Modelling of RCC Framed Structure with Bracing Using Random Forest and M5P Technique

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Abstract

When an earthquake strikes a region, most of the RC buildings collapse. As a result, selecting a lateral load resisting system that is effective is critical. The safety of the structure against lateral loads is prioritised in RCC frames. Steel bracings of various types are used to withstand lateral loads operating on the structure. The structural performance is greatly influenced by the bracing scheme. Steel bracing offers a potential benefit over alternative bracing because it allows for a substantial increase in stiffness with a little increase in weight, making it ideal for existing structures with weak lateral stiffness. Thus, the natural frequency is increased while the lateral displacement and drift are generally reduced. Steel bracing is inexpensive, easy to install, takes up less space, and may be customised to meet particular strength, stiffness, and stability requirements. With the aid of the Etabs software, the impact of steel bracing on the seismic behaviour of RC frames was investigated. In a G+7-story reinforced concrete skyscraper, many models were built with various types of bracing systems. Using E-TAB software, the models were examined for different seismic zones, characteristic strength, location of bracing, and type of bracings in accordance with IS 1893:2016. The results (maximum story displacement) of several CBF bracing system such as X bracing, V bracing, Inverted-V, Diagonal bracing were gathered through seismic analysis by response spectrum method. In this comparison between two AI techniques were discussed using Weka software on maximum story displacement data obtained through Etabs models. The results showed that Random Forest is more reliable than M5P technique.

Keywords. Seismic analysis, steel Bracings, Maximum story displacement, Random forest (RF), M5P, Etabs.

1. INTRODUCTION

In order to strengthen and stiffen multi-story structures, which are more sensitive to earthquake and wind stresses, the cross sections of the members rise from top to bottom, making the construction uneconomical due to structural safety. As a result, unique procedures and/or techniques to strengthen the lateral stability of the structure are required. Braced frames create their lateral force confrontation through the bracing action of diagonal elements. Frames that are fully braced are more rigid. Arbitrarily braced ones have the least forces produced in the structure while producing maximal displacement within set limitations.

In past many studies were carried out to find which type of bracing is suitable for RC building having different story height and symmetric or non-symmetric plan subjected to seismic analysis through various softwares [1-3]. But this process is time consuming and uneconomical. Therefore, the main aim of this study is to develop a trained model (AI) which can predict the output with the help of various input parameters available.

Steel bracing for reinforced concrete buildings has several advantages, including the fact that it is relatively inexpensive, does not considerably increase structural weight, is simple to install, and can be designed with the required strength and stiffness. The fundamental advantage of this technology is that no foundation system rehabilitation is required.

Considering the usage of tree - based regression in many civil engineering applications [4], two such techniques (I) RF regression and (II) M5P model tree-based modelling approaches [5-6] are employed in this research work to estimate the maximum story displacement of a building structure. Data set obtained through seismic analysis (Response spectrum analysis) of models in Etabs- structural analysis and design software for modelling purpose.

2. METHODOLOGY

Seismic analysis of models were done using Response spectrum method in Etabs.

Using this method of analysis, multiple modes of response may be considered Except for exceptionally complicated or basic structures, many building codes require such technique. The structure reacts in a way that may be described as a hybrid of several special modes. Dynamic analysis is used to figure out these modes. A response from the design spectrum is examined for each mode, taking into account the modal mass and modal frequency, and then combined to offer an assessment of the structure's overall reaction. In order to do so, we must first determine the magnitudes of the forces in all directions (X, Y, and Z) and then look at the repercussions for the structure. The following are a few different ways to combine things: 1) CQC, 2) SRSS, 3) Absolute-peak values are summed together.

2.1 AI Techniques

Random Forest Technique

The supervised learning approach is used by Random Forest, a well-known machine learning algorithm. In machine learning, It may be used for both classification and regression problems. It's based on ensemble learning, which is a method for merging several classifiers to solve a complex problem and improve the model's performance. Based on the decision trees' projections, the RF algorithm decides the outcome. It anticipates the production of numerous trees based on an average of their output. M and k [9] are the only user-defined variables. According to Breiman [7], the number of trees used enhances the accuracy of the result. The limitations of a decision tree algorithm are eliminated by using a random forest technique. It enhances accuracy while reducing dataset over fitting. It can provide forecasts without a significant number of package configurations (like scikit-learn). Random forests can generate non-linear relationships between input and output variables. Class labels are translated into numerical values throughout the regression procedure [7].

M5P Technique:

M5P is an enhanced version of Quinlan's M5, in which a conventional decision tree is merged with linear regression functions at the nodes. The M5 model's construction is divided into three major phases. To begin, a tree model is constructed using a splitting criterion to divide the data into subgroups. Then, in order to overcome data over fitting that occurred during tree creation, tree pruning is undertaken to delete or combine unnecessary sub trees. Finally, a smoothing procedure is carried out to compensate for the severe discontinuities that occur between consecutive linear models at the clipped tree leaves. The decision tree is created using a divergence metric known as Standard Deviation Reduction (SDR). Pruning, evacuation, and tree substitution are all part of the process. As a result, a final tree model is created.

The M5P algorithm produces accurate classifiers, especially when the majority of the characteristics are numerical. To evaluate the proposed model, the M5P method measures both MAE and MASE. The M5P has been utilised in a variety of disciplines, like predicting soaked CBR value of stabilized pond ash.

3. DATASET

For the modelling, Input parameters were type of bracing [x- bracing (1), v-bracing (2), inverted v-bracing (3) and diagonal bracing (4)], Fck (30, 40, 50), zone (III, IV, V) and location of bracing (model type) as shown in Figure 1. Data was obtained by keeping one parameter varying and other parameter constant in a model. A total of 369 data sets were gathered and seismic analysis of models were done in Etabs software. Using the WEKA 3.9 software [8], the maximum story displacement was estimated using random forest regression and the M5P model. In both models, 70 percent of the data was randomly picked for training, while 30 percent was utilized to test the models. Type of bracing, seismic zone, characteristic strength (Fck), and placement of bracing are all input parameters/dependent variables in models. The maximum story displacement, on the other hand, was used as an output parameter.

To compare the outcomes of the RF and M5P models, statistical measures such as coefficient of correlation (CC), mean absolute error (MAE), root relative square error (RRSE), root mean square error (RMSE), and relative absolute error (RAE) were discovered. The performance of both models is influenced by user-defined parameters. As a result, picking the correct choices for these parameters is crucial. Table 1 shows the statistical properties of various analytically obtained data. Table 2 shows the ideal values of the needed user-defined parameter in both modelling techniques.

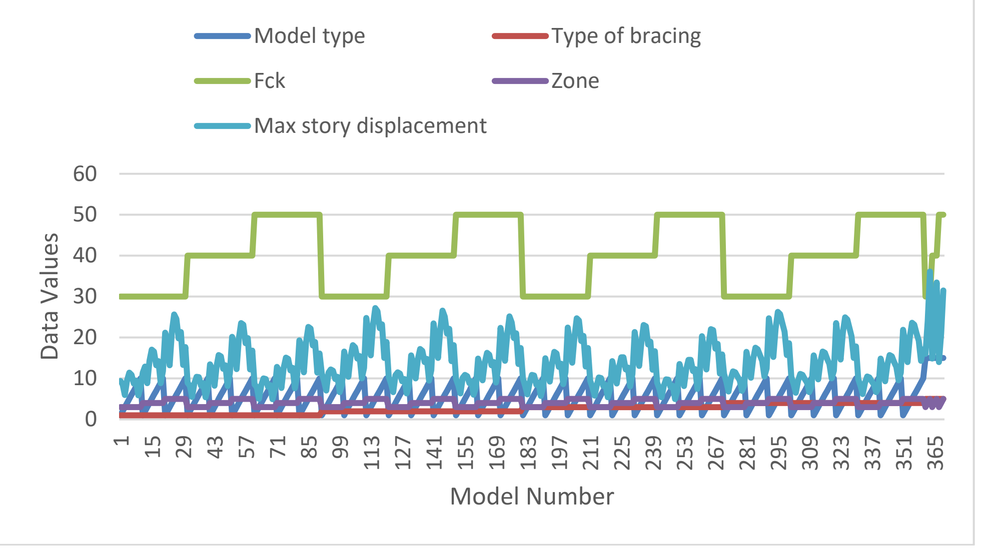

Figure 1. Data values of parameters with model number of full data set (Training-Testing)

Table 1. Predictive models' details of statistical parameters over training data

Used Parameters		Training dataset			
		Min.	Max.	Avg.	Standard deviation
Input data	zone	3	5	-	-
	F_{ck}	30	50	-	-
Output data	MSD	4.9629	36.127	14.083	5.799

Table 2. Predictive models' details of statistical parameters over testing data

Utilized parameters		Testing Dataset			
		Min.	Max.	Avg.	Standard deviation
Input data	zone	3	5	-	-
	F_{ck}	30	50	-	-
Output data	MSD	4.9704	33.4819	13.781	5.3064

Table 3. Details of numerical parameters in predictive models of RF over training and testing data

Methodology (RF) Training			Methodology (RF) Testing		
Parameters		CC	Parameters		CC
I-1, M-1, K-3		0.9769	I-1, M-1, K-3		0.8972
I-10, M-1, K-2		0.9917	I-10, M-1, K-2		0.9516
I-50, M-1, K-1		0.9903	I-50, M-1, K-1		0.9001
I-100, M-1, K-2		0.9944	I-100, M-1, K-2		0.9429
I-100, M-1, K-3		0.9967	I-100, M-1, K-3		0.9642
Optimized	I-100, M-1, K-3	0.9967	Optimized	I-100, M-1, K-3	0.9642

Table 4. Details of numerical parameters in predictive models of M5P over training and testing data

Methodology (M5P) Training				Methodology (M5P) Training			
Parameters	M-4	M-3	M-2	Parameters	M-4	M-3	M-2
CC	0.9443	0.9433	0.9433	CC	0.8352	0.8352	0.8352
Optimized	0.9443			Optimized	0.8352		

Table 3 and 4, depicted the implementation of AI technique i.e. RF and M5P. The variation in the performance criteria of correlation coefficient (CC) is given in Table 3, 4 and finally summarized in Table 5, 6 based on the optimization of various factors like I, M and M in RF and M in M5P models.

4. RESULTS AND DISCUSSIONS

The maximum story displacement with varied parameters was predicted using the RF and M5P models and compared to the analytically determined results. The adequacy level of anticipated MSD reading was determined using statistical metrics such as CC, MAE, RMSE, RAE, and RRSE. Tables 5 and 6 demonstrate the statistical parameters of MSD predicted by both modelling techniques. Figures 2, 3 show a scatter graph of the actual and predicted MSD values derived from the RF and M5P models using training and testing datasets, respectively.

The graphical results indicate that the projected MSD value by both models is in good accordance with the actual MSD value, although the M5P model predicts more error in both training and testing values. In comparison to the M5P model in predicting MSD values, the random forest model performs somewhat better than the M5P model due to greater CC and lower errors values (CC- 0.9642, RMSE-1.4467, MAE-1.1823, RAE-27.6024, and RRSE-27.3412).

Table 5. Details of numerical parameters over training data using prediction models

Methodology used	Data set for training				
	Coefficient correlation	MAE	RAE (%)	RMSE	RRSE (%)
RF	0.9967	0.3276	6.8518	0.5081	8.7772
M5P model	0.9443	1.4467	30.2583	1.9547	33.774

Table 6. Output data of testing data using prediction models

Methodology used	Data set for testing				
	Coefficient correlation	MAE	RAE (%)	RMSE	RRSE (%)
RF	0.9642	1.1823	27.6024	1.4467	27.3412
M5P model	0.8352	2.4086	56.234	3.0583	57.8013

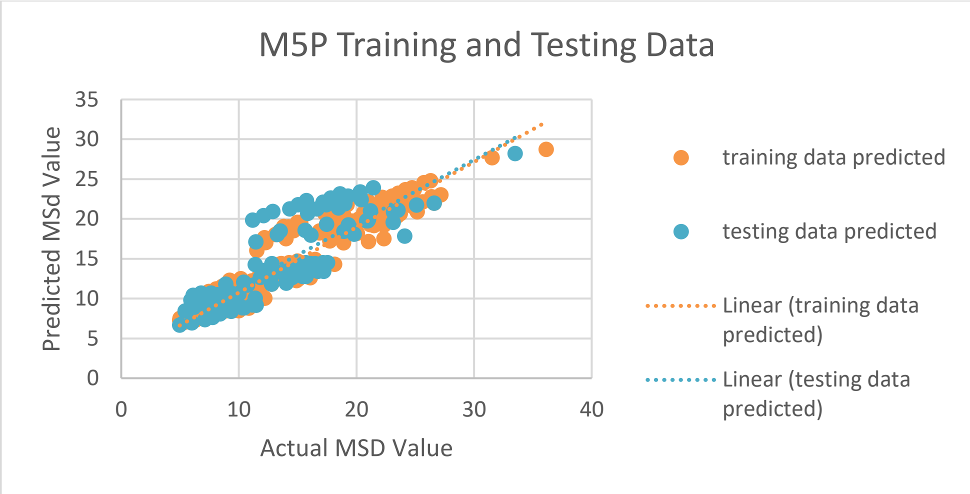

Figure 2. Predicted VS Actual MSD value using M5P with training and testing data set

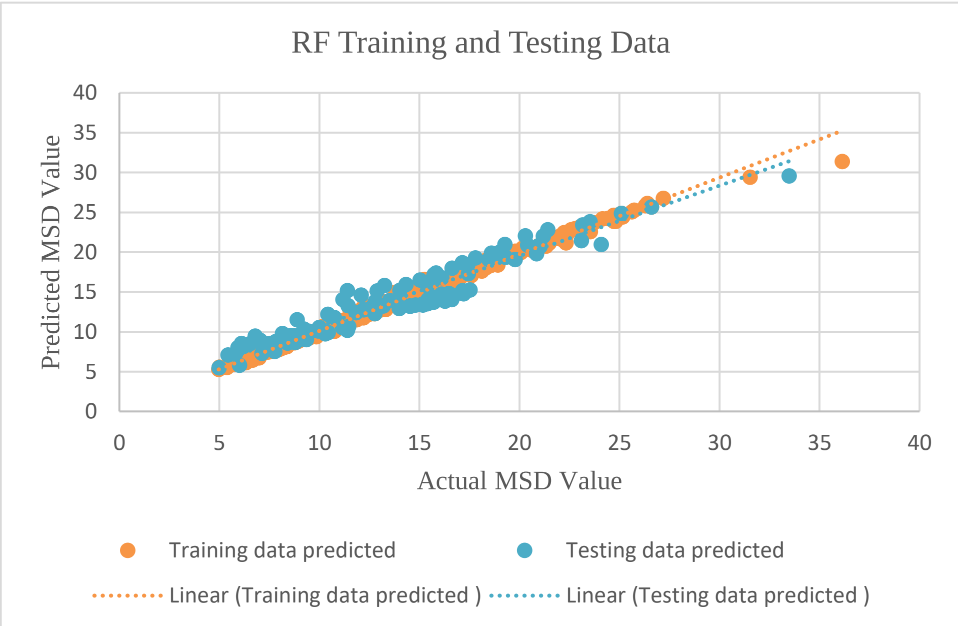

Figure 3. Predicted versus Actual MSD value calculated with RF utilising training and testing data sets

5. Conclusion

The present work models the analytically obtained MSD value of frames utilising two modelling methodologies (i) Random Forest and (ii) M5P. Figures 2 and 3 clearly show that the dispersion of data from the trend line is greater in M5P than in RF. Statistical parameters are used to assess the fitness of models. Random Forest performs better than M5P because to larger CC and smaller errors in Tables 5 and 6. RF has the following advantages over other machine learning tools: (a) It takes less time to train than other methods, (b) It estimates output with great precision, even for big datasets, and (c) It can retain accuracy even when a significant amount of data is absent.

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