Research Article

Estimating Concrete Workability Based on Slump Test with Least Squares Support Vector Regression

Nhat-Duc Hoang[1] and Anh-Duc Pham[2]

[1]*Institute of Research and Development, Faculty of Civil Engineering, Duy Tan University,*
 P809-K7/25 Quang Trung, Danang 550000, Vietnam
[2]*Faculty of Project Management, the University of Danang-University of Science and Technology,*
 54 Nguyen Luong Bang, Danang 550000, Vietnam

Correspondence should be addressed to Nhat-Duc Hoang; hoangnhatduc@dtu.edu.vn

Concrete workability, quantified by concrete slump, is an important property of a concrete mixture. Concrete slump is generally known to affect the consistency, flowability, pumpability, compactibility, and harshness of a concrete mix. Hence, an accurate prediction of this property is a practical need of construction engineers. This research proposes a machine learning model for predicting concrete slump based on the Least Squares Support Vector Regression (LS-SVR). LS-SVR is employed to model the nonlinear mapping between the mix components and slump values. Since the learning process of the LS-SVR necessitates two hyperparameters, the regularization and the kernel parameters, the grid search method is employed search for the most desirable set of hyperparameters. Furthermore, to construct the hybrid model, this research collected a dataset including actual concrete slump tests from a hydroelectric dam construction project in Vietnam. Experimental results show that the proposed model is capable of predicting concrete slump accurately.

1. Introduction

Concrete workability is defined as the effort required to manipulate a freshly mixed quantity of concrete with minimum loss of homogeneity [1]. This property of concrete is generally known to affect the consistency, flowability, pumpability, compactibility, and harshness of a concrete mix. Thus, concrete workability is a very crucial factor that must be considered in order to produce high quality concrete [2–4].

The slump test is the most common method for assessing the flow properties of fresh concrete; the slump provides a measure of workability [5]. Using this test, the slump can be derived by measuring the drop from the top of the slumped fresh concrete. In the task of concrete mixture design, the prediction of concrete flowability is critical for on-site construction. As the complexity of concrete construction escalates, there is an increasing pressure on material engineers to achieve high workability as well as to

maintain the necessary mechanical properties to meet design specifications.

Concrete has been increasingly utilized in high-rise building and infrastructure development projects and special ingredients are often employed to make the material satisfy a specific set of performance requirements [6]. Superplasticizers are often included to enhance the concrete workability [7–9]. This situation makes the concrete mixes to be highly complex materials and modeling their properties becomes a very challenging task. There are complex and nonlinear relationships between the characteristics and the components that constitute the concrete mixes [8, 10, 11].

Due to the importance of the research topic, various studies have been dedicated to concrete slump prediction. Traditional statistical models and machine learning are prevailing approaches to tackle the problem at hand. Öztaş et al. [2], Yeh [1, 3], Chine et al. [12], and Bilgil [13] employed the regression analysis and Artificial Neural Network (ANN)

Figure 1: Concrete slump test (image source: http://xaydungth-anhvinh.vn/).

models to estimate concrete slump; the common finding is that ANN is an effective nonlinear modeling method and its results are more accurate than the models based on the traditional regression analysis approach.

Baykasoğlu et al. [14] utilized the gene expression programming (GEP) to model high-strength concrete slump. Chen et al. [15] constructed a parallel hypercubic GEP to forecast the slump of high-performance concrete; this research showed that the improved method is better than the GEP and similar to the performance of ANN. Chandwani et al. [16] proposed a Genetic Algorithm assisted ANN; the study showed that the integrated approach can enhance the convergence speed of ANN and its prediction accuracy.

Due to the popularity of concrete in the construction industry, better alternatives for concrete slump prediction are of practical need for construction engineers in concrete mix design. This research contributes to the body of knowledge by proposing a new approach for improving the accuracy of concrete slump prediction which is based on the Least Squares Support Vector Regression (LS-SVR). LS-SVR is an advanced machine learning method which is designed for nonlinear modeling [17]; the superiority of the approach has been illustrated in recent applications [18–22].

Furthermore, a dataset that contains slump test records, collected from a hydroelectric dam construction project in central Vietnam, is used to establish and verify the proposed approach. The rest of the article is organized as follows: the second section presents the research method. The proposed slump prediction model is described in the third section. The next section reports the experimental results. The conclusion of this study is stated in the final section.

2. Research Method

2.1. The Concrete Slump Test Dataset. This research recorded testing results of 95 concrete mixes during the construction progress of the Song Bung 2 hydroelectric dam construction project in central Vietnam (http://www.sb2.vn/). The test is in conformity with the Vietnamese standard (TCVN-3106) for slump test which is equivalent to the ASTM-C-143. The equipment for the slump test includes a hollow frustum of a cone and a ruler as the measuring device (see Figure 1).

Table 1: Statistical description.

Factors	Notation	Min	Mean	Std. dev.	Max
Cement (kg/m^3)	x_1	201.0	338.6	62.3	446.3
Natural sand (kg/m^3)	x_2	384.0	690.1	154.2	827.0
Crushed sand (kg/m^3)	x_3	0.0	81.6	159.0	399.0
Coarse aggregate (kg/m^3)	x_4	1107.0	1155.7	33.0	1218.0
Water (liter/m^3)	x_5	164.0	174.2	6.4	186.0
Superplasticizer (liter/m^3)	x_6	1.0	3.1	0.9	4.5
Concrete slump (cm)	y	8.0	10.2	2.9	19.0

Table 2: The dataset of concrete slump test.

Mix	x_1	x_2	x_3	x_4	x_5	x_6	y
1	261.0	397.0	397.0	1200.0	176.0	1.3	8.0
2	248.0	399.0	399.0	1208.0	176.0	1.2	8.0
3	320.0	388.0	388.0	1154.0	179.0	3.2	9.0
4	304.0	391.0	391.0	1162.0	179.0	3.0	9.0
5	336.0	385.0	385.0	1148.0	178.0	3.4	9.5
6	356.0	769.0	0.0	1154.0	170.0	3.2	10.0
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
90	339.0	765.0	0.0	1154.0	177.0	3.4	8.5
91	375.0	770.0	0.0	1144.0	167.0	3.4	10.0
92	393.0	757.0	0.0	1144.0	166.0	3.5	11.0
93	404.0	767.0	0.0	1124.0	166.0	4.0	9.0
94	378.0	751.0	0.0	1108.0	186.0	3.8	18.0
95	359.1	765.0	0.0	1111.0	186.0	3.6	19.0

The height of the cone is 30 cm. The diameter of the top and bottom of the cone is 10 cm and 20 cm, respectively. The cone is filled with fresh concrete and then lifted vertically. The height difference between the concrete and the cone is the slump value.

In this study, the concrete slump conditioning factors are selected based on reviewing previous works [1, 12, 16, 23] on slump flow modeling and the availability of measuring equipment. The amounts of cement (kg/m^3), natural sand (kg/m^3), crushed sand (kg/m^3), coarse aggregate (kg/m^3), water (liter/m^3), and superplasticizer (liter/m^3) are mix ingredients. For each mix design, the slump value obtained from the actual slump test experiment is recorded. Statistical descriptions of all specimens are shown in Table 1. The whole dataset is partially described in Table 2. It is noted that the amounts of cement (x_1), natural sand (x_2), crushed sand (x_3), coarse aggregate (x_4), water (x_5), and superplasticizer (x_6) are used as input factors to predict the outputs which are the concrete slump (y).

2.2. Least Squares Support Vector Regression (LS-SVR). LS-SVR, proposed by Suykens et al. [17], is an advanced machine learning algorithm which is constructed on the principal of structural risk minimization. This approach has been proved to be very efficient in nonlinear modeling. Notably,
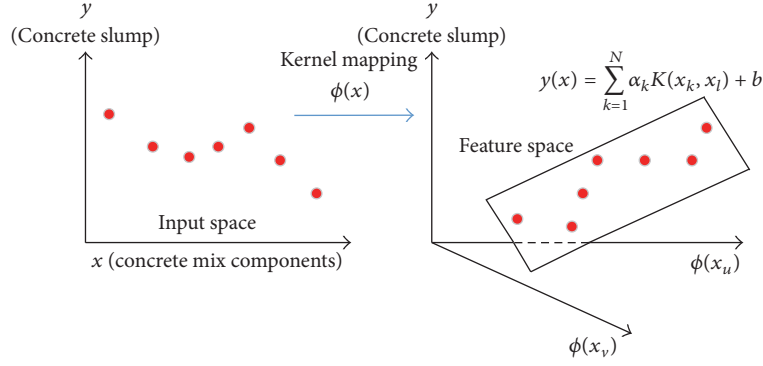
Figure 2: LS-SVR for concrete slump modeling.

the learning process of the LS-SVR is very fast since it only requires solving a set of linear equations.

To construct the prediction model, it is needed to prepare a dataset of slump test record in the form: $D = \{x_k, y_k\}$, $k = 1, 2, \ldots, N$. Herein, k denotes the kth data sample and N is the total number of data samples. It is noted that x_k is a vector with six elements; x_{k1}, x_{k2}, x_{k3}, x_{k4}, x_{k5}, and x_{k6} denote the amount of cement, natural sand, crushed sand, coarse aggregate, water, and superplasticizer, respectively. Meanwhile, y_k is the output of concrete slump of the kth data sample.

We aim to establish a mapping function $y(x)$ that derives the output of concrete slump based on the input vector x that describes the concrete mix components. Since the functional mapping between concrete mix components (x) and slump value (y) is possibly nonlinear, LS-SVR first maps the data from the original input space to a high-dimensional feature space via a mapping function $\phi(x)$. Accordingly, linear regression analysis can be possibly performed in such high-dimensional feature space. The operation of LS-SVR in concrete slump modeling is illustrated in Figure 2.

In the training phase of LS-SVR, the learning objective can be formulated as the following optimization problem [17, 24]:

$$\text{Minimize} \quad J_p(w, e) = \frac{1}{2}w^T w + \gamma \frac{1}{2}\sum_{k=1}^{N} e_k^2 \tag{1}$$

$$\text{Subjected to} \quad y_k = w^T \phi(x_k) + b + e_k, \quad k = 1, \ldots, N,$$

where $e_k \in R$ are error variables; $\gamma > 0$ denotes a regularization constant.

In order to solve the above optimization problem, the Lagrangian function is formulated as [17]

$$L(w, b, e; \alpha) = J_p(w, e)$$
$$- \sum_{k=1}^{N} \alpha_k \{w^T \phi(x_k) + b + e_k - y_k\}, \tag{2}$$

where α_k are Lagrange multipliers.

The Karush–Kuhn–Tucker conditions for optimality are used by differentiating the Lagrangian function $L(w, b, e, \alpha)$ with the variables as follows [17]:

$$\frac{\partial L}{\partial w} = 0 \longrightarrow$$
$$w = \sum_{k=1}^{N} \alpha_k \phi(x_k),$$
$$\frac{\partial L}{\partial b} = 0 \longrightarrow$$
$$\sum_{k=1}^{N} \alpha_k = 0, \tag{3}$$
$$\frac{\partial L}{\partial e_k} = 0 \longrightarrow$$
$$\alpha_k = \gamma e_k, \quad k = 1, \ldots, N,$$
$$\frac{\partial L}{\partial \alpha_k} = 0 \longrightarrow$$
$$w^T \phi(x_k) + b + e_k - y_k = 0, \quad k = 1, \ldots, N.$$

By solving linear system (3), the resulting LS-SVR model is expressed as follows [17, 18]:

$$y(x) = \sum_{k=1}^{N} \alpha_k K(x_k, x_l) + b, \tag{4}$$

where α_k and b are the solution to the linear system. k and N are the index and the total number of data points in the training set. x_k and x_l denote an input pattern in the training and testing set. It is worth reminding that x_k and x_l are both input vectors of concrete mix components with six elements. $K(\cdot)$ is the kernel function which maps the input data from
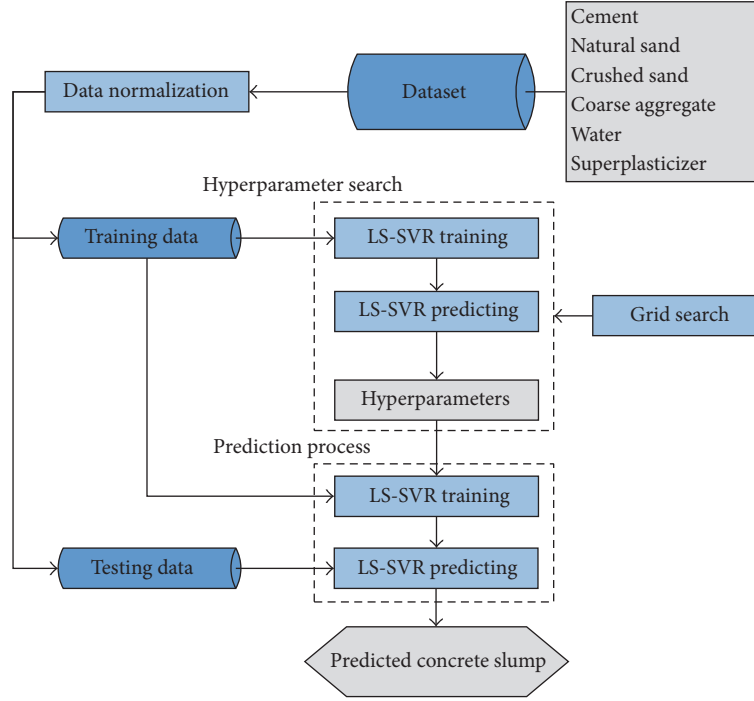
FIGURE 3: Concrete slump prediction using LS-SVR (CSP-LSSVR).

the feature space into the high-dimensional space. The radial basis kernel function is often employed [17, 19]:

$$K\left(x_k, x_l\right) = \exp\left(-\frac{\left\|x_k - x_l\right\|^2}{2\sigma^2}\right), \qquad (5)$$

where σ represents the radial basis kernel function parameter.

3. The Proposed Model for Concrete Slump Prediction

This section of the article describes the concrete slump prediction using LS-SVR (CSP-LSSVR). The prediction model relies on LS-SVR to discover the nonlinear mapping relationship between the concrete components and the slump. The flowchart of the CSP-LSSVR is demonstrated in Figure 3.

Given the input data of concrete mix ingredients (the amounts of cement, natural sand, crushed sand, coarse aggregate, water, and superplasticizer), the first step of the model is to carry out the data normalization process within which the whole data is normalized into a (0, 1) range. This process can help prevent the circumstance in which inputs with greater magnitudes dominate those with smaller magnitudes. The function used for normalizing data is provided as follows:

$$X_n = \frac{X_o - X_{\min}}{X_{\max} - X_{\min}}, \qquad (6)$$

where X_n is the normalized data. X_o is the original data. $X_{\max}$ and $X_{\min}$ denote the maximum and minimum values of the data, respectively.

The dataset, featuring six input factors and the output variable of concrete slump, is then randomly divided into a training set and a testing set. The training dataset is employed to establish the LS-SVR model. Since the LS-SVR with radial basis kernel function is employed, the learning process requires hyperparameters, the regularization parameter γ and the kernel parameter σ, and the grid search method [17, 25] is employed search for the most desirable set of hyperparameters.

In the grid search for tuning parameters, various pairs of (γ and δ) are tried and the one with the best fivefold cross-validation accuracy is chosen. Using exponential growing sequences of γ ($2^{-5}, 2^{-4}, \ldots, 2^{15}$) and σ ($2^{-15}, 2^{-4}, \ldots, 2^3$) is a common way to identify good parameters. The grid search approach is straightforward and easy to implement. After the hyperparameters have been determined appropriately and the training process is finished, the proposed CSP-LSSVR can be used to predict the slump flow values of new concrete samples.

4. Experimental Results

When the training process finishes, the slump of concrete mix in the testing cases can be predicted by providing mixture components for the trained model. In the experiments, besides the proposed CSP-LSSVR, the Artificial Neural Network (ANN) and the multiple linear regression (MLR) are utilized as benchmark methods. In order to measure model performance, this research employs Root Mean Squared
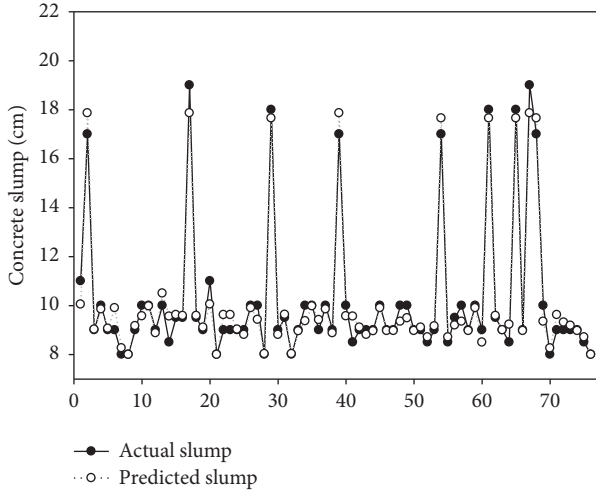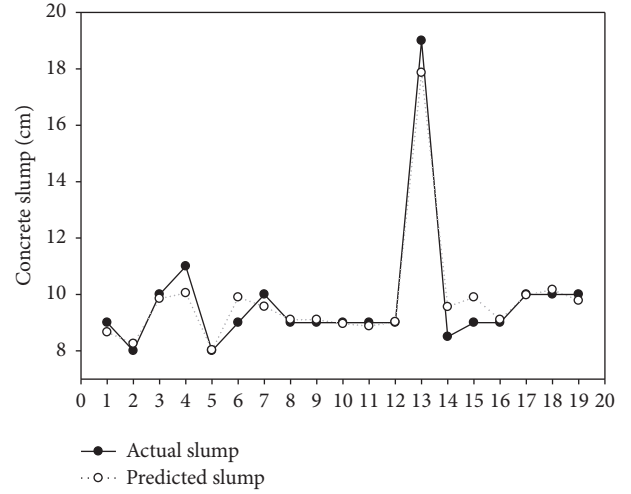
FIGURE 4: The CSP-LSSVR training results.

FIGURE 5: The CSP-LSSVR testing results.

Error (RMSE), Mean Absolute Percentage Error (MAPE), and Coefficient of Determination (R^2).

The motivation for using these benchmark approaches is that the ANN is an effective tool for nonlinear modeling and has been successfully employed for predicting concrete slump [3, 12, 23]. The MLR model is a basic statistical predictive method and comparing its result with other machine learning models may reveal useful insights [26].

To construct an ANN, the user needs to specify the network structure and the learning rate. Such parameters of the ANN model are usually selected via a trial-and-error process [26]. Based on experiments, the network configuration is set as follows: the number of hidden layers is set to be 1; the learning rate is 0.001; the number of neurons in the hidden layer is set to be 6. The Levenberg-Marquardt algorithm [27] is employed to train the ANN model.

In the first experiment, the dataset is randomly divided into 2 sets: the training set that occupies 80% of the dataset and the testing set that includes 20% of the dataset. In detail, the training and testing sets consist of 76 and 19 mixes, respectively. The training and testing results of the CSP-LSSVR are illustrated in Figures 4 and 5, respectively.

The MLR model for predicting concrete slump based on the collected dataset is established via the Least Squares Estimation method [28] and shown as follows:

$$y = 36.22 - 12.47x_1 - 27.03x_2 - 24.56x_3 - 7.39x_4 \\ - 3.00x_5 - 1.18x_6, \tag{7}$$

where the symbols of $x_1, x_2, x_3, x_4, x_5,$ and x_6 represent the amount of cement, natural sand, crushed sand, coarse aggregate, water, and superplasticizer within the concrete mix, respectively.

The ANN model structure, which contains the input, hidden, and output layers, is illustrated in Figure 6. It is noted that W_1 and W_2 are the weight matrices of the hidden layer and the output layer, respectively; $\Theta = 6$ denotes the number of neurons in the hidden layer; $b_1 = [b_{11}, b_{12}, \ldots, b_{1\Theta}]$

represents the bias vector of the hidden layer; b_2 denotes the bias vector of the output layer; n_i is the output of the ith neuron in the hidden layer; F is the tan-sigmoid activation function which is commonly used in the hidden layer [29, 30]:

$$f_A(v) = \frac{1}{1 + \exp(-v)}, \tag{8}$$

where v denotes an input for the function.

It is noted that the weight matrices (W_1 and W_2) and the bias vectors (b_1 and b_2) of the ANN model for concrete slump estimation are learnt via a training process with the error backpropagation algorithm [31]. After the training phase, results of the ANN parameters are shown as follows:

$$W_1 \\ = \begin{bmatrix} -1.4769 & 0.7164 & -1.2991 & -2.4781 & -0.1608 & -1.7888 \\ -2.4336 & -0.5163 & 0.0260 & 3.3005 & -2.5351 & -0.3737 \\ -2.6319 & 0.2066 & 2.9821 & -2.0341 & -4.2239 & 0.1737 \\ 1.0796 & 0.1646 & -0.6626 & -1.8433 & -0.0726 & -5.0730 \\ 2.7421 & -1.1328 & 0.0858 & -3.7346 & 3.4695 & 1.7114 \\ -0.8771 & 0.3779 & 0.5195 & -2.5811 & -0.7168 & -3.2345 \end{bmatrix}, \tag{9}$$

$$W_2 = [1.9870 \ 0.5667 \ 1.3222 \ 2.4838 \ 0.5420 \ -3.5485],$$

$$b_1 = [-2.6084 \ 1.4889 \ -0.3951 \ 0.2309 \ -1.1501 \ 0.3311],$$

$$b_2 = 0.7132.$$

Table 3 provides the result comparison between the proposed method and other benchmark models. The result of the MLR in the testing process is very poor (RMSE = 0.28, MAPE = 12.08%, R^2 = 0.28); this indicates that the linear model is insufficient to explain the behavior of concrete slump.

The ANN and CSP-LSSVR models achieve much better performances; both models have the R^2 values which are
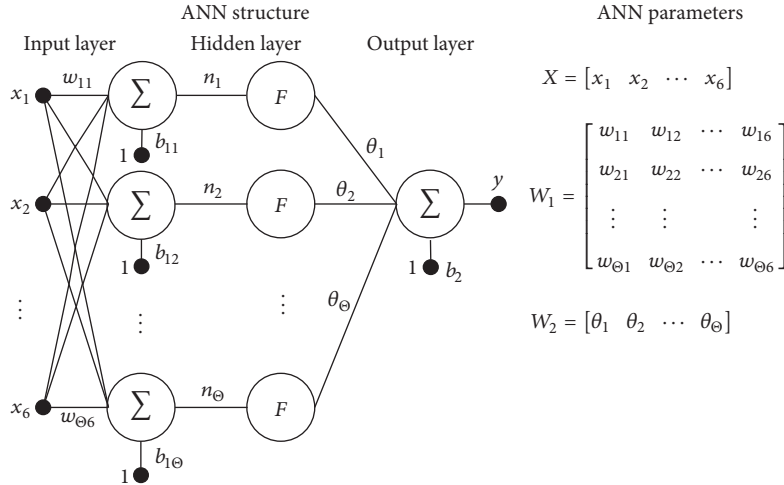
ANN structure

Input layer   Hidden layer   Output layer

ANN parameters

$$X = [x_1 \quad x_2 \quad \cdots \quad x_6]$$

$$W_1 = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{16} \\ w_{21} & w_{22} & \cdots & w_{26} \\ \vdots & \vdots & & \vdots \\ w_{\Theta 1} & w_{\Theta 2} & \cdots & w_{\Theta 6} \end{bmatrix}$$

$$W_2 = [\theta_1 \quad \theta_2 \quad \cdots \quad \theta_\Theta]$$

FIGURE 6: The ANN model structure.

TABLE 3: Result comparison.

	MLR	ANN	CSP-LSSVR
Training			
RMSE	1.23	0.94	0.46
MAPE (%)	9.62	3.63	3.07
R^2	0.82	0.91	0.97
Testing			
RMSE	1.54	1.05	0.54
MAPE (%)	12.08	5.96	3.68
R^2	0.28	0.83	0.96

greater than 0.8. According to Smith [32], such high values of R^2 imply strong correlations between the predicted and measured concrete slumps. Furthermore, the CSP-LSSVR has achieved the lowest prediction error (MAPE = 3.68% and RMSE = 0.54). Thus, benchmarked with the ANN, the new method has attained 38% and 49% reductions in terms of MAPE and RMSE.

Moreover, to avoid the randomness in selecting testing samples, the second experiment carries out a 10-fold cross-validation process. Using the cross-validation process, the whole dataset is randomly divided into 10 data folds in which each fold in turn serves as a testing set; and the performance of the model can be assessed by averaging results of the 10 folds. Because all of the subsamples are mutually exclusive, this experiment can evaluate the CSP-LSSVR more accurately.

Table 4 summarizes the result of the cross-validation process. Observably, the proposed approach has attained the lowest prediction error in both training and testing processes. The average RMSE and MAPE for testing data of the CSP-LSSVR are 0.50 and 2.81%, respectively. These prediction errors are significantly lower than the ANN (RMSE = 0.62

and 4.44%) and the MLR (RMSE = 1.36 and 10.64%). The proposed approach also yields the highest R^2 (0.90) when predicting the slump of testing concrete mixes. Hence, the experimental results have strongly demonstrated the superior predictive capability of the CSP-LSSVR model.

5. Conclusion

This study has established a new method for predicting concrete workability quantified by the slump values. The research extends the body of knowledge by investigating the capability of LS-SVR for concrete slump prediction. To establish the proposed CSP-LSSVR, a dataset consisting of actual concrete slump tests has been collected. From the experiments, the proposed model has achieved the most accurate prediction results.

The average MAPE of the method obtained from the cross-validation process is less than 3% which is very desirable because modeling concrete slump is known to be very complex and highly nonlinear. Since the tenfold cross-validation process is a very reliable way for model performance evaluation [33], it is expected that the proposed CSP-LSSVR can predict the flow of concrete based on the similar conditioning factors with the same accuracy. Accordingly, the newly established method can be a very useful tool to assist the engineers in the task of concrete mix design.

Nevertheless, in addition to the currently used six conditioning factors of concrete slump, other factors (e.g., the type, size, absorption, and the water amount of the fine and coarse aggregates) can be relevant and should be considered by the model. Furthermore, another limitation of the current study is that the employed dataset only consists of 95 data points. Thus, this dataset should be expanded in a future study to further enhance the generalization of the current model and better ensure the predictive accuracy of the model when dealing with new concrete mixes.

TABLE 4: The result of the 10-fold cross-validation process.

Data fold		1	2	3	4	5	6	7	8	9	10	Avg.
CSP-LSSVR	*Training*											
	RMSE	0.46	0.32	0.24	0.30	0.25	0.29	0.29	0.26	0.69	0.29	**0.34**
	MAPE	3.15	1.37	0.65	1.13	0.68	0.90	0.88	0.96	5.21	0.92	**1.59**
	R^2	0.97	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.94	0.99	**0.98**
	Testing											
	RMSE	0.68	0.33	0.64	0.46	0.58	0.39	0.38	0.67	0.49	0.37	**0.50**
	MAPE	4.50	2.29	2.22	2.60	2.69	1.70	2.16	3.51	3.92	2.52	**2.81**
	R^2	0.99	0.83	1.00	0.58	0.98	0.99	0.99	0.97	0.97	0.72	**0.90**
ANN	*Training*											
	RMSE	0.56	0.47	0.48	0.74	0.57	0.61	0.36	0.50	0.44	0.46	**0.52**
	MAPE	4.27	3.13	3.45	3.00	3.78	4.25	1.56	3.43	2.56	2.36	**3.18**
	R^2	0.96	0.97	0.96	0.94	0.96	0.96	0.98	0.97	0.98	0.97	**0.97**
	Testing											
	RMSE	0.62	0.53	0.71	1.10	0.51	0.58	0.40	0.83	0.31	0.63	**0.62**
	MAPE	4.97	5.21	4.33	6.30	3.58	4.11	2.38	6.68	1.65	5.17	**4.44**
	R^2	0.98	0.60	0.99	0.09	0.97	0.98	0.98	0.91	0.99	0.29	**0.78**
MLR	*Training*											
	RMSE	1.23	1.25	1.19	1.20	1.27	1.21	1.25	1.27	1.29	1.23	**1.24**
	MAPE	9.26	9.56	9.07	9.29	9.73	9.16	9.80	9.85	10.12	9.62	**9.55**
	R^2	0.79	0.81	0.75	0.83	0.80	0.79	0.79	0.79	0.79	0.82	**0.80**
	Testing											
	RMSE	1.56	1.28	1.78	1.67	1.09	1.58	1.28	1.04	0.78	1.54	**1.36**
	MAPE	11.56	11.10	11.59	11.93	9.44	14.40	10.53	8.10	5.67	12.08	**10.64**
	R^2	0.90	0.01	0.91	0.01	0.80	0.82	0.79	0.85	0.90	0.28	**0.63**

Note: Avg. denotes the average result.

Competing Interests

The authors declare that there is no conflict of interests regarding the publication of this manuscript.

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