Journal of Civil Engineering and Urban Planning (2025)
Clausius Scientific Press, Canada
DOI: 10.23977/jceup.2025.070120
ISSN 2616-3969 Vol. 7 Num. 1

Prediction of Axial Compression Bearing Capacity of Built-In Steel Reinforced Concrete Filled Circular Steel Tube Based on Support Vector Machine

Weijie Han

School of Urban Construction, Yangtze University, Jingzhou, China

Keywords: Steel-Reinforced Concrete Filled Steel Tube(SRCFST), Axial compressive capacity, Support Vector Machine(SVM)

Abstract: This paper developed a support vector machine (SVM) regression model to predict the axial compressive capacity of concrete-filled steel tubular (CFST) columns with built-in steel reinforcement. The input parameters of the regression model included the calculated length, outer diameter, wall thickness, and yield strength of the steel tube, the axial compressive strength of concrete, the cross-sectional area of the embedded steel reinforcement, and its yield strength. The output parameter was the experimentally measured axial compressive capacity. A dataset of 38 specimens was utilized, with 30 samples for model training and 8 for testing. The results demonstrated that the SVM regression model achieved a coefficient of determination (R^2) of 0.98435, a mean absolute error (MAE) of 49.119, and a mean bias error (MBE) of -3.679 on the training set. For the testing set, the model yielded an R^2 of 0.9455, an MAE of 96.6133, and an MBE of -19.9404. These findings indicate that the proposed SVM model provides accurate predictions for the axial compressive capacity of CFST columns with built-in steel reinforcement, offering robust theoretical support and a reliable predictive tool for related engineering design and performance evaluation.

1. Introduction

Steel-reinforced concrete-filled circular steel tube (SRCFCST) columns represent a novel composite structural member that leverages the interaction between the steel tube and concrete, as well as the synergistic effects of the embedded steel reinforcement, to fully exploit the advantages of each material[1-3]. This configuration significantly enhances the compressive, flexural, and shear resistance of the component[3]. The structure exhibits superior seismic performance due to the combination of the steel tube's plastic deformation capacity and the concrete's energy dissipation capacity, enabling excellent ductility and energy dissipation capabilities under seismic loading. In practical engineering applications, SRCFCST columns offer notable construction advantages[4]: the steel tube serves as formwork, reducing on-site formwork installation efforts, while post-concrete pouring and curing procedures are simplified, thereby enhancing construction efficiency. Additionally,the durability of SRCFCST columns is exceptional, as the steel tube provides effective protection against environmental degradation, including moisture ingress, freezing, and corrosive agents, thereby extending the service life of the structural element[5].

Support Vector Machine (SVM) is a machine learning method grounded in statistical learning theory, characterized by strong generalization capability and adaptability to small-sample datasets[9]. In predicting the axial compressive capacity of steel-reinforced concrete-filled circular steel tube (SRCFCST) columns, the axial load-bearing behavior is influenced by multiple interdependent factors, including the calculated length, outer diameter, wall thickness, and yield strength of the steel tube; the axial compressive strength of concrete; and the cross-sectional area and yield strength of the embedded steel reinforcement[10]. These parameters exhibit intricate nonlinear relationships. SVM effectively addresses such nonlinearity through kernel functions, enabling precise establishment of mapping relationships between input and output variables. Given the limited experimental data in this study, SVM demonstrates superior learning and predictive performance for small-sample scenarios, facilitating the development of reliable predictive models even with constrained datasets. Consequently, SVM represents a highly suitable approach for predicting the axial compressive capacity of SRCFCST columns[11].

2. Correlation analysis

To precisely quantify the linear correlations among input features, this study employs Pearson correlation analysis. By computing the Pearson correlation coefficient between any two parameters, this method enables efficient evaluation of the linear correlation strength among variables. The mathematical expression for the Pearson correlation coefficient is provided below as Equation (1):

$$r = \frac{\sum_{i=1}^{n}(X_i-\bar{X})(Y_i-\bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i-\bar{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i-\bar{Y})^2}} \tag{1}$$

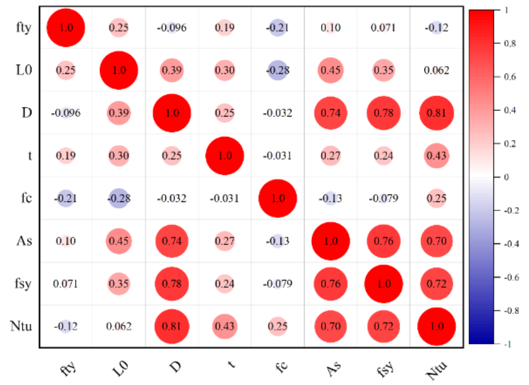

Figure1 Pearson correlation diagram

The Pearson correlation coefficient ranges from -1 to 1, where the sign reflects positive or negative linear correlations. A larger absolute value of r indicates a stronger linear relationship between variables. Figure1 illustrates the correlation matrix between input and output variables in the experimental dataset. Analysis reveals complex correlations between SRCFCST characteristic parameters and the axial compressive capacity. Notably, N_{tu} exhibits relatively strong positive correlations with the outer diameter of the steel tube(D) (r = 0.81) and the yield strength of the steel tube (Fsy) (r = 0.72), indicating that D and Fsy exert significant positive influences on the axial compressive capacity of SRCFCST in this dataset. While most other input parameters also show positive correlations with N_{tu}, these relationships are not governed by simple multivariate linear dependencies but instead reflect complex nonlinear mappings.

3. Data processing and assessment of indicators

This study employs MATLAB (R2020a) as the primary computational platform for developing machine learning predictive models. The experimental dataset comprising 38 samples[6-8] was partitioned into two distinct subsets: a training set (train_data) with 30 samples and a test set (test_data)containing 8 samples. During the model training phase, the training set was utilized for algorithm learning and hyperparameter optimization, with optimal model configurations selected through systematic evaluation metrics. Subsequently, the test set was employed to validate the generalizability of the finalized model. The mathematical formulations for these metrics are defined in Equations (2) through (5):

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2}\right) \tag{2}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|(\hat{y}_i - y_i)| \tag{3}$$

$$MBE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i) \tag{4}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2} \tag{5}$$

To address the heterogeneity in data scales across input features, this study implements min-max normalization to confine each feature dimension within the interval [-1, 1], thereby enhancing the model's convergence rate and predictive accuracy. The normalization process employs the mapminmax function, whose mathematical formulation is expressed as:

$$X^* = \frac{x_i - min(x)}{max(x) - min(x)}, x_i \in x \tag{6}$$

4. Optimal parameter selection for SVM

As a classical supervised learning algorithm, Support Vector Machine (SVM) has been extensively applied in regression prediction domains. Its fundamental principle involves identifying the optimal regression hyperplane by margin maximization to achieve effective data fitting. SVM demonstrates exceptional performance in addressing nonlinear problems, particularly in scenarios characterized by limited sample sizes and high-dimensional feature spaces, such as predicting the axial compressive capacity of steel-reinforced concrete-filled circular steel tube (SRCFCST) columns.

The selection of kernel functions and their hyperparameters profoundly influences SVM's internal mechanisms and predictive performance. Model optimization necessitates meticulous parameter tuning to balance fitting accuracy and generalization capability. The specific hyperparameter configurations are as follows[12]:

1) Kernel Function Selection: The Radial Basis Function (RBF) kernel was adopted. The RBF kernel effectively captures nonlinear relationships between input features, offering advantages such as parametric simplicity, automatic adaptation to complex interaction orders, and robustness against noise. These properties make it an ideal choice for modeling the coupled multi-physics behavior of SRCFCST systems.

2) Kernel Parameter Optimization: The kernel parameter γ was set to 0.8. This parameter regulates the local sensitivity of feature mapping, preventing model performance degradation caused by either excessive γ values (leading to high variance) or insufficient γ values (resulting in high bias)[13].

3) Penalty Factor Configuration: The penalty factor C was fixed at 4.0. This parameter mediates the trade-off between model complexity and training error tolerance. Experimental results indicate

that excessively high C values (C > 10) induce overfitting, while insufficient C values (C < 1) risk underfitting. For the present dataset, C = 4.0 achieves optimal equilibrium between error control and generalization capability[14].

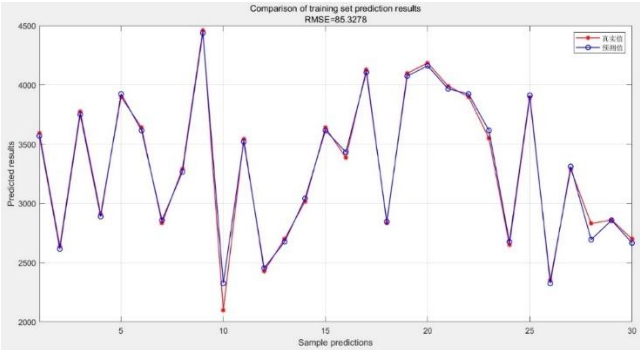

Figure 2 The comparison between the real value and the predicted value of the SVM train set

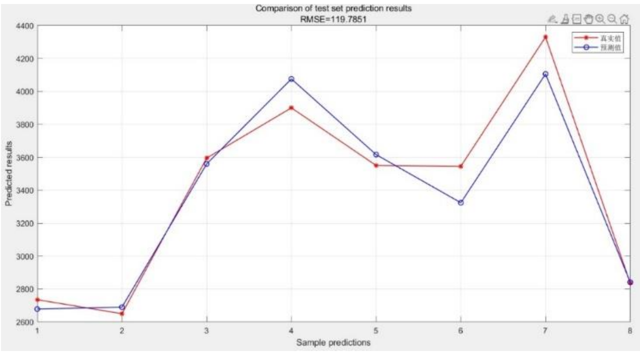

Figure 3 The comparison between the real value and the predicted value of the SVM test set

5. SVM model training results

Using the aforementioned SVM kernel function and hyperparameters, model training was conducted on the training set, followed by predictive validation on the test set. The training outcomes are presented in Figure 2, Figure 3 and Table 1.

Table 1 Calculated results of each statistical parameter of the SVM model

	R2	MAE	MABE	RMSE
train set	0.98435	49.119	-3.679	85.3278
test set	0.9455	96.6133	-19.9404	119.7851

Table 1 presents the statistical performance metrics of the Support Vector Machine (SVM) model on both training and testing datasets, including the coefficient of determination (R^2), mean absolute error (MAE), mean bias error (MBE), and root mean squared error (RMSE). These metrics collectively evaluate the model's fitting efficacy and predictive accuracy across different dimensions.

The model achieved an R^2 value of 0.98435, indicating its ability to explain 98.435% of the variance in the training data, which reflects excellent fitting performance. The MAE and RMSE values were 49.119 and 85.3278, respectively, confirming minimal deviations between predicted and actual values. Notably, the MBE of -3.679 suggests a slight systematic underestimation bias in the training phase. However, the magnitude of this bias remains negligible relative to the overall predictive accuracy, demonstrating limited impact on model reliability.

On the test set, the model maintained robust generalization capability with an R^2 of 0.9455, accounting for 94.55% of the variance in unseen data. The MAE and RMSE increased to 96.6133 and

119.7851, respectively, which is expected due to inherent uncertainties in extrapolating to new samples. While these error metrics exhibit moderate elevation compared to the training set, they remain within acceptable bounds for engineering applications. The MBE of -19.9404 indicates a more pronounced underestimation trend in testing, potentially attributable to dataset limitations or nonlinear interactions not fully captured during training.

This comparative analysis underscores the model's high fidelity in replicating training patterns while retaining reasonable generalizability, thereby validating its applicability for axial capacity prediction in SRCFCST systems.

6. Test set prediction results

Figure 4 shows the prediction results of the SVM model test set. From the comparison results in the figure, it can be seen that there is a high degree of agreement between the predicted values of the SVM model (red curve) and the actual axial compressive load bearing capacity values measured in the test (blue curve). In 8 groups of test samples, the maximum error between the predicted value of SVM model and the actual value of axial compressive load capacity is 7.29%, the minimum error is 0.73%, and the average error is 1.01%.The computational errors of the SVM model are 68.18KN,151.86KN,206.69,69.73KN,19.74KN,192.43KN,30.26KN ,34KN.

Further analyzing these error data, it can be found that although the errors of individual samples are relatively large, the overall error level is low and more evenly distributed. This indicates that the SVM model has good stability and adaptability when dealing with different combinations of input parameters.

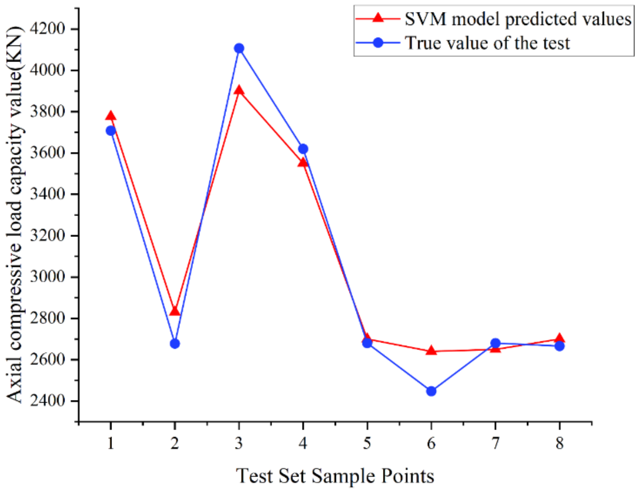

Figure 4 Comparison of Ntu values and SVM model predicted values

References

[1] WANG Qingxiang, ZHAO Dazhou, GUAN Ping. Experimental study on the stress performance of axial compression composite columns made of steel-steel tubes and high-strength concrete[J]. Journal of Building Structures,2003,(06):44-49.

[2] Elchalakani M, Zhao X L, Grzebieta R H. Concrete-filled circular steel tubes subjected to pure bending[J]. Journal of constructional steel research, 2001, 57(11): 1141-1168.

[3] Elremaily A, Azizinamini A. Behavior and strength of circular concrete-filled tube columns[J]. Journal of Constructional Steel Research, 2002, 58(12): 1567-1591.

[4] Deng Y, Tuan C Y. Design of concrete-filled circular steel tubes under lateral impact[J]. ACI Structural Journal, 2013, 110(4): 691.

[5] Hou C, Han L H, Zhao X L. Concrete-filled circular steel tubes subjected to local bearing force: Experiments[J]. Journal of Constructional Steel Research, 2013, 83: 90-104.

[6] Xiao A-Lin. Research on the stress performance and design method of axial compression composite column with steel bone-steel tube high-performance concrete[D]. Hunan University,2009.
[7] Zhao Dazhou. Research on the mechanical properties of steel bone-steel tube high-strength concrete composite column[D]. Dalian University of Technology,2003.
[8] WANG Qingxiang, ZHAO Dazhou, GUAN Ping. Study on mechanical properties of axially compressed steel-steel tube high-strength concrete composite columns[J]. Journal of Southeast University (Natural Science Edition), 2002,(05):710-714.
[9] Jakkula V. Tutorial on support vector machine (svm)[J]. School of EECS, Washington State University, 2006, 37(2.5): 3.
[10] Xue H, Yang Q, Chen S. SVM: Support vector machines[M]//The top ten algorithms in data mining. Chapman and Hall/CRC, 2009: 51-74.
[11] Schuldt C, Laptev I, Caputo B. Recognizing human actions: a local SVM approach[C]//Proceedings of the 17th International Conference on Pattern Recognition, 2004. ICPR 2004. IEEE, 2004, 3: 32-36.
[12] Shevade S K, Keerthi S S, Bhattacharyya C, et al. Improvements to the SMO algorithm for SVM regression[J]. IEEE transactions on neural networks, 2000, 11(5): 1188-1193.
[13] Soman K P, Loganathan R, Ajay V. Machine learning with SVM and other kernel methods[M]. PHI Learning Pvt. Ltd., 2009.
[14] Cherkassky V, Ma Y. Practical selection of SVM parameters and noise estimation for SVM regression[J]. Neural networks, 2004, 17(1): 113-126.