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Prediction of Shear Capacity of RC Deep Beams Via a Soft Computing Method

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A B S T R A C T

It is well known that the shear capacity of RC deep beams is affected by many mechanical and geometric parameters. The accurate prediction of the shear capacity still stands out as one of the major stumbling blocks in structural engineering practice. Traditional prediction methods have often proven less than precise. On the other hand, artificial intelligence-based methods, particularly those represented by SVMs, have presented themselves as a promising alternative. This research employed an enhanced machine learning technique, known as WLS-SVM, to estimate the shear capacity of reinforced concrete deep beams. In assembling a comprehensive dataset, 214 experimental results are obtained from the literature. From selected inputs and outputs, under the supervision of a teaching-learning type approach, a predictive model is derived via WLS-SVM. This model is compared with other AI-based methods and codified design procedures. It presented the best accuracy, with major statistical indicators, including an R^2 of 0.9804, showing the superiority of the WLS-SVM approach when compared to other methods. Therefore, the study's results reveal WLS-SVM as a very accurate and viable option for the structural calculation and design of reinforced concrete deep beams.

1. Introduction

Reinforced concrete (RC) deep beams play a crucial role in construction as structural members and as elements that help in distributing loads, particularly in systems like folded plates, base walls, and pile caps found in tall buildings [1]. Although widely adopted and valued, RC deep beams exhibit notable design differences compared to conventional structural components, mainly because numerous factors considerably affect their nonlinear response and resistance to shear forces. Because of the complex behavior of these beams, there is no universally accepted and precise definition that is consistent across all design codes. However, most codes define a beam as “deep” if the span-to-depth ratio (*L/D*) is less than 5 [2]. This ratio varies across standards: it is less than 5 in European codes, less than 2.5 in Canadian codes, and less than 4 in American codes. Due to the complexity of the shear mechanism and the wide range of influencing parameters in RC deep beams, developing a general and accurate model to estimate their shear strength is quite challenging. As a result, it is not feasible to calculate the exact shear strength of such beams through a closed-form analytical solution [3]. Over the past few decades, the shear behavior and strength of RC deep beams have received relatively little attention in research. Among the various analytical methods introduced in this context, the strut-and-tie method has emerged as one of the most commonly utilized techniques [4].

In recent decades, the use of artificial intelligence (AI) has gained significant traction as an emerging subject of study within the field of structural engineering [5, 6]. AI has demonstrated great success in simulating complex problems, making it a powerful tool for prediction. It enables structural designers to estimate the performance of reinforced concrete members more accurately. AI-based approaches have proven effective in accurately capturing the complex nonlinear correlations between the shear strength of RC deep beams and the various influencing factors [7]. Therefore, AI-based techniques are increasingly being recognized as innovative and promising tools in the field of civil engineering. Numerous studies have employed artificial intelligence (AI) methods and their

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various subfields, such as fuzzy logic and metaheuristic algorithms, in the field of structural engineering [5, 8]. A common trend in AI-based approaches involves developing more efficient models through ensemble modeling [9]. In this approach, new group models are created by combining individual models such that the ensemble model achieves higher learning accuracy and reduced error diversity among its components. In contrast to a single model that is trained on a limited portion of the dataset or under fixed training conditions, ensemble approaches typically produce more reliable and better-generalizing models. This is because different learners may complement each other by avoiding similar errors. Additionally, ensemble learning allows the full exploitation of the training dataset, which is particularly beneficial when only a limited amount of data is accessible. According to Chou and Pham [10], integrating two or more powerful learners within an ensemble framework yields markedly better performance than relying on single learners alone. Therefore, combining multiple learners can help reduce prediction errors and variance in results, as the aggregated outcome typically offers higher accuracy than that of a single learner [7, 9].

Support vector machine (SVM) is recognized as a leading artificial intelligence technique for capturing nonlinear patterns, often outperforming older methods like neural networks in tasks involving classification and regression [11]. First introduced by Vapnik in 1995 [12], SVM falls under the category of supervised learning techniques. In comparison to other similar methods, SVM provides a wide array of advantages, including strong predictive capabilities and the capacity to create precise decision boundaries, even when the training data is limited in size. Additionally, SVM can effectively model complex nonlinear relationships [13]. SVM has been widely applied in various civil engineering applications. For instance, Chen et al. [14] used SVM to predict deformation and stress parameters in tunnels, and Liu et al. [15] employed SVM to model energy consumption in buildings. Several studies [16-18] have made noteworthy contributions in civil engineering that have applied machine learning as a powerful modeling tool.

The least squares support vector machine (LS-SVM) represents an enhanced variant of the standard SVM, integrating additional capabilities and achieving computational efficiency through rapid processing [19]. This approach has shown success in addressing both nonlinear and complex engineering tasks [20]. During the training phase, LS-SVM applies a least squares objective to derive linear equations in the dual formulation. Accordingly, the resulting linear system can be efficiently solved using iterative techniques, such as the conjugate gradient algorithm.

To ensure the best possible performance from both SVM and LS-SVM models, it is essential to accurately tune their parameters. In the case of SVM, this involves selecting suitable values for the regularization factor (γ) and the parameter associated with the RBF kernel (σ). Inappropriate choices for these parameters can significantly reduce the prediction accuracy of the model. Similarly, LS-SVM requires predefined values for the regularization and kernel parameters. It is important to highlight that selecting the best parameter values is a non-trivial process and can be framed as a standard optimization challenge. WLS-SVM, or weighted least squares support vector machine, represents an improved form of LS-SVM, in which error terms are weighted to enhance the performance of the original algorithm [21]. Integrating these weights leads to improved model accuracy in predictions. When evaluated against LS-SVM, the WLS-SVM approach demonstrates superior effectiveness in function approximation applications [22].

In the present study, the WLS-SVM method is employed to predict the shear capacity of reinforced concrete deep beams. Accordingly, the following sections first examine the performance of the WLS-SVM approach, and then assess the prediction results. These outcomes are compared with those obtained from existing design codes and other artificial intelligence methods reported in the literature. The rest of this article will cover parts, shear strength of reinforced concrete deep beams, experimental data, research methodology, data processing, results and discussion, and conclusion.

2. Shear strength of reinforced concrete deep beams

Various methods have been proposed for the design of deep beams. The american concrete institute (ACI) code [23] is based on a truss model, in which the concrete contribution is determined through empirical observations. The shear strength of reinforced concrete deep beams, as defined by ACI provisions, can be calculated using Eqs. 1 to 4.

$$V_c = v_c b_w d = \left(3.5 - 2.5\frac{M_u}{V_u d}\right) \times \left(1.9\sqrt{f_c'} + 2.5\rho_w \frac{V_u d}{M_u}\right) b_w d \tag{1}$$

in these equations, f_c' is the 28-day compressive strength, and ρ_w is the longitudinal reinforcement ratio, calculated using Eq. 2.

$$\rho_w = A_s / b_w d \tag{2}$$

the parameters b_w, M_u, V_u, and d represent the beam width, bending moment at the critical section, shear force, and effective depth of the beam, respectively. In beams containing transverse reinforcement, the nominal shear capacity V_n is calculated as the combined effect of the concrete contribution V_c and the shear reinforcement component V_s, as presented in Eq. 3.

$$V_n = V_c + V_s \tag{3}$$

the term V_s is determined using Eq. 4, where:

$$V_s = \left[\frac{A_v}{12s}\left(1 + \frac{L_n}{d}\right) + \frac{A_{vh}}{12s_2}\left(11 - \frac{L_n}{d}\right)\right] f_y d \tag{4}$$

in Eq. 4, Ln is the effective span of the beam; A_v and A_{vh} are the areas of vertical and horizontal shear reinforcement perpendicular and parallel to the longitudinal reinforcement within spacings s and s_2, respectively; fy is the yield strength of the stirrups; s is the stirrup spacing; and ρv is the ratio of vertical shear reinforcement. Similarly, the canadian standards ssociation (CSA) code [24] estimates the total shear strength of RC deep beams as the sum of concrete and shear reinforcement contributions. In CSA provisions, two different expressions are provided for the concrete contribution v_c, depending on the amount of transverse reinforcement and the effective depth, as shown in Eq. 5, subject to conditions given by Eqs. 6 and 8, or alternatively, Eqs. 7 and 8.

$$v_c = \frac{V_c}{b_w d} = 0.2\sqrt{f_c'} \quad (5)$$

if:

$$A_v \geq \frac{0.006\sqrt{f_c'}b_w s}{f_{yv}} \text{ and } d \leq 300\text{mm} \quad (6)$$

or:

$$v_c = \frac{V_c}{b_w d} = \left(\frac{260}{1000+d}\right)\sqrt{f_c'} \geq 0.1\sqrt{f_c'} \quad (7)$$

if:

$$A_v < \frac{0.006\sqrt{f_c'}b_w s}{f_{yv}} \text{ and } d > 300\text{mm} \quad (8)$$

the shear contribution from reinforcement in the CSA code is expressed in a manner similar to that defined in the ACI code.

3. Experimental data

3.1. Data description

This work utilizes a dataset comprising 214 experimental observations related to reinforced concrete deep beams. These data were gathered from eight separate experimental investigations reported in the literature [25-32]. Fig. 1 illustrates the details of the RC deep beams.

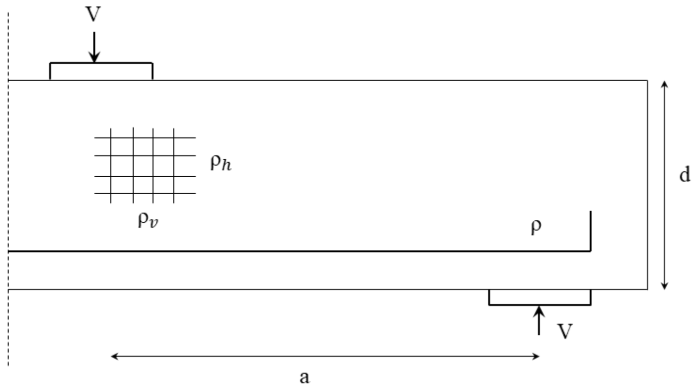


Fig. 1. Geometry of a reinforced concrete deep beam.

The input variables in the WLS-SVM method were selected based on the key parameters influencing the shear capacity of RC deep beams as defined in design codes. Table 1 presents the statistical descriptions of the input and output variables.

Table 1. Summary statistics of input and output data in the current study.

Variables	Unit	Min	Max	Mean	Sdt
Effective depth (*d*)	mm	217	802	420.7	108.5
Web width of the beam (*b*)	mm	77	306	134.1	49.1
Concrete compressive strength (*f'c*)	MPa	13.9	73.7	33.4	15.89
Shear span-to-effective depth ratio (*a/d*)	-	0.28	2.8	1.23	0.54
Longitudinal reinforcement ratio (ρ)	%	0.53	4.1	1.79	0.69
Horizontal shear reinforcement ratio (ρ_h)	%	0	2.48	0.33	0.46
Vertical shear reinforcement ratio (ρ_v)	%	0	2.66	0.55	0.67
Ultimate shear strength (*V/bd*)	MPa	1.74	13.3	5.4	2.15

4. Research methodology

Support Vector Machines (SVMs) face two significant drawbacks: (1) difficulty in fine-tuning kernel parameters, and (2) heavy dependence on support vectors for defining the decision boundary. To overcome these shortcomings, Suykens et al. [33] proposed the WLS-SVM, which enhances the LS-SVM framework by incorporating weights into the error terms, thereby improving the efficiency in solving a broad range of problems.

Considering a training sample set of size N, denoted by $\{(x_k, y_k)\}_{k+1}^{N}$, where $x_i \in R^d$ represents input data and $y_i \in R$ is the output. Based on this setup, the WLS-SVM model is expressed as the following optimization task in the primal weight domain [34]:

$$\text{Minimize: } J(w,e) = \frac{1}{2}w^T w + \frac{1}{2}\gamma \sum_{i=1}^{N} \bar{v}_i e_i^2$$
$$\text{Subjected to: } y_i = w^T \emptyset(x_i) + b + e_i \quad (9)$$
$$i = 1,2,\dots,N$$

here, $\emptyset(0): R^d \rightarrow R^{\bar{d}}$ is a mapping function that transforms the input data into a higher-dimensional feature space. The vector $w \in R^d$ represents the weight function in the primal space, while $b \in R$ and $e_i \in R$ represent the bias and error terms, respectively. Within the primal formulation, the learning and optimization task of the WLS-SVM corresponding to Eq. 9 can be written as follows:

$$\mathrm{y(x)} = w^T \emptyset(x) + b \quad (10)$$

in general, the structure of the mapping function $\emptyset$(x) is unknown, and its direct computation is complex. Hence, solving Eq. 9 directly for w is infeasible. Consequently, the WLS-SVM regression formulation is derived by constructing a corresponding Lagrangian function, as illustrated in:

$$L(w,b,e_i,x) = j(w,e) - \sum_{i=1}^{N} \alpha_i (w^T \emptyset(x_i) + b + e_i - y_i) \quad (11)$$

where α_i are the Lagrange multipliers. The optimality conditions are determined from:

$$\frac{\partial L}{\partial w} = 0, \frac{\partial L}{\partial b} = 0, \frac{\partial L}{\partial e_i} = 0, \dots, \frac{\partial L}{\partial \alpha_i} = 0 \quad (12)$$

by eliminating *w* and *e*, the resulting system becomes:

$$\begin{bmatrix} \Omega + V_Y & I_N^T \\ I_n & 0 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} y \\ 0 \end{bmatrix} \quad (13)$$

where:

$$V_Y = diag\left\{\frac{1}{\overline{\overline{r_1}}} \dots \frac{1}{\overline{\overline{r_N}}}\right\}$$
$$\Omega_{i,j} = \langle \emptyset(x_i), \emptyset(x_j) \rangle_H \quad (14)$$
$$i,j = 1,2,\dots,N$$

$$y = [y_1, \dots, y_N]^T;\ I_N^T[1,\dots,1]$$
$$\alpha = [\alpha_1, \dots, \alpha_N] \quad (15)$$

Widodo and Yang [35] proposed the following expression for the weight coefficients $\overline{v_N}$:

$$\overline{v_N} = \begin{bmatrix} 1 & if\!: \left|\frac{e_i}{\hat{s}}\right| \leq c_1 \\ \dfrac{c_2 - \left|\frac{e_i}{\hat{s}}\right|}{c_2 - c_1} & if\!: c_1 \leq \left|\frac{e_i}{\hat{s}}\right| \leq c_2 \\ 10^{-1} & otherwise \end{bmatrix} \quad (16)$$

where $\hat{s}$ is a robust estimate of the standard deviation of the error variable $\left(e_{i = a_i / D_{ii}^{-1}}\right)$. Constants c_1 and c_2 are typically taken as 2.5 and 3, respectively. The term D_{ii}^{-1}refers to the i-th diagonal entry of the inverse matrix *D*, which appears on the left-hand side of Eq. 13. According to Mercer's theorem, the kernel function *K*(.,.) must be selected so that:

$$K(x_i.\overline{x_j}) = \langle \emptyset(x_i), \emptyset(x_j) \rangle_H$$
$$i,j=1,2,\dots,N \quad (17)$$

as a result, the WLS-SVM formulation is obtained as:

$$y(x) = \sum^{N} \alpha_i K(x_i, x) + b \quad (18)$$

the function $K(x_i.\bar{x_j})$ is essentially an inner product of two vectors in the feature space. To represent it as such, the kernel function $K(x_i.\bar{x_j})$ must be a symmetric, positive-definite function satisfying Mercer's condition. Support Vector Machines (SVMs) typically employ one of three kernel types in practical applications: radial basis function (RBF), polynomial, or linear. Among these, the RBF kernel is the most widely utilized within the WLS-SVM framework, and its formulation is given below [33]:

$$K_{RBF}(x, \bar{x}) = exp(-\frac{\|x - \bar{x}\|^2}{\sigma^2}) \quad (19)$$

here, σ^2 represents a positive constant, typically known as the kernel width. An illustration of the WLS-SVM model's architecture is provided in Fig. 2.

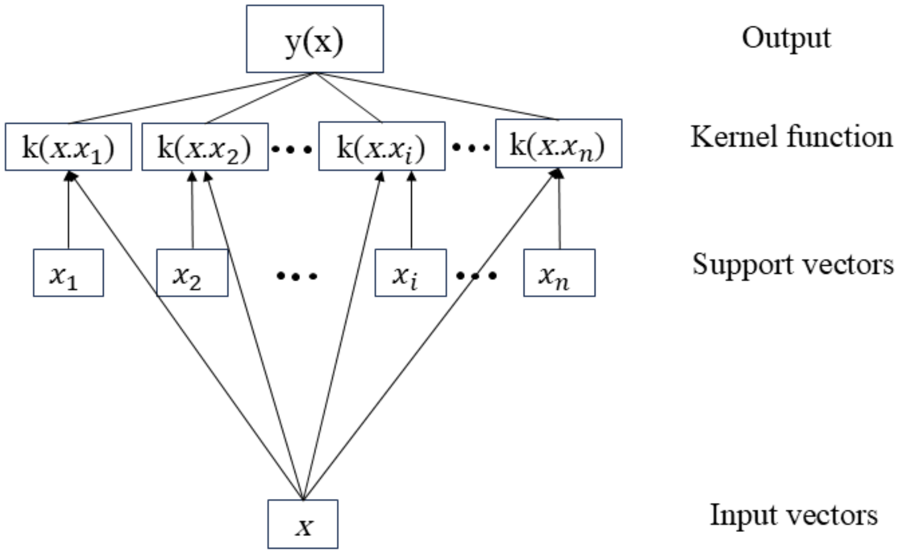


Fig. 2. Structure of the WLS-SVM method.

5. Data processing

To normalize the input and output parameters, Eq. 20 was used. Normalization should be performed prior to applying many data mining methods, such as neural networks, SVM, and K-Means clustering. This process ensures that all input parameters are treated equally by the algorithm and that no single parameter dominates the others due to differences in scale.

$$x_i^n = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad (20)$$

in this equation, x_i refers to the input data, x_{min} and x_{max} represent the minimum and maximum values of x within the entire dataset, and x_i^n denotes the normalized value.

5.1. Initial parameters

Before initiating the search loop within the predefined parameter domains, six parameters (C, γ_1, γ_2, σ^2, α, and β) must be initially estimated. Proper tuning of these parameters in various SVM-based methods significantly enhances model performance. Table 2 presents the parameter ranges considered in this study [36].

Table 2. Adjust the initial control parameters.

Parameters	**Symbol**	**Upper bound**	**Lower bound**	**Ref.**
Regularization parameter in the SVM method	C	10^5	10^{-5}	[37]
RBF kernel parameter in SVM method	γ_1	10^5	10^{-5}	[37]
Regularization parameter in the WLS-SVM method	γ_2	10^5	10^{-5}	[37, 38]
RBF kernel parameter in WLS-SVM method	σ^2	10^5	10^{-5}	[37, 38]
Ensemble learning coefficients	(α,β)	0	1	-

5.2. WLS-SVM evaluation using k-fold cross-validation

To develop the prediction model, the data must be divided into training and validation subsets. Although simple splitting techniques exist for this purpose, such approaches are highly sensitive to which data points are selected for training and which for validation. This sensitivity can lead to fluctuations in model accuracy—sometimes overestimating, and at other times underestimating, performance. To overcome this issue and provide a more reliable evaluation of model accuracy, the present study adopts the k-fold cross-validation method, which is widely used in AI research [10]. k-fold cross-validation is one of the most common forms of cross-validation and is extensively applied in machine learning. In this method, the dataset is divided into k equally sized folds, ensuring that both training and validation subsets exhibit similar distributions and adequate variability.

In the present work, a three-fold cross-validation approach was applied, allocating 67% of the dataset for training purposes and the remaining 33% for validation. The dataset was randomly partitioned into three distinct subsets. During each fold, one subset served as the validation set, while the other two were utilized for training. This strategy guarantees that every data sample contributes to both the training and validation phases at least once. Given that $k = 3$ was selected, each model underwent training three separate times throughout the parameter tuning process. As a result, three separate validation error averages are obtained for the objective function. The overall average of these three validation scores provides a reliable indicator of the WLS-SVM model's general predictive performance.

5.3. Prediction using the WLS-SVM method

At this stage, the WLS-SVM method begins its training process using the initial parameter values (C, γ_1, γ_2, σ^2), and subsequently, the trained model is validated using the validation dataset. It is important to note that data preprocessing is carried out to achieve the highest prediction accuracy.

5.4. Performance metrics

To assess the effectiveness of the WLS-SVM model, multiple statistical metrics were employed, including the correlation coefficient (R), mean absolute percentage error (MAPE), mean absolute error (MAE), and root mean square error (RMSE), and the coefficient of determination (R^2), which quantifies the average error observed during validation. When R and R^2 approach a value of 1, it indicates a higher agreement between predicted and actual outputs. Similarly, lower values of MAPE, MAE, and RMSE indicate higher accuracy in the predictions made by the WLS-SVM method. Eqs. 21-25 present the mathematical formulas for these performance evaluation metrics.

$$MAE = \left(\frac{1}{n}\right) \times \sum_{i=1}^{n} \left(|p_i - y_i|\right) \tag{21}$$

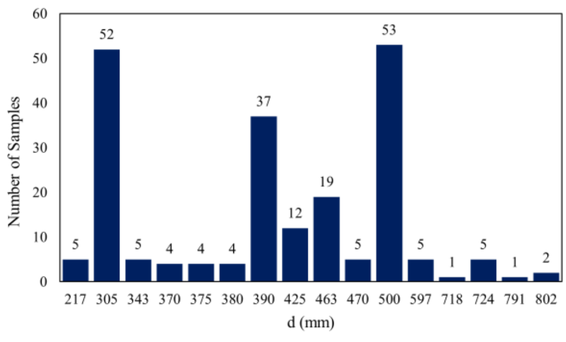
$$MAPE = \left(\frac{1}{n}\right) \times \sum_{i=1}^{n} \left(|p_i - y_i|/y_i\right) \times 100 \tag{22}$$

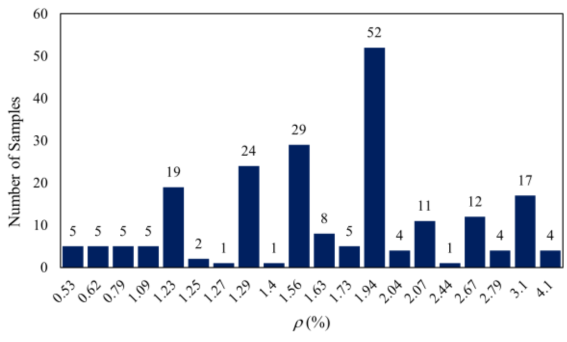
$$RMSE = \sqrt{\left[\left(\frac{1}{n}\right) \times \sum_{i=1}^{n} \left(|p_i - y_i|\right)^2\right]} \tag{23}$$

$$R^2 = \left(\frac{n\sum y_i \times p_i - (\sum y_i)(\sum p_i)}{\sqrt{(n(\sum y_i^2) - (\sum y_i^2))} \times \sqrt{(n(\sum p_i^2) - (\sum p_i^2))}}\right)^2 \tag{24}$$

$$R = \frac{n\sum y_i \times p_i - (\sum y_i)(\sum p_i)}{\sqrt{(n(\sum y_i^2) - (\sum y_i^2))} \times \sqrt{(n(\sum p_i^2) - (\sum p_i^2))}} \tag{25}$$

where p_i is the predicted value, y_i is the actual value, and n is the sample size. The histograms of the input variables are shown in Fig. 3.





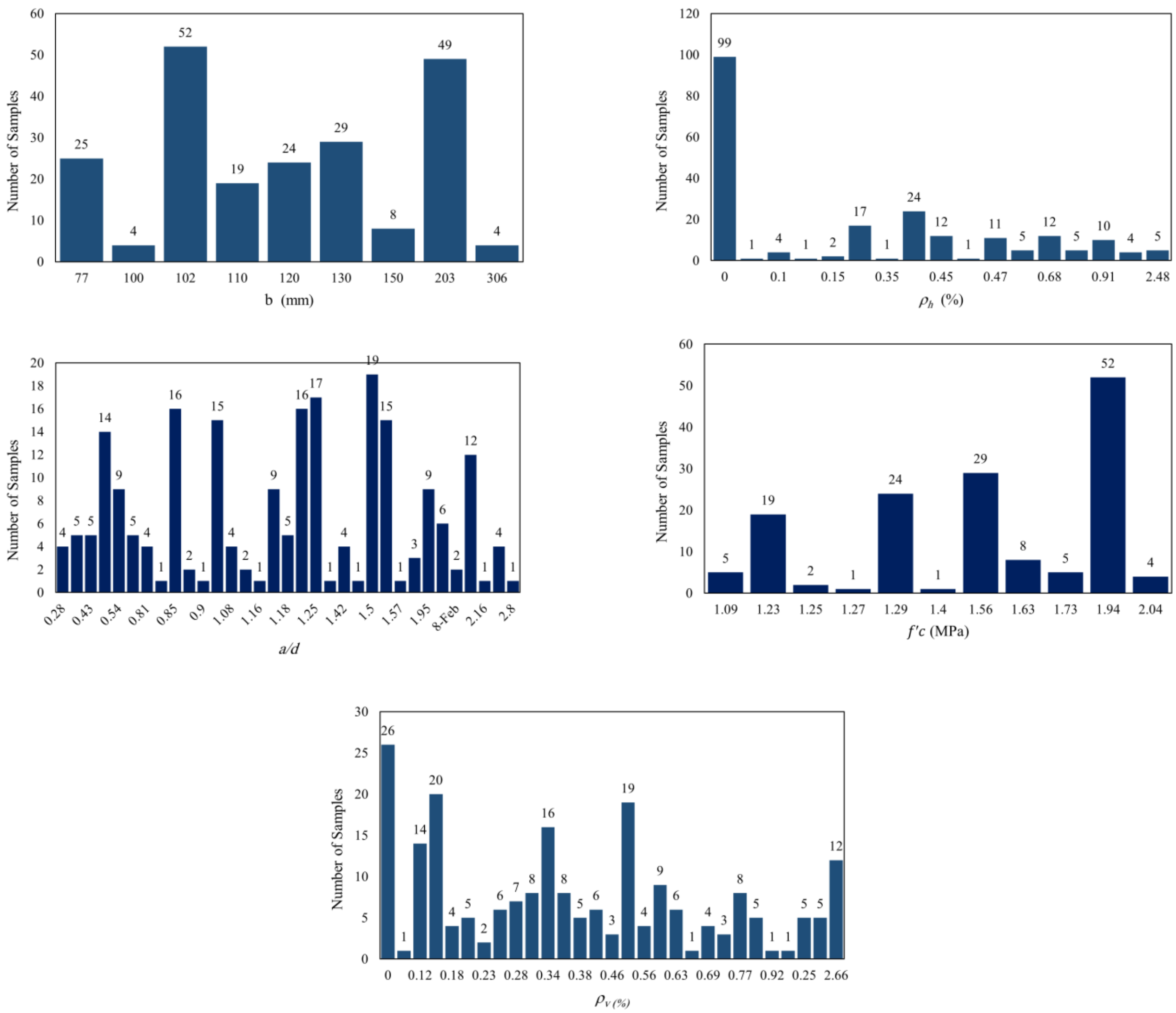


Fig. 3. Histogram of the input variables.

6. Results and discussion

In this work, a three-fold cross-validation strategy (k = 3) was applied by randomly splitting the dataset into separate subsets for training and validation purposes. To develop a predictive model for the shear strength of reinforced concrete deep beams using the WLS-SVM method, the data were split into a training set and a validation set. The validation data was used to test the trained and deployed model. In total, using fold cross-validation, 171 randomly selected samples were assigned to the training set and 43 to the validation set. The training set itself was further divided into two internal subsets: one for fitting the model and the other for validating the training performance and fine-tuning the learned model.

6.1. Training phase and parameter selection

Optimal performance of the WLS-SVM technique relies on appropriately selecting the values of the regularization factor γ^2 and the RBF kernel width σ^2. In this study, the best parameter values were identified through a trial-and-error process. Table 3 presents the optimal values of the tuning parameters for WLS-SVM. As shown in Fig. 4, the training results obtained using WLS-SVM with the optimized tuning parameters demonstrate strong model performance. Based on the evaluation metrics (R, R^2, MAE, MAPE, RMSE), the WLS-SVM approach produces values near 1 for R and R^2, and low values for MAE, MAPE, and RMSE, indicating high prediction accuracy. Therefore, the tuned model is ready to predict new test data.

Fig. 5 compares multiple WLS-SVM runs and the statistical outcomes. As shown, the 19th run achieved the lowest MAE, MAPE, and RMSE values, while its R and R^2 values were closest to 1 compared to other runs.

6.2. Validation phase and prediction outcomes

Based on the optimized parameters provided in Table 3 and the trained WLS-SVM model, the predicted outcomes for both training and validation stages are illustrated in Figs. 6a and 6b, respectively. The results indicate that WLS-SVM achieved an R^2 of 0.9279 during training and 0.9804 during validation ($R^2 \geq 0.95$), demonstrating a high level of accuracy in predicting the shear strength of RC deep beams.

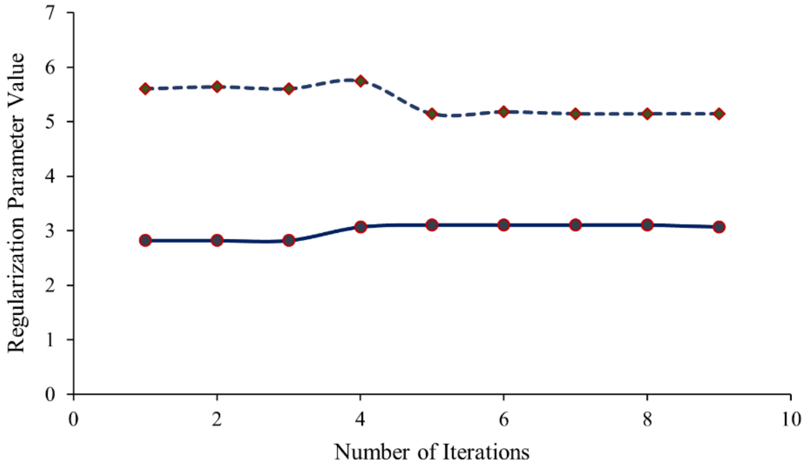


Fig. 4. Parameter tuning procedure and convergence behavior.

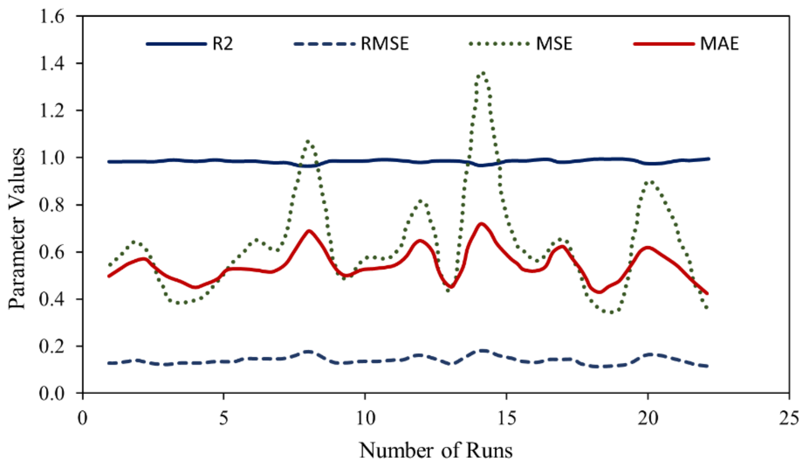


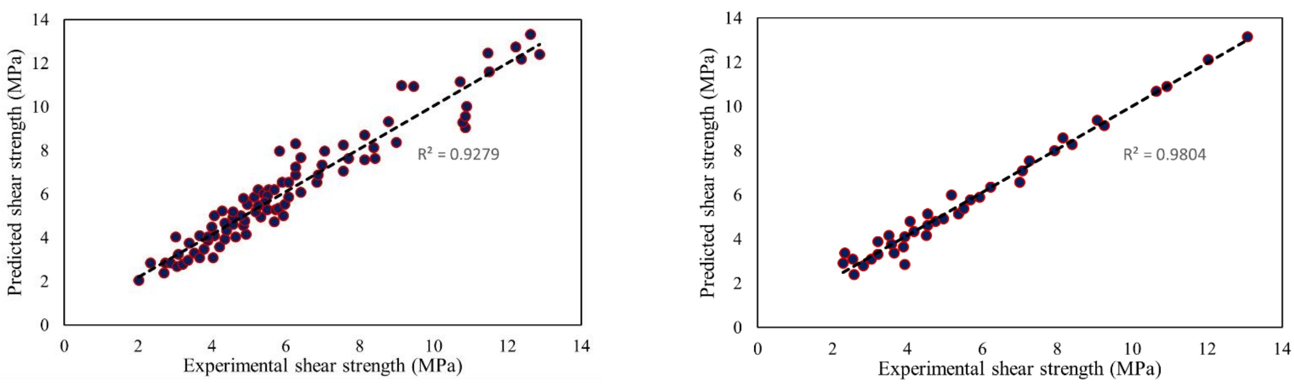
Fig. 5. Comparative analysis of performance metrics (R², MAPE, MAE, RMSE) across multiple runs.

Furthermore, the low MAPE value, which is close to zero, confirms that the predicted shear strength using the WLS-SVM method is reliable. Hence, this method can be considered an effective tool for designing and predicting the shear strength of reinforced concrete deep beams.

Additionally, the statistical results indicate that the proposed WLS-SVM method can minimize discrepancies between training and test performance metrics, thereby avoiding significant prediction issues.

Table 3. Tuned parameter values for the WLS-SVM model during the training stage.

WLS-SVM		
Parameters	γ_2	σ_2
Value Selected in This Study	5.13	3.1037



(a) **(b)**

Fig. 6. Comparison between predicted and experimental shear capacities: (a) Results from the training dataset, (b) Results from the validation dataset.

6.3. Comparison of WLS-SVM with other AI methods

To comprehensively assess the effectiveness of the WLS-SVM model, its results were benchmarked against various alternative AI techniques, which include:

(1) a basic SVM model without parameter adjustment,

(2) LS-SVM without tuning,

(3) SVM optimized using the Symbiotic Organisms Search (SOS) algorithm,

(4) LS-SVM enhanced through SOS,

(5) Tree-based multiple linear regression (MLR-Reg), and

(6) a hybrid SVM–LS-SVM approach applied without parameter calibration [39].

Table 4 presents the average values and standard deviations of performance metrics for each method. The results show that the proposed WLS-SVM method achieved the best values:

RMSE = 0.107, R^2 = 0.9887, MAPE = 9.48, and MAE = 0.478. Furthermore, Table 4 confirms that WLS-SVM outperformed the compared AI methods in terms of accuracy.

Table 5 presents a comparison between the WLS-SVM results, the CSA and ACI code-based predictions, and the results obtained from the Gravitational Search Algorithm (GSA), which is an optimization method based on gravitational laws and mass interactions.

Table 4. Performance comparison between WLS-SVM and other AI-based techniques.

Methods	Results validation					
	R^2	R	MAPE (%)	MAE (MPa)	RMSE (MPa)	Ref.
SVM	0.7598	0.8717	16.51	0.904	1.2167	[39]
LS-SVM	0.8525	0.9271	12.27	0.5669	0.736	[39]
Optimized SVM	0.9189	0.9586	8.26	0.4035	0.5508	[39]
Optimized LS-SVM	0.9189	0.9586	8.09	0.4084	0.5514	[39]
MLR-Reg Tree	0.9285	0.9636	10	0.515	0.6799	[39]
SVM-LSVM	0.8383	0.9156	11.31	0.594	0.7812	[39]
WLS-SVM	0.9804	0.9945	9.48	0.48	0.11	Present study

Table 5. Comparison of WLS-SVM prediction results with those obtained from various design codes and the GSA algorithm.

Methods	$V_{actual}/V_{predicted}$	MAPE	MAE	Ref.
ACI 318-11	0.569	16.19	1.23	[23]
Canadian Standards Association	0.58	18.8	0.91	[24]
General Services Administration	0.15	10.9	0.49	[1]
WLS-SVM	0.998	9.48	0.478	Present study

7. Conclusion

In this study, a novel artificial intelligence method known as Weighted Least Squares Support Vector Machine (WLS-SVM) was employed to predict the shear strength of reinforced concrete deep beams. For this purpose, the relevant shear-influencing parameters were first collected, and a dataset consisting of 214 experimental samples was compiled. The WLS-SVM model was implemented using eight selected input features, and its performance was assessed through evaluation metrics such as R^2, MAEP, RMSE, and MAE.

The results demonstrated that WLS-SVM is a powerful computational tool capable of analyzing complex relationships among various parameters involved in predicting the shear strength of RC deep beams. When compared with alternative AI methods and conventional design standards, the WLS-SVM approach demonstrated superior predictive accuracy, yielding RMSE = 0.107, R^2 = 0.9804, MAEP = 9.48%, and MAE = 0.478. This study confirms that the WLS-SVM method, due to its high predictive performance, can be considered a strong alternative to conventional AI methods and code-based approaches in predicting the shear capacity of RC deep beams. Finally, it can be concluded that WLS-SVM offers the added advantage of being readily implementable in parallel computing architectures, resulting in significantly reduced processing time compared to other techniques while maintaining similar levels of prediction accuracy.

Statements & Declarations

Author contributions

Masoud Mahmoudabadi: Conceptualization, Methodology, Formal analysis, Resources, Writing - Original Draft.

Seyed Mohammad Reza Hasani: Resources, Writing - Original Draft.

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Data availability

The data presented in this study will be available on interested request from the corresponding author.

Declarations

The authors declare no conflict of interest.

References

[1] Cakir, F., Acar, V., Aydin, M. R. Experimental and numerical assessment of intraply hybrid composites strengthened RC deep beams. Mechanics of Advanced Materials and Structures, 2025; 1-24. doi:10.1080/15376494.2025.2476208.

[2] Fathalla, E., Mihaylov, B. Shear behaviour of deep beams strengthened with high-strength fiber reinforced concrete jackets. Engineering Structures, 2025; 325: 119404. doi:10.1016/j.engstruct.2024.119404.

[3] Liu, C., Xu, D., Duanmu, X. Analysis of shear strength influencing factors in reinforced concrete deep beams: A modified calculating model. Journal of Building Engineering, 2024; 95: 110243. doi:10.1016/j.jobe.2024.110243.

[4] Tamimi, M. F., Alshannaq, A. A., Abu Qamar, M. a. I. Enhancing reliability in reinforced concrete deep beams through probabilistic analysis and topology optimized strut-and-tie models. Structures, 2024; 70: 107872. doi:10.1016/j.istruc.2024.107872.

[5] Prayoonwet, W., Koshimizu, R., Ozaki, M., Sato, Y., Jirawattanasomkul, T., Yodsudjai, W. Shear strength prediction for RC beams without shear reinforcement by neural network incorporated with mechanical interpretations. Engineering Structures, 2024; 298: 117065. doi:10.1016/j.engstruct.2023.117065.

[6] AlHamaydeh, M., Markou, G., Bakas, N., Papadrakakis, M. AI-based shear capacity of FRP-reinforced concrete deep beams without stirrups. Engineering Structures, 2022; 264: 114441. doi:10.1016/j.engstruct.2022.114441.

[7] Zhang, G., Ali, Z. H., Aldlemy, M. S., Mussa, M. H., Salih, S. Q., Hameed, M. M., Al-Khafaji, Z. S., Yaseen, Z. M. Reinforced concrete deep beam shear strength capacity modelling using an integrative bio-inspired algorithm with an artificial intelligence model. Engineering with Computers, 2022; 38: 15-28. doi:10.1007/s00366-020-01137-1.

[8] Baghdadi, A., Babovic, N., Kloft, H. Fuzzy Logic, Neural Network, and Adaptive Neuro-Fuzzy Inference System in Delegation of Standard Concrete Beam Calculations. Buildings, 2023; 14: 15. doi:10.3390/buildings14010015.

[9] Feng, D.-C., Wang, W.-J., Mangalathu, S., Hu, G., Wu, T. Implementing ensemble learning methods to predict the shear strength of RC deep beams with/without web reinforcements. Engineering Structures, 2021; 235: 111979. doi:10.1016/j.engstruct.2021.111979.

[10] Chou, J.-S., Pham, A.-D. Enhanced artificial intelligence for ensemble approach to predicting high performance concrete compressive strength. Construction and Building Materials, 2013; 49: 554-563. doi:10.1016/j.conbuildmat.2013.08.078.

[11] Kaloop, M. R., Roy, B., Chaurasia, K., Kim, S.-M., Jang, H.-M., Hu, J.-W., Abdelwahed, B. S. Shear strength estimation of reinforced concrete deep beams using a novel hybrid metaheuristic optimized SVR models. Sustainability, 2022; 14: 5238. doi:10.3390/su14095238.

[12] Vapnik, V. N. The Nature of Statistical Learning Theory. 2nd ed. New York (NY): Springer International Publishing; 1999. doi:10.1007/978-1-4757-3264-1.

[13] Megahed, K. Prediction and reliability analysis of shear strength of RC deep beams. Scientific Reports, 2024; 14: 14590. doi:10.1038/s41598-024-64386-w.

[14] Chen, R., Zhang, P., Wu, H., Wang, Z., Zhong, Z. Prediction of shield tunneling-induced ground settlement using machine learning techniques. Frontiers of Structural and Civil Engineering, 2019; 13: 1363-1378. doi:10.1007/s11709-019-0561-3.

[15] Liu, Z., Wu, D., Liu, Y., Han, Z., Lun, L., Gao, J., Jin, G., Cao, G. Accuracy analyses and model comparison of machine learning adopted in building energy consumption prediction. Energy Exploration & Exploitation, 2019; 37: 1426-1451. doi:10.1177/0144598718822400.

[16] Acar, E., Rais-Rohani, M. Ensemble of metamodels with optimized weight factors. Structural and Multidisciplinary Optimization, 2009; 37: 279-294. doi:10.1007/s00158-008-0230-y.

[17] Chou, J.-S., Yang, K.-H., Lin, J.-Y. Peak shear strength of discrete fiber-reinforced soils computed by machine learning and metaensemble methods. Journal of Computing in Civil Engineering, 2016; 30: 04016036. doi:10.1061/(ASCE)CP.1943-5487.0000595.

[18] Hoang, N.-D., Tran, X.-L., Nguyen, H. Predicting ultimate bond strength of corroded reinforcement and surrounding concrete using a metaheuristic optimized least squares support vector regression model. Neural Computing and Applications, 2020; 32: 7289-7309. doi:10.1007/s00521-019-04258-x.

[19] Luo, H., Paal, S. G. Metaheuristic least squares support vector machine-based lateral strength modelling of reinforced concrete columns subjected to earthquake loads. Structures, 2021; 33: 748-758. doi:10.1016/j.istruc.2021.04.048.

[20] Gharehbaghi, S., Yazdani, H., Khatibinia, M. Estimating inelastic seismic response of reinforced concrete frame structures using a wavelet support vector machine and an artificial neural network. Neural Computing and Applications, 2020; 32: 2975-2988. doi:10.1007/s00521-019-04075-2.

[21] Luo, H., Paal, S. G. A novel outlier-insensitive local support vector machine for robust data-driven forecasting in engineering. Engineering with Computers, 2023; 39: 3671-3689. doi:10.1007/s00366-022-01781-9.

[22] Prayogo, D., Cheng, M.-Y., Wu, Y.-W., Tran, D.-H. Combining machine learning models via adaptive ensemble weighting for prediction of shear capacity of reinforced-concrete deep beams. Engineering with Computers, 2020; 36: 1135-1153. doi:10.1007/s00366-019-00753-w.

[23] American Concrete Institute (ACI). ACI 318-25: Building Code for Structural Concrete—Code Requirements and Commentary. Farmington Hills (MI): ACI; 2025.

[24] Canadian Standards Association (CSA). CSA A23.3:19: Design of Concrete Structures. Longueuil (QC): CSA; 2019.

[25] Clark, A. P. Diagonal Tension in Reinforced Concrete Beams. ACI Journal Proceedings, 1951; 48: 145-156. doi:10.14359/11876.

[26] Kong, F.-K., Robins, P. J., Cole, D. F. Web Reinforcement Effects on Deep Beams. ACI Journal Proceedings, 1970; 67: 1010-1018. doi:10.14359/7336.

[27] Smith, K. N., Vantsiotis, A. S. Shear Strength of Deep Beams. ACI Journal Proceedings, 1982; 79: 201-213.

[28] Anderson, N. S., Ramirez, J. A. Detailing of Stirrup Reinforcement. ACI Structural Journal, 1989; 86: 507-515. doi:10.14359/3005.

[29] Tan, K.-H., Kong, F.-K., Teng, S., Guan, L. High-Strength Concrete Deep Beams With Effective Span and Shear Span Variations. ACI Structural Journal, 1995; 92: 395-405. doi:10.14359/991.

[30] Oh, J.-K., Shin, S.-W. Shear Strength of Reinforced High-Strength Concrete Deep Beams. ACI Structural Journal, 2001; 98: 164-173. doi:10.14359/10184.

[31] Aguilar, G., Matamoros, A. B., Parra-Montesinos, G. J., Ramírez, J. A., Wight, J. K. Experimental Evaluation of Design Procedures for Shear Strength of Deep Reinforced Concrete Beams. ACI Structural Journal, 2002; 99: 539-548. doi:10.14359/12123.

[32] Quintero-Febres, C. G., Parra-Montesinos, G., Wight, J. K. Strength of Struts in Deep Concrete Members Designed Using Strut-and-Tie Method. ACI Structural Journal, 2006; 103: 577-586. doi:10.14359/16434.

[33] Suykens, J. A. K., De Brabanter, J., Lukas, L., Vandewalle, J. Weighted least squares support vector machines: robustness and sparse approximation. Neurocomputing, 2002; 48: 85-105. doi:10.1016/S0925-2312(01)00644-0.

[34] Li, H.-s., Lü, Z.-z., Yue, Z.-f. Support vector machine for structural reliability analysis. Applied Mathematics and Mechanics, 2006; 27: 1295-1303. doi:10.1007/s10483-006-1001-z.

[35] Widodo, A., Yang, B.-S. Wavelet support vector machine for induction machine fault diagnosis based on transient current signal. Expert Systems with Applications, 2008; 35: 307-316. doi:10.1016/j.eswa.2007.06.018.

[36] Faris, H., Hassonah, M. A., Al-Zoubi, A. M., Mirjalili, S., Aljarah, I. A multi-verse optimizer approach for feature selection and optimizing SVM parameters based on a robust system architecture. Neural Computing and Applications, 2018; 30: 2355-2369. doi:10.1007/s00521-016-2818-2.

[37] Hoang, N.-D., Pham, A.-D. Hybrid artificial intelligence approach based on metaheuristic and machine learning for slope stability assessment: A multinational data analysis. Expert Systems with Applications, 2016; 46: 60-68. doi:10.1016/j.eswa.2015.10.020.

[38] Cheng, M.-Y., Prayogo, D., Wu, Y.-W. Prediction of permanent deformation in asphalt pavements using a novel symbiotic organisms search–least squares support vector regression. Neural Computing and Applications, 2019; 31: 6261-6273. doi:10.1007/s00521-018-3426-0.

[39] Prayogo, H. Prediction of Concrete Compressive Strength from Early Age Test Result Using an Advanced Metaheuristic-Based Machine Learning Technique. In: Proceedings of the 34th International Symposium on Automation and Robotics in Construction (ISARC); 2017 July 1-3; Taipei, Taiwan. p. 856-863. doi:10.22260/ISARC2017/0120.