Analysis of Design for One-Way Reinforced Concrete Slabs using Machine Learning Models

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Abstract. Preliminary design parameters of one-way Reinforced Concrete (RC) slabs are one of the significant factors and needs to be precisely determined. Though, these parameters can be suitably determined by using the guidelines laid down by various Indian Standards, a high level of expertise is required to perform this operation. At the same time analysing and fixing design parameters considering different configurations of slab make the prediction somewhat more time consuming. In such a condition, one of the supports for a design engineer is the Machine learning (ML) techniques. This paper investigates the performance of various ML techniques in predicting and analysing the design inputs and outputs for a one war RC slabs. The comparison results show the appropriate machine learning model learning to predict the compressive strength of one-way slab.

1. Introduction
On daily basis, we come across various types of structures. Amongst these, most common type are the building structures. All sort of buildings consists of structural members such as slabs, beams and columns. Slabs are the building components that represents a floor or a roof. The entire load coming on the slab is transferred to the beams and the beams transfers this load to the columns and finally to the foundations. Depending on the geometry of the slab, it can be classified as a One-Way Slab (OWS) or a two-way slab. In OWS, the proportion of longer measure to shorter measure is larger than two. Similarly, for a two-way slab, the proportion of longer span to shorter span is less by two. In the presented study, one-way concrete slab has been designed for various configurations. OWS is generally, used as an overhang such as a cantilever in chajjas or a balcony platform. Such platforms are supported at the two short edges by the extended beams. Due to the upcoming load, these slabs have a deflected shape that resembles a cylinder. The whole purpose of designing is to meet the increasing needs of sustainability [1] by avoiding any structural deformation like cracking [2] in the slab due to upcoming load over it. This greatly depends on the compacting strength of concrete that is used to construct the slab. Since, concrete is a mix of various raw materials, same properties cannot be found at various sections of structural members. In this case, there is a need of some technique or methodology that could predict the correct results. Machine learning models have been shown to be useful for predicting and evaluating structural efficiency, for recognizing
structural conditions and for informing preventive and recovery decisions by extracting trends from data collected from various sources and media.

2. Literature Review

Review conducted on research work based on machine learning indicates its influence on various domains. These include both engineering and non-engineering domains such as sciences, medical, arts and humanities and several others. Of these several domains civil engineering is one such area, where these machine learning techniques can be effectively and conveniently applied. Particularly, in design of structural members and estimating or fixing the preliminary design inputs, these machine learning techniques gives a very good prediction. Some literatures provide a summary of the study whereas some other provides advances in the computer vision domain for tracking and observing and checking civil facilities by some procedures.

To ensure proper serviceability of one-way RC slabs, its cracking behaviour was analyzed by Gomes J. et al (2020) using thermo-hygro-mechanical simulation (THMS) framework. This method comprised of simulation of temperature, relative humidity and mechanical field in a staggered manner. Afterward the data from the moisture and thermal models were transferred into automated mechanical model. The developed models supported in understanding the influence of these parameters in long term application [3]. Kang S.B. et al. (2020) proposed analytical models for resisting collapse of RC structures. The objective was to forecast the load resistance for one-way RC beam slab structure. These models were effective in determining the axial forces, load resistances, axial tension forces, compressive arch method capacity and the associated forces and effect of the region of longitudinal strengthening in the slab. It was suggested to have more experimental results so that predictions can be precise [4]. An analytical study was performed by Hosseini M.R.M et al (2020) for analyzing the one-way RC slabs. This study determined the cracking behaviour of slab, its yielding and the flexural strength of slab against the maximum load. A very good predictions were obtained in this work [5]. Thoma K. and Malisia F. (2018) investigated the membrane action in RC slabs. A non-linear Finite Element methodology was adopted for analyzing one-way slabs. Relationship between thrust and pressure line was assessed with the compressive, bending and arching action. It was concluded that effective predictions are possible with equilibrium conditions [6]. Ceniceros J.F. et al (2013) proposed a decision support system for predicting the design attributes of a one-way floor slab. The parameters considered for decision-making were in material form CO₂ and the total cost of the slabs. It was concluded that in the span range of 6 to 7 meters, CO₂ can be reduced significantly with less than 6% increase in construction cost [7].

3. Methodology

Various OWS configurations have been developed with various design inputs and outputs. The design inputs are the parameters that governs the overall design of slab. These slab configurations are represented in Table 1.

| S. No. | Physical parameters     | Units | Range          |
|-------|-------------------------|-------|----------------|
| 1.    | Length                  | m     | 5, 6, 7, 8, 9, 10 |
| 2.    | Breadth                 | m     | 2, 2.5, 3, 3.5, 4, 4.5 |
| 3.    | Rank of Concrete        | N/mm² | 20, 25, 30, 35, 40 |
| 4.    | Rank of Steel           | N/mm² | 250, 415, 500  |
The outputs are in the terms of economical depth of slab section and main steel reinforcement requirement as per the slab design. The OWS considered in this study is designed for the dead load that consists of self-weight of the slab along with the weight of the floor finish, wall load etc., and the live load that includes the weight of furniture and the people. Based on this overcoming load, the bending moments and shear force in the slab is calculated and the required reinforcement is provided to take care of the deflection criteria. For benchmarking the design methodology, it is compared with various regression techniques such as Linear regression, cubic SVM, linear SVM, regression tree, quadratic SVM, ensemble boosted trees and random forest methods. Using these techniques, mean absolute error and $R^2$ values have been compared.\[8\][9][10][11]

Regression: It is commonly used in institutions for health care. Basically, it points out the relationship between the defined special functions and the relevant function variables \[12\][13\]. There is also Logistic Regression (LR) that can be used to derive the binary objective on a given set of features, either continuous, discrete, or a combination of both forms. For the inputs, LR calculates a linear combination and passes through the logistics function. This approach is usually implemented for ease of use and execution, followed by competitive outcomes. In their respective research work, several authors have adopted LR because LR provides better results for larger datasets \[14\].

\[ y = a_0 + a_1 * x \]  ## Linear Equation (1)
\[ h(x) = \frac{1}{1 + e^x} \]  ## Logistic Function (2)

Regression Tree: In this case the decision tree has a constant target variable. According to research, the regression tree is being used for the price of a newly presented product as price may be something depending on a variety of parameters \[15\][16\]. Several studies that examined the method of the regression tree to interpret civil knowledge. The decision tree algorithm has been used by numerous authors in their research work. As, regression trees, because of their rules are used to make a forecast, have the property to analyse data and make the tree. In order to enhance the analytical presentation in terms of precision, most related work has used the decision tree for the data collection. Furthermore, the essence of the data set taken into account is a more balanced set \[17\][18\].

Support Vector Machine: It can be used as a linear model for the purpose of classification as well as regression issues. It is used to explain linear and non-linear problems. It also works fine for variety of real-time problems. The basic idea of SVM is simple: The algorithm generates a line or a hyper plane dividing the data into classes. A novel quadratic kernel-free non-linear support vector machine (generally called as QSVM) is proposed. A quadratic decision function which has the ability of separating non-linearly the data is considered. The geometrical margin is demonstrated is found to be equivalent to the inverse of the norm of the gradient in the decision function. The SVM classification technique is helpful when a dilemma of low memory space is considered. The technique describes a hyper plane in multidimensional space by dividing the classes into best probable means where cubic SVM type classifier is in use \[19\].

Ensemble boosted trees: The machine learning techniques similar to decision trees can be used in businesses to make improved decisions and make extra benefit. The Decision trees are implemented in variety of applications but sufferers from bias and variance. A high bias with simple trees and a high variance with complex trees has been experienced. Ensemble techniques merge several decision trees to generate efficient analytical presentation as compared to usage of a single decision tree. The key idea in the using ensemble model is to groups weak learners together to build a strong learner. It is useful in reducing the variance of a decision tree. The focus is to create a number of subsets of data from available training sample selected arbitrarily with substitution. Afterwards, every compilation of subset data is considered to train their decision trees. Due to this, an ensemble of dissimilar models is less used. The
average of each and every prediction from different trees is calculated and it is observed to be more error-free than a single decision tree.

Random Forest: RF is an ensemble learning method which is widely used for the activities like classification, regression, etc. which operate by developing a multitude of decision trees for training time and evaluating the output of class the class which is generally mode of the classes or mean/average forecast of the individual trees. Random forest is very useful algorithm as it uses often produce a good prediction result. The use of hyperparameters is straight forward. One of the main issue in machine learning is over-fitting, This will not be a case if there are sufficient trees in the forest then there will be no over-fitting.

The implementation of Random Forests (RF) algorithm for one way slab application is inspired by features of algorithm. RF is acting to reduce prediction variance while retaining low prediction, which is structured to suit the data adequately. In addition, the forecast performance is evaluated by a category of cross-validation during the training phase. These characteristics are among others appealing to the use of RF. Table 2 further shows that the current implementation is not compatible with other types of learning algorithms.

This algorithm is basically a series of decision trees, where each tree is developed by a bootstrap (random sample) and replaced by a training set.

The subset of features is considered for best possible partitioning. The method is used till every point in the sample is allocated. The terminal node of the earlier partitioned nodes is replicated till the required number of trees has been increased. With the use of trees Bootstrap samples, the trees produced would usually less correlated with every tree that makes a prediction. The final prediction in regression calculated as an average of the actual predictions. The final classification that is predicted class is the mainly common class of individual predictions [20].

4. Results

4.1 Preliminary Measurement of Regression Models

There are several factors that influence the design of RC slabs. Most important of these are the length and width, the loading coming on slab, the grade of concrete used, and the steel reinforcement used to bear the tensile stresses. These factors have the direct impact on the thickness of the RC slab, diameter of the reinforcement used and the spacing between the reinforcing bars. These parameters were fixed, and a range of these parameters were specified for the experimental work and is represented in Table 1. Some of these parameters are uninterrupted and some other are categorical. Each design input selected had an influence on all other design parameter. At the same time, each of these inputs are unique to every other parameter. Table 2 presents the mean and standard deviation for each of the selected design parameter.

| Notation | Feature/ Output         | Mean/Count | Standard Deviation |
|----------|-------------------------|------------|-------------------|
| X1       | Length                  | 8.18       | 1.21              |
| X2       | Breadth                 | 3.42       | 1.01              |
| X3       | Compressive strength    | 27.53      | 5.45              |
| X4       | Tensile strength        | 387.37     | 104.5             |
| X5       | Effective depth         | 152.46     | 42.8              |
Various regression algorithms for learning purpose were selected for collection of data and analysed for their suitability of which some were carried out. Learning algorithms have been tested using the MATLAB platform of by random forest and by regression learner algorithm. The models assessed consisted of LR Models, support vector machines (SVM), regression trees and tree set. In addition, all model preserved its original characteristics and associated parameters.

The differentiation was made on the basis of the absolute mean error and value of R². Initial analysis of these models was focused exclusively on seven continuous features. Table 3 list the models experienced, and their performance measurements followed by figures 1 and 2.

Accuracy of Machine learning classifier can be calculated as:

\[
\text{Accuracy} = \frac{\text{Correct predictions}}{\text{all predictions}} (3)
\]

Table 3. Performance Measure of Machine Learning Techniques

| Model Name                | Mean absolute error | R²  |
|---------------------------|--------------------|-----|
| Linear Regression         | 19.41              | 0.27|
| Regression Tree           | 7.89               | 0.84|
| Linear SVM                | 19.39              | 0.2 |
| Quadratic SVM             | 12.54              | 0.41|
| Cubic SVM                 | 12.02              | 0   |
| Ensemble boosted trees    | 8.12               | 0.78|
| Random Forest             | 6.65               | 0.93|

Figure 1. Graph for Mean Absolute Error
The variance ($R^2$) usually calculated by:

$$R^2 = 1 - \frac{\text{sum}((\hat{y}-\text{mean}(y))^2)}{\text{sum}((\text{mean}(y)-y)^2)} \quad (4)$$

5. Conclusion

Machine learning model as applied to the design database indicate satisfactory prediction in terms of estimation. Compared with other methodologies, machine learning result proves to be better for associated problems of structures and illustrated experimentally with excellent ability to identify the cause of each input function. Also, this methodology saves computing time and effort. By analysis of Mean absolute error and R square value Random forest model gives better results as random forest has features such as stimulating the versatility, parallelizable, greater dimensionality, quick prediction and training speed, robustness to outliers and non-linear Data, low bias, and fair variance.

6. References

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