engineering proceedings

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Proceeding Paper

Predictive Model for Load-Carrying Capacity of Reinforced Concrete Beam–Column Joints Using Gene Expression Programming †

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† Presented at the 4th International Electronic Conference on Applied Sciences, 27 October–10 November 2023; Available online: https://asec2023.sciforum.net/.

Abstract: This study emphasizes the significance of beam–column joints (BCJs) within reinforced concrete (RC) structures and investigates their performance when subjected to seismic forces. Accurately predicting the load-carrying capacity of exterior BCJs under seismic loading poses a significant challenge. The development of a reliable and user-friendly predictive model is of paramount importance for facilitating cost-effective and safe design practices for RC structures. To address this requirement, we propose an artificial intelligence (AI)-based model that utilizes gene expression programming (GEP) to accurately predict the load-carrying capacity of exterior BCJs under monotonic loading conditions. The model is developed using GEP and utilizes a database of 128 joint load-carrying capacity results of exterior BCJs obtained from a validated finite element (FE) model using ABAQUS, which considers the effects of material and geometric factors, which have often been overlooked in prior studies. These factors encompass multiple aspects, including the beam and column dimensions, concrete material properties, longitudinal reinforcements in beams and columns, and axial loads applied to the columns. This study also compared the results of the proposed GEP model with the numerical data obtained from the validated FE model, demonstrating good accuracy and reliability. The proposed model has the potential to improve the accuracy and reliability of joint load-carrying capacity predictions, thereby aiding the design of safe and cost-effective RC structures.

Keywords: RC structures; exterior BCJs; GEP; load-carrying capacity

Citation: Waqas, H.A.; Sahil, M.; Khan, M.M.; Hasnain, M. Predictive Model for Load-Carrying Capacity of Reinforced Concrete Beam–Column Joints Using Gene Expression Programming. *Eng. Proc.* **2023**, *56*, 67. https://doi.org/10.3390/ASEC2023-15363

Academic Editor: Simeone Chianese

Published: 26 October 2023

1. Introduction

In existing buildings, which were not designed following modern seismic codes and the recommended capacity design method, the most commonly observed mode of failure is joint shear failure. Researchers have identified several influential parameters affecting the shear strength of BCJs, including the joint's aspect ratio, the compressive strength of concrete, and the presence of transverse reinforcement. These studies have shown that increasing the compressive strength of concrete can result in a corresponding improvement in the shear strength of RC joints [1,2]. Researchers have developed numerous analytical and empirical models to predict the behavior of RC BCJs under cyclic loading conditions. Lima et al. [3] conducted a comprehensive analysis, summarizing the existing models documented in the literature that aim to predict the shear strength of RC exterior BCJs. The field of computer engineering has witnessed a notable surge in the prominence of AI over the recent years, permeating various industries. This advancement in AI technology, specifically in machine learning (ML), has brought about a paradigm shift in the used approach, enabling the utilization of ML techniques to predict the shear strength of BCJs. In his research, Murad [4] employed GEP as a computational tool to anticipate the shear strength of exterior beam-to-column joints under both biaxial and uniaxial cyclic loading conditions. These computational methods have demonstrated their potential in developing explicit models for forecasting the behavior of RC members. These techniques encompass a range of applications, including the evaluation of cement strength utilizing fuzzy logic, ANN, and GEP [5]. Prior research has predominantly relied on individual-type learning algorithms, such as ANN-PSO [6], support vector machines (SVM), XGBoost [7], and decision tree (DT) families [8], as the principal ML algorithms. This array of ML algorithms has been employed effectively in previous studies, underscoring their potential to enhance prediction capabilities within the domain of structure engineering. Alwanas et al. [9] employed the extreme learning machine method to predict joint failure modes while utilizing a multivariate adaptive regression spline model to estimate shear capacity. On the other hand, Naderpour and Mirrashid [10] introduced two distinct failure mode classifiers, based on decision tree algorithms, for both interior and exterior BCJs. These contributions offer valuable insights into the prediction of failure modes and shear capacities in BCJs, utilizing advanced machine learning and decision tree techniques.

Previous research studies addressing the recognition of failure modes in BCJs have been constrained by limited training datasets. However, leveraging more extensive and diverse data sets can enhance the accuracy and precision of models used for recognizing failure modes. It is imperative to maintain continuous data collection and analysis to enhance the reliability and practical applicability of these models. The failure mode of BCJs is influenced by numerous parameters, including beam and column dimensions, concrete strength, stirrup ratios within beams, columns, and joint cores, as well as the reinforcement ratios in both beams and columns. These interconnected factors collectively play a pivotal role in determining the failure modes of BCJs.

For this investigation, a numerical dataset of 128 interior BCJs was collected using ABAQUS to construct a robust model employing GEP for predicting their load-carrying capacity. Subsequently, the GEP model was compared with the numerical results to demonstrate the robustness and reliability of the equation in accurately predicting the load capacity of exterior BCJs.

2. Materials, Methods, and Model Validation

The goal of this study was to investigate how a BCJ, a crucial part of special moment-resisting frame (SMRF) structures, behaves in an RC structure. This study utilizes experimental data from a large-scale BCJ test conducted by Badrashi et al. [11]. The model was designed to meet the codes and standards set for SMRF buildings and was constructed using the ABAQUS software (Abaqus/CAE/2019). The reinforcement detailing of the model is illustrated in Figure 1. The CDP (concrete damage plasticity) model [12] is used as the governing constitutive model for concrete materials. The elastic–plastic model is adopted for modeling the steel behavior of steel materials. Table 1 shows the properties of concrete and steel materials. At the lower end, the column was secured by a pin joint, while it was supported by a roller joint at the upper end, with the out-of-plane degree of freedom constrained. The embedded region method was utilized to account for the bond between steel and concrete. The upper end of the column was subjected to a vertical axial load of 191.229 kN. The cantilever end of the beam was subjected to a displacement-controlled loading, which imposed a monotonic load of 124 mm. To evaluate the performance of an RC BCJ using FEM, it is essential to validate the numerical model against experimental findings. The load–displacement response of the numerical model was compared to experimental findings, and shows a good agreement in terms of ultimate and failure load, and deformation, as shown in Figure 2.

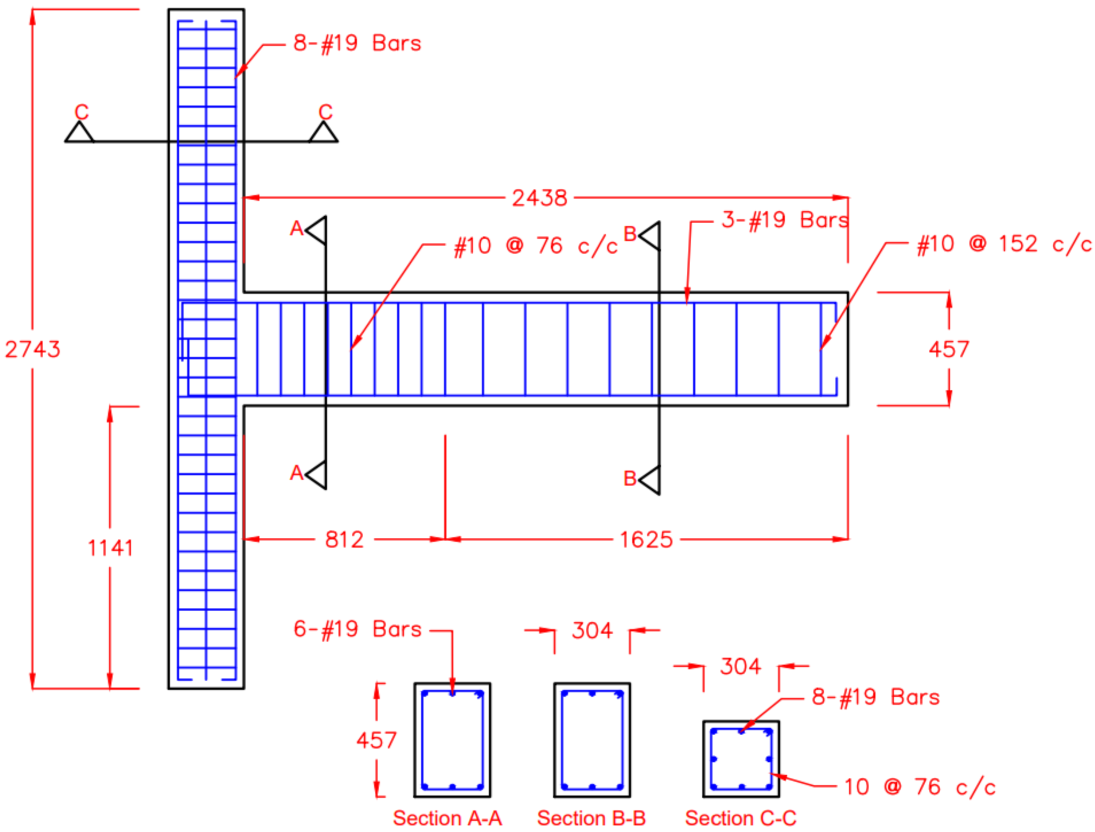

Figure 1. Dimensions and details of the exterior BCJ; all units are in mm.

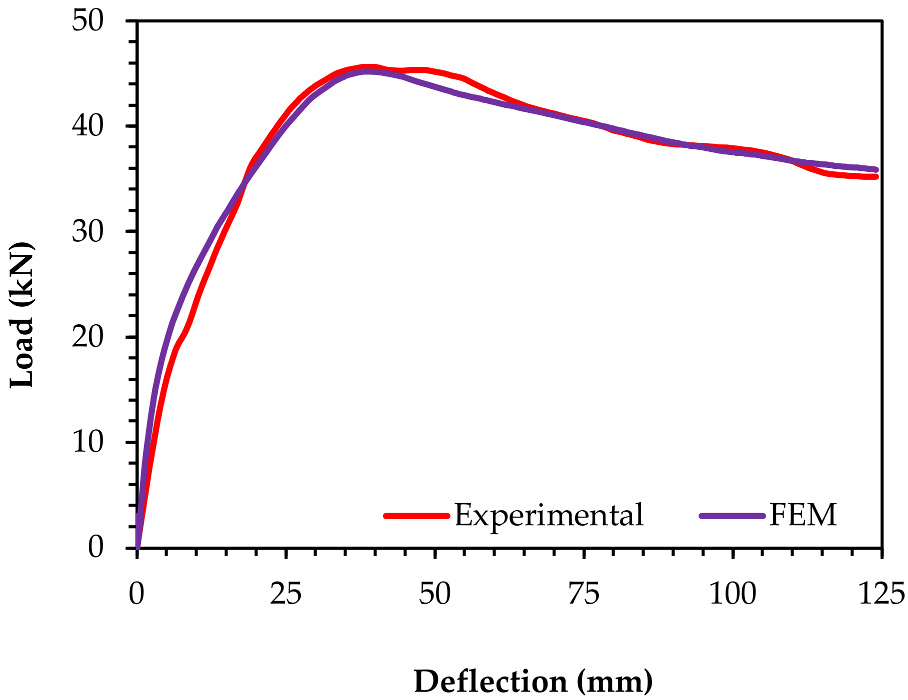

Figure 2. Comparison of FEM and numerical results.

Table 1. Information of material properties of this study.

Details	Concrete	Reinforcement Steel
Mass Density(kg/m^3)	2400	7850
Compressive Strength (MPa)	13.79	414
Yield Strength (MPa)	-	275
Tensile Strength (MPa)	1.379	414
Poisson's Ratio	0.2	0.3
Elastic Modulus (MPa)	19,546	200,000

3. GEP Algorithm

GEP stands out as a genetic algorithm (GA) employed for the creation of mathematical models from input data, demonstrating domain independence. In contrast to traditional GAs and genetic programming (GP), GEP employs an exceptional chromosome representation approach. While GAs utilize linear strings of consistent length, and GPs employ a variety of nonlinear entities with differing sizes and shapes [13–15], GEP innovatively integrates a fixed-length linear string with a branching structure that exhibits diversity in both size and shape.

In the last decade, the benefits of GEP have led to its increasing recognition within the field of structural engineering. Numerous researchers [16] have harnessed GEP's capabilities to develop sophisticated models that accurately assess the capacity of various structural elements. In the scope of this study, GEP was effectively employed to predict the load-carrying capacity of exterior BCJs.

Figure 3 illustrates the different stages that comprise the optimization process within a GEP. This process begins with the selection of control parameters, which encompass the function set, terminal set, fitness function, control parameters, and stopping condition. Prior to executing the evolutionary algorithm, the fitness function is defined, and an initial population of random strings, referred to as "chromosomes" in genetic programming terminology, is generated. These strings are then transformed into expression trees, and the fitness scores of each chromosome are evaluated based on their results. If the fitness criterion is not met, a roulette-wheel sampling method is employed to select specific chromosomes for mutations, resulting in the creation of new generations. Conversely, when the variables align closely with the fitness function, the chromosomes undergo optimization.

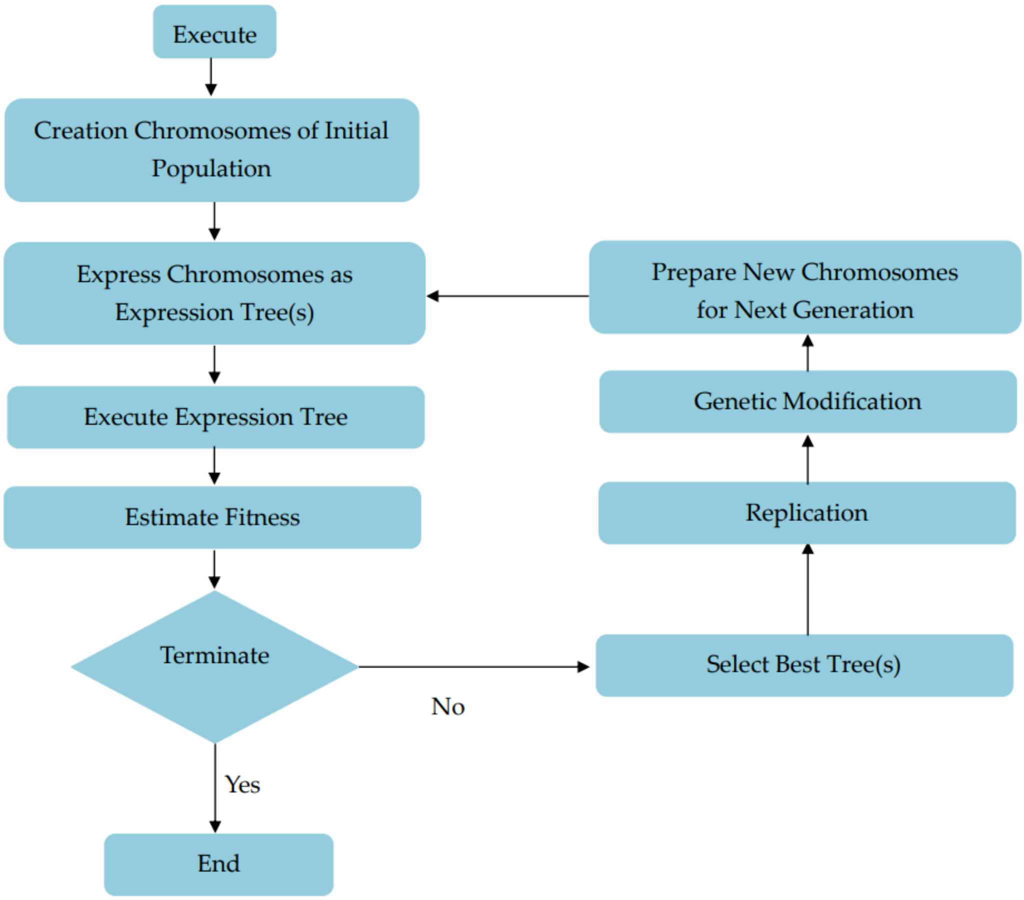

Figure 3. Flow chart representing steps of GEP [17].

4. Results and Discussions

4.1. Parametric Study

A total of 128 models were created in ABAQUS by changing different key parameters, as shown in Figure 4. The dataset used for developing a reliable predictive model includes important influencing parameters. Identifying these parameters necessitates a thorough examination of experimental investigations. Critical factors, including the concrete compressive strength (f'_c), beam reinforcement area (A_b), column reinforcement area (A_c), beam depth (D), column width (B), and axial load on column (P), play a pivotal role in this parametric study.

4.2. Proposed GEP Model for Estimating Load-Carrying Capacity of BCJs

In this section, a GEP model is introduced to predict the flexural capacity of an RC beam. The equation utilized to represent the GEP models, derived from the earlier mentioned dataset, is extracted from the sub-ET (sub-elemental tail) of the genetic algorithm as follows:

$$Capacity = A \times B \times C \tag{1}$$

$$A = \left\{ L - \left(\frac{1061.2 + P}{2} \right)^{3/4} \right\}^{1/2} \tag{2}$$

$$B = \frac{D + \left(\frac{B^2 + {f'_c}^3}{4} - 29.75D \right)^{1/2}}{L} \tag{3}$$

$$C = 1.5\left(\frac{B + f'_c - 80.8}{A_c + 2B - D}\right) + 1.4 \tag{4}$$

The graphical representation of the estimation model's expression tree can also be observed in Figure 5.

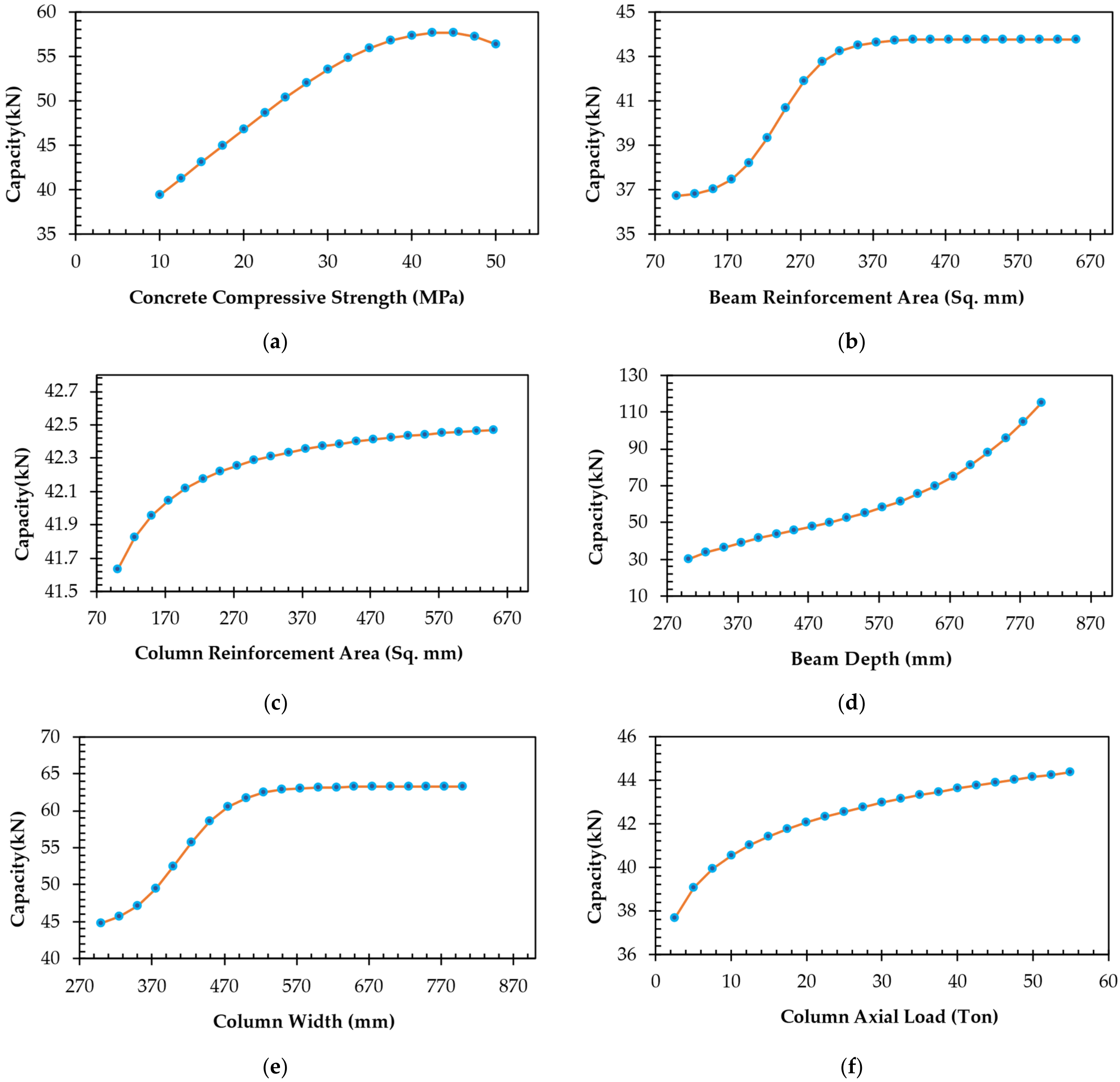

Figure 4. Parametric study: (**a**) capacity vs. f'_c; (**b**) capacity vs. A_b; (**c**) capacity vs. A_c; (**d**) capacity vs. D; (**e**) capacity vs. B; (**f**) capacity vs. P.

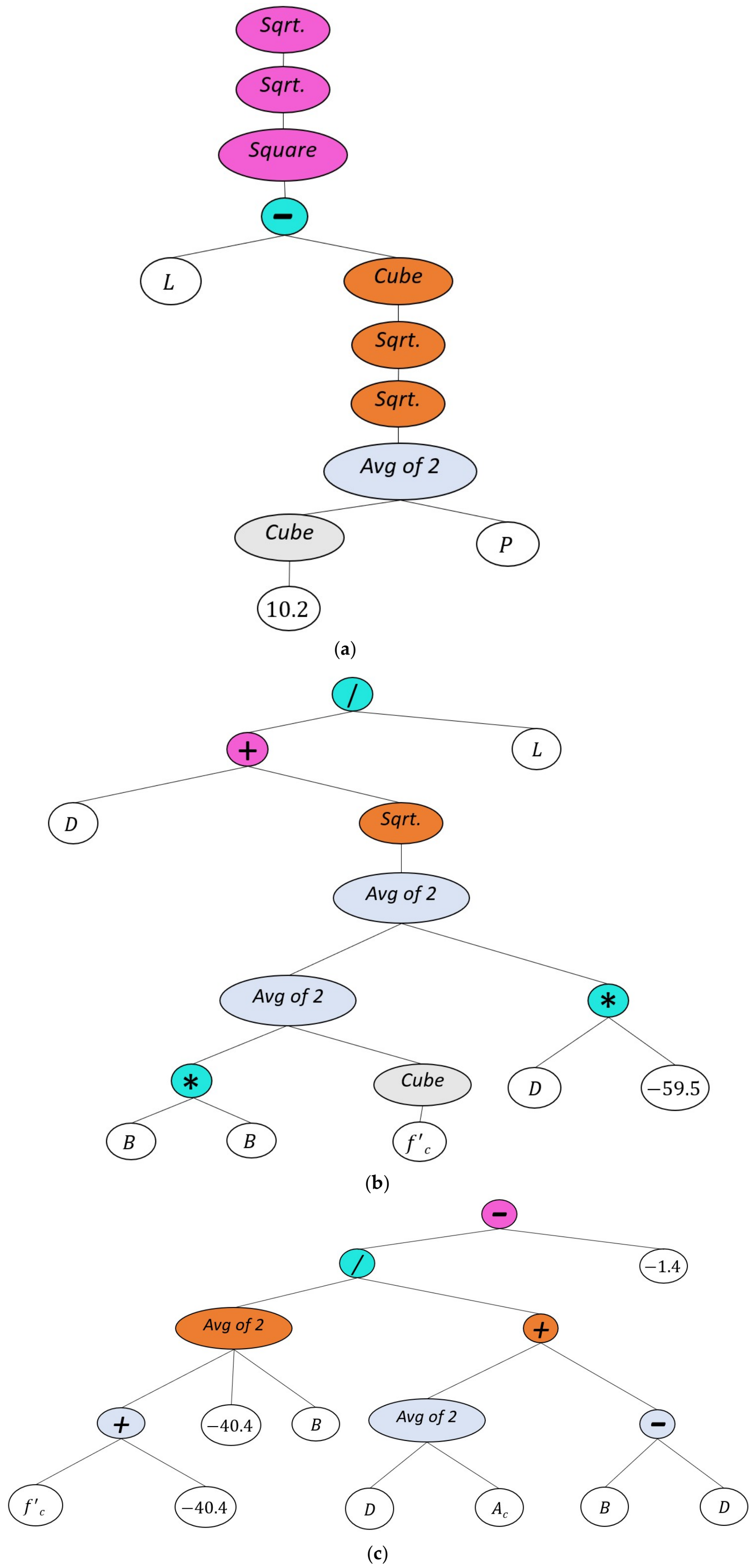

Figure 5. Gene expression tree for the calculation of load-carrying capacity. (**a**) Sub-ET-1. (**b**) Sub-ET-2. (**c**) Sub-ET-3.

After developing the model, a statistical evaluation of its performance is conducted, often using metrics such as the coefficient of determination to quantitatively assess the model's effectiveness. The coefficient of determination (R^2), which assesses the reliability of the model, can be calculated using the following expression:

$$R^2 = 1 - \frac{\sum[Experimental\ value - predicted\ value]^2}{\sum[Experimental\ value - Experimental\ value_{mean}]^2} \tag{5}$$

An R^2 value approaching 1 indicates a precise prediction. The statistical evaluation of the proposed model's performance against the numerical results (referred to as 'Target') is presented in Figure 6. The values for the calculated coefficient of determination (R^2) and correlation coefficient for the regression analysis are 0.91 and 0.95, respectively, and are in close proximity to 1.

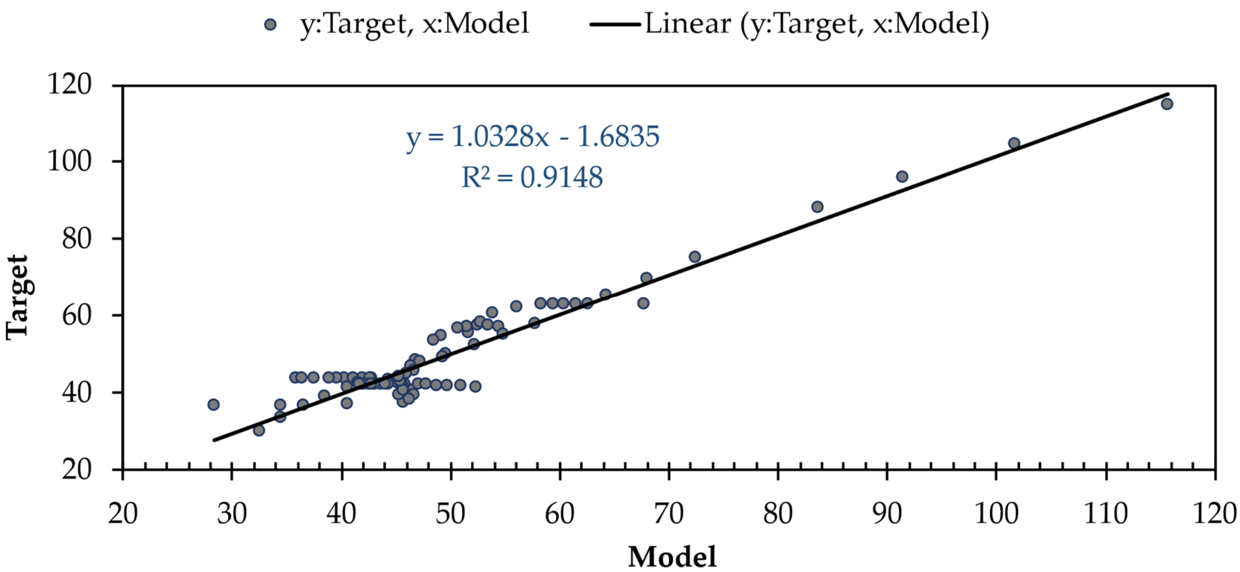

Figure 6. Model comparison with targeted capacity.

5. Conclusions

The developed GEP-based predictive model proved to be a robust tool for estimating the load-carrying capacity of RC BCJs. By incorporating key parameters, such as the concrete compressive strength, beam reinforcement area, column reinforcement area, beam depth, column width, and axial load on the column, this model achieved impressive accuracy. This highlights its potential as a valuable tool for engineers and designers in the construction industry.

Author Contributions: Conceptualization, methodology, visualization, and investigation, H.A.W., M.S., M.M.K. and M.H.; validation, H.A.W., M.S. and M.M.K.; formal analysis, H.A.W., M.S., M.M.K. and M.H.; resources, H.A.W. and M.S.; writing—original draft preparation, H.A.W., M.S., M.M.K. and M.H.; writing—review and editing, H.A.W. and M.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data are available upon request.

Conflicts of Interest: The authors declare no conflict of interest.

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