Predicting the rheological flow of fresh self-consolidating concrete mixed with limestone powder for slump, V-funnel, L-box and Orimet models using artificial intelligence techniques

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Abstract. In this paper, selected materials that influence the viscosity of the self-consolidating concrete (SCC) are introduced like the Limestone Powder (LSP), the High Range Water Reducing Admixture (HRWRA), which reduce the interparticle force between concrete constituents like the aggregates, and other superplasticizers. Moreover, in serious attempts to design the SCC for different infrastructure requirements, there have been repeated laboratory visits, which need to be reduced. In this research paper, the artificial intelligence (AI) methods: Artificial Neural Network (ANN), Evolutionary Polynomial Regression (EPR), and Genetic programming (GP) have been deployed to predict the slump flow (SF), V-funnel flow time (VFFT), L-box ratio (LBR) or passing ratio, and Orimet flow time (OFT) of LSP-admixed SCC. The independent variables of the predictive model were cement, LSP, water, water-binder ratio, HRWRA, sand, and coarse aggregates of 4/8 mm and 8/16 mm sizes. The flow tests were conducted after 5 minutes of waiting time after mixing. The model results showed ANN with superior intelligent learning ability over previous models in terms of overall performance.

1 Introduction

The flow of concrete became an important aspect of sustainable concrete technology due to serious needs occasioned by compact and heavy reinforcement practices in the construction industry [1-3]. This was developed to overcome the segregation, dynamic stability, flow time, and shear deformation problems associated with concrete handling and placement through heavily reinforced structural members [4-9]. Hence, the innovative development of the Self-Consolidating Concrete (SCC) was born based on EFNARC requirements [10-13]. The SCC has the necessary flowability advantages, which include flow time, flow ratio, dynamic stability and segregation resistance, shear resistance, settlement resistance, etc. [11-16]. There has also been the need to experiment with the SCC flowability properties through various experimental setups and propose possible models with which to monitor the performance of the fresh concrete [17, 18]. The most dominant of these experimental setups include slump flow, V-funnel flow, L-box flow, and the Orimet flow models [17, 18]. While the slump flow exercise studies the vertical collapse in flow outward flow of the fresh concrete, the V-funnel, the L-box, and the Orimet flow exercises study the standard flow time, passing ratio, and Orimet flow time respectively [19-22]. However, to achieve the required flowability of the SCC, certain structural materials are introduced into the traditional concrete that changes the behavior of the fresh concrete and its ability to flow [17, 18-21]. These materials could be either cement, fine aggregates, coarse aggregates, and limestone powder or in combination with plasticizers and high-rate water-reducing admixtures [18]. Further developments have shown solid waste-based admixtures perform the same purpose of increasing the SCC flowability [22-26]. Limestone Powder (LSP) has been used in previous research works as an admixture in the production of the SCC [18]. This research showed substantial improvements in the flowability behavior of the SCC [17, 18]. In addition, the composition of the mixes in the production of concrete also affects the SCC behavior in terms of flow [18, 27, 28]. Some other materials like steel fiber have also been introduced in the production of SCC with remarkable results. Various numerical and soft computing techniques have been deployed in the modeling of the SCC properties according to the literature [2, 16, 18, 22, 27, 29-31]. However, in this research paper, three intelligent models have been proposed each for the slump flow (SL), V-funnel flow time (V5), L-box flow ratio (L5), and the Orimet flow time (O5). This was performed for SCC measured after 5 minutes of mixing and the intelligent techniques include the Artificial Neural

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Network (ANN), the Evolutionary Polynomial Regression (EPR), and the Genetic Programming (GP).

2 Methodology

2.1 SCC Data Preparation

The multiple databases of 20 SCC mixes were collected from literature [18] consisting of the following mix components and properties measured after 5 minutes of mixing: cement content (C) kg/m^3, Limestone Powder content (LSP) kg/m^3, water content (W) [kg/m^3], HRWRA content (H) [kg/m^3], sand content (S) [kg/m^3], coarse aggregate (4 to 8mm) content (CA1) [kg/m^3], coarse aggregate (8 to 16mm) content (CA2) [kg/m^3], slump flow after 5 minutes (S5) [mm], V-funnel flow time after 5 minutes (V5) [seconds], L-box ratio after 5 minutes (L5), Orimet flow time after 5 minutes (O5) [seconds]. The measured records were divided into a training set (15 records) and a validation set (5 records). Their statistical characteristics are summarized in Tables 1 and 2. Finally, Figure 1 shows the distribution histograms for both inputs and outputs.

2.2 Research Plan

Three different Artificial Intelligence (AI) techniques were utilized [32-37] to predict the flowability parameters of the tested concrete mixes. These AI techniques were the Artificial Neural Network (ANN), the Evolutionary Polynomial Regression (EPR), and the Genetic programming (GP) based on known training algorithms [32-37]. All three developed models were used to predict the Slump flow (S5) [mm], V-funnel flow (V5) [seconds], L-box ratio (L5), and Orimet flow time (O5) [seconds], all after 5 minutes of mixing using Cement content (C) [kg/m^3], Limestone powder content (LSP) [kg/m^3], Water content (W) [kg/m^3], HRWRA content (H) [kg/m^3], Sand content (S) [kg/m^3], Coarse aggregate (4 to 8mm) content (CA1) [kg/m^3], and Coarse aggregate (8 to 16mm) content (CA2) [kg/m^3]. Each of the three developed models was based on a different method (mimicking biological neurons for the ANN, optimized mathematical regression technique for the EPR, and evolutionary approach for the GP). However, for each developed model, the prediction accuracy was calculated by the Sum of Squared Errors (SSE). The accuracies of the developed models were evaluated by comparing the SSE between the predicted and the calculated shear strength parameters values.

Table 1. Statistical analysis characteristics of the collected database.

	Min.	Max.	Range	Mean	Variance	S.D.	Skewness	Kurtosis
C	430.0	509.0	79.0	469.7	399.8	20.0	-0.03	-0.19
LSP	122.0	144.0	22.0	133.0	30.7	5.5	0.00	-0.17
W	181.0	215.0	34.0	198.0	72.5	8.5	0.00	-0.15
H	3.10	6.40	3.30	4.80	0.71	0.84	-0.06	-0.24
S	478.0	1100.0	622.0	789.2	24670	157.1	0.00	-0.19
CA1	139.0	328.0	189.0	234.0	2260	47.5	-0.01	-0.17
CA2	323.0	762.0	439.0	542.8	12242	110.6	-0.01	-0.18
S5	51.5	94.5	43.0	75.6	134.3	11.6	-0.61	0.15
V5	3.0	47.4	44.4	11.4	105.8	10.3	2.53	7.63
L5	0.26	1.00	0.74	0.84	0.06	0.23	-1.58	1.26
O5	1.6	47.1	45.5	8.9	123.8	11.1	2.49	6.98

Table 2. Pearson correlation matrix.

	C	LSP	W	H	S	CA1	CA2	S5	V5	L5	O5
C	1.00										
LSP	1.00	1.00									
W	-1.00	-1.00	1.00								
H	-0.09	-0.08	0.00	1.00							
S	0.00	0.00	0.00	0.00	1.00						
CA1	0.00	0.00	0.00	0.00	-1.00	1.00					
CA2	0.00	0.00	0.00	0.00	-1.00	1.00	1.00				
S5	-0.83	-0.83	0.80	0.48	-0.12	0.12	0.12	1.00			
V5	0.45	0.45	-0.46	0.06	-0.55	0.55	0.55	-0.30	1.00		
L5	-0.68	-0.69	0.66	0.36	0.09	-0.10	-0.09	0.85	-0.33	1.00	
O5	0.34	0.35	-0.36	0.12	-0.63	0.63	0.63	-0.19	0.97	-0.28	1.00

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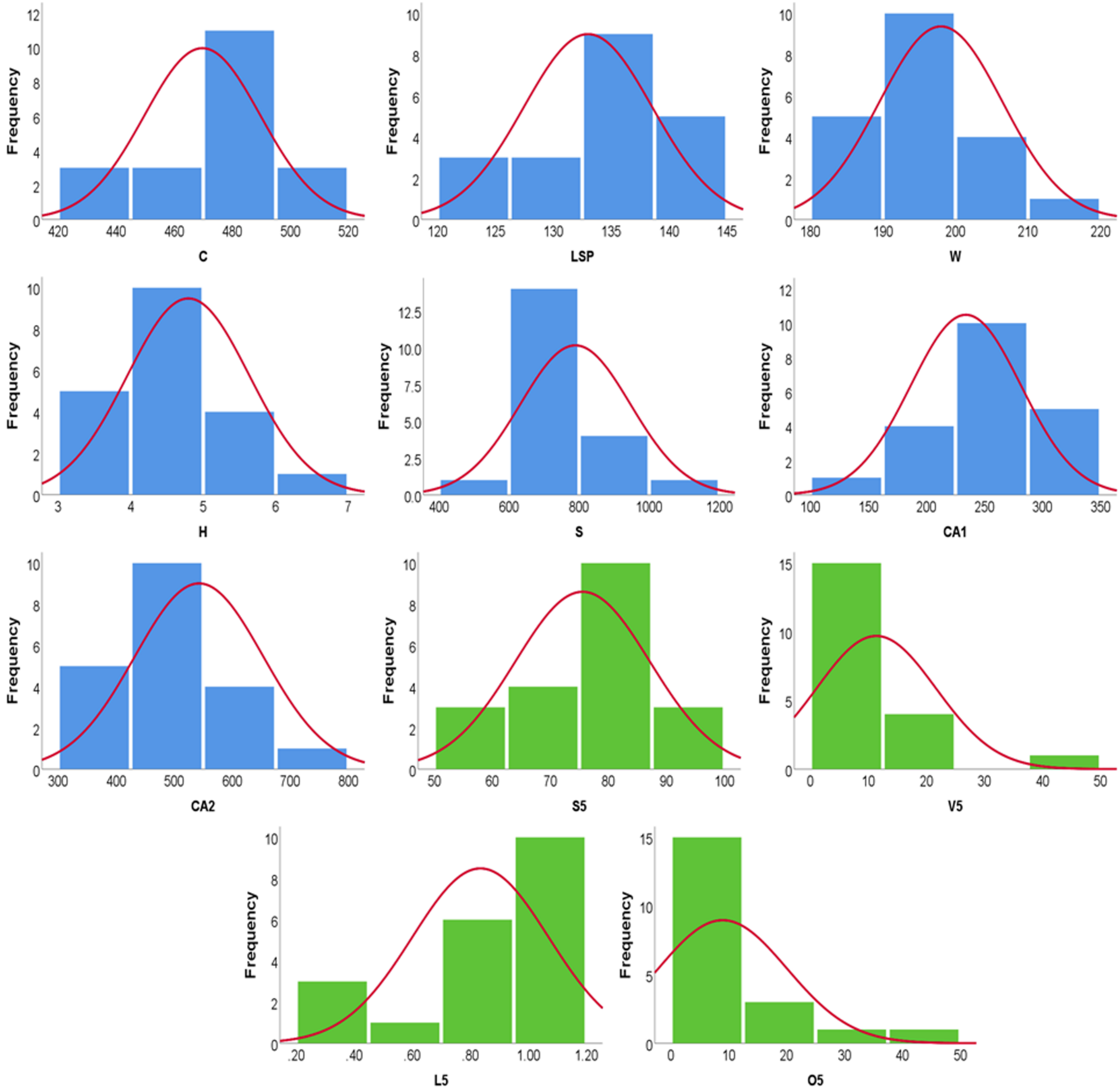

Fig. 1. Distribution histograms for inputs (in blue color) and outputs (in green color).

3 Results and Discussion

3.1 ANN Prediction of Flowability Parameters

A back-propagation ANN with one hidden layer and nonlinear activation function (Hyper Tan) was used to predict (S5), (V5), (L5) and (O5) values. The used networks layout and their connection weights are illustrated in Figure 2 and Table 3. The average error % of the total dataset for these equations are (1.0, 5.3, 1.1 and 4.5%) and the (R^2) values are (0.996, 0.996, 0.998 and 0.999) respectively. This model prediction is based on the replacement of cement with LSP thereby reducing footprints of carbon from cement utilization in concrete production.

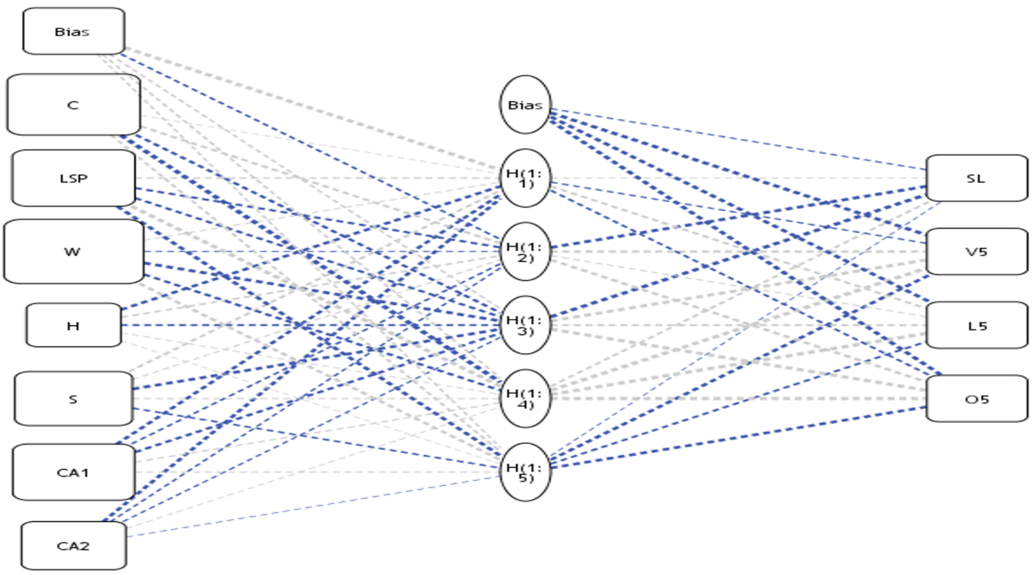

Fig. 2. Architecture layout of the developed ANN model.

Table 3. Weights matrix for the developed ANN model.

		Hidden Layer					Output Layer			
		H(1:1)	H(1:2)	H(1:3)	H(1:4)	H(1:5)	S5	V5	L5	O5
Input Layer	(Bias)	3.50	-0.70	0.58	0.70	0.39				
	C	0.05	1.16	-1.25	-5.09	0.84				
	LSP	0.44	-1.07	-1.13	3.30	-2.33				
	W	0.17	-0.14	-2.52	-1.27	1.67				
	H	-1.78	0.71	-0.85	0.14	0.04				
	S	0.99	0.24	-2.40	0.30	-0.70				
	CA1	-1.67	-0.65	-1.33	0.31	0.25				
	CA2	-1.76	-0.38	-0.30	0.11	-0.04				
Hidden Layer	(Bias)						-0.30	-2.95	-2.41	-2.93
	H(1:1)						0.07	-0.33	1.06	-0.77
	H(1:2)						-2.80	1.50	0.20	1.75
	H(1:3)						-3.16	3.11	0.98	3.39
	H(1:4)						0.92	3.79	5.08	3.62
	H(1:5)						-0.05	-1.89	-0.87	-1.90

3.2 EPR Prediction of Flowability Parameters

The developed EPR model was limited to the pentagonal level, for 7 inputs, there are 792 possible terms (462+210+84+28+7+1=792) as follows:

$$\sum_{i=1}^{i=7}\sum_{j=1}^{j=7}\sum_{k=1}^{k=7}\sum_{l=1}^{l=7}\sum_{m=1}^{m=7} X_i\,.X_j.X_k\,.X_l.X_m + \sum_{i=1}^{i=7}\sum_{j=1}^{j=7}\sum_{k=1}^{k=7}\sum_{l=1}^{l=7} X_i\,.X_j.X_k\,.X_l + \sum_{i=1}^{i=7}\sum_{j=1}^{j=7}\sum_{k=1}^{k=7} X_i\,.X_j.X_k + \sum_{i=1}^{i=7}\sum_{j=1}^{j=7} X_i\,.X_j + \sum_{i=1}^{i=7} X_i + C$$

GA technique was applied on these 792 terms to select the most effective five terms to predict the values of (S5), (V5), (L5) and (O5). The outputs are illustrated in Eq. (1) to (4) and their finesses are shown in Fig. 3. The average error% and (R^2) values were (2.6%-0.970), (35.7%-

0.819), (11.2%-0.805) and (42.7%-0.869) for the total datasets respectively.

$$S5 = 220 - \frac{C^2 H}{141\ W} - \frac{3.742 \times 10^{10}}{C^2\ H\ S} - \frac{22225\ S}{W^2\ H} + \frac{1.013\ S}{H^2} \quad (1)$$

$$V5 = 38 - \frac{C^2\ CA2}{3885773} - \frac{1.146 \times 10^{10}\ H}{C\ S^2} + \frac{1.564 \times 10^{6}\ H}{C\ CA2} + \frac{CA1\ H\ CA2}{5\ S} \quad (2)$$

$$L5 = 628 - \frac{C^2\ W}{102160} - \frac{1.743 \times 10^{8}}{C^2} + \frac{1.123 \times 10^{10}}{C^2\ LSP} + \frac{LSP^2\ W^2}{3380811} \quad (3)$$

$$O5 = 43.8 - \frac{C^2\ CA2}{2759130} - \frac{1.134 \times 10^{10}\ H}{C\ S^2} + \frac{629750\ H}{C\ \ CA1} + \frac{H\ CA2^2}{11\ S} \quad (4)$$

3.3 GP Prediction of Flowability Parameters

The developed GP model has six levels of complexity. The population size, survivor size, and the number of generations were 100 000, 25 000, and 200 respectively. Eq. 5 to 8 present the output formulas for (S5), (V5), (L5) and (O5) respectively, while Fig. 3 show their fitness respectively. The average error % of the total set for (S5), (V5), (L5) and (O5) are (3.3, 26.0, 7.0 and 24.5%) respectively, while the (R^2) values are (0.949, 0.901, 0.929 and 0.959) respectively.

$$S5 = 6.66H + 0.88W - 4X - \left(\frac{CA2}{X^2}\right) - 85, \quad where\ X = \left(\frac{S}{W - 107}\right) \quad (5)$$

$$V5 = \frac{H.X^2}{H^2 - H.X^2 + 1} + X^4Y^2 + Y - X, \quad where\ X = \left(\frac{CA1}{W}\right)^2, \quad Y = \left(\frac{S + H}{CA2}\right) \quad (6)$$

$$L5 = 1.05 + \frac{H.X}{(C - S)} - \frac{0.95\ X}{(H.X)^3}, \quad where\ X = \left(\frac{H + W - 0.95LSP}{LSP}\right) \quad (7)$$

$$O5 = \frac{H - (1 - X)^2}{X^3 - X - H} - \frac{1}{X^2 - 1} + (X^3 - X)[H - (1 - X)^2] + 1 - X, \quad where\ X = \left(\frac{CA1}{W}\right)^2 \quad (8)$$

3.4 Performance of the Predicted Flowability Parameters

Figure 3 shows the relations between calculated and predicted values due to ANN, EPR, and GP for the slump flow (SF) designated as SL, V-funnel flow time (VFFT) designated as V5, L-box ratio (LBR) or passing ratio designated as L5 and Orimet flow time (OFT) designated as O5 of LSP-admixed SCC. Figure 4 shows the Taylor charts to compare the accuracies of developed models for each flowability parameter and Table 4 summarizes the overall performance of the AI models. It can be shown that the ANN showed the best fit and performance with the coefficient of determination for all the modeled SCC parameters above 90%. Also, the GP showed performances above 90% but is rated below the ANN in overall performance and fit between measured and predicted values. The EPR performed above 80% but showed the lowest strength in terms of the overall performance compared to the ANN and the GP. In comparing the present model results with previous literature [18], which had used the Support Vector Regression (SVR), with the following characteristics; $R^2 = 0.974$ for slump flow prediction, $R^2 = 0.990$ for V-funnel time prediction, $R^2 = 0.976$ for Orimet time prediction, and $R^2 = 0.988$ for L-box ratio prediction, the ANN of this research work with $R^2 > 0.99$ outperformed it with some margins. Generally, it should be noted that the predictions are based on the role of LSP on the concrete behavior as a replacement of cement for a sustainable construction environment.

4 Conclusions

This paper presents three different models using three (AI) techniques (ANN, EPR and GP) to predict Slump flow (S5), V-funnel flow (V5), L-box ratio (L5), and Orimet flow time (O5) all after 5 minutes of mixing using Cement content (C), Limestone powder content (LSP), Water content (W), HRWRA content (H), Sand content (S), Coarse aggregate (4 to 8mm) content (CA1), and Coarse aggregate (8 to 16mm) content (CA2). The results of comparing the accuracies of the developed models could be concluded in the following points:

- The prediction accuracy levels of the “ANN” model (95.5 to 99%) are higher than the accuracy levels of “EPR” (57.3 to 97.4%) and “GP” (74.0 to 96.6%) for all flow-ability parameters.
- The “EPR” model presents simpler equations than “GP”, but the “GP” model showed better accuracy.
- Eq. 1, 2, 5 and 6 indicated that S5 and V5 didn’t use LSP.

- Neglecting Eq. 4 due to low accuracy (57.3%), Eq. 8 showed that O5 depends mainly on (H, W and CA1)
- Eq. 3, 7 indicated that the L-box ratio doesn't depend on coarse aggregates content (CA1, CA2).
- Although, (ANN) showed better accuracy than (GP), but (GP) presents closed-form equations that could be manually used for preliminary estimations.
- The GA technique effectively reduced the 792 terms of the conventional PLR pentagonal formula to only five terms, without any significant effect on its accuracy.
- Overall, the replacement of cement with limestone powder reduced the negative environmental impact of concrete production due to cement use.

As in other regression techniques, the herein generated formulas are valid only within the considered range of parameter values, and beyond this range, the prediction accuracy should be verified.

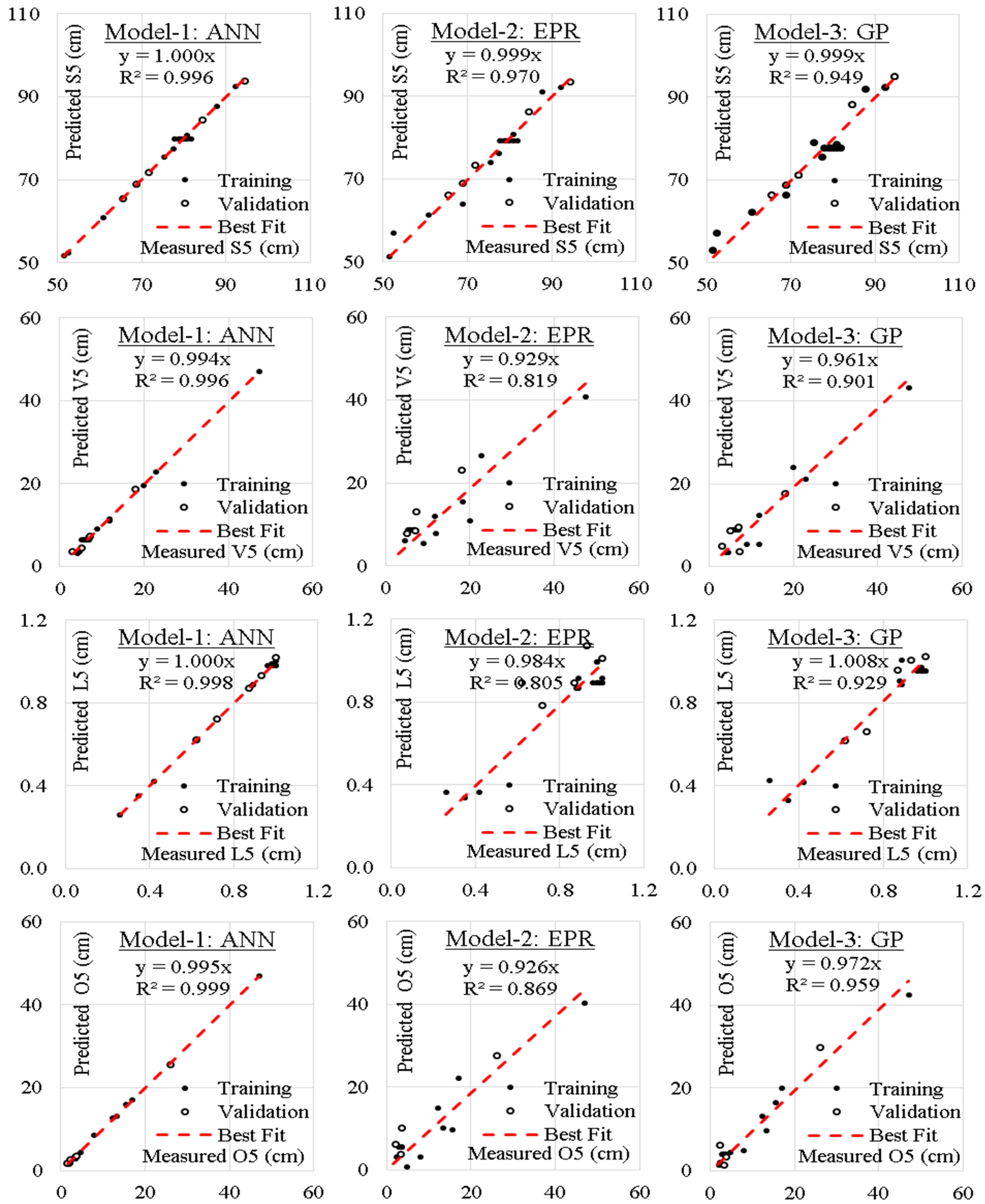

Fig. 3. Relation between predicted and calculated flowability for different developed models.

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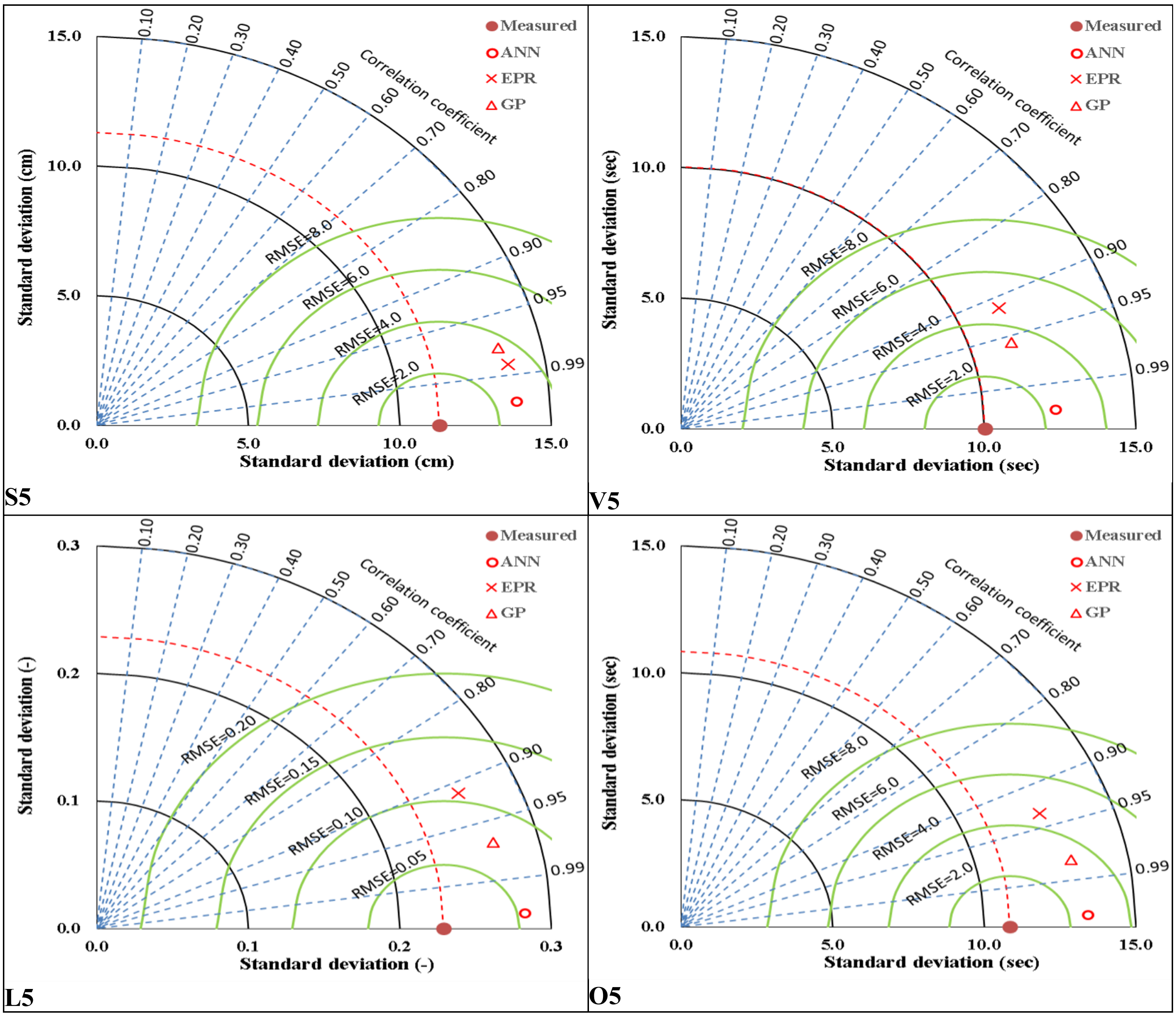

Fig. 4. Taylor charts to compare the accuracies of developed models for each flow-ability parameter.

Table 4. Accuracies of developed models.

Technique	**S5**		**V5**		**L5**		**O5**	
	Error %	R^2	Error %	R^2	Error %	R^2	Error %	R^2
ANN	1.0	0.996	5.3	0.996	1.1	0.998	4.5	0.999
EPR	2.6	0.970	35.7	0.819	11.2	0.805	42.7	0.869
GP	3.3	0.949	26.0	0.901	7.0	0.929	24.5	0.959

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