements of 340 MPa and 400 MPa, resulting in values of F of 0.08 and 0.075, respectively. By varying these parameters, over three hundred RC frames were modeled and analyzed. These models were then designed based on ACI-138-19 The behavior factor was estimated by performing nonlinear static and pushover analysis. The resulting behavior factor values and parameters above were imported into GeneXpro Tools software to establish a correlation between the input and output parameters.

2.4. GEP methodology

One of the optimization techniques is a GA that is inspired by the biological processes of evolution. The technique is designed to select the most fit individuals who pass on their traits to the next generation [12]. Among the different types of GAs, GEP, and GP are two variants that employ selection based on fitness and create genetic variation through various operators such as mutation, gene transposition, root transposition, and gene recombination [34]. Ferreira introduced the GEP method, representing individuals as computer programs of varying sizes and shapes, whereas GP solutions are equations with tree structures. GEP is a powerful algorithm that uses principles of evolution and natural selection to evolve computer programs that solve complex problems [35,36]. In GEP, the individuals are encoded as linear or nonlinear strings of different sizes and shapes, translated into expression trees (ETs). An ET represents the expression of a chromosome, where each chromosome comprises multiple sub-ETs. The structure of GEP genes can be better understood in terms of open reading frames (ORFs).

The GEP consists of five primary elements: the fitness function, the set of terminals, the set of functions, the stopping criterion, and the control parameters. The function set consists of mathematical functions and operations that can be used in the programs, while the terminal set includes constants and variables. The program's performance can be evaluated through the fitness function in a specific task. The evolution process is guided by control parameters that direct its course. Additionally, the stopping criterion plays a crucial role in determining when the algorithm should cease evolving and present the optimal solution found [36].

A sample of a chromosome containing two genes is depicted in Fig. 5. The mathematical representation for this GEP gene is expressed $\sqrt{(a+b)\times(c-d)}$.

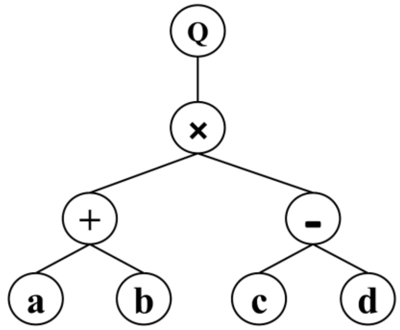

Fig. 5. Example of an expression tree.

The GEP process commences with generating an initial population of chromosomes at random. These chromosomes undergo evaluation via fitness assessment, which occurs within a specific selection environment. Roulette wheel sampling is then applied to select the fittest individuals based on their performance within this environment. The creation of new traits through mutation, crossover, and rotation results in the formation of subsequent generations, and defective chromosomes are removed from the selection environment. This iterative process is repeated for a specified number of generations until a satisfactory solution is obtained. Fig. 6 provides a schematic representation illustrating the fundamental steps of GEP. Additional details on the GEP method are available in the related reference [36].

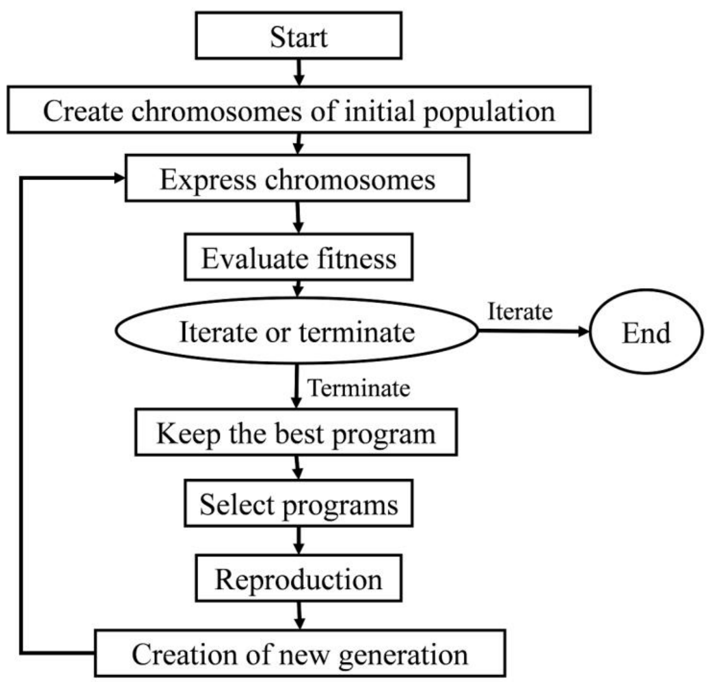

Fig. 6. The flowchart of a GEP algorithm.

After completing the mentioned steps, the best model is selected. This model is then assessed using different metrics and performance indicators to confirm its efficacy in addressing the current issue. The R-squared (R^2) index serves as a measure of a model's fit. In the context of regression analysis, a high coefficient of determination (R^2) denotes a robust correlation between the predicted and observed data points. It is important to note that a high correlation coefficient is a valuable indicator, it does not necessarily ensure the model's precision. Hence, it is crucial to conduct a thorough assessment of the model, utilizing indices such as RMSE and MAE for a comprehensive evaluation. The RMSE is a measure for regression models, offering insights into the average disparity between predicted and observed values.

This index provides a reliable indication of the model's predictive capabilities and accuracy in forecasting the target value. MAE represents another critical metric to gauge the model's performance, shedding light on its accuracy and the magnitude of errors present. The MAE is measured as the average of the absolute error values in a set of forecasts. Therefore, a thorough examination considering these metrics in conjunction with R^2 is imperative to ascertain the model's efficacy. The closer the values of RMSE and MAE are to zero, the less error they indicate. In other words, lower RMSE and MAE values suggest that the model's predictions are closer to the actual values, resulting in a more accurate and reliable model. These measures are presented in Eqs. 4, 5, and 6, respectively [12]

$$R^2 = \left[\frac{\sum_{i=1}^{n}(X_o-\overline{X_o})(X_p-\overline{X_p})}{\sqrt{\sum_{i=1}^{n}(X_o-\overline{X_o})\sum_{I=1}^{n}(X_o-X_p)^2}}\right]^2 \quad (4)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_o-X_p)^2} \quad (5)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|X_o-X_p\right| \quad (6)$$

In the given equations, "o" represents the observed value, "p" represents the predicted value, and "n" represents the total number of data points.

3. Results of GeneXpro tools application

3.1. Using GEP to develop the model

A mathematical equation is required to simplify predicting the behavior factor in RC frames. The current study aims to develop and validate such an equation using GeneXpro Tools and the GEP method. Therefore, a database consisting of 336 RC frames was utilized. The specifications of RC frames, designed for various numbers of stories and diverse L/H ratios, featuring yield stress of 400 MPa for longitudinal reinforcements, are outlined in Table 1. It should be noted that the frames have a soil site class of C and a design base acceleration of 0.35. In order to avoid lengthening the text, additional data has not been included.

The typical approach for utilizing this database involves using 75% of the data for training and the remaining 25% for testing. Accordingly, 252 RC frames were randomly selected for training, while the results of the remaining 84 RC frames were reserved for testing. After defining the databases and organizing the data for both training and testing purposes, it is imperative to identify the functional set. Subsequently, individuals are assessed. The functions utilized in this research study comprise of {+, -, /, ×, Neg, Min, Max, Avg, Not, Ramp, Step}, whereas the terminals are outlined as follows:

$$\left\{\mathrm{S.N.}\frac{L}{H}.F.A\right\}$$

In the evaluation of individuals, genetic operators such as gene transportation, RIS transportation, IS transportation, inversion, mutation, one-point recombination, two-point recombination, and gene recombination were employed. The specific rates associated with these parameters can be found in Table 2.

Table 1
Specifications of moment resistance RC frames used in the study.

N	L/H	F	R_u	N	L/H	F	R_u	N	L/H	F	R_u	N	L/H	F	R_u
2	1	0.08	7	4	1	0.08	7	6	1	0.08	6.2	8	1	0.08	6.1
	1	0.075	5.8		1	0.075	5		1	0.075	4.5		1	0.075	5.5
	1.5	0.08	7.5		1.5	0.08	5.5		1.5	0.08	5		1.5	0.08	5
	1.5	0.075	6		1.5	0.075	4.9		1.5	0.075	4		1.5	0.075	4.5
	2	0.08	9		2	0.08	7		2	0.08	6		2	0.08	4.8
	2	0.075	6.5		2	0.075	5		2	0.075	5		2	0.075	4.5
	2.5	0.08	9.5		2.5	0.08	8		2.5	0.08	7		2.5	0.08	6
	2.5	0.075	7.2		2.5	0.075	6		2.5	0.075	4.5		2.5	0.075	4.5
10	1	0.08	6.1	12	1	0.08	5.5	15	1	0.08	5.5				
	1	0.075	5.5		1	0.075	5		1	0.075	5				
	1.5	0.08	5.5		1.5	0.08	4.5		1.5	0.08	4.4				
	1.5	0.075	4.3		1.5	0.075	4.1		1.5	0.075	4.5				
	2	0.08	4.9		2	0.08	4.5		2	0.08	3.7				
	2	0.075	4.2		2	0.075	3.6		2	0.075	3.4				
	2.5	0.08	6		2.5	0.08	5.5		2.5	0.08	4.8				
	2.5	0.075	4.8		2.5	0.075	5.3		2.5	0.075	4				

Table 2
Parameters of the GEP model.

Parameters	Setting	Parameters	Setting
Number of chromosomes	30	IS transposition rate	0.00546
Number of genes	3	RIS transposition rate	0.00546
Linking function	Additional	Gene transposition rate	0.00277
Mutation rate	0.00138	One-point recombination rate	0.00277
Inversion rate	0.00546	Two-point recombination rate	0.00277
		Gene recombination rate	0.00277

Given that the utilization of three distinct sub-expressions in this research has led to the identification of three genes, it is essential to connect these genes to achieve the outcome, thus requiring the identification of the linking function. As a result, the {+} operator has been utilized as the linking function among the genes in this study. The simulation of the model initiates once the necessary parameters have been identified.

3.2. Derivation of behavior factor based on GEP

Different GEP models were run using variable functions, and the best model was selected based on its performance for both testing and training data using the MAE, RMSE values, and R^2. The statistical performance summary for various models developed by GEP is presented in Table 3.

Table 3
Calculated performance indicators for the developed models.

Number of models	Training				Testing			
	RMSE	MAE	MSE	R^2	RMSE	MAE	MSE	R^2
1	0.082	0.06	0.0067	0.87	0.077	0.06	0.0059	0.88
2	0.071	0.059	0.0051	0.89	0.076	0.064	0.0058	0.78
3	0.078	0.06	0.0061	0.87	0.089	0.072	0.0079	0.71
<u>4</u>	<u>0.061</u>	<u>0.049</u>	<u>0.0037</u>	<u>0.93</u>	<u>0.071</u>	<u>0.056</u>	<u>0.0051</u>	<u>0.82</u>
5	0.082	0.065	0.0067	0.83	0.085	0.068	0.0072	0.87

In Table 4, both the training and testing sets show that model 4 had low MAE and RMSE, as well as high R^2 values. The mathematical equation for predicting the behavior factor of moment-resisting RC frames with special ductility is presented in Eqs. (7)-(13). The expression tree depicted in Fig. 7 can be expressed as follows.

$$R = 6.1\,Y + 3.4 \tag{7}$$

$$Y = \frac{M_5 - 0.33\,N + 9.86 - \frac{2L}{3H}}{M_1} + M_4 + \frac{4\,M_2}{2S + 0.38\,N - 0.51} \tag{8}$$

$$M_1 = min\begin{Bmatrix} \frac{1}{3}(15.7 + S) \\ 200F - 15 \\ S - 2 \end{Bmatrix} \tag{9}$$

$$M_2 = min\begin{Bmatrix} M_3 \\ \frac{S-2}{2} + \left(\left(\frac{2L}{3H} - 0.66\right) \times \frac{0.21L}{H}\right) \\ 50F - \frac{15.15}{4} \\ \frac{1}{3}\left(\frac{2L}{3H} + \frac{N-2}{13}\right) - 0.17 \end{Bmatrix} \tag{10}$$

$$M_3 = max\begin{Bmatrix} 0.15 \\ 10A - 2.5 \end{Bmatrix} \tag{11}$$

$$M_4 = max\begin{Bmatrix} -0.19 \\ \frac{1}{4}\left(S + \frac{2L}{3H} - \frac{3N-6}{52}\right) - 0.77 \\ \left(\frac{L}{3\,H} + \frac{N-2}{52} - 1.16\right) \times \left(\frac{2L}{3H} - 0.66\right) \\ \frac{L}{2H} - 0.33 \end{Bmatrix} \tag{12}$$

$$M_5 = max\begin{Bmatrix} \frac{N-2}{13} \\ \frac{2L}{3H} - 0.66 \end{Bmatrix} \tag{13}$$

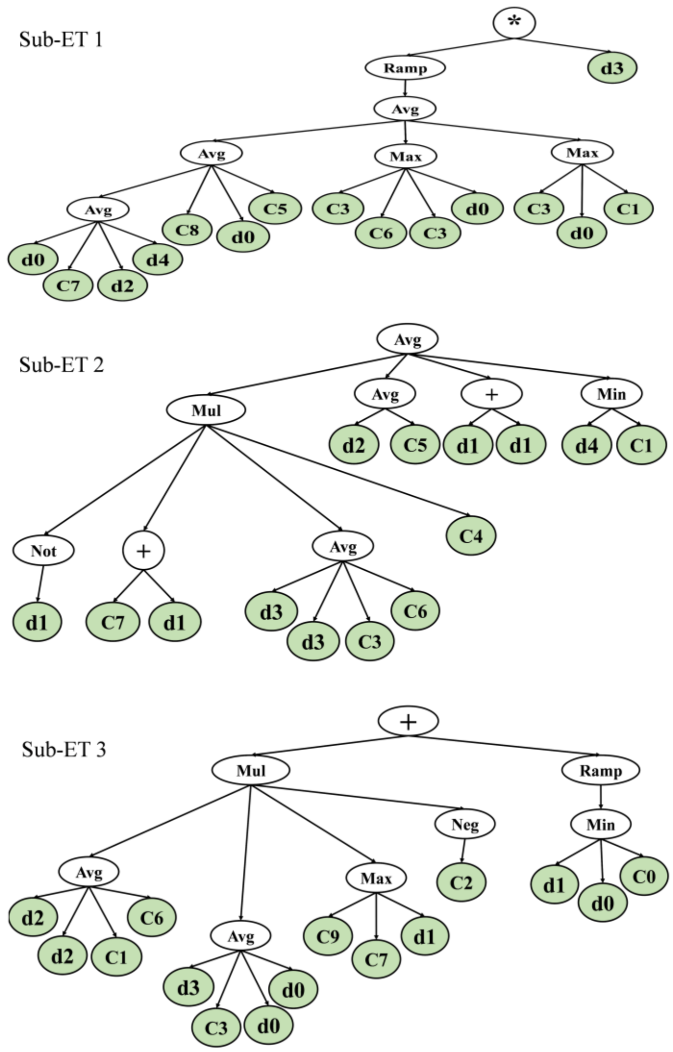

Fig. 7. Expression trees of GEP predicted formula.

In the expression tree, the designations d0, d1, d2, and d3 correspond to N, L/H, F, S, A. Furthermore, Table 4 includes the list of constants utilized in the formulation.

Table 4
Parameter values used in ET.

G1C7	G1C8	G1C5	G1C3	G1C6	G1C2	G2C7	G2C3	G2C6	G2C4
1.87	-5.13	1.47	0.08	0.0219	-2.63	0.97	4.08	6.75	0.267
G2C5	G2C1	G3C1	G3C6	G3C3	G3C9	G3C7	G3C2	G3C5	
0.56	0.16	0.71	-0.53	-1.73	-8.69	0.51	1.044	0.44	

Fig. 5 illustrates a linear regression analysis of the observed and predicted values of the behavior factor in RC frames, which was achieved by applying the GEP formulation.

Fig. 8 depicts a linear regression analysis of the observed and predicted values of the behavior factor in RC frames. The observed values were determined through design and analysis in SAP2000 software, while the predicted values were obtained by applying the suggested formulation in GEP.

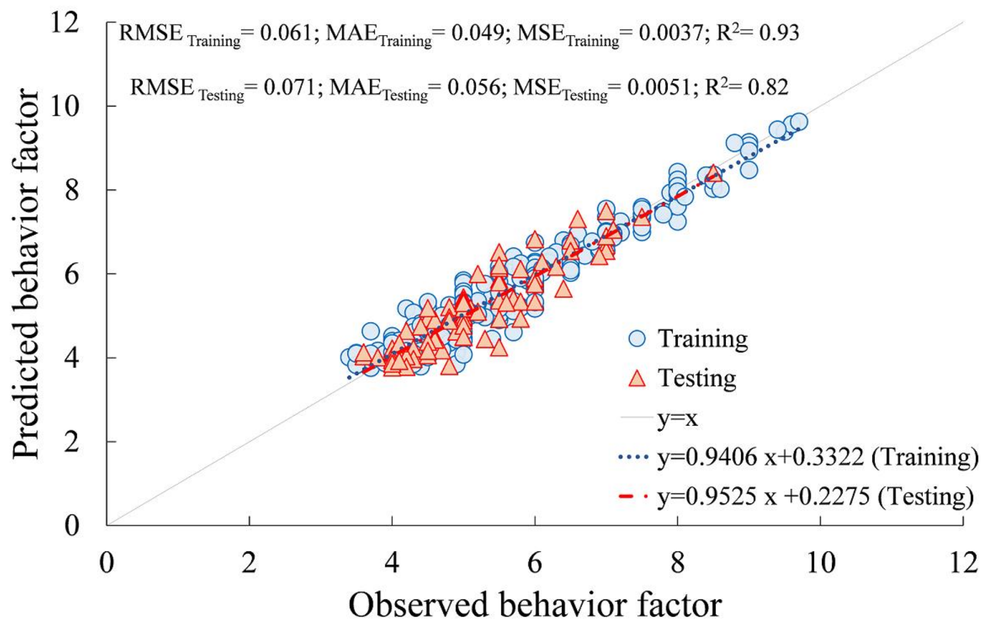

Fig. 8. Comparison between the observed and predicted data.

4. The effect of the parameters on the behavior factor

Geometric parameters play a crucial role in determining the seismic response of RC frames. Among these parameters, the L/H ratio and the number of stories significantly impact the behavior factor, an essential seismic design parameter. Any parameter alteration leads to a different RC frame configuration with distinct seismic behavior. Fig. 9(a) presents the variations in the behavior factor of RC frames to the number of stories for different L/H ratios. The plots consider an F value of 0.08, A value of 0.35g, and the site soil class of D. The outcomes obtained under the assumptions of A as 0.3g, F as 0.075, and site soil class C are presented in Fig. 9(b). The behavior factor of the RC frame exhibits a nearly uniform trend for all L/H=1 models across various numbers of stories. However, for larger values of the L/H ratio up to 2.5, an increase in the number of stories leads to a decrease in the behavior factor. Specifically, the behavior factor of RC frames with 2, 4, and 6 stories surpasses that of other RC frames. This observation holds for all values of F and A in site soil class D.

In Figs. 9(a)-(b), it is evident that the behavior factor of 2- and 4-story RC frames increases with an increase in L/H ratio, while for 6-story RC frames, the behavior factor first decreases up to an L/H ratio of 1.5 and then increases for larger ratios. For RC frames with different numbers of stories between 8 and 15, the behavior factor decreases to an L/H ratio of 2 and then increases. Furthermore, an increase in the L/H ratio enhances the sensitivity of the behavior factor to the number of stories. The effect of the F value on the behavior factor is illustrated for RC frames with different numbers of stories and L/H ratios, assuming A of 0.35g and site soil class of C (Fig. 10(a)). Moreover, the impact of the yield stress of longitudinal reinforcements on the behavior factor has been studied, and results showed that changing the yield stress from 340 MPa to 400 MPa leads to a decrease in the behavior factor's value, ranging from 11% to 23%.

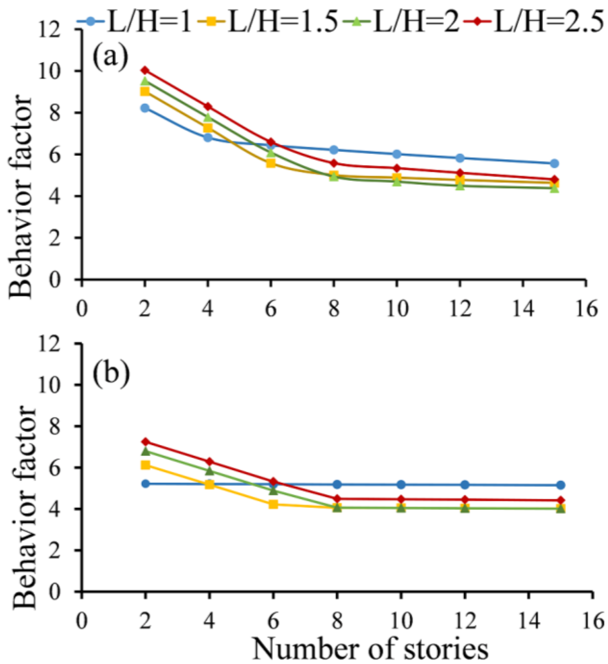

Fig. 9. Behavior factor versus the number of stories for L/H values of 1, 1.5, 2, and 2.5: (a) F=0.08 and A=0.35g; (b) F=0.075 and A=0.3g.

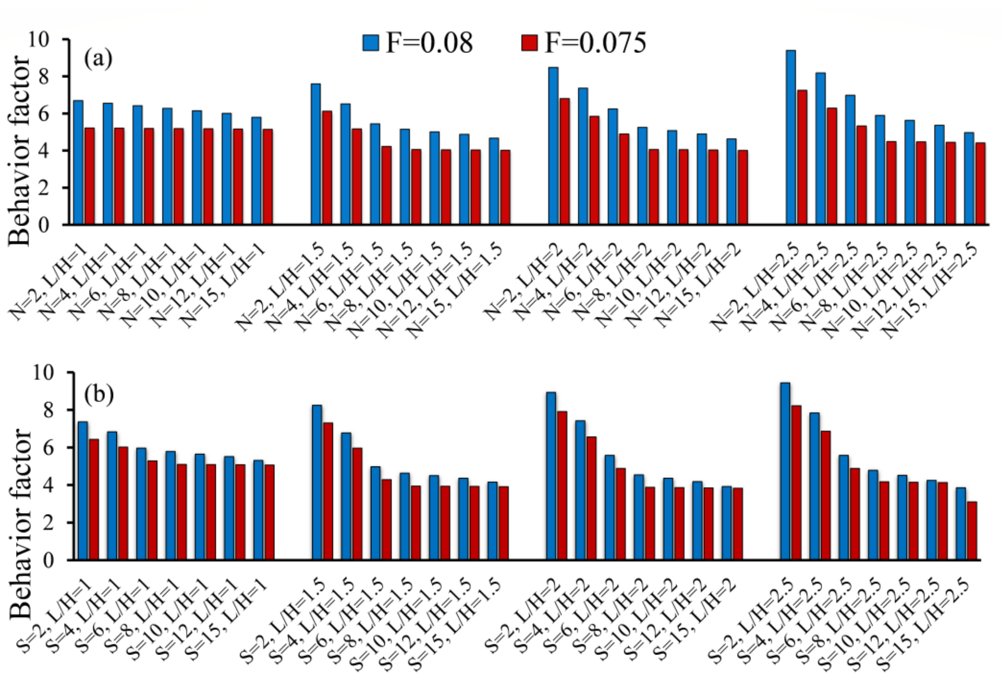

Fig. 10. The effect of F value on the behavior factor models with different L/H ratios and number of stories: (a) A=0.35, soil class C; (b) A=0.25, soil class D.

Fig. 10 (b) illustrates the influence of F on the behavior factor of RC frames; while considering a fixed value of A at 0.25g and site soil class D. It has been observed that the behavior factor of various RC frames experiences a decrease ranging from 2% to 14% as the yield stress of longitudinal reinforcements increases from 340 MPa to 400 MPa (corresponding to a decrease in F from 0.08 to 0.075). This reduction in the behavior factor, influenced by F, is observed across different values of A and site classes.

In the context of RC frames, changes in seismic conditions can lead to variations in the seismic load applied to the structures. Consequently, RC frames respond differently to varying seismic conditions. Fig. 11 presents variations in the behavior factor for RC frames, considering a fixed value of F equal to 0.08, site soil class of C, and L/H ratio of 1.5 versus different numbers of stories. The findings indicate that a change in the seismic coefficient A from, 0.35g to 0.25g leads to a reduction in the behavior factor of the RC frame by approximately 4.5%. This finding is observed for all L/H ratios and site soil classes studied.

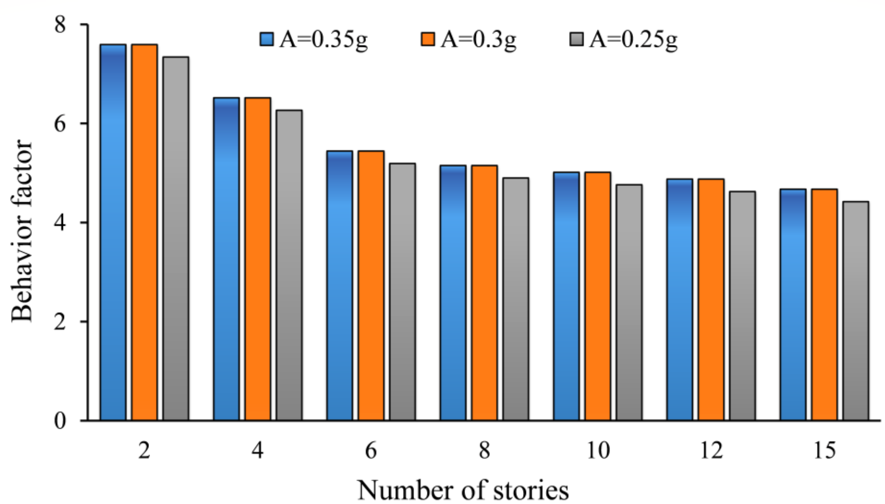

Fig. 11. The effect of seismic conditions on the behavior factor for the frames with different numbers of stories.

Modifying the site soil class influences the seismic load imposed on RC frames. This variation in the soil class parameter may alter the value of the behavior factor. Fig. 12 presents variations in the behavior factor of RC frames, considering different numbers of stories and L/H ratios, assuming fixed values of A equal to 0.35g and F equal to 0.075 while changing the site soil class.

In Fig. 12, it can be observed that changing the site soil class from C to D increases the behavior factor of 2-story and 4-story RC frames. However, the behavior factor decreases with the change in site soil class from C to D for RC frames with more than four stories.

Seismic design codes such as EC8, BIS, and ASCE/SEI-7-22 prescribe specific behavior factor values based on ductility and building system type. For example, for special moment resisting RC frame in EC8, BIS, and ASCE/SEI-7-22 standards recommend values of 6.5, 5, and 8, respectively. However, it is noted that current seismic codes do not account for structural characteristics.

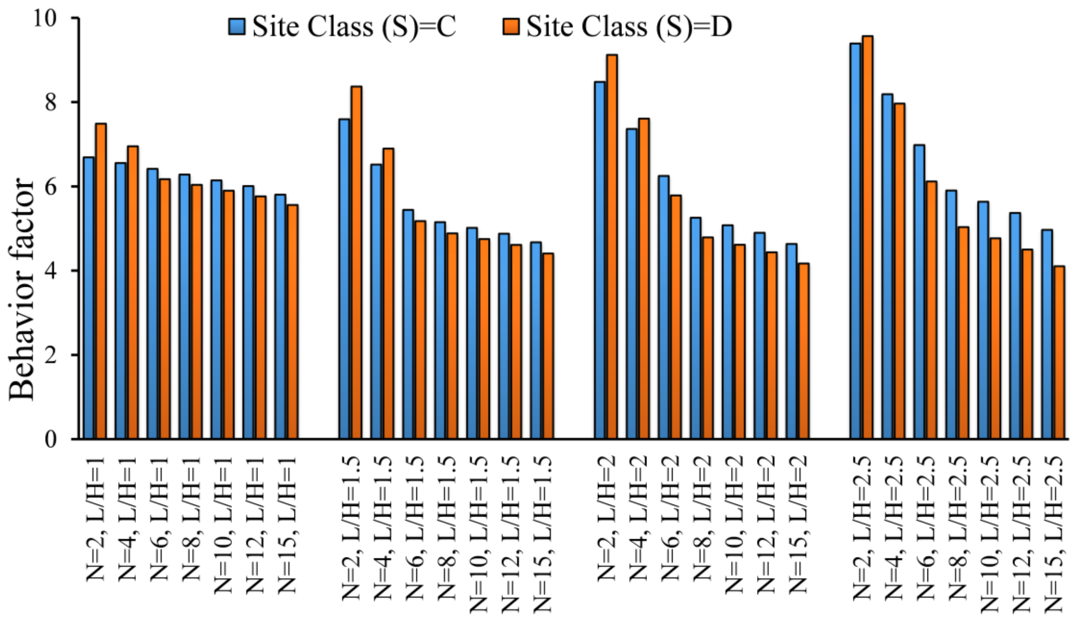

Fig. 12. The effect of site soil class on the behavior factor for the frames with different numbers of stories and different L/H ratio.

The current study has indicated that behavior factor values exhibit variability based on geometric attributes and materials in the structure, resulting in behavior factor values ranging between 4 and 10 for different frames. For example, the behavior factor of a 2-story moment-resistant RC frame with an L/H ratio of 1, the design base acceleration of 0.35, yield stress of longitudinal reinforcements of 340 MPa, and the site soil class from C is 8. However, altering the yield stress of longitudinal reinforcements from 340 to 400 MPa, changing the design base acceleration from 0.35 to 0.3, and adjusting the soil class to D results in a behavior factor value of 5. The observed value disparity can be attributed to differences in the characteristics of frame design. According to that existing studies suggest the dependence of behavioral coefficient values on various parameters, considering the impact of parameters on the behavior coefficient value is crucial during structural design.

5. Conclusions

This study estimates the behavior factor of moment-resisting RC frames using GEP. Therefore, over three hundred RC frames were designed and analyzed through SAP2000 software, resulting in the creation of a database containing the fundamental parameters influencing the behavior coefficient value. Finally, a mathematical equation with high accuracy is obtained to calculate the behavior factor of the RC frames using GeneXpro Tools software. The following is a summary of the research findings:

- The method proposed in this study uses GEP to analyze numerous datasets, taking into account the key parameters influencing the behavior factor so the resulting equations can help engineers assess the behavior factor of RC frames without the need for modeling.

- The R^2 obtained in this study suggests that the GEP method performs well in predicting the behavior factor of RC frames.
- The R^2 for the training and testing datasets are 0.93 and 0.82, respectively. This indicates that the predicted models closely match the experimental results.
- According to the parametric analysis results, the suggested formula has incorporated the input variables to predict the trends in the behavior factor with accuracy.
- The statistical parameters RMSE, MSE, and MAE have been evaluated for the model, and the results indicate a high level of accuracy for the proposed models, with values of 0.061, 0.0037, and 0.049, respectively.
- The behavior factor of the RC frames decreases by increasing the number of stories.
- Increasing the L/H ratio does not uniformly affect the behavior factor.
- As the L/H ratio increases, the behavior factor becomes more sensitive to changes in the number of stories.
- The study observed that an increase in the yield stress of longitudinal reinforcements leads to a decrease in the behavior factor of moment-resisting RC frames.
- The impact of seismic conditions on the behavior factor is found to be insignificant.
- In the investigated RC frames, altering the site soil class from C to D results in fluctuations in the behavior factor, ranging from 2% to 17%.

Funding

This research received no external funding.

Conflicts of interest

The authors declare no conflict of interest.

Authors' contributions statement

NA, SSHH, AF: Conceptualization; NA: Data curation; NA, SSHH: Formal analysis; SSHH, AF: Investigation; SSHH, AF: Methodology; SSHH, AF: Project administration; SSHH, AF: Resources; NA, SJ: Software; SSHH, AF: Supervision; NA, SSHH, AF: Validation; NA, SSHH, SJ, AF: Writing – original draft; NA, SJ: Review & editing.

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