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PREDICTING THE FLEXURAL CAPACITY OF CORRODED REINFORCED CONCRETE BEAMS USING ARTIFICIAL INTELLIGENCE MODELS

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Abstract. Predicting the residual flexural capacity of corroded reinforced concrete (RC) structures is to help civil engineers decide to repair or strengthen the structures. This study presents the application of six single algorithm-based models of artificial intelligence, such as artificial neural network (ANN), support vector machine (SVM), classification and regression trees (CART), linear regression (LR), general linear model (GENLIN), and automatic Chi-squared interaction detection (CHAID) to predict the residual flexural capacity of corroded RC structures. The predicting results are compared to the surveyed data including 120 corroded RC beams from the projects built before 1975 to rank the efficiency of single models. Some combined models are applied to investigate the improvement in predicting the flexural capacity of corroded RC structures compared to the single models. The result shows that LR and GENLIN models give almost the same results and the best efficiency. The combined models can not improve the efficiency compared to the two best single models.

Keywords: residual flexural capacity, corroded reinforced concrete beams, artificial intelligence, single model, combined model, repairing, strengthening.

1. INTRODUCTION

The integration in the world economy has stimulated the growth and development of Vietnam. To improve the civil infrastructure for economic development, many bridges, buildings, ports, and so on have been built from steel and reinforced concrete (RC) structures. In addition, Vietnam is located in a wet tropical zone. It is characterized by strong monsoon influences and has a high rate of rainfall and high humidity. Vietnam also has a coastline of 3260km from the North to the South. The salt in the air from the sea makes a high chloride concentration in the coastal areas. Therefore, steel structures and normal reinforcing bars in concrete structures have a high potential for corrosion in the coastal areas. Moreover, the seawater invading deeply into the mainland in the Mekong area also increases the area causing corrosion problems in the steel and reinforced concrete structures.

The corrosion in the steel and reinforced concrete structures may cause serious deterioration and damage to the structures. Therefore, retrofitting and strengthening the corroded steel and reinforced concrete structures are needed to save the budget compared to building new structures. A lot of structures such as buildings, bridges, and so on, having been built since 1975 are recognized to be corroded. Before repairing and strengthening the corroded reinforced concrete structures, evaluation of these structures is needed. However, the evaluation of the corroded reinforced concrete structures has been complex work. Therefore, predicting the flexural capacity of the corroded reinforced concrete structures based on artificial intelligence is conducted in this paper. The results from this prediction are used for retrofitting and strengthening the corroded RC structures.

In the world, some studies related to the corrosion problems of RC structures have been conducted to predict the initial corrosion process and its harmful effects by intelligent algorithms. Imam *et al.* [1] showed that using the correction factor (C_f) in the artificial neural network (ANN) model has an improvement of up to 49% compared to the experimental model from Azad *et al.* [2]. Based on experimental research on the corrosion of RC structures, artificial intelligence (AI) models and algorithms can gradually solve more and more problems of evaluation and prediction with higher accuracy. Tsai and Hsu [3] diagnosed the damage of reinforced concrete structures based on the displacement time history by using the back-propagation neural network technique. The results predicted from the damage scenario of each test beam from the study are much closer to the real situation. In addition, Chou *et al.* [4] used four well-known AI techniques including artificial neural networks (ANN), support vector machine/regression (SVR/SVM), classification tree and regression (CART), and linear regression (LR) to model pitting risk and corrosion rate. A major contribution in the research is to suggest that the combined AI model (SFA-LSSVR) is more effective than the remaining models.

Furthermore, new corrosion studies incorporating artificial intelligence methods into the assessment have also been developed. Imam and Kazmi [5] used a modified regression method and an ANN model to predict the load capacity of corroded RC beams. The results show that the ANN predictions are much better with the experimental values than those obtained from the predictions of Azad *et al.* [2]. The residual strength of the corroded RC beam predicted from the model proposed by Azad *et al.* [2] is quite conservative and underestimates the residual flexibility of the testing corroded beam. Therefore, the model to predict the residual strength of the corroded RC beam [2] needs to modify the model to increase the accuracy and reliability. In addition, Alabduljabbar *et al.* [6] predicted the flexural behavior of corroded concrete beams by using the combined method. In their research, a new statistical method using the neural network (NN) model was built to estimate the behavior models of materials based on the data from 107 concrete members. Outputs from the NN are fed into finite element analysis models to analyze concrete beams damaged by corrosion.

Recently, Ahmadi *et al.* [7] used an ANN to predict the bond strength of the corroded reinforcing bar. The Levenberg – Marquardt algorithm is applied for the training procedure. The proposed model is checked with the collected experimental data. Based on the mean absolute error of the optimal network by 15%, the proposed model could be used in the reliability assessment of corroded concrete structures in a corrosive environment. Seghier *et al.* [8] proposed a reliable method for the multi-state assessment of corroded RC beams. The reliability method is the three-term conjugate map (TCM) based on the first-order reliability method (FORM). The results from the TCM method show better efficiency, higher reliability, and more robustness in prediction.

The above methods have advantages in predicting the effect of corrosion problems on the behavior of RC structures. However, each method is applied to one problem with different accuracy. It may not be applied to other problems with the effect of environmental causes on the corrosion of RC structures. Therefore, in this study, six single models such as ANN, SVM, CART, LR, GENLIN, and CHAID models applied to the artificial intelligence analysis are investigated. The results from single models are compared to corroded RC beams from surveyed data. The single models are evaluated and ranked based on their deviations. Some combined models are also suggested to examine their accuracy improvement. In addition, some parameters such as effective depth of cross section and reinforcement grade of corroded steel bars are not easy to get. Some parameters such as the dimensions of beams such as length, width and depth, compressive strength of concrete, the area of steel bars and residual moment from the surveyed data are used for training. The efficient model is suggested to predict the residual flexural capacity of corroded RC structures.

2. ARTIFICIAL INTELLIGENCE METHODS

2.1 Artificial Neural Network - ANN

ANN is an information processing model based on the nervous system of organisms consisting of many artificial neurons combined with the weights of the variables (Fig. 1). The connection strength of the artificial neurons can be adjusted. The artificial neural network has been used to predict the bearing capacity of beams in many previous studies [9-11]. In Figure 1, the structure of the neural system consists of 3 sub-layers: the input layer (input), the hidden layer (hidden), and the output layer (output). Each circular node represents an artificial neuron while the arrow represents the connection from the input of one neuron to the output of another neuron. The input layer is the layer that has a connection to the external data. The hidden layer has no connection to the data. The output layer will provide the result after the input data is processed by the network.

2.2. Support Vector Machine - SVM

Figure 2 illustrates the use of vector machines for classification. It is assumed to have a given number of data points in the form of a p-dimensional vector. Each point belongs to one of two classes. The goal is to decide the class to which the new data point should belong through a hyperplane (p-1). This method is considered a linear classification. SVM is recognized as one of the most powerful and accurate methods among the well-known algorithms for data classification. Therefore, the SVM applies to many types of recognition and classification problems such as image recognition, as well as prediction [13].

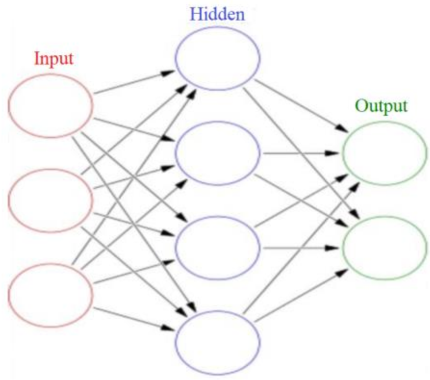

Figure 1. Simple Neural Network [12].

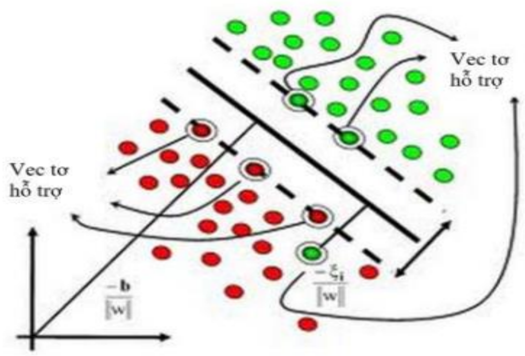

Figure 2. Support Vector Machine [14].

2.3 Classification and Regression Trees - CART

CART is a predictive model which is a mapping from observations about an object or phenomenon to the conclusions of the target value of that thing/phenomenon. Each node corresponds to a variable. The line connecting the node to its child node represents a specific value for that variable. Each leaf node (last branching node) represents the predicted value of the target variable. The given values of the variables are represented by the path from the root node to that leaf node. The machine learning technique used in decision trees is called decision tree learning, also based on statistical probability, depending on the stage of the tree [15].

2.4 Linear Regression - LR

Multivariable linear regression used to determine the relationship between two or more variables simultaneously is an extension of simple regression as shown in Eq. (1):

$$Y = \beta_o + \sum_{i=1}^{n} \beta_i \chi_i + \varepsilon \tag{1}$$

Where Y is the limiting moment of the corroded beam [M]; β_0 is constant; β_i is the regression coefficient (i = 1, 2, ..., n); ε is the error, and X_i represents specific factors [16].

2.5 Generalized linear model - GENLIN

The general linear model is developed by Nelder and Wedderburn [17]. The model can analyze different probability distributions for a dependent variable using the association function as a computational model to determine the relationship between the linear predictors and the mean distribution function.

2.6 Chi-square automatic interaction detector - CHAID

Chi-square automatic interaction detector for data classification was developed by Kass [18]. It tests for independence using the Chi-square test to assess whether splitting a node improves data cleanliness significantly. Comprehensive Chi-squared automatic interactive detection was developed to address the limitations of CHAID [19]. Comprehensive CHAID avoids the model overfitting a fully grown decision tree into the training data by continuously merging the classifier predictors until only the two best classifiers remain. It then determines the predictor in each sequence of mergers and computes an adjusted p-value for the categorical variable set that gives the best association with the target variable.

2.7 Ensemble method:

The ensemble method is a method that combines selected sub-algorithms. To have a good prediction result, the combinator usually combines sub-algorithms with good predictive/classifier ability and the results of the sub-algorithms are not highly correlated with each other [16]. Combined models could estimate more accurately than conventional individual models [20, 21].

2.8 Methods of performance evaluation:

To evaluate the accuracy of the prediction process of single and combined models, the following methods are used such as the coefficient of determination (R^2) as in Eq. (2), mean absolute percentage error (MAPE) as in Eq. (3), mean absolute error (MAE) as in Eq. (4), and root mean squared error (RMSE) as in Eq. (5):

$$R^2 = 1 - \sum_{i=1}^{n}(y_i - p_i)^2 / \sum_{i=1}^{n}(y_i - \overline{y})^2 \tag{2}$$

$$MAPE = (1/n)\sum_{i=1}^{n}(|p_i - y_i| / y_i) \times 100 \tag{3}$$

$$MAE = (1/n) \times \sum_{i=1}^{n}(|p_i - y_i|) \tag{4}$$

$$RMSE = \sqrt{(1/n) \times \sum_{i=1}^{n}[p_i - y_i]^2} \tag{5}$$

Where y_i is the actual value, p_i is the predicted value, $\overline{y}$ is the average of actual values, and n is the number of data samples. R^2 varies between 0 and 1. An R^2 value of 1.0 indicates a perfect fit. Meanwhile, small errors show good forecast data. Composite index (SI) is also used to evaluate based on four methods of R^2, MAPE, MAE, and RMSE following Eq. (6).

$$SI = \frac{1}{m}\sum_{i=1}^{m}\left(\frac{P_i - P_{min,i}}{P_{max,i} - P_{min,i}}\right) \tag{6}$$

Where m is the number of evaluation methods, P_i is the result of the i^{th} evaluating method. $P_{min,i}$ and $P_{max,i}$ are the minimum and maximum evaluation results of the i^{th} evaluating method. The value of SI also varies between 0 and 1. SI value close to 0 shows a high efficiency of the predicting model.

3. SURVEY DATA

The actual surveyed data come from 39 projects with 120 corroded reinforced concrete beams located in Ho Chi Minh City [22]. These projects are buildings and collective residences which were built mostly before 1975 consisting of from 2 to 7 floors. Undergone the service time, the quality of the buildings has been seriously degraded, especially the reinforced concrete beam element. This data has been surveyed since 2016 by the Center for Housing Management and Construction Inspection of Ho Chi Minh City Department of Construction. The data focus on investigating the corrosion of reinforced concrete beams. The boundary dimensions of structures including the cross-sectional dimensions (B×H) and length (L) were measured by steel tape with an accuracy of 1mm. The phenomenon such as spalling of concrete due to blistering by corrosion of reinforcing bars has been recorded by location and area. The existing cross-sections of the corroded RC beams are also recorded.

In the report [22], the compressive strength of concrete is surveyed by both non-destructive and destructive methods. For the non-destructive method, both ultrasonic pulse velocity and rebound hammer tests based on TCVN 9334:2012 [23] and TCVN 9357:2012 [24] are often used for assessing the quality of concrete and estimation of its compressive strength. For the destructive method, some cylinder concrete samples of the existing concrete structures are drilled out. They are compressed in the laboratory to determine the compressive strength. The destructive method should be according to TCVN 3105:1993 [25], TCVN 3118:1993 [26], TCXDVN 239:2006 [27]. When corroded reinforcing bars are exposed to the atmosphere by concrete spalling, they could be clean by mechanical wire-brushing or by sandblasting. An electronic calliper is used to determine the diameter of corroded reinforcing bars based on TCVN 8634:2010 [28] and TCVN 4101:1985 [29]. In the report [22], the residual flexural capacity are estimated based on TCVN 2737:1995 [30] and TCVN 5574: 2012 [31]. In this paper, the dimensions of beams as length, width and depth, compressive strength of concrete, area of steel bars and residual moment from the report [22] are collected for analysis. All surveyed data used in the study are showed in [32].

Before putting the data into the model, surveyed data are divided into six input parameters and one output as shown in Table 1. All input parameters and output are normalized to avoid too large values. All the variable values should be converted to (-1,1) or (0,1) [16]. For this study, the data are all positive. Therefore, the data is set (0,1).

Table 1. Data description.

Description of corroded beam	Variable	Min	Max	Average
Length (L, mm)	X1	1000	5300	3456.25
Width (B, mm)	X2	95	294.86	176.48
Height (H, mm)	X3	195	498.34	317.50
Uniform load (P, kN/m)	X4	2.72	39.73	16.70
Compressive strength of concrete (R_{bt}, MPa)	X5	14.4	23.0	18.36
Area of reinforcement ($A_{s,}$ mm^2)	X6	661.37	962.11	782.57
Moment [kNm]	Y	0.924	21.001	9.793

4. MODEL BUILDING

The prediction process is conducted by using Clementine 12.0 software. Six single models including ANN, SVM, CART, LR, GENLIN, and CHAID are applied. Six single models are ranked based on their accuracy. The combined models are then proposed. The process is divided into 5 steps. Fig. 3 describes the model of data with complete nodes for analysis and prediction :

- Step 1: The data are divided into 10 groups. The data are then applied the Cross-Validation algorithm [16] to divide data sets. The software is trained 10 times. Each time training for the software, one group in the Cross-Validation algorithm is not used in training.

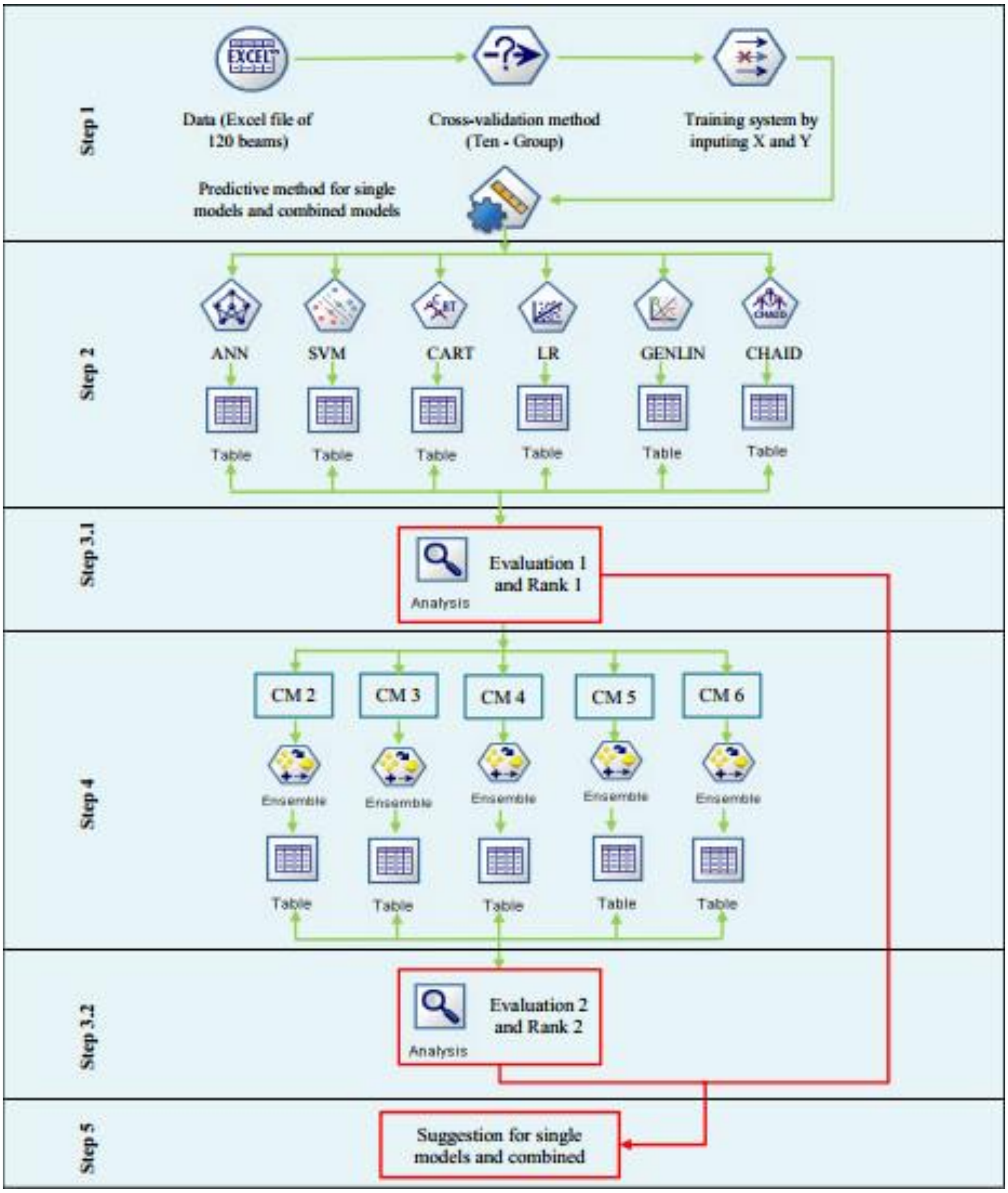

Figure 3. Diagram predicting the flexural capacity of reinforced concrete beams corroded using single models and combined models

- Step 2: After a training time, the data in the ignored group in training (12 beams) is input the trained software to predict the flexural capacity of the beams. In the trained software, six data mining techniques including ANN, SVM, CART, LR, GENLIN, and CHAID models are applied to predict the flexural capacity of the corroded RC structures.
- Step 3: The predicted flexural capacities from the trained software are compared to those from surveyed data. Based on the accuracy based on the evaluation methods, the single models are ranked.
- Step 4: Based on the accuracy of single models, the combined models are proposed. These combined models are used in trained software by Ensemble function in the software to predict the flexural capacity of the corroded RC structures, as well. The accuracy of the result from the combined models is also evaluated to rank the combined models.

Step 5: Suggestion the model to predict the flexural capacity of corroded RC beams

5. PREDICTED RESULTS FROM MODELS

Fig. 4 shows the comparison among the predicting the flexural capacity of the six single models and the surveyed results. Average values and results from evaluation methods for accuracy are listed in Table 3. The average result of the single model is larger than the surveyed value from 5% to 14%. The average result of the LR and GENLIN models is only 5% larger than the surveyed value, while the average result from the CART and CHAID models is 14% larger than the surveyed value. However, the results from models are scattered in different ways. The output results predicted from the single LR and GENLIN models are almost the same and scattered the closest to the average line. Therefore, the most efficient single model is the LR and GENLIN models. Meanwhile, the predicting moments from the single CHAID and CART models scattered widely. Evaluation results from CHAID and CART models show a higher error than other models. Based on the analysis results, the accuracy ranks of six single models are listed in Table 2. The accuracy of the single LR and GENLIN models is ranked the 1st, the rank of the single CART model is the 6th.

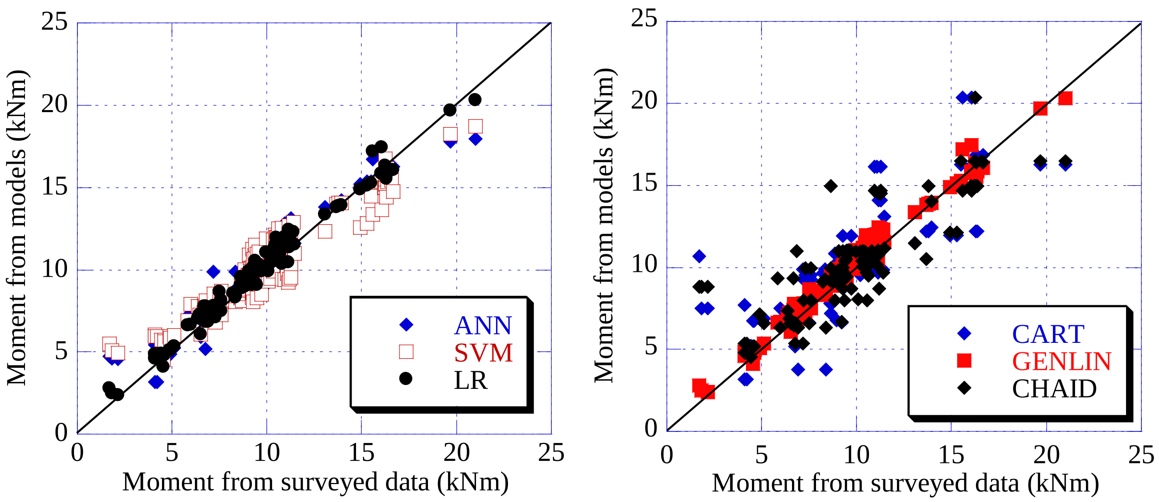

Figure 4. Comparison prediction results of single models to surveyed data

Table 2. Summary of evaluating results

Model	Average	RMSE	MAE	MAPE (%)	R^2	SI	Rank
ANN	1.077	0.964	0.736	11.0	0.9454	0.196	3
SVM	1.089	1.278	1.067	15.3	0.9034	0.421	4
CART	1.143	2.172	1.525	23.8	0.6870	1.000	6
LR	1.053	0.633	0.522	6.6	0.9820	0.000	1
GENLIN	1.053	0.633	0.522	6.6	0.9820	0.000	1
CHAID	1.140	1.992	1.377	22.1	0.7240	0.870	5

Based on the accuracy rank of six single models, some combined models are proposed as following:

- Combined model 2 (CM2) : GENLIN + LR
- Combined model 3 (CM3) : GENLIN + LR + ANN
- Combined model 4 (CM4) : GENLIN + LR + ANN + SVM
- Combined model 5 (CM5) : GENLIN + LR + ANN + SVM + CHAID
- Combined model 6 (CM6) : GENLIN + LR + ANN + SVM + CHAID + CART

Fig. 5 shows the comparison among the prediction moments of the five combined models and the surveyed results. Average values and evaluated methods for accuracy are listed in Table 3. The results show that the combined model could not improve the accuracy. The combined model 2 including the two best single models has almost the same result as the best single models. Other results from the combined models reduce the accuracy compared to the combined model 2. However, combining the best models to other models could improve the accuracy compared to the results from the worse single models.

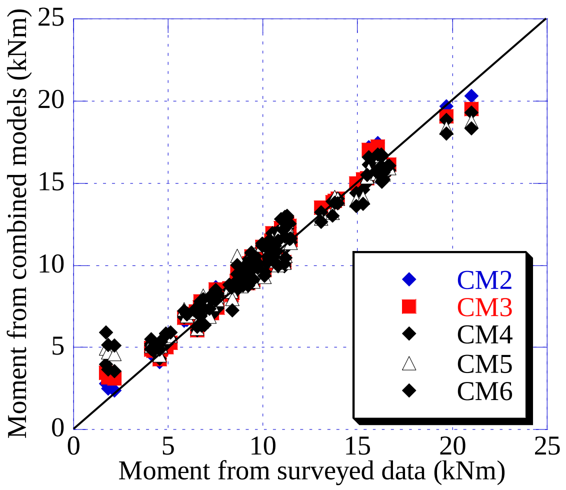

Figure 5. Comparison prediction results of the combined models to surveyed data

Table 3. Summary of evaluating results

Model	Average	RMSE	MAE	MAPE (%)	R2	SI	Rank
CM2	1.053	0.633	0.522	6.55	0.9820	0.0000	1
CM3	1.062	0.689	0.566	7.69	0.9778	0.1775	2
CM4	1.069	0.753	0.618	8.96	0.9739	0.3751	3
CM5	1.083	0.864	0.671	10.59	0.9659	0.6576	5
CM6	1.093	0.974	0.741	12.01	0.9523	1.0000	4

6. CONCLUSION

In this study, the 10-group cross-validation method is applied for minimizing the error in the model training process to predict the flexural capacity of corroded RC beams. The data used in training and comparing includes 120 corroded reinforced concrete beams surveyed from several projects built mostly before 1975 in Ho Chi Minh City. Some parameters such as dimensions of beams such as length, width and length, area of steel bars, compressive strength of concrete could be use in predicting residual flexural capacity. Six single predictive models including ANNs, SVM, CART, LR, GENLIN, and CHAID models are used. The results show that the predicted moments from the single LR and GENLIN models have almost the same values and the best accuracy. Other single models show worse accuracy compared to the surveyed data. The combined models are set and applied. The results from the combined model could not improve the accuracy compared to the results from the two best single models.

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