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DEVELOPING A NEW MODEL USING GENE EXPRESSION PROGRAMMING ON THE PREDICTION OF MOMENT CAPACITY OF FERROCEMENT ELEMENTS

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ABSTRACT

This study proposes a new equation to predict the moment capacity of ferrocement elements by using Gene Expression Programing (GEP) method that is one of the machine learning techniques. The experimental parameters that are selected to propose an equation are the beam width, beam height, cube compressive strength of concrete, ultimate tensile strength of the wire mesh and the volume fraction of the wire mesh. The predictions obtained from the proposed GEP model are compared with the experimental results obtained on the dataset available in the literature.

In addition, the predictions of theoretical and GEP-based models in the literature are also compared with experimental results. Statistical analysis is performed on these comparative results. It is concluded that the proposed GEP model is superior to theoretical and the other GEP based model on prediction of moment capacity of ferrocement elements in the light of statistical data. Moreover, sensitivity and parametric analysis are conducted. It is also a conclusion to sensitivity analysis that the most effective parameters on the proposed GEP model are beam height, the volume fraction of the wire mesh and beam width, while the least effective parameters are cube compressive strength of concrete and ultimate tensile strength of the wire mesh. Finally, the conclusions of the analyses indicate that the predictive capacity of the proposed GEP model is acceptable in terms of accuracy and robustness of the model.

Keywords: Gene expression programming, Ferrocement, Machine learning, Moment capacity, Robustness.

1 INTRODUCTION

Ferrocement is a composite structural element consisting of cement and various types of wire mesh such as square, expanded and hexagonal meshes. Ferrocement is used in important structural elements such as walls, water tanks, deep beams, low-cost housing, ships, and panels [1, 2]. The cross-section of ferrocement elements is schematically shown in Figure 1. The ferrocement elements are also used in the practical applications of repairing, strengthening and jacketing in structural projects. It is reported that ferrocement elements are included in the construction process in different parts of the world [3]. In addition, these elements have not only practical advantages, such as the ability to be formed into any shape, easy procurement of raw materials, economical, ease of construction and easy workmanship, but also mechanical advantages, such as enhanced load carrying capacity, cracking behavior, ductility and resistance against earthquakes [2, 4-10].

However, these elements have some disadvantages. One of these disadvantages is thermal problems in the structure due to the thinness of the ferrocement element. Another disadvantage is the difficulty in determining the moment capacity of this element due to the complex interaction among its components. It is necessary to make theoretical assumptions and simplifications to predict the moment capacity of the ferrocement elements. These assumptions and simplifications lead to deviations when predicting the flexural behavior of ferrocement elements. To reduce the effect of these deviations, machine learning techniques have recently been used to solve complex problems. According to the results of studies in the literature, predictions using machine learning techniques have given statistically more reliable results than theoretical models [1, 2, 11-14].

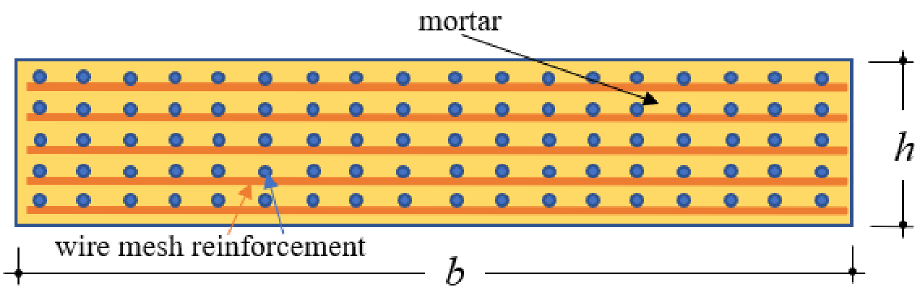

Figure 1. Cross-sectional representation of ferrocement elements [2].

GEP is a computer program that produces mathematical equations as output, distinguishing it from other machine learning tools in its ability to express complex problems. GEP, one of the machine learning-based approaches, combines the advantages of programming and genetic algorithms. This provides users with highly accurate predictions in the form of mathematical expressions [15-16]. GEP has recently been the subject of academic studies in many fields. In civil engineering, studies were carried out using GEP to express the complex relationship between parameters affecting behavior in a simple and reliable way [17-23].

Alacali et al. [24] derived GEP models to predict the contribution of fiber-reinforced polymers (FRP) to the shear capacity of reinforced concrete (RC) beams. Three different GEP models were derived for three different forms of strengthening with FRP strips. The prediction accuracy of these models was found to be high compared to various design codes and studies in the literature. In another study, it was understood that the equation derived from the GEP model for predicting the moment redistribution coefficient of a two-span RC beam yielded the most accurate results [25]. Additionally, the equation developed using GEP was observed to provide fairly accurate predictions for determining the plastic hinge length in RC columns [26]. Positive findings have also been reported in several studies on equation derivation using the GEP model in structural engineering [27–33]. From the studies mentioned above, it can be concluded that the use of the GEP technique is sufficient for the safe solution of a complex problem. Additionally, many machine learning tools have been used to predict the moment capacity of ferrocement elements [2, 3, 12-14, 34, 35].

This study aims to propose an equation that predicts the moment capacity of ferrocement elements with high accuracy from available experimental data in the literature using the GEP technique. The predictions of the proposed GEP equation will be statistically compared with the experimental results. In addition, Comparison results of both theoretical and GEP-based models in the literature will also be given. Then, these statistical results are interpreted. Finally, sensitivity and parametric analysis of the proposed GEP equation are performed.

2 MATERIAL AND METHOD

2.1 Overview of Existing Equations

In the literature, the equations of theoretical and GEP models that predict the moment capacity of ferrocement elements were given below.

- Plastic Analysis Method [36]

$$M_u = \sigma_{tu} b(h - x_1)(h/2) \tag{1}$$

where M_u, b, h, x_1 and σ_{tu} are, respectively, the moment capacity, the beam width, the beam height, and the depth of neutral axis and the ultimate tensile strength of wire mesh.

- Mechanism Approach Method [37]

$$M_u = \sigma_{tu} bh^2/2 \tag{2}$$

- Simplified Method [38]

$$y = 0.005 + 0.422 - 0.0772x^2 \tag{3}$$

$$x = \frac{v_f \sigma_y}{f_c'} \tag{4}$$

$$y = \frac{M_u}{n_o f_c' bh^2} \tag{5}$$

where v_f, σ_y , n_o and f_c' are, respectively, the volume fraction of the wire mesh, the yield tensile strength of wire mesh, efficiency factor of wire mesh and cylinder compressive strength of concrete.

- GEP model [2]

$$M_{u,GEP} = \frac{b(h-11)(h+f_{cu})}{5184} \frac{(f_{ul} v_f)^{0.6}}{\sqrt{f_{cu}}} \tag{6}$$

2.2 Summary of Experimental Data

The data set used to derive the GEP equation was taken from the study published by Mashrei et al [12]. It includes a total of 75 test specimens compiled by Mashrei et al [12] from nine different experimental studies in the literature [12, 36, 37, 39-44]. This dataset contains five input parameters: b, h, f_{cu}, f_{ul} , v_f, as well as one output parameter: M_u. To determine the most appropriate input parameters, similar studies based on machine learning techniques were reviewed, and it was observed that these parameters are commonly used in the literature [2, 3, 12, 14]. The maximum, minimum, and mean values of these parameters are presented in Table 1. Also, Figure 2 illustrates the frequency histograms of the parameters used to develop the GEP model.

Additionally, Figure 3 provides a visual representation of the Pearson correlation matrix, which helps understand the strength and direction of linear relationships between the input parameters and the moment capacity of ferrocement elements. The heat map is a useful analysis tool that helps identify the strongest relationships between the input variables and the target output. Figure 3 shows that the beam width (b) and height (h) have a more significant effect on the structural behavior compared to the material properties, exhibiting the highest positive correlations with the moment capacity. These results also agree well with the sensitivity analysis results and support the reliability of the proposed GEP model.

Table 1. Properties of the experimental parameters in database.

Number	Reference		b (mm)	h (mm)	f_{cu} (MPa)	f_{ul} (MPa)	v_f -	M_u (Nm)
4	[39]	Min.	400.00	50.00	12.60	371.00	0.0060	955.00
		Max.	400.00	75.00	12.60	371.00	0.0120	5393.00
		Mean	400.00	62.50	12.60	371.00	0.0095	2933.25
16	[12]	Min.	200.00	50.00	40.40	600.00	0.0016	393.50
		Max.	300.00	80.00	50.80	600.00	0.0130	3752.00
		Mean	250.00	65.00	47.84	600.00	0.0066	1376.38
9	[40]	Min.	100.00	20.00	29.90	500.00	0.0362	171.00
		Max.	100.00	100.00	29.90	533.00	0.0392	3375.00
		Mean	100.00	44.44	29.90	518.33	0.0375	931.67
6	[37]	Min.	100.00	25.00	29.90	371.00	0.0148	137.50
		Max.	100.00	100.00	50.00	500.00	0.0418	3937.00
		Mean	100.00	40.83	46.65	392.50	0.0282	831.58
6	[36]	Min.	100.00	25.00	38.00	371.00	0.0172	125.00
		Max.	100.00	35.00	56.00	371.00	0.0296	355.00
		Mean	100.00	26.67	46.50	371.00	0.0240	180.83
8	[41]	Min.	130.00	13.00	62.00	513.00	0.0154	33.00
		Max.	130.00	13.00	62.00	714.00	0.0664	155.30
		Mean	130.00	13.00	62.00	600.63	0.0391	84.26
7	[42]	Min.	100.00	13.00	24.20	382.60	0.0070	76.10
		Max.	130.00	26.00	62.00	562.00	0.0682	270.20
		Mean	104.29	24.14	29.60	408.23	0.0371	165.39
3	[43]	Min.	100.00	25.00	24.20	382.60	0.0081	102.50
		Max.	200.00	26.00	28.30	979.00	0.0825	293.50
		Mean	166.67	25.33	26.93	780.20	0.0356	195.73
16	[44]	Min.	76.00	25.00	28.30	628.00	0.0032	144.00
		Max.	200.00	50.00	36.00	979.00	0.0504	1367.30
		Mean	83.75	48.44	35.52	649.94	0.0217	678.16
Full Dataset (n = 75)		Min.	76.00	13.00	12.60	371.00	0.0016	33.00
		Max.	400.00	100.00	62.00	979.00	0.0825	5393.00
		Mean	150.80	42.92	39.95	543.10	0.0243	819.79

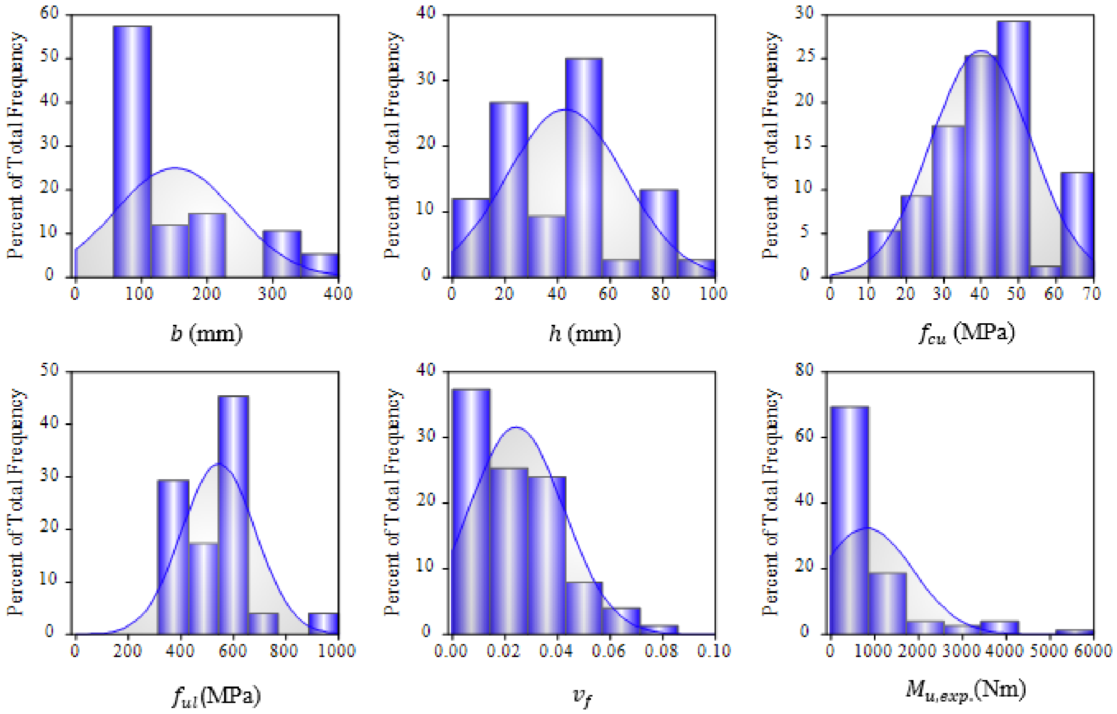

Figure 2. Frequency histograms of the parameters in dataset.

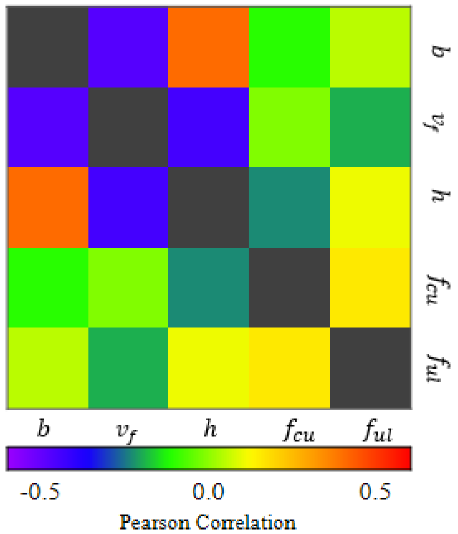

Figure 3. Heat map of the Pearson correlation matrix for the moment capacity of ferrocement elements.

2.3 Gene Expression Programming (GEP)

GEP, which is one of the most frequently used genetic methods in engineering problems in recent years, was first developed by Ferreira [45]. The basic steps of the gene expression programming (GEP) are shown schematically in Figure 4. The chromosomes of a certain number of individuals are randomly generated and selected according to their fitness. Selected individuals pass on their genetic information to the next generation, resulting in new characteristics emerging in subsequent generations. The generated chromosomes are then converted into expression trees (ETs) [45]. ETs can be expressed as a mathematical function, as shown in Figure 4. Each node represents either an operation or an operator. Each leaf node represents either a variable or a constant value. This study uses Subexpression Trees (Sub-ETs), which refer to simplified expression structures derived from GEP or other machine learning models. These subtrees are systematically integrated to form the main expression tree, which represents the predictive formulation of the model and highlights the influence of input variables on individual predictions. Sub-ETs with different shapes and sizes are combined through linking functions to generate more complex and effective expressions. Each GEP gene consists of a head, which contains functions and terminals, and a tail, which contains only terminals.

Within the scope of this study, a detailed analysis was made on a total of 75 data points using the GEP model to predict the moment capacity of ferrocement member. The data set presented in Table 1 was evaluated using GeneXproTools 5.0 software [46]. The data set was randomly divided into training and validation sets with 56 data points (75%) for the training set and 19 data points (25%) for the validation set. The parameter configurations used in the GEP model presented on Table 2. In this study, the size of chromosomes 30, size of genes 3 and head size 8 were selected as the most suitable values for the development of the GEP optimization model. Additionally, other optional GEP parameter settings are also seen in Table 2.

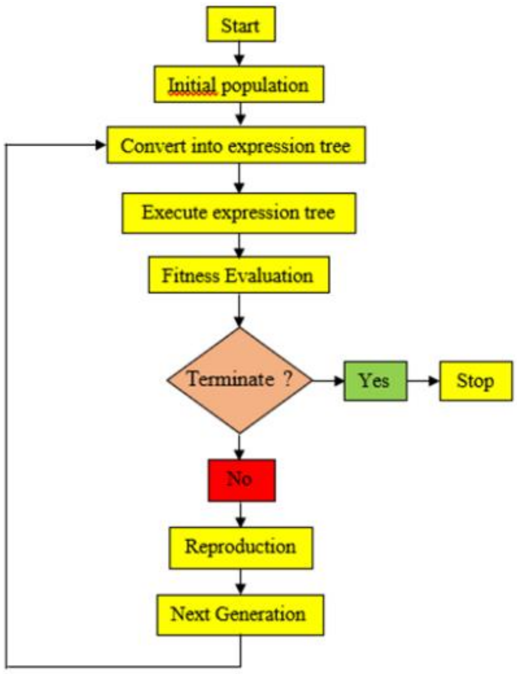

Figure 4. The flowchart of GEP [45].

Table 2. GEP parameter settings.

Definition	Values
Input parameters	b(mm), h(mm), f_{cu}(MPa), f_{ul}(MPa), v_f
Output parameter	M_u (Nmm)
Genes	3
Function set	+. −. ∗. /. $\sqrt[4]{}$. ^3. ^5. Avg(x.y)
Chromosomes	30
Head Size	8
Linking function between	Addition
Mutation	0.00138
Inversion rate	0.00546
Constants per gene	10
Data type	Floating type

The ETs of the GEP model proposed for ferrocement elements in this study are shown in Figure 5. The model consists of three different Sub-ETs, which are combined using a linking function. These ET models are converted into the mathematical expression presented in Equation 7.

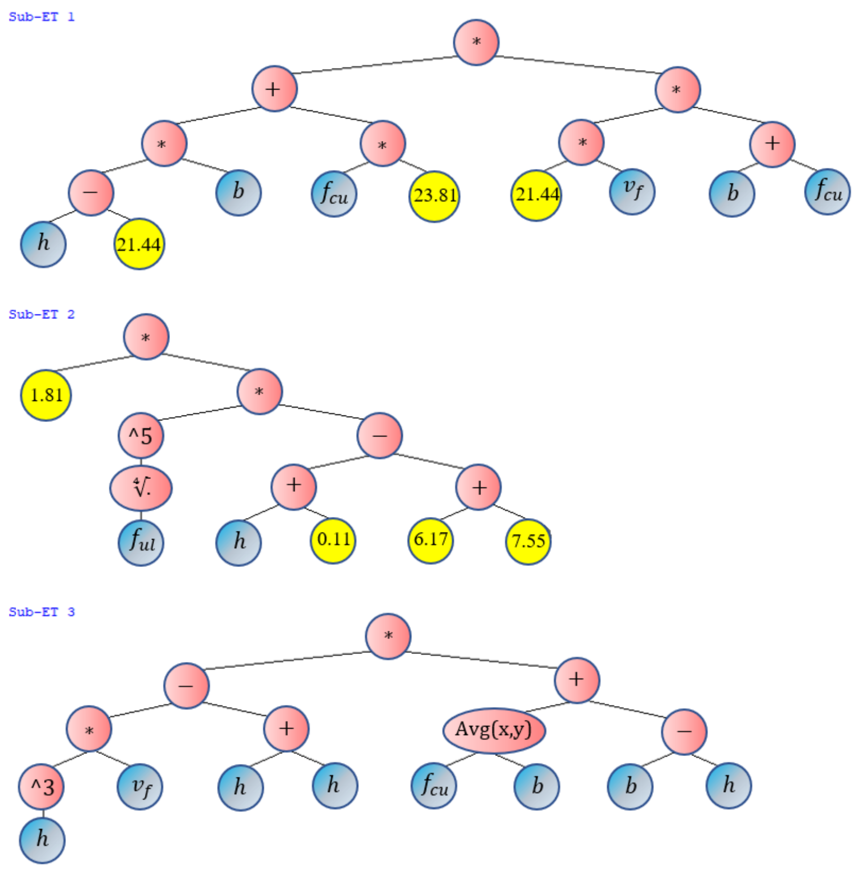

Figure 5. Expression trees (ETs) of GEP model for moment capacity.

$$\boldsymbol{M_{u,proposed}}(\text{Nmm}) = [b(h-21.44)+23.81f_{cu}][21.44v_f(b+f_{cu})] + 1.81\left[f_{ul}^{\frac{5}{4}}(h-13.61)\right] + (v_f h^3 - 2h)(0.5f_{cu}+1.5b-h) \tag{7}$$

2.4 Statistical Metrics

The equations of the statistical metrics used to assess and compare the performance of the proposed GEP model with those of previous researchers are defined in Equations (8)–(13), as presented in Table 3. The mean value (M) is calculated by dividing the experimental values by the predicted values. In addition, the statistical metrics SD, MAPE, and RMSE indicate the degree of error in the predictions. Lower values of SD, MAPE, and RMSE correspond to smaller prediction errors. Moreover, a high R^2 value and a low COV value indicate greater reliability in the model's predictions.

Table 3. Statistical metrics for evaluating prediction performance.

Statistical Indices	Expression	Equation
Mean (M)	$M = \frac{\sum_{i=1}^{n}\frac{exp}{model}}{n}$	(8)
Standard deviation (SD)	$SD = \sqrt{\frac{\sum_{i=1}^{n}(\frac{exp}{model}-M)^2}{n-1}}$	(9)
Root mean square error (RMSE)	$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(exp-model)^2}{n}}$	(10)
Mean absolute percentage error (MAPE)	$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left\lvert\frac{exp-model}{exp}\right\rvert$	(11)
Coefficient of variation (COV)	$COV = \frac{SD}{M}$	(12)
Coefficient of determination (R^2)	$R^2 = \left[\frac{[\sum_{i=1}^{n}(exp-\overline{exp})(model-\overline{model})]}{[\sum_{i=1}^{n}(exp-\overline{exp})\sum_{i=1}^{n}(model-\overline{model})]}\right]^2$	(13)

3 RESULT AND DISCUSSION

This section presents a comparison between the experimental results and the predicted values of the moment capacity of ferrocement elements, using the proposed GEP model, theoretical equations [36–38], and the GEP model developed by Gandomi et al. [2].

Table 4 presents the statistical results of the proposed GEP model for both the training and validation datasets. The R^2 values were 0.974 for the training set and 0.989 for the validation set, indicating a strong correlation between the predicted and experimental outcomes. The mean values were 0.983 and 1.061, both close to 1, which demonstrates a high level of agreement between the predictions and actual results. Regarding statistical metrics, the RMSE values were 163.178 for training and 149.088 for validation, while the MAPE values were 22.198 and 18.138, respectively. The COV values were also low, with 0.251 for training and 0.212 for validation. These findings confirm that the model provides accurate and consistent predictions without signs of overfitting, and the similarity between the training and validation results highlights its strong generalization capability.

Table 4 Training and validation results of the GEP model.

	M	**SD**	**MAPE**	**RMSE**	**R^2**	**COV**
Training	0.983	0.247	22.198	163.178	0.974	0.251
Validation	1.061	0.225	18.138	149.088	0.989	0.212

Also, Figure 6 shows the comparison between the experimental moment capacities and those predicted by the GEP model for both the training and validation datasets. The orange vertical line in the figure is used to clearly separate the training data from the validation data. Figure 6 also illustrates the error rates between the predicted and experimental values for both datasets, highlighting the consistency of the proposed GEP model. Figure 7 presents the average absolute error percentages for each of the 75 experimental specimens, providing a clear view of the prediction accuracy of the proposed GEP model. According to the figure, 22 specimens have an absolute error below 10 percent, and approximately 80 percent of the specimens have an error below 30 percent. This distribution confirms that the model yields low prediction errors for most of the dataset, highlighting its reliability and consistency.

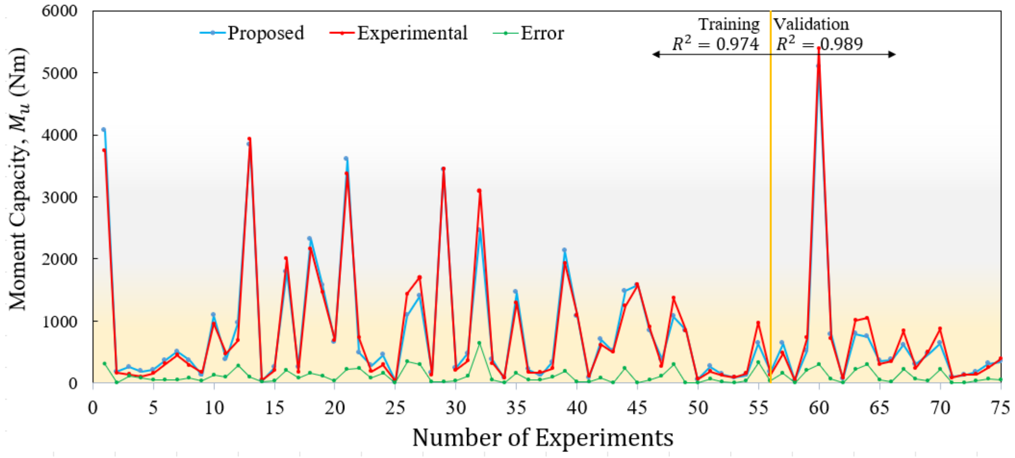

Figure 6. Comparison of experimental and proposed moment capacities for GEP model.

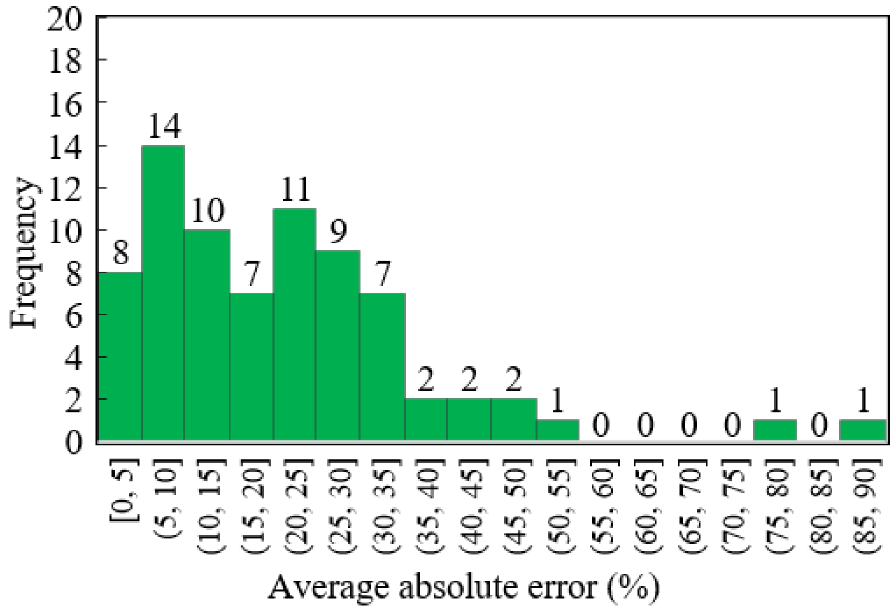

Figure 7. Frequency distribution of average absolute error (%).

Moreover, Figure 8 shows the scatter plot of experimental and predicted values for the moment capacity of ferrocement elements. As seen in Figure 7, the R² values were high for both the training and validation datasets, indicating a strong correlation. The GEP model predictions were observed to be homogeneously distributed. These results suggest a close relationship between the predicted and experimental values, confirming the reliability of the proposed GEP model.

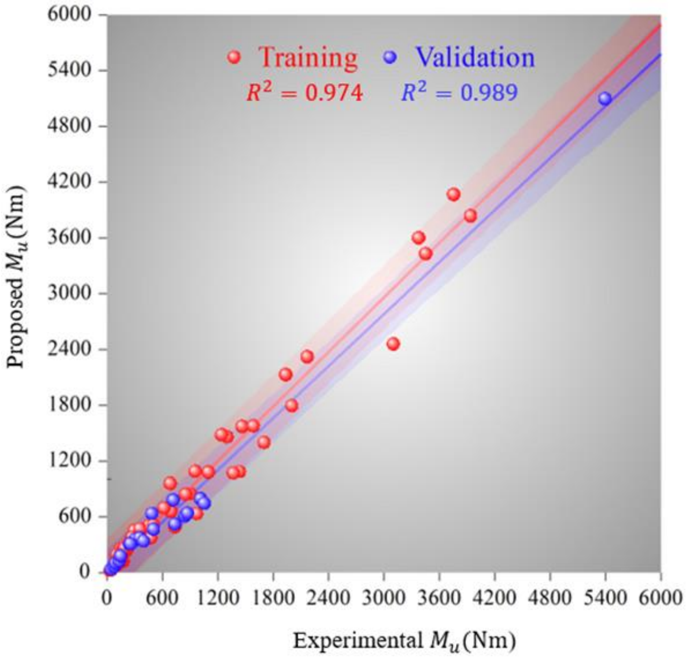

Figure 8. Scatter plots of experimental and proposed values for moment capacity.

The prediction results of the proposed GEP model, Plastic Analysis [36], Mechanism [37], Simplified Method [38], and the GEP model proposed by Gandomi et al. [2] were compared with the experimental results. It was seen that the predictions obtained using the Plastic Analysis [36], Mechanism [37], Simplified [38] methods are consistent with those obtained in Mashrei et al [12]. The comparison results are presented in Table 5. According to the mean value, the predictions closest to the experimental results belong to the proposed GEP model developed in this study. In contrast, the Simplified Method [38] yielded the highest mean value of 2.315, indicating that this approach may not provide economical results. Among all models, the proposed GEP model exhibited the lowest SD, MAPE, and RMSE values, which were 0.243, 21.141, and 159.777, respectively. The R^2 value of the proposed GEP model was 0.977, representing the highest level of correlation compared to the other models. Additionally, the COV value of 0.242 was the lowest among all compared approaches. Based on these statistical indicators, the proposed GEP model outperforms both the theoretical models [36–38] and the GEP model developed by Gandomi et al. [2]. Following the proposed GEP model, the most consistent prediction accuracy was observed in the GEP model developed by Gandomi et al [2]. Among the theoretical models, Plastic Analysis [36], Mechanism [37], and Simplified Method [38] ranked from best to worst in terms of predictive accuracy. As shown in Table 5, the difference in MAPE and RMSE values between the theoretical models, especially Mechanism and Simplified Method, and the GEP models was significant.

Table 5. Statistical data obtained from the comparisons between the predictions and experimental findings.

Model	M	SD	MAPE	RMSE	R^2	COV
GEP model [2]	1.025	0.329	25.538	199.644	0.964	0.321
Plastic Analysis [36]	1.348	0.418	28.682	564.326	0.843	0.310
Mechanism [37]	1.111	0.429	33.036	518.582	0.764	0.386
Simplified Method [38]	2.315	0.869	51.519	876.941	0.757	0.375
Proposed GEP model	1.003	0.243	21.141	159.777	0.977	0.242

The 3D surface and 2D contour plots of absolute error are presented in Figures 9a and 9b to better illustrate the prediction reliability of the proposed GEP model. The frequency of large prediction errors was generally low. It was observed that higher error percentages were more common in elements with lower moment capacity, whereas the error decreased in elements with higher moment capacity. As a result, based on Figure 8, the proposed GEP model demonstrated strong overall predictive ability when evaluated across the entire dataset.

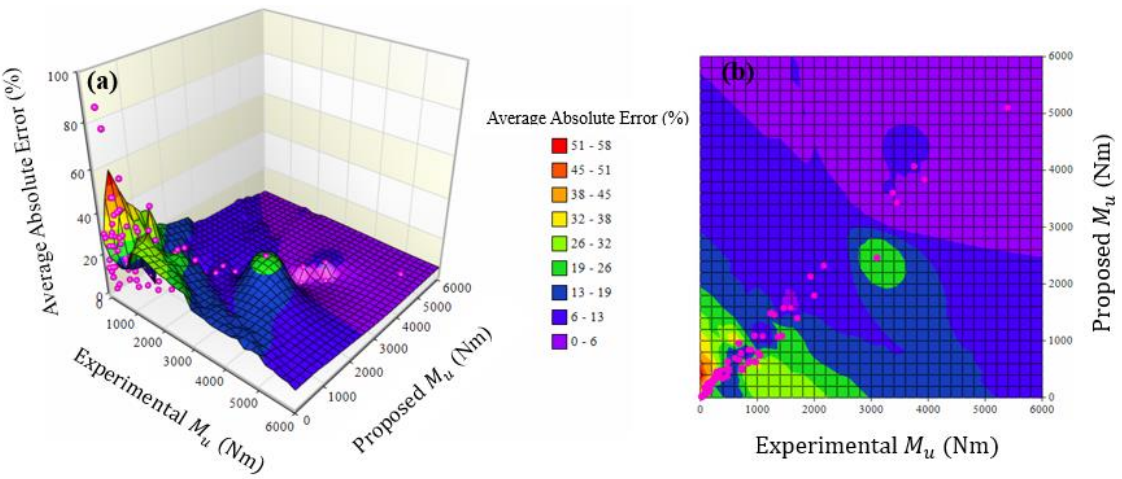

Figure 9. 3D surface and 2D contour plots of absolute error of the GEP model for moment capacity (a) 3D surface plot. (b) 2D contour plot.

3.1 Sensitivity and Parametric Analysis

A sensitivity and parametric analysis (SA) were presented using Equations (14) and (15) to identify the relative contribution of the parameters to the moment capacity.

$$N_i = f_{max}(x_j) - f_{min}(x_j) \tag{14}$$

$$SA = \frac{N_j}{\sum_n^{j=1} N_j} \tag{15}$$

where $f_{max}(x_j)$ and $f_{min}(x_j)$ refers to the maximum and minimum predicted outputs corresponding to the i^{th} input parameter, while the other input parameters are held constant their mean values [47, 48]. Additionally, the results of the sensitivity analysis showing the relative contributions of each input parameter to the moment capacity of ferrocement elements are presented in Figure 10. According to the figure, the most influential input parameter affecting the model output is h, with a contribution of 54.06%, followed by v_f at 27.18%. The next most significant parameter is b, with a contribution of 15.68%. In contrast, the f_{cu} and f_{ul} have relatively minor effects on the model output. The results are consistent with findings reported in the literature [2, 3, 12]. As is evident from these results, the robustness of the proposed GEP model is acceptable.

The parametric analysis was also performed besides sensitivity analysis in this study. The purpose of parametric analysis is to show the impact of changing the input parameters of the given model on the predicted output. The findings of the parametric analysis performed to better prove the accuracy of the model in evaluating and optimizing the performance of the GEP Model are shown in Figure 11. In addition, as presented in Figure 11, the moment capacity of ferrocement elements increases when each input variable is increased in general. Additionally, it was observed that f_{cu}, f_{ul}, v_f parameters linearly increase the moment capacity, while b and h have a non-linear effect on the moment capacity. These findings are consistent with the findings of parametric analysis in other studies [2, 12].

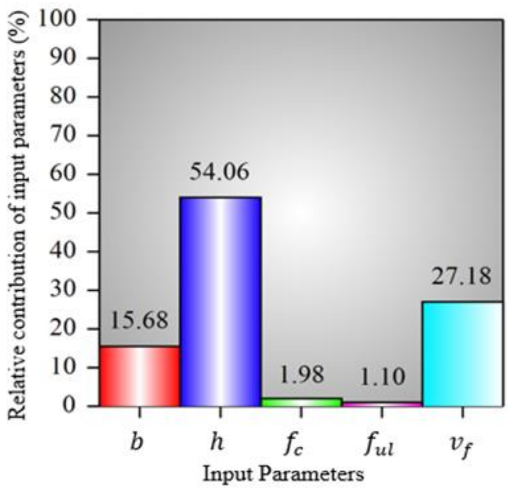

Figure 10. Sensitivity analysis of input parameters on moment capacity.

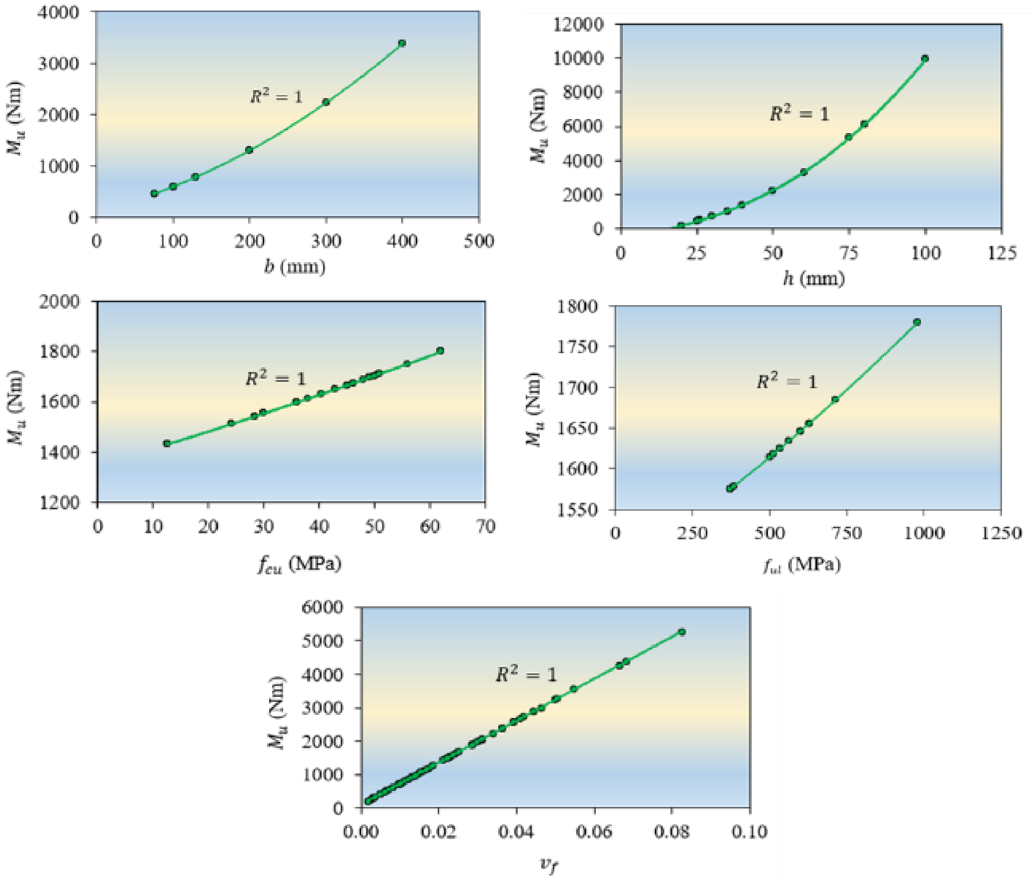

Figure 11. Parametric analysis of input parameters on moment capacity.

4 CONCLUSION

In this study, the GEP model is proposed to predict the moment capacity of ferrocement elements using a data set of 75 test specimens and five input parameters. The findings obtained are given below;

1) It is observed that the statistical values calculated in this study for both the training and validation datasets are close to each other. This result shows that the GEP model has sufficient accuracy in predicting M_u.

2) The M, SD, MAPE, RMSE, R^2 and COV values of the proposed GEP were 1.003, 0.243, 21.141, 159.777, 0.977 and 0.242, respectively. These values prove that it is statistically ahead of the theoretical studies and the findings of a different GEP model in the literature. In particular, the high R^2 and low COV value of the proposed GEP model shows that there is a high correlation between the experimental findings and the predictions.

3) It is seen that the error percentage of the predictions with the proposed GEP model is higher for test elements with low moment capacity compared to the experimental findings given in the data set.

4) According to the sensitivity analysis findings, the most effective parameters on M_u are h, v_f and b while the least effective parameters are f_{cu} and f_{ul}. The findings of the parametric analysis and sensitivity analysis show that the proposed GEP model achieve the physical characteristics of the moment capacity of ferrocement elements with respect to robustness.

5) As a result, it can be said that GEP provides effective and reliable findings and therefore, it can facilitate the solution of many complex problems in civil engineering.

6) The proposed GEP model in this study and the predictions findings obtained are valid for the maximum and minimum range of input parameters in the used dataset. To obtain more accurate findings, it is recommended to propose new equations for M_u by increasing the number of experiments and input parameters.

Conflict of Interest Statement

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

The study is complied with research and publication ethics

Artificial Intelligence (AI) Contribution Statement

This manuscript was entirely written, edited, analyzed, and prepared without the assistance of any artificial intelligence (AI) tools. All content, including text, data analysis, and figures, was solely generated by the authors.

Contributions of the Authors

Hasan Cem Akkaya: Conceptualization, Methodology, Investigation, Writing-Original draft preparation, Visualization, Analyses, Reviewing and Editing

Sema Alacalı: Conceptualization, Methodology, Investigation, Writing-Original draft preparation, Visualization, Software, Analyses, Reviewing and Editing

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