



Modeling approach for estimation of ultimate load capacity of concrete-filled steel tube composite stub columns based on relevance vector machine

Beton-dolgu çelik tüplü kompozit kısa kolonların nihai yük taşıma kapasitesinin ilgililik vektör makinesine dayalı tahmini için modelleme yaklaşımı

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Abstract

In this paper, the applicability of relevance vector machine (RVM) has been explored to predict the ultimate axial load capacity of concrete-filled steel tube composite stub columns (CFSTCSCs) with circular sections under axial compression loadings. As an extension of support vector machine, RVM employs Bayesian inference to achieve parsimonious solutions for regression and classification. By using MATLAB software and 150 comprehensive experimental data presented in the previous studies, a model to predict the ultimate load of circular CFSTCSCs was developed by properly training the data. Utmost care has been taken in grouping the data for training and validation. About 80% dataset for training and 20% dataset for validation have been used, respectively. The results show that the predicted ultimate axial compression load capacity of CFSTCSC members is comparable with that of the corresponding experimental data and the percentage difference is about $\mp 11\%$.

Keywords: Concrete-filled steel tube composite stub columns (CFSTCSCs), Ultimate axial load capacity, Relevance vector machine (RVM), Nonlinear regression algorithm

1 Introduction

Concrete-filled steel tube composite stub columns (CFSTCSCs) are being used in the civil infrastructure sector such as high-rise buildings, bridges, towers, etc., as they offer many structural advantages such as high strength, promising ductility, and large energy absorption capacities. The enhanced strength and ductility are due to the confinement of concrete. CFSTCSCs were used for various applications such as (i) retrofitting applications in earthquake-prone areas [1] (ii) bridge piers [2]. It was understood from the literature that the ultimate load of CFSTCSCs largely depends on material properties and steel ratio [3, 4] and several cross-sections of CFSTCSCs, namely, circular, square and rectangular, etc., were with various grades of concrete [5-10]. Design specifications used to predict the load capacity of composite stub columns, the ANSI/AISC 360-16 [11], and the Eurocode 4 (EC4) [12].

Özet

Bu makalede, dairesel kesitli beton-dolgu çelik tüplü kompozit kısa kolonların aksel basınç yükleri altındaki nihai yük taşıma kapasitesini tahmin etmekte ilgililik vektör makinesinin (İVM) uygulanabilirliği incelenmiştir. Destek vektör makinesinin bir eklentisi olarak İVM, regresyon ve sınıflandırmada sağlam çözümler elde etmek için Bayesyen yaklaşımını kullanmaktadır. MATLAB yazılımı ve 150 adet daha önceki çalışmalarda sunulan kapsamlı deneysel veriler kullanılarak ve bu verilerin uygun şekilde düzenlenmesiyle, dairesel kesitli beton-dolgu çelik tüplü kompozit kısa kolonların nihai yük taşıma kapasitesini tahmin etmek için bir model geliştirilmiştir. Verilerin düzenleme ve doğrulama için gruplandırılmasında azami özen gösterilmiştir. Sırasıyla, düzenleme için yaklaşık %80 veri seti ve doğrulama için %20 veri seti kullanılmıştır. Sonuçlar, beton-dolgu çelik tüplü kompozit kolon elemanının tahmini nihai aksel basınç yük taşıma kapasitesinin, ilgili deneysel verilerle kıyaslanabilir olduğunu ve aradaki yüzde farkının yaklaşık $\mp 11\%$ olduğunu göstermektedir.

Anahtar kelimeler: Beton-dolgu çelik tüplü kompozit kısa kolonlar, Nihai aksel yük taşıma kapasitesi, İlgililik vektör makinesi (İVM), Lineer olmayan regresyon algoritması

The axial compressive stiffness and ultimate capacity are the basic properties of CFSTCSCs. In the literature, there are different opinions and conclusions about the axial compressive stiffness of the stub columns, and one of the main reasons may be that researchers used different deformation measurement methods for the stub columns under axial compressive loading. However, there have been very few reports that compare these measurement methods for CFSTCSCs.

It is well known that analytical models are very much useful to predict the responses of the structural members. In the present scenario, machine learning techniques have attracted much importance to develop a model for the prediction of the future response. In any machine learning model, there are basically two major steps, namely, training, and testing. For training the data, mixed data with all variations should be required. One should have knowledge

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of the data preparation for training and testing. From the wide literature, it is noted that numerous statistical models or metamodels are available for developing the models to predict the required response. The models cover artificial neural networks, multivariate adaptive regression splines, Gaussian regression process, least squares support vector machine, relevance vector machine (RVM), and extreme learning machine, etc., to develop the models by training the mixed data [13-20].

After carefully study of the above models, it is observed that each model has its own advantages and limitations. RVM is a revised version of the support vector machine (SVM) and a machine learning methodology that uses Bayesian treatment to achieve parsimonious solutions for regression and classification [21, 22]. RVM is conceptualized under a complete probabilistic approach. In RVM, weights will be assigned to each dataset based on a defined algorithm and relate to hyperparameters. The significant feature of the RVM is that it uses very few kernel functions so that it will be computationally efficient. RVM concepts were used by many researchers in different domains for developing a model [23-29]. The applications of RVM concepts for the structural engineering domain are found to be scarce. When viewed from this aspect, this work will be a remarkable contribution to the existing knowledge base and engineers about the estimation of ultimate load capacity of CFSTCSCs based on RVM.

In the present study, RVM, one of the sophisticated statistical models is proposed to estimate the ultimate load capacity of CFSTCSCs with circular sections under axial loading by using the features of MATLAB. A dataset containing 150 experimental testing results available in the literature on CFSTCSC members under axial loading has been compiled for the present study.

2 Experimental dataset

Many experimental investigations were carried out by several researchers on the performance of circular CFSTCSCs under axial compression loading. The test configuration considered is the uniaxial compression test which is schematically depicted in Figure 1. A total of 150 data with 22 published literature sources has been collected from different sources. These experimental studies for stub/short CFSTCSCs have been compiled and the geometrical parameters, material strengths, and failure loads of various circular CFSTCSCs are tabulated in Table 1. It can be clearly sighted that the ultimate axial load capacity (P_u) is related to several variables such as (i) the outer diameter of steel tube, D (ii) wall thickness of steel tube, t (iii) unconfined concrete strength, f_c (iv) Young's modulus of concrete, E_c (v) yield strength of steel, f_y (vi) Young's modulus of steel, E_s (vii) length of circular CFSTCSC, L (viii) confinement factor, ξ . Table 1 shows the geometrical parameters of CFSTCSC sections, mechanical properties of steel and concrete, confinement factor, and failure load of a member under axial loadings. The compiled dataset has a wide range of column parameters such as normal to high yield strength steels ($f_y = 186\sim 853\text{ MPa}$), normal concrete to ultra-high-strength concrete ($f_c = 18\sim 193\text{ MPa}$), the

outer diameter of circular sections ($D = 60\sim 450\text{ mm}$), the ratio of the outer diameter to the thickness ($D/t = 17\sim 221$), and the ratio of the height to the outer diameter ($L/D = 1.8 - 4.9$), respectively. The aim of the developed model in the present research is to provide a unique study to the researcher to obtain the decreasing errors, complexity, and reducing convergence of scattering amplitudes of numerical results to the experimental ones that can be an alternative to experimental studies and to estimate the ultimate load capacity of circular CFSTCSCs. It can be obviously noted from Table 1 that E_c varies between $17810\text{ MPa}\sim 66000\text{ MPa}$ and for E_s , it varies in the range of 177000 MPa and 213000 MPa . These variations have been considered while producing model processes to increase the possibility of obtaining a stronger model.

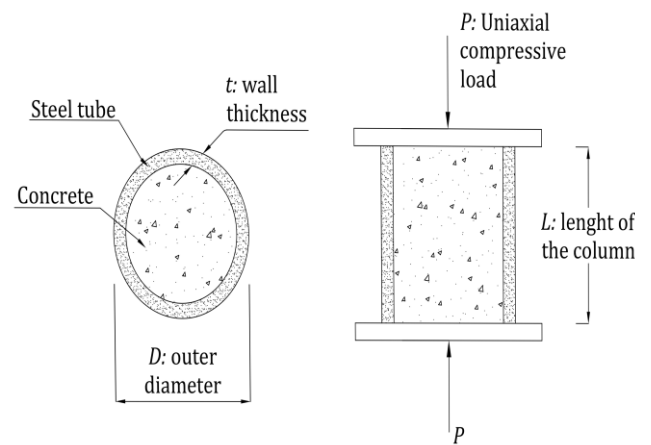


Figure 1. Geometrical configuration of CFSTCSC

3 Relevance vector machine (RVM)

RVM is a modified version of SVM, employs Bayesian concepts, and kernel function [21, 22]. RVM starts with the base of linear models, i.e., the function of $y(x)$ can be predicted at any point x with a set of measurements of the function $t = (t_1, y, t_N)$ and with some training points $x = (x_1, y, x_N)$:

$$t_i = y(x_i) + \varepsilon_i \quad (1)$$

where ε_i = the noise component of the measurement having mean 0 and variance σ^2 . The unknown function $y(x)$ can be expressed as a linear combination of known basis function as

$$y(x) = \sum_{i=1}^M w_i \varphi_i(x) \quad (2)$$

where, $w_i = (w_1, y, w_M)$ = a vector consisting of the linear combination weights

$$y(x) = \text{output, a linearly weighted sum of } M \\ \varphi_i(x) = (\varphi_1(x), \varphi_2(x), \dots, \varphi_M(x))^T$$

For good predictions, most of the parameters are default set to zero [21, 22].

$$t = \Phi w + \varepsilon \quad (3)$$

where, $\Phi = NxM$ design matrix $\Phi_i(x)$ at all the training points

$$\varepsilon_i = (\varepsilon_1, \dots, \varepsilon_N) = \text{noise vector}$$

RVM begins with a set of data input $\{x_n\}_n^N = 1$, and the associated vector $\{t_n\}_n^N = 1$. The prediction is of the form similar to SVM as given below:

$$y(x) = \sum_{i=1}^N w_i K(x, x_i) + w_0 \quad (4)$$

where, $w_i = w_1, w_2, \dots, w_N =$ weight vector
 $K(x, x_i) =$ kernel function
 $w_0 =$ bias function

Equation (5) shows the radial basis kernel function is employed in this work as follows:

$$K(x_i, x) = \exp\left\{-\frac{(x_i - x)^T(x_i - x)}{2\sigma^2}\right\} \quad (5)$$

where x_i and x are the training and test patterns, σ is the width of basis function, respectively. For a given input dataset, it is assumed as $\{x_n, t_n\}_n^N = 1$. It is assumed that $p(t|x)$ is Gaussian N (or Normal) $(t|y(x), \sigma^2)$. The mean of this distribution for a given x can be modeled by $y(x)$ as mentioned in Equation (4). The likelihood of dataset can be written as

$$p(t|w, \sigma^2) = (2\pi\sigma^2)^{-N/2} \exp\left\{-\frac{1}{2\sigma^2} \|t - \Phi w\|^2\right\} \quad (6)$$

where, $t_i = (t_1, \dots, t_N)^T$
 $w_i = (w_0, \dots, w_N)$

$$\Phi^T = \begin{bmatrix} 1 & K(x_1, x_1) & K(x_1, x_2) & \dots & K(x_1, x_n) \\ 1 & K(x_2, x_1) & K(x_2, x_2) & \dots & K(x_2, x_n) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & K(x_n, x_1) & K(x_n, x_2) & \dots & K(x_n, x_n) \end{bmatrix} \quad (7)$$

where $K(x_i, x_n)$ is the kernel function. The next higher-level parameters are useful to constrain an explicit zero-mean Gaussian prior probability distribution to the weights.

$$p(w|\alpha) = \prod_{i=0}^N N(w_i | 0, \alpha_i^{-1}) \quad (8)$$

where $\alpha =$ a vector of $(N + 1)$ hyperparameters, useful for monitoring the weight deviations [25]. By applying Bayes' rule, the posterior unknowns can be computed as follows:

$$p(\alpha) = \prod_{i=0}^N \text{Gamma}(\alpha_i | a, b) \quad (9)$$

$$p(\beta) = \prod_{i=0}^N \text{Gamma}(\beta | c, d) \quad (10)$$

where, $\beta = \sigma^{-2}$. Hence, for α and σ , the distribution followed is gamma; for w , the normal distribution is followed and after the prior-distributions, Bayes' rule is followed.

$$p(w, \alpha, \sigma^2 | t) = \frac{p(t|w, \alpha, \sigma^2)p(w, \alpha, \sigma^2)}{p(t)} \quad (11)$$

The predictive distribution for a new test point (x^*) corresponding to the target (t^*) is determined as

$$p(t^* | t) = \int p(t^* | w, \alpha, \sigma^2) p(w, \alpha, \sigma^2 | t) dw d\alpha d\sigma^2 \quad (12)$$

By using the decomposition of posterior, the above equation can be solved as below in Equation (13):

$$p(w, \alpha, \sigma^2 | t) = p(w | t, \alpha, \sigma^2) p(\alpha, \sigma^2 | t) \quad (13)$$

The posterior distribution was analyzed by considering the appropriate weights due to the property of normalization integral is the convolution of Gaussians [22]. Accordingly, Equation (13) can be re-written as

$$p(w | t, \alpha, \sigma^2) = \frac{p(t|w, \sigma^2)p(w, \alpha)}{p(t|\alpha, \sigma^2)} \quad (14)$$

By using the Bayes' rule, Equation (14) can be modified as follows:

$$p(w | t, \alpha, \sigma^2) = (2\pi)^{-(N+1)/2} |\Sigma|^{-1/2} \exp\left\{-\frac{1}{2}(w - \mu)^T \Sigma^{-1}(w - \mu)\right\} \quad (15)$$

The solution for the above equation is given below in Equation (16) and Equation (17):

$$\Sigma = (\sigma^{-2}\Phi^T\Phi + A)^{-1} \quad (16)$$

$$\mu = \sigma^{-2}\Sigma\Phi^T t \quad (17)$$

where, $\Sigma =$ covariance
 $\mu =$ mean
 $A = (\alpha_0, \alpha_1, \dots, \alpha_N)$

Table 1. Experimental data for ultimate axial load capacity of circular CFSTCSCs with the general details

Source	Specimen	D (mm)	t (mm)	f_c (MPa)	E_c (MPa)	f_y (MPa)	E_s (MPa)	L (mm)	ξ	D/t	L/D	P_u (kN)
[30, 31]	SPICIMEN8	120.8	4.06	34.40	27566	452	191536	241.3	1.962	30	2.0	1201
	SPICIMEN9	120.8	4.09	29.58	25562	452	191536	241.4	2.300	30	2.0	1201
	SPICIMEN10	120.8	4.09	25.92	23928	452	191536	241.4	2.625	30	2.0	1112
	SPICIMEN13	152.6	3.18	20.89	21482	415	203395	304.8	1.766	48	2.0	1201
	SPICIMEN14	152.6	3.15	23.10	22589	415	203395	304.8	1.581	48	2.0	1201
	SPICIMEN4	101.7	3.07	31.16	26236	605	207050	203.3	2.575	33	2.0	1068
	SPICIMEN3	101.7	3.07	34.13	27458	605	207050	203.3	2.351	33	2.0	1112
	SPICIMEN3a	169.3	2.62	36.54	28411	317	195811	305	0.563	65	1.8	1307
[32]	4HN	150	4.3	28.71	25183	280	209720	450	1.222	35	3.0	1203
	4HN	150	4.3	28.71	25183	280	209720	450	1.222	35	3.0	1225
	4HN	150	4.3	28.71	25183	280	209720	450	1.222	35	3.0	1200
	3HN	150	3.2	28.71	25183	287	190120	450	0.911	47	3.0	1040
	3HN	150	3.2	28.71	25183	287	190120	450	0.911	47	3.0	998
	3HN	150	3.2	28.71	25183	287	190120	450	0.911	47	3.0	980
	2HN	150	2	28.71	25183	336	211680	450	0.65	75	3.0	882
	2HN	150	2	28.71	25183	336	211680	450	0.65	75	3.0	882
	4MN	150	4.3	21.95	22020	280	209720	450	1.599	35	3.0	1065
	4MN	150	4.3	21.95	22020	280	209720	450	1.599	35	3.0	1087
	4MN	150	4.3	21.95	22020	280	209720	450	1.599	35	3.0	1096
	3MN	150	3.2	21.95	22020	287	190120	450	1.191	47	3.0	841
	3MN	150	3.2	21.95	22020	287	190120	450	1.191	47	3.0	840
	3MN	150	3.2	21.95	22020	287	190120	450	1.191	47	3.0	858
	2MN	150	2	21.95	22020	336	211680	450	0.85	75	3.0	773
	2MN	150	2	21.95	22020	336	211680	450	0.85	75	3.0	756
	4LN	150	4.3	18.03	19957	280	209720	450	1.946	35	3.0	963
	3LN	150	3.2	18.03	19957	287	190120	450	1.45	47	3.0	790
	3LN	150	3.2	18.03	19957	287	190120	450	1.45	47	3.0	790
	3LN	150	3.2	18.03	19957	287	190120	450	1.45	47	3.0	747
2LN	150	2	18.03	19957	336	211680	450	1.035	75	3.0	656	
2LN	150	2	18.03	19957	336	211680	450	1.035	75	3.0	638	
2LN	150	2	18.03	19957	336	211680	450	1.035	75	3.0	672	
[33]	L-20-1	178	9	22.15	22120	283	200000	360	3.036	20	2.0	2042
	L-20-2	178	9	22.15	22120	283	200000	360	3.036	20	2.0	2102
	H-20-1	178	9	45.37	31658	283	200000	360	1.482	20	2.0	2667
	H-20-2	178	9	45.37	31658	283	200000	360	1.482	20	2.0	2677
	L-32-1	179	5.5	22.15	22120	248	200000	360	1.514	33	2.0	1467
	L-32-2	179	5.5	23.91	22982	248	200000	360	1.403	33	2.0	1530
	H-32-1	179	5.5	43.61	31038	248	200000	360	0.769	33	2.0	2040
	H-32-2	179	5.5	43.61	31038	248	200000	360	0.769	33	2.0	2030
	L-58-1	174	3	23.91	22982	266	200000	360	0.809	58	2.1	1135
	L-58-2	174	3	23.91	22982	266	200000	360	0.809	58	2.1	1135
	H-58-1	174	3	45.67	31762	266	200000	360	0.423	58	2.1	1608
	H-58-2	174	3	45.67	31762	266	200000	360	0.423	58	2.1	1677

Table 1. Experimental data for ultimate axial load capacity of circular CFSTCSCs with the general details (continued)

Source	Specimen	D (mm)	t (mm)	f_c (MPa)	E_c (MPa)	f_y (MPa)	E_s (MPa)	L (mm)	ξ	D/t	L/D	P_u (kN)
	R12CF1	190	1.15	110.3	32405	202	193200	662	0.045	165	3.5	2991
	R12CF3	190	1.15	110.3	32405	202	193200	662	0.045	165	3.5	3137
	S10CS50A	190	0.86	41	17810	211	177000	659	0.094	221	3.5	1350
	S12CS50A	190	1.13	41	17810	186	178400	664.5	0.11	168	3.5	1377
	S16CS50B	190	1.52	48.3	21210	306	207400	664.5	0.208	125	3.5	1695
[34, 35]	S20CS50A	190	1.94	41	17810	256	204700	663.5	0.263	98	3.5	1678
	S30CS50B	165	2.82	48.3	21210	363	200600	580.5	0.541	59	3.5	1662
	S10CS80B	190	0.86	74.7	27576	211	177000	663.5	0.052	221	3.5	2451
	S12CS80A	190	1.13	80.2	28445	186	178400	662.5	0.056	168	3.5	2295
	S16CS80A	190	1.52	80.2	28445	306	207400	663.5	0.125	125	3.5	2602
	S20CS80B	190	1.94	74.7	27576	256	204700	663.5	0.144	98	3.5	2592
	S30CS80A	165	2.82	80.2	28445	363	200600	580.5	0.326	59	3.5	2295
[36]	C1	140.8	3	28.18	25599	285	189475	602	0.92	47	4.3	790
	C2	141.4	6.5	23.81	23528	313	206011	602	2.797	22	4.3	1332
	A1-1	125	1	106	48389	232	200000	438	0.072	125	3.5	1275
	A1-2	125	1	106	48389	232	200000	438	0.072	125	3.5	1239
	A2-1	127	2	106	48389	258	200000	445	0.161	64	3.5	1491
	A2-2	127	2	106	48389	258	200000	445	0.161	64	3.5	1339
	A3-1	133	3.5	106	48389	352	200000	465	0.379	38	3.5	1995
[37]	A3-2	133	3.5	106	48389	352	200000	465	0.379	38	3.5	1991
	A4-1	133	4.7	106	48389	352	200000	465	0.524	28	3.5	2273
	A4-2	133	4.7	106	48389	352	200000	465	0.524	28	3.5	2158
	C-1	133	4.7	92	45081	352	200000	465	0.604	28	3.5	1854
	C-2	133	4.7	92	45081	352	200000	465	0.604	28	3.5	1933
	B-3	108	4.5	96	46050	358	200000	378	0.709	24	3.5	1518
	C10A-2A-3	101.8	3.03	23.2	22638	371	200000	305	2.088	34	3.0	628
	C20A-2A	216.4	6.61	24.3	23169	452	200000	650	2.499	33	3.0	3278
[38]	C30A-2A	318.3	10.36	24.2	23121	335	200000	950	1.995	31	3.0	6319
	C20A-4A	216.4	6.61	46.8	32153	452	200000	650	1.298	33	3.0	4214
	C10A-4A-1	101.9	3.03	51.3	33663	371	200000	305	0.943	34	3.0	877
	C30A-4A	318.5	10.36	52.2	33957	334	200000	950	0.921	31	3.0	8289
	CU-040	200	5	27.15	24490	266	200000	600	1.058	40	3.0	1951
[39]	CU-070	280	4	31.15	26232	273	200000	840	0.523	70	3.0	3025
	CU-150	300	2	27.23	24526	342	200000	900	0.342	150	3.0	2608
[3]	scv2-1	200	3	49.5	37420	304	206500	600	0.386	67	3.0	2383
	scv2-2	200	3	49.5	37420	304	206500	600	0.386	67	3.0	2256
	C7	114.9	4.91	28.23	24972	365	200000	300.5	2.53	23	2.6	1020
	C9	115	5.02	48.6	32765	365	200000	300.5	1.506	23	2.6	1378
[40]	C11	114.3	3.75	48.6	32765	343	200000	300	1.026	30	2.6	1033
	C12	114.3	3.85	25.71	23831	343	200000	300	1.997	30	2.6	761
	C4	114.6	3.99	83.6	42974	343	200000	300	0.637	29	2.6	1308

Table 1. Experimental data for ultimate axial load capacity of circular CFSTCSCs with the general details (continued)

Source	Specimen	D (mm)	t (mm)	f_c (MPa)	E_c (MPa)	f_y (MPa)	E_s (MPa)	L (mm)	ξ	D/t	L/D	P_u (kN)
[40]	C8	115	4.92	94.9	45786	365	200000	300	0.753	23	2.6	1787
	C14	114.5	3.84	88.9	44315	343	200000	300	0.575	30	2.6	1359
[41]	CC4-A-4-1	149	2.96	40.5	29911	308	200000	447	0.642	50	3.0	1064
	CC8-A-8	108	6.47	77	41242	853	200000	324	3.221	17	3.0	2667
	CC8-C-8	222	6.47	77	41242	843	200000	666	1.397	34	3.0	7304
	CC8-D-8	337	6.47	85.1	43357	823	200000	1011	0.788	52	3.0	13776
	CC4-D-4-1	450	2.96	41.1	30131	279	200000	1350	0.182	152	3.0	6870
	CC4-D-4-2	450	3	41	30131	279	200000	1350	0.182	152	3.0	6985
[4]	CA1-1	60	1.87	75.2	41540	282	201500	180	0.515	32	3.0	312
	CA1-2	60	1.87	75.2	41540	282	201500	180	0.515	32	3.0	320
	CA2-1	100	1.87	75.2	41540	282	201500	300	0.297	53	3.0	822
	CA2-2	100	1.87	75.2	41540	282	201500	300	0.297	53	3.0	845
	CA3-1	150	1.87	75.2	41540	282	201500	450	0.194	80	3.0	1701
	CA3-2	150	1.87	75.2	41540	282	201500	450	0.194	80	3.0	1670
	CA4-1	200	1.87	75.2	41540	282	201500	600	0.144	107	3.0	2783
	CA4-2	200	1.87	75.2	41540	282	201500	600	0.144	107	3.0	2824
	CA5-1	250	1.87	75.2	41540	282	201500	750	0.115	134	3.0	3950
	CA5-2	250	1.87	75.2	41540	282	201500	750	0.115	134	3.0	4102
	CB2-1	100	2	75.2	41540	404	207000	300	0.457	50	3.0	930
	CB2-2	100	2	75.2	41540	404	207000	300	0.457	50	3.0	920
	CB3-1	150	2	75.2	41540	404	207000	450	0.298	75	3.0	1870
	CB3-2	150	2	75.2	41540	404	207000	450	0.298	75	3.0	1743
	CB4-1	200	2	75.2	41540	404	207000	600	0.222	100	3.0	3020
	CB4-2	200	2	75.2	41540	404	207000	600	0.222	100	3.0	3011
	CB5-1	250	2	75.2	41540	404	207000	750	0.176	125	3.0	4442
	CB5-2	250	2	75.2	41540	404	207000	750	0.176	125	3.0	4550
	CC2-1	150	2	80	41540	404	207000	450	0.281	75	3.0	1980
	CC2-2	150	2	80	41540	404	207000	450	0.281	75	3.0	1910
CC3-1	250	2	80	41540	404	207000	750	0.166	125	3.0	4720	
CC3-2	250	2	80	41540	404	207000	750	0.166	125	3.0	4800	
[42]	D3M4C2	89.32	2.74	33	26999	360	200000	340	1.473	33	3.8	494
	D3M4F13	89.32	2.74	31.48	26370	360	200000	340	1.544	33	3.8	495
	D3M4F22	89.32	2.74	31.48	26370	360	200000	340	1.544	33	3.8	478
	D3M4F33	89.32	2.74	28.19	24954	360	200000	340	1.724	33	3.8	529
	D4M4C1	112.6	2.89	30.84	26101	360	200000	340	1.297	39	3.0	702
	D4M4F13	112.6	2.89	31.48	26370	360	200000	340	1.271	39	3.0	757
	D4M4F21	112.6	2.89	25.28	23631	360	200000	340	1.583	39	3.0	659
	D4M4F32	112.6	2.89	26.2	24057	360	200000	340	1.527	39	3.0	638
[43]	SZ3S4A1	165	2.72	48	32563	350	213000	510	0.506	61	3.1	1750
	SZ3S6A1	165	2.73	67.2	38529	350	213000	510	0.363	60	3.1	2080

Table 1. Experimental data for ultimate axial load capacity of circular CFSTCSCs with the general details (continued)

Source	Specimen	D (mm)	t (mm)	f _c (MPa)	E _c (MPa)	f _y (MPa)	E _s (MPa)	L (mm)	ξ	D/t	L/D	P _u (kN)	
[44]	C-30-3D	114.3	3.35	32.7	26876	287	206000	342.9	1.128	34	3.0	669	
	C-60-3D	114.3	3.35	58.7	36009	287	206000	342.9	0.629	34	3.0	946	
	C-80-3D	114.3	3.35	88.8	44290	287	206000	342.9	0.416	34	3.0	1133	
	C-100-3D	114.3	3.35	105.5	48275	287	206000	342.9	0.350	34	3.0	1455	
[45]	049C36 30	360	6	31.5	26379	498	202000	1760	1.109	60	4.9	6888	
[46]	C3	114.3	3.6	173.5	63000	403	213000	250	0.323	32	2.2	2422	
	C4	114.3	3.6	173.5	63000	403	213000	250	0.323	32	2.2	2340	
	C5	114.3	3.6	184.2	63000	403	213000	250	0.304	32	2.2	2497	
	C6	114.3	3.6	184.2	63000	403	213000	250	0.304	32	2.2	2314	
	C7	114.3	6.3	173.5	63000	428	209000	250	0.649	18	2.2	2610	
	C8	114.3	6.3	173.5	63000	428	209000	250	0.649	18	2.2	2633	
	C9	219.1	5	51.6	28000	377	205000	600	0.684	44	2.7	3118	
	C10	219.1	5	185.1	66000	377	205000	600	0.199	44	2.7	7813	
	C11	219.1	5	193.3	66000	377	205000	600	0.191	44	2.7	8527	
	C12	219.1	10	51.6	28000	381	212000	600	1.489	22	2.7	4309	
	C13	219.1	10	185	66000	381	212000	600	0.435	22	2.7	9085	
	C14	219.1	10	193.3	66000	381	212000	600	0.416	22	2.7	9187	
	C15	219.1	6.3	163	66000	300	202000	600	0.231	35	2.7	6915	
	C16	219.1	6.3	175.4	59000	300	202000	600	0.215	35	2.7	7407	
	C17	219.1	6.3	148.8	52000	300	202000	600	0.254	35	2.7	6838	
	C18	219.1	6.3	174.5	52000	300	202000	600	0.216	35	2.7	7569	
	[47, 48]	CF3-1	76.19	2.99	145	56595	278	200000	300	0.341	25	3.9	795
		CF3.3-1	76.18	3.31	145	56595	305	200000	300	0.419	23	3.9	847
C4NG-1		114.2	4.02	115	50402	306	200000	400	0.418	28	3.5	1428	
C6NG-1		114.3	5.98	115	50402	314	200000	400	0.675	19	3.5	1833	
[49]	c0	160	3.83	51	33900	409	200000	480	0.827	42	3.0	2023	

Maximization of $p(\alpha, \alpha_{\epsilon_n}^2 | y) \alpha p(y | \alpha, \alpha_{\epsilon_n}^2) p(\alpha) p(\alpha_{\epsilon_n}^2)$ concerning α and σ^2 provide a search for the hyperparameters posterior. For the case of uniform hyperpriors, maximization is to be performed for the terms of $p(y | \alpha, \alpha_{\epsilon_n}^2)$, as described below:

$$\begin{aligned}
 & p(y | \alpha, \alpha_{\epsilon_n}^2) \\
 = & \int p(y | w, \alpha_{\epsilon_n}^2) p(w | \alpha) dw = (2\pi)^{-1/2} |\alpha_{\epsilon_n}^2|^{-1} \\
 & + \Phi A^{-1} \Phi^T |^{1/2} \exp \left\{ -\frac{1}{2} y^T (|\alpha_{\epsilon_n}^2|^{-1} I \right. \\
 & \left. + \Phi A^{-1} \Phi^T)^{-1} y \right\}
 \end{aligned} \tag{18}$$

The predictions can be made based on the posterior distribution over the weights, conditioned on the maximized most probable values of α , $\sigma_{\epsilon_n}^2$, α_{MP} , and σ_{MP}^2 , respectively.

$$\begin{aligned}
 & p(y^* | y, \alpha_{MP}, \sigma_{MP}^2) \\
 = & \int p(y^* | w, \alpha_{MP}^2) p(w | y, \alpha_{MP}, \sigma_{MP}^2) dw
 \end{aligned} \tag{19}$$

Equation (19) can be evaluated as follows:

$$p(y^* | y, \alpha_{MP}, \sigma_{MP}^2) = N(y^* | t^*, \sigma_*^2) \tag{20}$$

$$t^* = \mu^T \Phi(x^*) \tag{21}$$

$$\sigma_*^2 = \sigma_{MP}^2 + \Phi(x^*)^T \sum \Phi(x^*) \tag{22}$$

The result of the optimization involved in RVM (i.e., max of $p(y | \alpha, \sigma_{\epsilon_n}^2)$), is that many of α tend to infinity such that “w” will have only a few nonzero weights that can be considered as relevant vectors [50].

4 RVM based analysis

In the present study, the main goal is to develop a model by using the concepts of RVM. To train the data and develop

a model, MATLAB software was used. The dependent parameters, such as f_c , E_c , f_y , E_s , ξ , D/t , and L/D are considered as the input parameters for developing the RVM model. The output from the model is the ultimate load capacity of CFSTCSCs, P_u . There are a total of 150 datasets for training as well as validation. On closer examination of Table 1, the input vector has a significant variation in magnitude. Hence, a normalization of the data was done before inputting into the algorithm. Equation (23) has been used for the linear normalization of the data ranging between 0 and 1.

$$x_i^n = \frac{x_i^a - x_i^{min}}{x_i^{max} - x_i^{min}} \quad (23)$$

where x_i^a and x_i^n = i^{th} component of the input vector before and after normalization, x_i^{max} and x_i^{min} = the maximum and minimum values of all the components of the input vector before the normalization, respectively. About 80% of dataset was for training the data and about 20% of the dataset is used for testing and verification of the RVM model. The most important input parameter is the selection of kernel width. Further, the training and testing R values are dependent on the number of relevance vectors (NRV) used in the model and their corresponding weights and variation in the kernel width. In the present study, the value of kernel width (σ) is assumed as 0.12. The efficiency of the model has been verified with the coefficient of correlation (R), which is given below:

$$R = \frac{\sum_{i=1}^n (E_{ai} - \bar{E}_a)(E_{pi} - \bar{E}_p)}{\sqrt{\sum_{i=1}^n (E_{ai} - \bar{E}_a)^2} \sqrt{\sum_{i=1}^n (E_{pi} - \bar{E}_p)^2}} \quad (24)$$

where E_{ai} and E_{pi} are the actual and predicted values, \bar{E}_a and \bar{E}_p are the mean of actual and predicted E values corresponding to n patterns, respectively. Figure 2 presents the schematic diagram of the RVM model. Table 2 presents the coefficient of correlation, the number of relevance vectors used in the development of the model. Table 3 shows the weights for the developed RVM model. By using Equation (18) and Equation (19) with w_0 as zero, the following equation has been deduced to predict P_u values of CFSTCSC members under axial compression loadings. The values of weights, w_i , for all the training datasets are available in Table 3.

$$y = P_u = \sum_{i=1}^{105} w_i \exp \left\{ - \frac{(x_i - x)^T (x_i - x)}{0.034} \right\} \quad (25)$$

By using Equation (25), the normalized output vector has been converted back to original value as

$$x_i^a = x_i^n (x_i^{max} - x_i^{min}) + x_i^{min} \quad (26)$$

where, x_i^n = normalized result obtained after the test for the i^{th} component

x_i^a = actual result obtained for i^{th} component
 x_i^{max} and x_i^{min} = maximum and minimum values of all the components of the corresponding input vector before the normalization

The developed model is applicable for the dataset in the range of yield strength of steels ($f_y = 186 \sim 853 \text{ MPa}$), concrete compressive strength ($f_c = 18 \sim 193 \text{ MPa}$), the outer diameter of circular sections ($D = 60 \sim 450 \text{ mm}$), the ratio of the outer diameter to the thickness ($D/t = 17 \sim 221$), and the ratio of the height to the outer diameter ($L/D = 1.8 - 4.9$). Table 4 presents the predicted ultimate axial load, P_u^{RVM} , and the corresponding experimental value, P_u^E . It can be very clearly seen that the predicted values by using the developed RVM model are comparable with each other. The maximum % difference between the predicted and the corresponding experimental value is about 11. The model can be used for the prediction of the ultimate load of CFSTCSC members under axial loading within the ranges of input data. The predicted values will be useful for the design of steel-concrete composite structures.

5 Conclusions

The concept of RVM has been employed for developing a model to predict the ultimate load of CFSTCSC members under axial loading. Large experimental data available in the literature on this concept has been collected. The data consists of large variations of geometry, mechanical properties, and ultimate loads. The influencing variables on the ultimate load have been identified after a close examination of the collected data. RVM is a machine learning methodology that uses Bayesian treatment to obtain parsimonious solutions for regression and classification. RVM is formulated based on the probabilistic concept and weights have been assigned iteratively and also related to a set of hyperparameters. RVM model was developed by using MATLAB software for training and prediction of the ultimate load capacity of CFSTCSCs. About 80% of the total datasets were used for training and about 20% of the remaining total datasets have been used for verification and validation of the developed model.

It was found that the predicted values are very much comparable with that of the corresponding experimental values. The predicted ultimate capacity is compared with that of the corresponding experimental value and the percentage difference between the predicted value and the corresponding experimental value is found to be less than 11%. The ratio of predicted and the corresponding experimental ultimate load P_u^{RVM}/P_u^E was found to vary between 0.90 and 1.06, respectively.

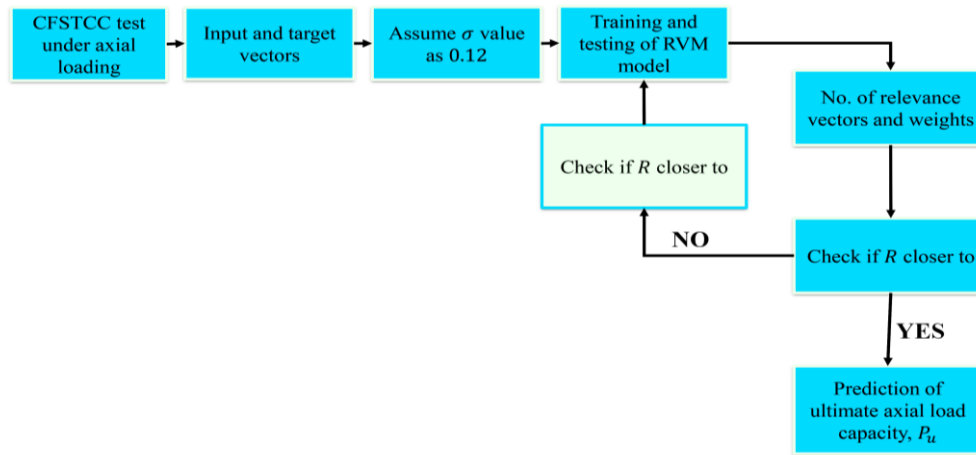


Figure 2. Schematic diagram for the proposed RVM model of CFSTCSC

Table 2. Performance of developed RVM models

Parameters	Coefficient of correlation (R)		Width	No. of RVs used out of total 105 dataset	No. of RVs (% of training dataset)
	Training	Testing			
P_u	0.996	0.991	0.12	85	80.5%

Table 3. Weights (w_i) for RVM models

$i = 1,2, \dots, 105$	w_i	$i = 1,2, \dots, 105$	w_i	$i = 1,2, \dots, 105$	w_i	$i = 1,2, \dots, 105$	w_i
1	0.0	30	0.0	60	0.0	90	0.1
2	0.052	31	0.0	61	0.20	91	0.01
3	0	32	0.01	62	0.0	92	0.02
4	0	33	0.012	63	0.02	93	0.01
5	0.06	34	0.06	64	0.01	94	0.0
6	0.03	35	0.001	65	0.04	95	0.01
7	0.1	36	0.01	66	0.0	96	0.1
8	0.12	37	0.03	67	0.0	97	0.21
9	0.04	38	0.01	68	0.03	98	0.0
10	0.160	39	0.02	69	0.05	99	0.0
11	0.11	40	0.3	70	0.23	100	0.03
12	0.05	41	0.02	71	0.02	101	0.02
13	0.054	42	0.0	72	0.01	102	0.10
14	0.05	43	0.0	73	0.10	103	0.0
15	0.11	44	0.08	74	0.0	104	0.0
16	0.10	45	0.0	75	0.08	105	0.01
17	0.212	46	0.001	76	0.01		
18	0.6	47	0.3	77	0.03		
19	0.1	48	0.01	78	0.02		
20	0.01	49	0.02	79	0.01		
21	0.01	50	0.012	80	0.02		
22	0.02	51	0.1	81	0.0		
23	0.03	52	0.6	82	0.3		
24	0.01	53	0.12	83	0.10		
25	0.12	54	0.06	84	0.02		
26	0.1	55	0.04	85	0.01		
27	0.11	56	0.03	86	0.01		
28	0.013	57	0.04	87	0.0		
29	0.03	58	0.0131	88	0.01		
		59	0.013	89	0.03		

Table 4. Comparison of experimental ultimate axial load values with predicted results obtained from RVM model

f_c (MPa)	f_y (MPa)	ξ	D/t	L/D	P_u (kN)		P_u^{RVM}/P_u^E
					P_u^E (kN)	P_u^{RVM} (kN)	
25.92	452	2.625	30	2.0	1112	1067	0.96
23.10	415	1.581	48	2.0	1201	1103	0.92
34.13	605	2.351	33	2.0	1112	1043	0.94
28.71	287	0.911	47	3.0	1040	1012	0.97
28.71	287	0.911	47	3.0	998	943	0.94
21.95	280	1.599	35	3.0	1087	1043	0.96
21.95	280	1.599	35	3.0	1096	1021	0.93
21.95	287	1.191	47	3.0	840	862	1.03
18.03	280	1.946	35	3.0	963	955	0.99
18.03	287	1.45	47	3.0	790	811	1.03
18.03	287	1.45	47	3.0	747	722	0.97
18.03	336	1.035	75	3.0	672	652	0.97
22.15	283	3.036	20	2.0	2102	2143	1.02
45.37	283	1.482	20	2.0	2667	2521	0.95
23.91	248	1.403	33	2.0	1530	1621	1.06
43.61	248	0.769	33	2.0	2030	2045	1.01
45.67	266	0.423	58	2.1	1608	1612	1.00
110.3	202	0.045	165	3.5	2991	2826	0.94
48.3	306	0.208	125	3.5	1695	1623	0.96
74.7	211	0.052	221	3.5	2451	2312	0.94
80.2	186	0.056	168	3.5	2295	2132	0.93
28.18	285	0.92	47	4.3	790	754	0.95
23.2	371	2.088	34	3.0	628	612	0.97
24.3	452	2.499	33	3.0	3278	3387	1.03
24.2	335	1.995	31	3.0	6319	6561	1.04
77	843	1.397	34	3.0	7304	7240	0.99
85.1	823	0.788	52	3.0	13776	14352	1.04
41.1	279	0.182	152	3.0	6870	6543	0.95
75.2	282	0.515	32	3.0	320	305	0.95
75.2	282	0.115	134	3.0	4102	3697	0.90
80	404	0.166	125	3.0	4800	4654	0.97

Hence the developed model will serve as a robust and reliable tool for the design of circular CFSTCSCs. The main focus of the present paper was to develop a model to predict the ultimate load capacity of CFSTCSCs based on RVM. Accordingly, the model was developed and the efficacy of the model was verified by the experimental data. The proposed model can be used in the modeling approach for the estimation of the ultimate load capacity of CFSTCSCs based on RVM.

Acknowledgments

Some or all raw/processed data required to reproduce these findings of this study will be made available from the corresponding author upon reasonable request. This research

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Similarity rate (iThenticate): 15%

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