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Shear strength prediction of steel fiber reinforced concrete beam using hybrid intelligence models: A new approach

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ABSTRACT

Despite modern advancements in structural engineering, the behavior and design of reinforced concrete beams in shear are still a major concern for structural engineers. In this research, a new Support Vector Regression algorithm coupled with Particle Swarm Optimization (SVR-PSO) is developed to predict the shear strength (S_s) of steel fiber-reinforced concrete beams (SFRC) using several input combinations denoting the dimensional and material properties. The experimental test data are collected from reliable literature sources. The main variables used to construct the predictive model are related to the dimensional and material properties of the beams. SVR-PSO, the objective predictive model, is validated against a classical neural network model tuned with the same metaheuristic optimizer algorithm. The findings of the modeling study provide a clear evidence of the superior capability of the SVR-PSO used to predict the SFRC shear strength relative to the benchmark model. In addition, the construction of the predictive models with a lesser number of input data attributes are attained, leading an acceptable prediction accuracy of the SVR-PSO compared to the ANN-PSO model. In summary, the proposed SVR-PSO methodology has demonstrates an effective engineering strategy that can be applied in problems of structural and construction engineering prospective, applied to predict shear strength of steel fiber reinforced concrete beam using advanced hybrid artificial intelligence models developed in this study.

1. Introduction

Steel fibers are the most prevalent types of fibers that are used for reinforcement of concretes, known as steel fiber-reinforced concretes (SFRC) [1–3]. Several mechanical advantages have been identified as the possible merits of utilizing the SFRC as the structural components [4]. However, their dominant effect is notable in enhancing the post-cracking behavior [5]. SFRCs have been extensively used in different types of construction problems, but not in buildings that are likely due to a lack of the design provisions in the respective building codes [6,7]. SFRC beams are therefore one of the common components that have been widely studied in terms of their structural performance, and especially in their shear failures because of its complex mechanisms [8,9].

The methods for modeling the SFRC beam shear strength prediction can be categorized into experimental, analytical, numerical, and soft computing (SC) based techniques. Laboratory studies are able to exactly monitor the structural behavior, but they are very costly and time consuming, including the leftover questions, such as how to set up the materials, geometries, physical and mechanical properties, and the loading conditions that are different in many isolated studies [10–17]. Analytical methods are therefore a cost-effective way to address this issue, however, these methods are significantly based on empirical and semi-empirical approaches that can yield precise results for the range of experimental data from which they were derived, but they do not fit well when applied to the other (unseen) experimental data [8,18–20]. In this regard, a limited number of studies have been performed to develop semi-empirical [5], non-empirical, and even a range of theoretical models for the shear resistance estimation of the SFRC beams [21,22]. A numerical simulation of the SFRC beams applied to predict

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their shear resistance behavior has not been addressed adequately [23,24], mainly because the RC beams are characterized by a non-stabilized manner but the SFRC behaves as a composite material.

Over the past decade, SC approaches have been successfully implemented in the field of material and structural engineering, and especially in the area of reinforced concrete engineering [25,26]. However, a survey of the literature on the popular SC-based techniques demonstrates a lack of studies in the prediction of SFRC beam's structural performance. Adhikary and Mutsuyoshi [31] developed two different ANN-based models with four and five input parameters using historical experimental beams data set. The study, followed by another attempt conducted by [27] where the authors have used the ANN model for the presumption of the shear strength of the SFRC beams considering 5 input parameters (i.e., steel fiber blend ratio, aspect ratio, reinforcement ratio, effective depth, and ratio between the shear length and depth). Recently, a set of 173 SFRC beams without stirrups, having concrete compressive strength ranging from 20.6 to 175 MPa (as medium-strength, high-strength and ultra-high-strength concrete), and steel fiber of various shapes (hooked, crimped and straight/plain), is used to develop an ANN model [28]. ANNs have also been used in some of the other studies with an emphasis on investigating the influence of some of the input parameters [29–31], and predicting the mechanical properties of SFRC [32,33].

A linear genetic programming-based model has been developed by [34] using total of 213 data sets and 9 input parameters. Several models were developed by considering different combinations of the 9 input parameters, and the best model, based on a multi-objective strategy, was presented with four parameters. Genetic programming has also been recently used by [35] for this problem. This was conducted using linear and non-linear regression analyses with a total of 5 input parameters, resulting in the development of six models after dividing a set of 222 experimental dataset into six groups [36]. The study of Kara [37] proposed an empirical equation based on the gene expression programming using a total of 101 datasets and considering their 5 different input attributes. Both multiple linear regression models and principal component regression models have also been established using a total of 222 experimental dataset [38]. Utilizing multi-expression programming [39], two new equations for normal and high strength SFRC beams proposed based on 104 data sets for each one and a new equation without categorizing the strength of concrete using all 208 data sets. Very recently a genetic-algorithm-based approach was used to simplify the proposed analytical models from existing experimental results of 222 SFRC beams without stirrups [40].

Studies in published literature has revealed that the utilization of SC-based techniques for predicting the complex systems always raises two problems: first is the transformation of all the information into numerical input parameters to feed the technique, which is a key pre-process step in any SC based modeling, and second is the need to find the best topology of the technique that can be used to address the prediction problem [41]. Based on a review of the published literature of SC-based techniques, these two problems have become quite evident.

In this study, we propose a new coupled data-intelligent model using the vector regression integrated with Particle Swarm Optimization algorithm for the prediction of shear strength of steel fiber-reinforced concrete beams. Seven input variables are used as the feature attribute combinations where the input data representing the attributes defined by reinforcement ratio (ρ%), concrete compressive strength (f_c'), fiber factor (F_1), volume percentage of fiber (V_f), fiber length to diameter ratio (l_f/l_d), effective depth (d), and shear span-to-strength ratio (a/d) are applied and the shear strength (S_s) is the output (target) matrix. The defined variables are demonstrated on the free-body diagram as shown in Fig. 1. An input approximation technique is applied to firstly reduce the most suitable input matrix to generate a computationally efficient and an accurate artificial intelligence model trained with a small number of input variables. The models based on the proposed SVR-PSO method is then validated in respect to a hybrid

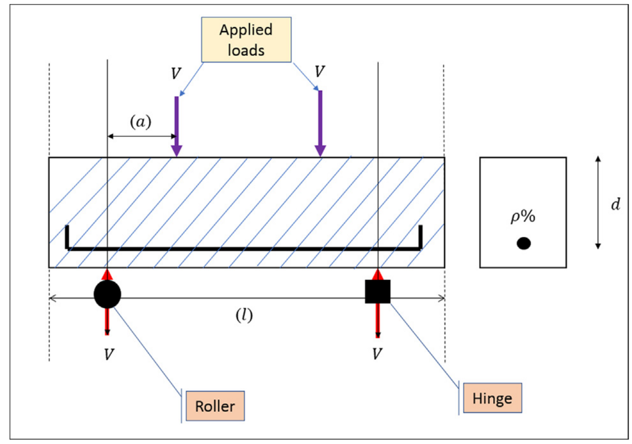

Fig. 1. The general description of physical properties of steel fiber reinforced concrete beam.

Artificial Neural Network model integrated with the Particle Swarm Optimization algorithm (ANN-PSO) to create a comparative framework with the hybrid SVR-PSO model. By extensive analysis of predicted and measured dataset in the independent testing phase, the work therefore, aims to generate a robust and a reliable soft computing tool that can be used for predicting the *Ss* with a high level of accuracy to support key engineering decisions made in structural design engineering.

In the next section, a brief overview of the mathematical framework and the methodology is presented, while the third section present the investigated experimental dataset. The application, analysis and discussion of the proposed hybrid SVR-PSO model is presented in Section 4 and the last section presents the conclusions and closing remarks of this study.

2. Methodology overview and model development

2.1. Support Vector Regression (SVR)

Among the several artificial intelligences, soft computing models used in the field of engineering and science, the SVM model is the most popular version of all data-driven models due to its ability to solve classification and regression problems and its ability to attain a global-optima rather than getting trapped in a local maxima/minima issue [25]. Relevant to the investigated problem in this study, the regression problem was formulated by a dataset of the form $\{x_i, y_i\}$. The SVR regression formulation can therefore be expressed as [42]:

$$f(x) = w\varphi(x) + b \tag{1}$$

The optimization of this regression function [43] can be obtained using:

$$Minimum\quad 0.5\,||w||^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \tag{2}$$

and is subjected to the following conditions [42]:

$$\left\{\begin{array}{c} y_i - w\varphi(x_i) - b \le \varepsilon + \xi_i \\ -y_i - w\varphi(x_i) + b \le \varepsilon + \xi_i^*, \qquad i = 1, 2, \cdots, n \\ \xi_i,\ \xi_i^* \ge 0 \end{array}\right\} \tag{3}$$

where w and b = the undetermined paraments, φ = the non-linear transfer function, ε = the loss function, C = regularization parameter, ξ_i, ξ_i^*: slack parameters.

In this paper, a Radial Basis Function (RBF) has been used as a kernel equation to transform the non-linear problem to a linear problem as described below [44]:

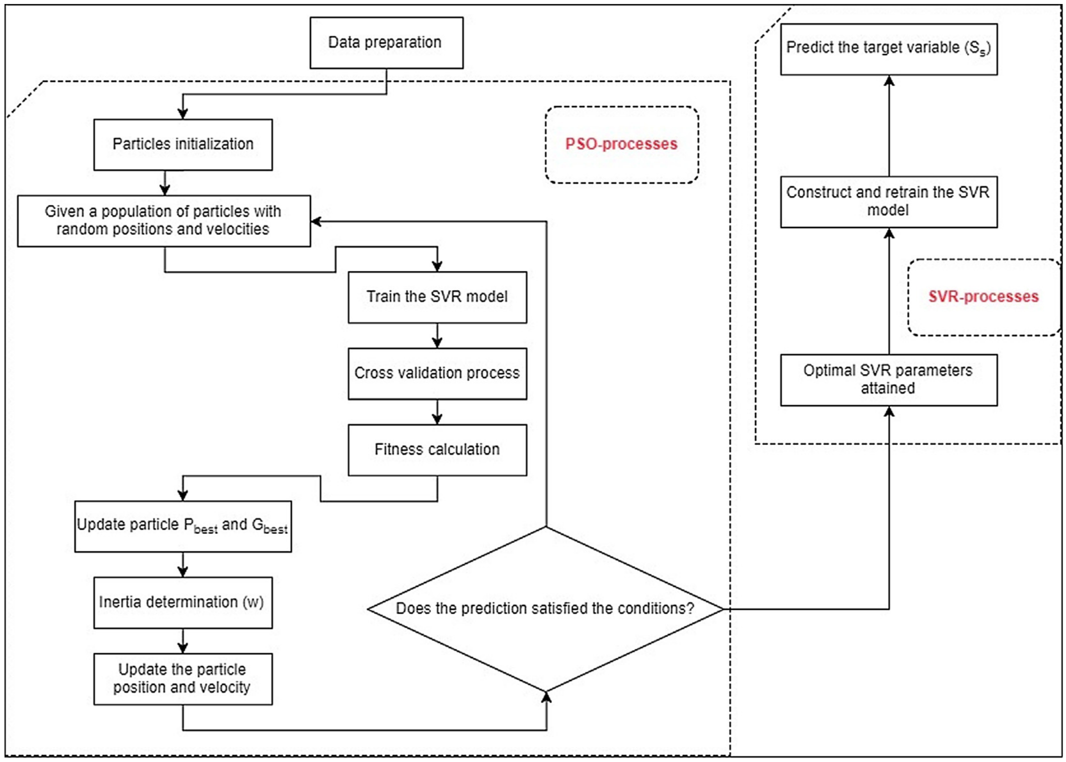

Fig. 2. A schematic flow chart of the hybrid SVR-PSO predictive model.

$$K(X_i, X_j) = \exp(-0.5\left(\frac{||X_i, X_j||}{\sigma}\right)^2) \quad (4)$$

where σ represents the tuned parameter of the RBF. The optimality of the solution of the SVR model relies on the most suitable combination of the loss function, regularization parameter, and kernel function parameters. Thus, the PSO algorithm has been used in this study to select and tune these parameters.

2.2. Artificial Neural Network (ANN)

In order to benchmark the proposed hybrid SVR-PSO model, the ANN model, a commonly used machine learning model, was integrated with the PSO algorithm to construct a hybrid predictive model. Typically, the ANN model is used as a mapping tool leading to a neural network model structure between the input combinations and the output (*i.e.*, the targeted variable) [45]. The two layers of the input and output are sandwiched within a hidden layer that handles the feature extraction and computation processes. The ANN model must be trained, and there are several learning algorithms currently available for this purpose. Feed Forward Backpropagation is one of the predominant algorithms recognized in many studies over the past three decades. The main feature that determines the learning process is the cost function in terms of the root mean square error (*RMSE*) [46].

The main drawback of this cost function is the risk of the model being trapped in the local minima problem, emphasizing the need for the implementation of the evolutionary PSO algorithm in order to optimize the learning process [41]. Hence, in this study PSO algorithm is integrated as a training procedure for updating the weights and biases of the internal connection of the input-output variables. The main merits that distinguished this algorithm are the robustness, flexibility, simplicity, and superior convergence features. The hidden layer activation function is configured as (Logsing); whereas, the output layer activation function is (Purelin). The learning iteration is set 500 and the number of the particles is designated to be 25.

2.3. Hybrid model development (SVR-PSO)

According to recent studies on the implementation of SVM models, the main drawback of this model is the optimization values for the internal parameters, including the ε, C, and σ. These parameters reflect the same commonality of successions and can be computed through the learning experience. The magnitude of the RBF parameter (*i.e.*, σ), that governs the learning accuracy, must be optimized in the SVR model. Hence, to solve these internal parameters of the SVR model, researchers are motivated to use nature-inspired optimization algorithms. In the present research, the PSO algorithm has been used to tune the internal parameters of the SVR model, leading to a fully optimized model for an effective feature extraction and prediction.

The PSO algorithm, used to acquire the most optimal internal parameters of the SVR model in this study, was firstly proposed by [47] with the purpose of solving complex non-linear optimization problems. The mechanism of the algorithm is that it mimics the pattern of the birds' flocking in the concept of function optimization. In a greater detail, the PSO algorithm performs a population search in a nature-inspired manner where it analyzed the input data features. The population tails the leader that instructs as the best position of the whole swarm. This form of nature-inspired behavior is called the global PSO solution (G_{best}). Each of the population regulates its optimal position by tailing the group objective. The best local PSO is achieved when the best particle (P_{best}) corresponds to the neighboring position through learning experience. Finally, all the particles migrate to the desired location, and to achieve this, the updating process must be accomplished for the particle velocity (v_i) through:

$$v_{id} = wv_{id} + c_1 r_1 (P_{best,id} - x_{id}) + c_2 r_2 (G_{best,id} - x_{id}) \quad (5)$$

$$x_{id} = x_{id} + v_{id} \quad (6)$$

where x_i is the i-th particle, d is the d-th dimension of the particle, c_1 and c_2 are the acceleration coefficients, w is the inertia weight, r_1 and r_2 are the random coefficients limited between zero and one [48]. Figure 2 reports the proposed hybrid predictive model.

Table 1
The investigated input variable combinations used to predict shear strength of steel fiber reinforced concrete beam.

Designated Model	V_f	l_f/l_d	F_1	$\rho\%$	d	a/d	f_c'
M1	√	√	√	√	√	√	√
M2		√	√	√	√	√	√
M3			√	√	√	√	√
M4				√	√	√	√
M5					√	√	√
M6						√	√
M7							√

To apply the proposed hybrid soft computing methodology, laboratory test data were gathered from previous studies. The shear strength of the SFRC beams are normally computed empirically as a function of the dimensional and the material characteristics of the concrete [49]. The experimental tests of the shear strength of the steel fiber reinforced concrete beam were gathered from several published literature [50–58]. The data information collected included all the relevant concrete properties and the dimensions of the tested beams.

2.4. Performance indicators

The performance of the objective and the benchmark data-

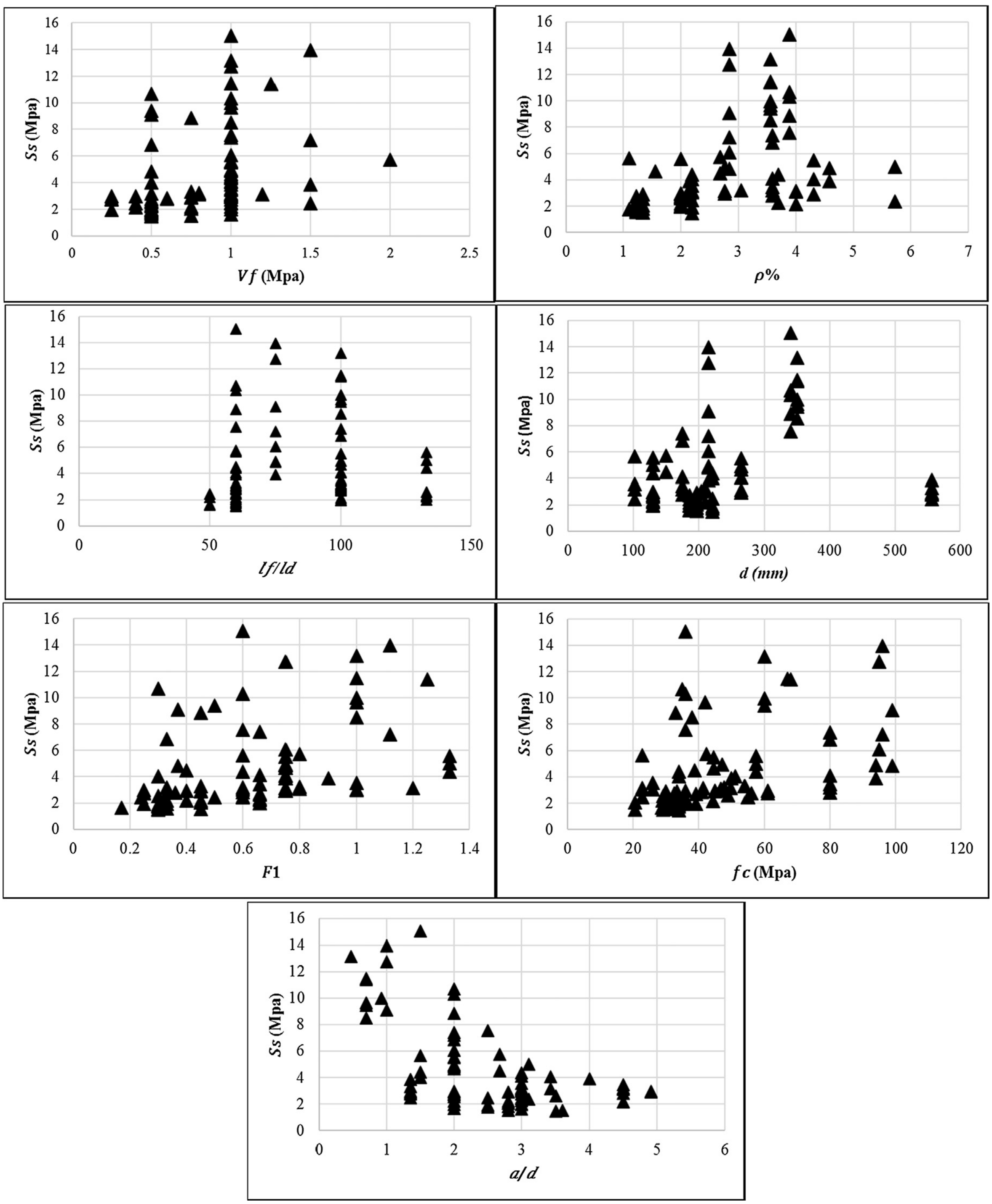

Fig. 3. The correlation between each input attribute with the targeted shear strength.

Table 2
The statistical performance metrics used to validate the prediction skills of the SVR-PSO model. Note: scatter index (SI), mean absolute percentage error (MAPE), root mean square error (RMSE), root mean square relative error (RMSRE), mean relative error (MRE), and determination coefficient (R^2).

Designated Model	SI	MAPE	RMSE	MAE	RMSRE	MRE	R^2
M1	**0.109022**	**0.104873**	**0.379718**	**0.336975**	**0.117292**	**0.059311**	**0.92**
M2	0.209286	0.174004	0.728932	0.584532	0.210569	−0.05777	0.80
M3	0.249318	0.200678	0.868361	0.653435	0.256814	0.096696	0.60
M4	0.226509	0.18811	0.788918	0.642933	0.222154	−0.00569	0.65
M5	0.299375	0.241571	1.042706	0.824208	0.284978	−0.0283	0.42
M6	0.281746	0.242075	0.981304	0.752063	0.329061	0.035542	0.43
M7	0.274653	0.296064	0.956601	0.818625	0.381303	0.19006	0.51

Bold values are the best prediction results.

Table 3
The statistical performance metrics used to validate the prediction skills of the ANN-PSO model.

Designated Model	SI	MAPE	RMSE	MAE	RMSRE	MRE	R^2
M1	**0.163009**	**0.139598**	**0.567751**	**0.431836**	**0.187582**	**0.0736**	**0.82**
M2	0.255982	0.250799	0.89157	0.707388	0.344815	0.078637	0.53
M3	0.356054	0.209241	1.240113	0.795926	0.281143	0.02279	0.57
M4	0.261816	0.199685	0.911889	0.713362	0.235003	−0.08833	0.63
M5	0.314045	0.339185	1.09380	0.947857	0.439236	0.245039	0.45
M6	0.276832	0.270301	0.964189	0.837391	0.320553	0.178213	0.51
M7	0.319047	0.309346	1.11122	0.903424	0.415262	0.224901	0.36

Bold values are the best prediction results.

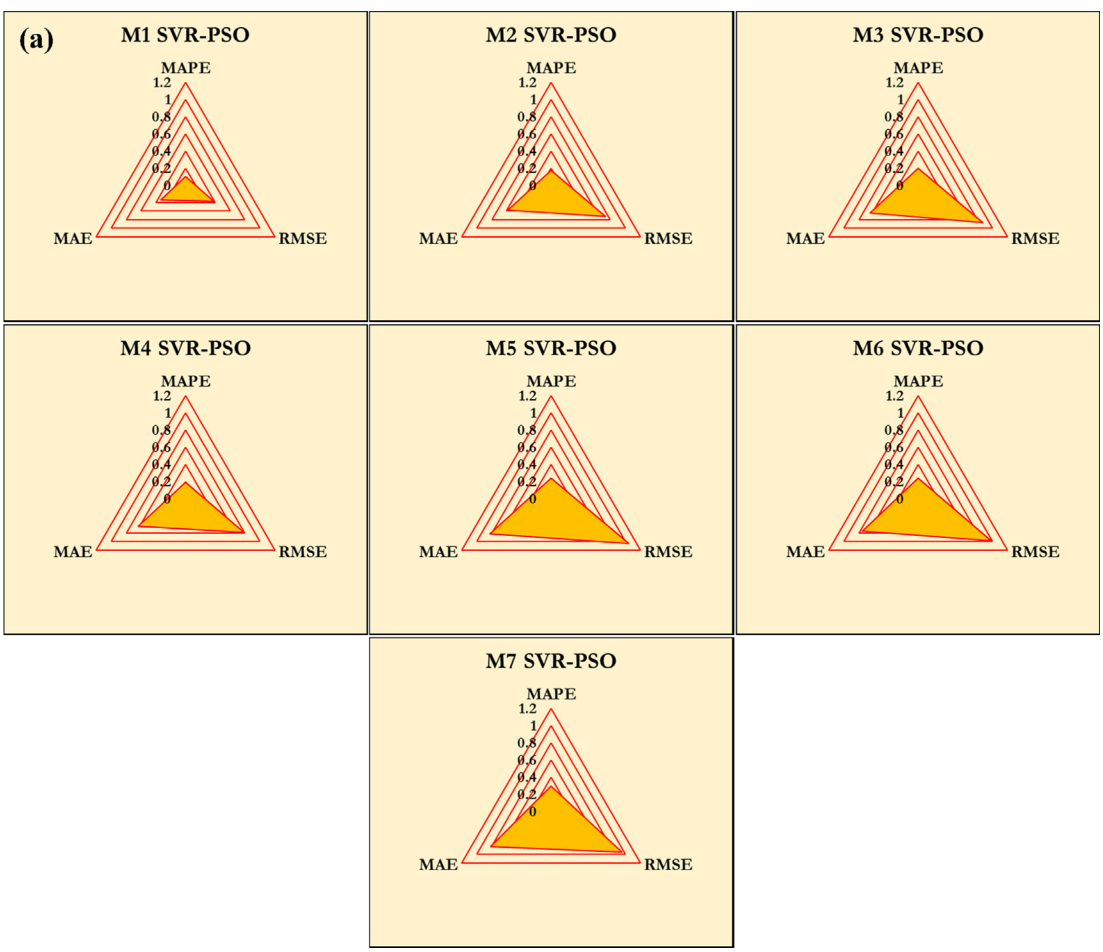

Fig. 4. Three-dimension visualization of the absolute error metrics to indicate the performance of the superior hybrid predictive model (a) SVR-PSO and (b) ANN-PSO.

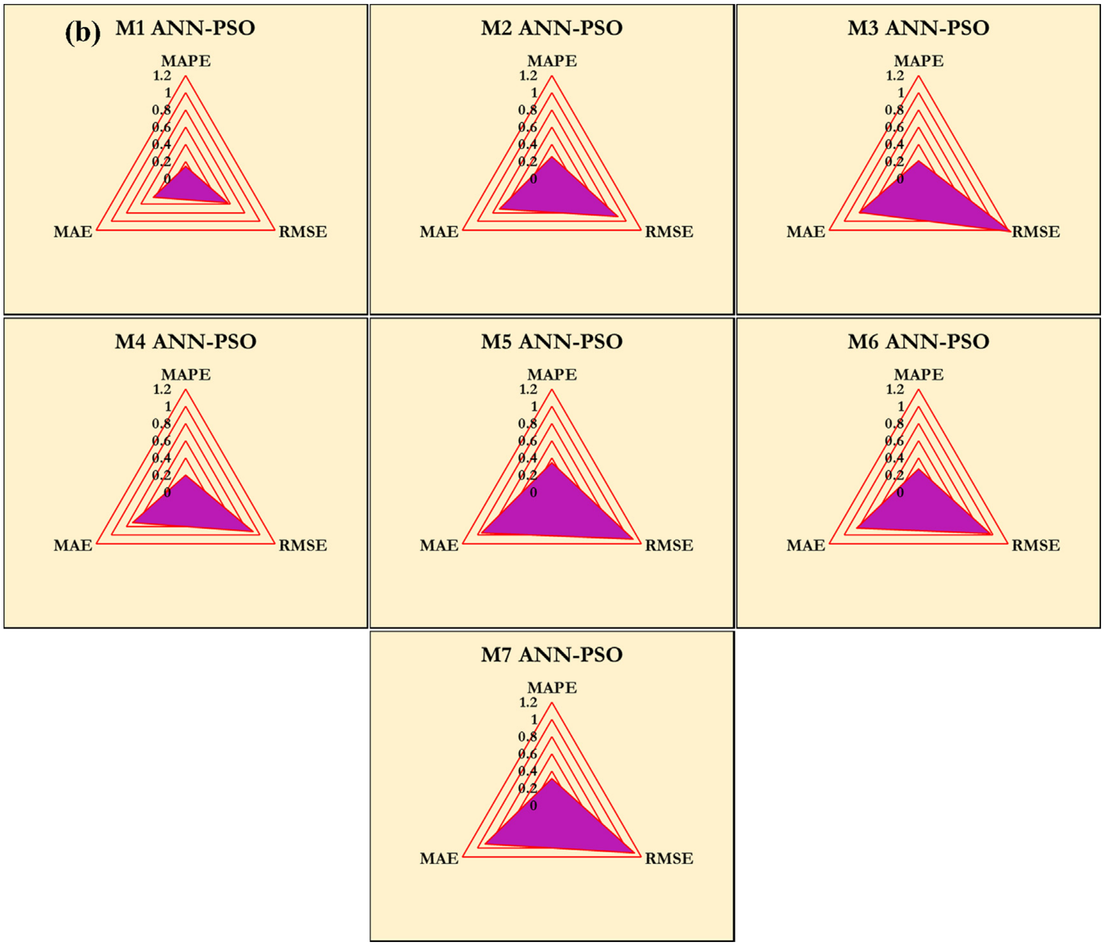

Fig. 4. (*continued*)

intelligent models is evaluated using several statistical indicators, such as the absolute error criteria, the best-of-goodness criteria, the scatter index (*SI*), mean absolute percentage error (*MAPE*), root mean square error (*RMSE*), root mean square relative error (*RMSRE*), mean relative error (*MRE*), mean absolute errors (*MAE*), *BIAS*, determination coefficient (R^2), and relative error (*RE*). Note that in this study, the different performance indicators are investigated here to visualize the prediction models with deeper detailed analysis. The mathematical expressions are presented as follows:

$$SI = \frac{\sqrt{\frac{\sum_{i=1}^{n}(S_{sa}-S_{sp})^2}{n}}}{\bar{S}_{sa}} \tag{7}$$

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{S_{sa}-S_{sp}}{S_{sa}}\right| \tag{8}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(S_{sa}-S_{sp})^2}{n}} \tag{9}$$

$$RMSRE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{S_{sa}-S_{sp}}{S_{sa}}\right)^2} \tag{10}$$

$$MRE = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{S_{sa}-S_{sp}}{S_{sa}}\right) \tag{11}$$

$$MAE = \frac{\sum_{i=1}^{n}|S_{sa}-S_{sp}|}{n} \tag{12}$$

$$R^2 = \frac{(\sum_{i=1}^{n}(S_{sa}-\bar{S}_{sa})(\sum_{i=1}^{n}(S_{sp}-\bar{S}_{sp})^2)}{\sum_{i=1}^{n}(S_{sa}-\bar{S}_{sa})^2(\sum_{i=1}^{n}(S_{sp}-\bar{S}_{sp})^2}*100 \tag{13}$$

$$RE = \left(\frac{S_{sa}-S_{sp}}{S_{sa}}\right)*100 \tag{14}$$

where S_{sa} and S_{sp} are the actual "observed experimental shear strength" and predicted value based on the established data-intelligence models whereas $\bar{S}_{sa}$ and $\bar{S}_{sp}$ are the mean of the actual and predicted shear strength observation. Note that, to evaluate the model accuracy, the root mean square relative error (RMSRE) should typically be less than 10% (for excellent), $10 \le \text{RMSRE} < 20$ (for a good) and $20 \le \text{RMSRE} < 30$ (for a fair) model [59].

3. Application, analyses and discussions

In this study, the hybrid predictive models based on the SVR and ANN models integrated with evolutionary algorithms is developed to predict the shear strength of SFRC beams. To build the most optimal predictive models, different input combinations based on seven model attributes are considered. As mentioned in the introductory section, the main objective of this study is to investigate the efficiency and accuracy of the final hybrid SVR-PSO model and to validate its predictability with the ANN-PSO equivalent model for shear strength prediction using different input variables. The model accuracy is assessed using model efficiency indices, including dimensionless indices (*SI* and R^2) and residual error-based indices (*MAPE*, *RMSE*, *MAE*, *RMSRE* and *MRE*).

Table 1 shows the investigated input combinations for the shear strength prediction. It is noteworthy that the model designated as M1 consists of seven input variables, including the reinforcement ratio

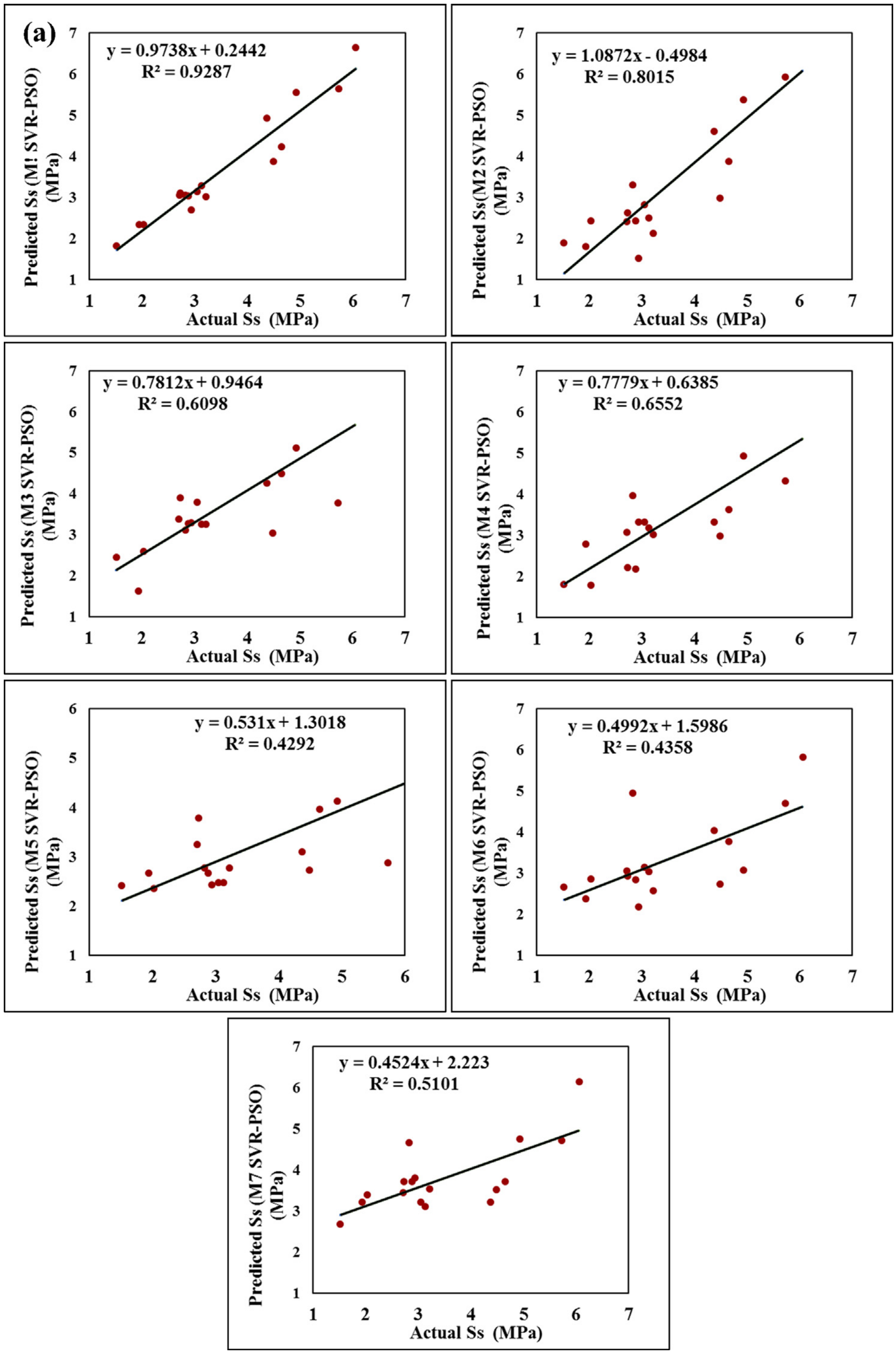

Fig. 5. Scatter plots showing the actual and predicted values of the shear strength (a) SVR-PSO and (b) ANN-PSO.

(ρ%), concrete compressive strength (f_c'), fiber factor (F_1), volume percentage of fiber (V_f), fiber length to diameter ratio (l_f/l_d), effective depth (d), and shear span-to-strength ratio (a/d) while the model M2 consists of six input variables determined by excluding the V_f. Finally, the model M7 consists of only one variable, which is the concrete compressive strength. Note that f_c' is one of the significant constraint that influence several typical behaviors [60–65], hence, it was included in all the input combinations.

Fig. 3 shows the correlation between each input variable and the target shear strength. The correlation values for the output variable (*i.e.*, the shear strength) shows positive values in the reinforcement ratio (ρ%), effective depth (d), fiber factor (F_1), and concrete compressive strength (f_c'), while a negative value is revealed in the shear span-to-strength ratio (a/d). In addition, there appears to be no correlation for the volume percentage of fiber (V_f) and fiber length to diameter ratio (l_f/l_d).

Table 2 presents the results of shear strength prediction using the hybrid SVR-PSO model. The values stated in Table 2 evaluate the accuracy of the model. When a model is able to yield a higher R^2 value and a lower residual error-based indices, it indicates that the performance is better than the others. Based on the achieved performances of the hybrid SVR-PSO model using different input variables, it could be seen that the model M1 (SI = 0.109 and R^2 = 0.92) and the residual error-based indices with MPa unit ($MAPE$ = 0.105, $RMSE$ = 0.380,

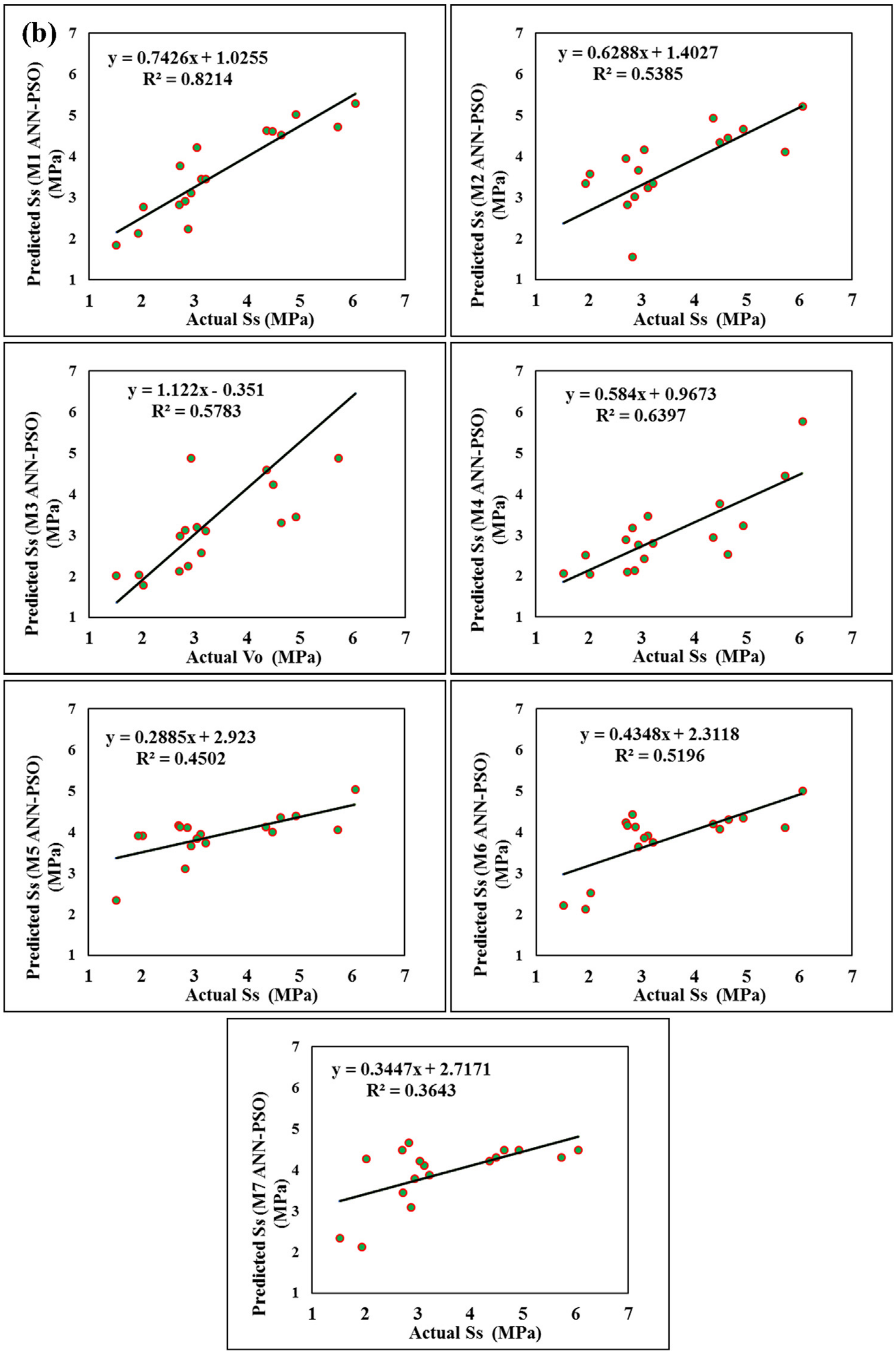

Fig. 5. (*continued*)

MAE = 0.337, *RMSRE* = 0.117, and *MRE* = 0.059) achieve good prediction efficiencies, while the hybrid model SVR-PSO attained the best prediction among all of the developed models using seven inputs combination (*i.e.*, Model M1). In general, models denoted as M2, M3, and M4 appear to have performed better prediction than the model M5, M6, and M7 based on the different efficiency indices. However, it is worthy noting that Model M2 model is seen to perform with a good degree of accuracy, with an R^2 value of about 0.80. This confirms the acceptable level of efficiency of the developed hybrid data-intelligence model without including a large volume of fiber as an input variable.

Table 3 presents the results of shear strength prediction using the hybrid ANN-PSO model. The performance metrics show the accuracy and the efficiency of the model predictions. There is a remarkable consistency between the primary (SVR-PSO) and the comparable model (ANN-PSO) on the best input combinations. Accordingly, that the model M1 is seen to perform the best with a best-fit-of-goodness index of *SI* = 0.163 and R^2 = 0.82 and a residual error-based metric of *MAPE* = 0.140, *RMSE* = 0.568, *MAE* = 0.432, *RMSRE* = 0.188, and *MRE* = 0.074. A comparison of the performance of the hybrid models showed that the hybrid SVR-PSO model registered a better efficiency than the hybrid ANN-PSO model except for the case of M5 and M6, respectively. It is found from these results that the hybrid (SVR-PSO) model surpassed the (ANN-PSO) model accuracy in terms of the prediction performance. In addition, the models with several inputs (*i.e.*, 4,

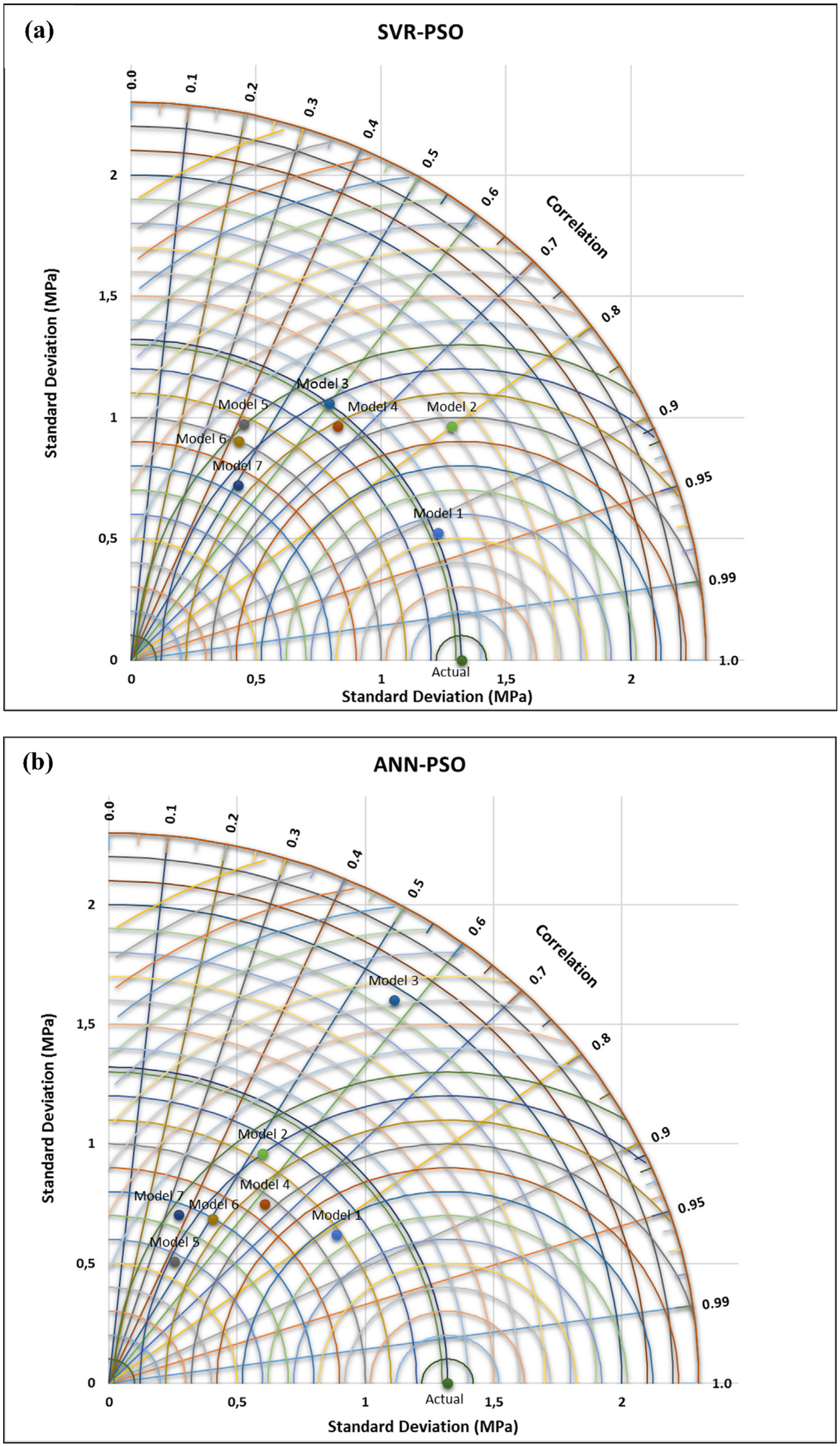

Fig. 6. Graphical visualization of the Taylor diagram for the hybrid predictive models.

5, 6 and 7 variables) had better accuracies than those with few inputs (*i.e.*, 1, 2 and 3 variables). Quantitatively, there appears to be a notable enhancement in the model accuracies (e.g., *SI* and *RMSE*) (33.12 and 18.8%) for the first input combination (M1).

Based on the graphical inspection, Fig. 4 shows the three-dimensional relationships of the absolute errors among *MAE*, *MAPE*, and *RMSE* for both predictive models. The absolute errors in Fig. 4a leads to the smallest triangle diagram for the model designated as M1 (SVR-

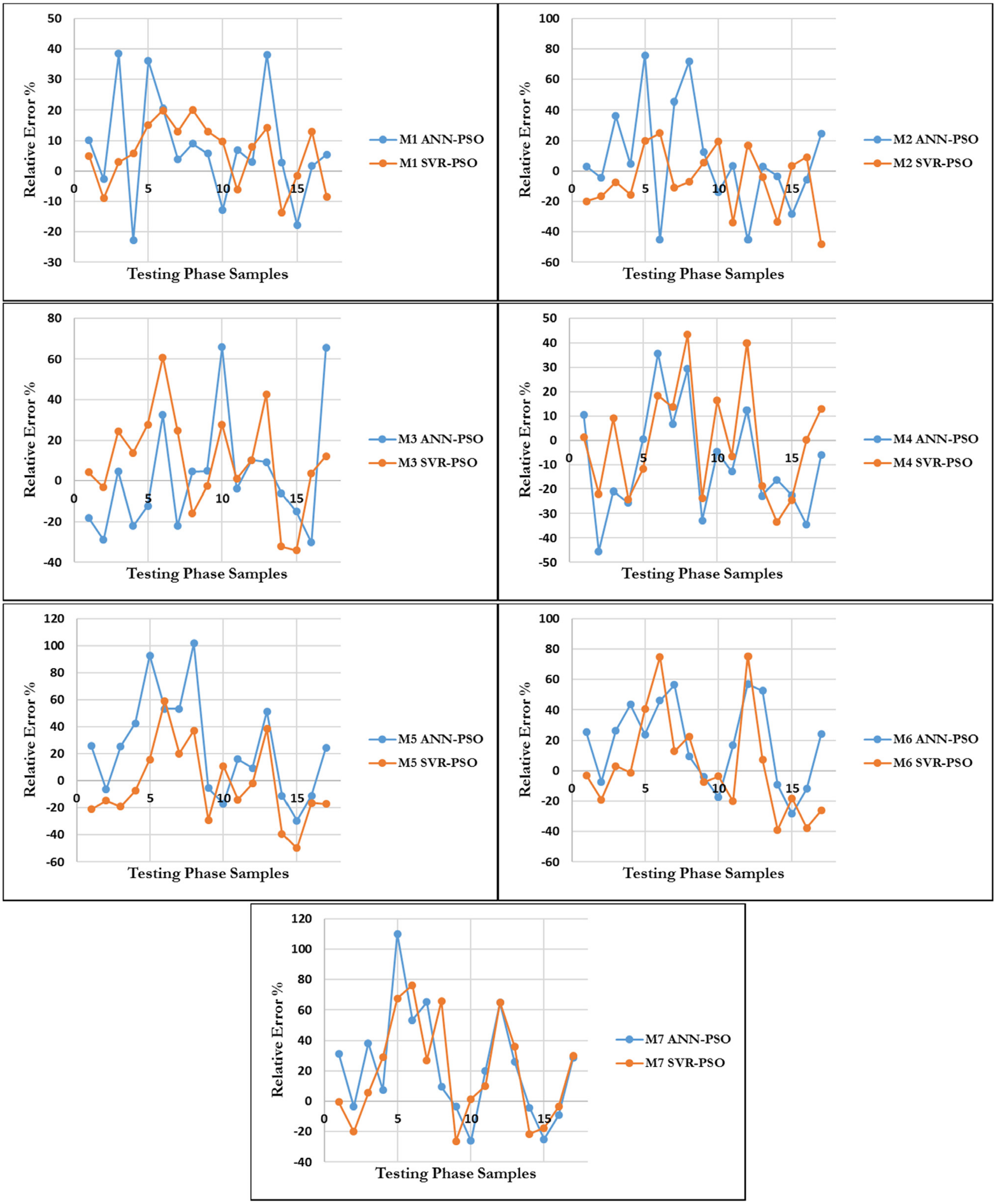

Fig. 7. The relative error distribution over the testing phase of the modeling using the hybrid SVR-PSO and hybrid ANN-PSO for different input attribute combinations.

PSO). In addition, the models M1, M2, and M4 register the smaller triangle diagrams compared to the models M3, M5, M6, and M7. It can therefore be judged from Fig. 4a that the models M1, M2, and M4 are considerably superior compared to the models M3, M5, M6, and M7 based on the absolute error of the specific residual error-based indices (*i.e.*, MAE, MAPE and RMSE). The hybrid ANN-PSO model, on the other hand, exhibited a three-dimensional relationship of the absolute errors, as shown in Fig. 4b. The absolute errors in Fig. 4b also yields the smallest triangle diagram for model M1 as well similar to original model. In addition, the models M1, M2, and M4 appear to produce a smaller triangle diagrams than the models M3, M5, M6, and M7. It can be seen clearly from Fig. 4b that the models M1, M2, and M4 were superior to the models M3, M5, M6, and M7 based on the absolute error of specific residual error-based indices (i.e., MAE, MAPE and RMSE) in ANN-PSO model contribution.

For a detailed comparison, we also show the different graphical comparisons, including the scatter plots, Taylor diagrams [66], and relative error distribution [67]. Fig. 5a and b display the observed and predicted shear strength values for the hybrid SVR-PSO and the hybrid ANN-PSO model, respectively. The ideal 45° line representing the best-fit line equation of the form $y = ax + b$ indicates an 'a' value close to one and the 'b' value close to zero [68]. In accordance with these results, it is clearly evident from the best-fit line equations and R^2 values that the models M1 and M2 appear to predict the shear strength more accurately than the other models based on the hybrid SVR-PSO model, while only model M1 could surpass the performance level of the other models in the hybrid ANN-PSO. It can be also judged that the hybrid SVR-PSO models with several input datasets (i.e., 4, 5, 6, and 7 variables) was able to predict the shear strength more accurately than the corresponding hybrid ANN-PSO model from the best-fit line equations.

Fig. 6a and b illustrate the Taylor diagrams for the hybrid SVR-PSO and the hybrid ANN-PSO model, respectively. Taylor diagram provides a graphical method of qualifying the similarity between the simulated and the observed values based on the correlation coefficient and standard deviation [66]. It can highlight the efficiency of developed models, where the diagram can be used to visualize a series of points on a polar plot. The ratio of the variance is calculated to produce the relative depths of the predicted and the observed variations [66]. Evidently, the results show that model M1 is closer to the observed point compared to the other models in the hybrid SVR-PSO and the hybrid ANN-PSO model.

In Fig. 7, we show the relative error distribution of the developed hybrid SVR-PSO and the hybrid ANN-PSO models. Changes in the relative error indicate that the developed models have a fluctuating distribution when the testing phase samples were increased one. Increasing the testing samples resulted in a strong nonlinear transition from negative to positive (or inverse) in the relative error distribution. It can be seen from Fig. 7 that the developed hybrid ANN-PSO model has a wider variation compared to the hybrid SVR-PSO model. This indicates that serious variations could affect the models' performances when the test samples are increased. A comparison of model M1 between hybrid ANN-PSO and hybrid SVR-PSO models, for instance, indicates that the relative error distribution moved from approximately -25–40% in the case of the hybrid ANN-PSO model, while it shifted approximately from −15% to 15% in the hybrid SVR-PSO model. Therefore, these results suggest that the relative error distribution can be considered as one of the model evaluation methods based on graphical observations.

4. Conclusion

In this research paper that also aims to extend our previous study [25], a new hybrid data-intelligence model, the hybrid SVR-PSO is proposed to investigate the internal relationships between the dimensional/material properties of concrete beam and its ultimate shear strength, which was the target variable in this paper. A reliable database of information of different material properties related to the shear strength is established from published research and explored for the model development and evaluation. The proposed model is then validated with the Artificial Neural Network model optimized with the Particle Swarm Algorithm. The following findings are evident:

- In general, the proposed hybrid SVR-PSO model reveals a superior performance over the comparable hybrid ANN-PSO model.
- The achieved results analyzed in the testing period demonstrates the hybrid SVR-PSO model as a robust and a reliable hybrid data-intelligent model for predicting the ultimate shear strength of SFRC beams, providing an opportunity to explore the predictive model as a useful decision-support tool for structural design engineers.
- In spite of the current research advocating the superiority of the hybrid SVR-PSO model, the approach can be further explored with nature-inspired evolutionary algorithms such as the Genetic Algorithm [69,70] where the influence of each parameter required to predict shear strength can help avoid the manual trial and error procedures.

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Compliance with Ethical Standards

Conflict of interest: The authors have no conflict of interest to declare for publishing this article.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.engstruct.2018.09.074.

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