Stacking Ensemble-Based Hybrid Algorithms for Discharge Computation in Sharp-Crested Labyrinth Weirs

Khabat Khosravi
Ferdowsi University of Mashhad
Mir Jafar Sadegh Safari
Yasar University
Zohreh Sheikh Khozani (zohreh.khozani.sheikh@uni-weimar.de)
Bauhaus University Weimar
Brian Crookston
Utah State University Eastern
Ali Golkarian
Ferdowsi University of Mashhad

Research Article

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Posted Date: November 3rd, 2021

DOI: https://doi.org/10.21203/rs.3.rs-729477/v1

Stacking ensemble-based hybrid algorithms for discharge computation in sharp-crested labyrinth weirs

Khabat Khosravi*[1], Mir Jafar Sadegh Safari[2], Zohreh Sheikh Khozani*[3], Brian Crookston[4], Ali Golkarian[1]

1. Department of Watershed Management Engineering, Ferdowsi University of Mashhad, Mashhad, Iran. golkarian@um.ac.ir
2. Department of Civil engineering, Yaşar University, Izmir, Turkey. jafar.safari@yasar.edu.tr
3. Institute of Structural Mechanics, Bauhaus Universität Weimar, 99423 Weimar, Germany. zohreh.khozani.sheikh@uni-weimar.de
4. Department of Civil and Environmental Engineering, Utah Water Research Laboratory, Utah State University, Logan, Utah, USA. brian.crookston@usu.edu

*Corresponding author: Z. Sheikh Khozani (zohreh.khozani.sheikh@uni-weimar.de), and K.Khosravi (khabat.khosravi@gmail.com and kh.khosravi@um.ac.ir)

Abstract

Labyrinth weirs are utilized to increase the weir crest length to transport a greater discharge during floods in contrast to conventional weirs. Nevertheless, due to the increased geometric complexity of labyrinth weirs, determination of accurate discharge coefficients and accordingly, head-discharge ratings are quite essential issues in practical application. Hence, as a first step the present study proposes the following eight standalone algorithms: decision table (DT), Kstar, least median square (LMS), M5 prime (M5P), M5 rule (M5R), pace regression (PR), random forest (RF), and sequential minimal optimization (SMO). Then, applying the stacking (ST) algorithm, these stand-alone models were hybridized to develop ST-LMS, ST-PR, ST-SMO, ST-Kstar, ST-DT, ST-M5R, ST-M5P, and ST-RF to predict the discharge coefficient (C_d) for sharp-crested labyrinth weirs. Modeling resulted in 123 experimental data sets including consideration of vertex angle (θ), channel width (B), head over the crest of the weir (h), crest heights (W), crest length of the weir (L), C_d, and flow discharge (Q). These effective variables were re-arranged in the form of several independent dimensionless parameters (θ, h/W, L/B, L/h, Froude number (Fr), B/W and L/W) to predict C_d as an output. Datasets were randomly divided into two groups;

70% of data used for model training while 30% used for model validation. The accuracy of the developed models was examined in terms of different statistical error measurement criteria of visually-based (line graph, scatter plot, box plot) and quantitative-based [root mean square error (RMSE), mean absolute error (MAE), the Nash-Sutcliffe efficiency (NSE), and percentage of bias (PBIAS)]. Results illustrate that h/W and B/W parameters have the highest and lowest effect on the C_d prediction, respectively. It was found that the most effective input combination included all input parameters except B/W. According to NSE, all developed algorithms provided accurate performances, while ST-Kstar has the highest prediction power (NSE=0.976, RMSE=0.011, MAE=0.008, PBIAS=0.027). Through incorporation of predicted C_d into discharge equation, promising results are obtained for accurate discharge computation.

Keywords: Discharge coefficient; Hybridization; Labyrinth weir; Stacking algorithm; Machine learning

1. Introduction

Weirs are among the simplest form of spillway that are widely used in water resources engineering structures including dam projects. When possible, weirs are installed perpendicular to the flow, aligned with the channel axis and used to control and measure the water level as well as discharge. Due to the effects of seasonality and climate change, droughts and floods are becoming more severe; indeed many flood control structures require discharge capacity upgrades (FEMA 2013). Hence, accurate information about the flow discharge is necessary for accurate planning of watershed management, irrigation and water usage, flood modeling, etc.

Investigations in hydraulic laboratories have been heavily utilized in the past as direct measurement of flow discharge in the field is a difficult and time-consuming task. So far, many experimental studies have been applied using different weir types with variety of shapes to measure flow discharge to investigate their efficiencies. Labyrinth weirs were first introduced by (Gentilini 1940) and later developed by (Taylor 1968) and (Hay and Taylor 1970). This nonlinear weir has an advantage over straight over-flow weirs and ogee crest; although capacity of this type of weir varies with head, but overall, their discharge capacity can easily exceed twice with the same width comparing to the linear weirs (Tullis et al. 1995). Thus, labyrinth weirs are a common type of spillway that is used for dam reservoirs and even is more efficient than ogee spillway (Suprapto 2013). Taylor (Taylor 1968) conducted the first study of applying non-linear labyrinth weirs with various form including triangular, rectangular, and trapezoidal in a laboratory condition and declared that trapezoidal shape is preferred due to its balance of hydraulics and constructability. Houston (Houston 1982) used a monograph approach, which was proposed by (Hay and Taylor 1970) to design labyrinth weirs and declared that this method leads to about 25% error if the project-specific geometry and conditions deviate from the underlying data. The study conducted by Tullis et al. (1995) showed that discharge capacity is strongly depended on the total head, effective length of weir crest and corresponding coefficient of discharge. Emiroglu and Kisi (Emiroglu and Kisi 2013) reported that the coefficient of discharge has a high relationship with main channel hydraulic flow and geometric weir characteristics. Due to the constraints of a physical model study (cost, facilities, etc.) and to facilitate usage by industry, different empirical equations were developed based on the regression analysis to predict flow discharge (Q). One of the most well-known and widely used equations is $Q=(2/3)C_d\sqrt{2g}Lh^{1.5}$, where C_d, g, L and h are coefficient of discharge, gravitational acceleration, crest length of the weir and piezometric head over the crest, respectively. According to this equation, L, and h are the readily available parameter and g is a constant value, thus the only challengeable parameter that has a significant effect on the result and its calculation is the experimentally determined C_d.

Weirs have been regularly studied by researchers for decades, including published values of C_d. For straight weirs, classical studies include (Rehbock 1929) who reported that h and its ratio to the weir height (h/W) strongly effects C_d values ($C_d = 0.611 + 0.08(h/w)$). Kindsvater and Carter (Kindsvater and RW Carter 1959) proposed several equations as a function of h/W and weir width over the channel width (b/B) ($C_d = 0.602 + 0.075(h/w)$). Also Kandaswamy and Rouse (Kandaswamy and Rouse 1957) conducted experiments, for different ranges of h/W as $h/W \leq 5$, $5 < h/W < 15$ and $h/W \geq 15$. Swamee (Swamee 1988) proposed an equation in the form of $C_d = 0.611 + 0.075(h/W)$. According to the relevant literature, so far, different methods, different effective parameters, and also different equations for a specific condition were proposed which is challenging task to select a more appropriate method for hydrologic analyses. Furthermore, modern risk analyses consider experimental uncertainties which is a challenge of these proposed models. C_d can be predicted through computational fluid dynamic (CFD) models (Babaali et al. 2015; Su et al. 2015), but approach needs high-accuracy calibration data with detailed information of the data set(i.e. boundary conditions for energy, momentum, and continuity law, nappe behavior for local pressure over weir's crest, tailwater submergence, weirs geometry, crest shape, and so on) since model development and calibration is a difficult task. Also, due to the complexity of the process (three-dimensional flow over the weir); it is very difficult to have an exact prediction using an analytical approach (Crookston and Tullis 2013).

Therefore, to expand hydraulic estimations beyond physical and CFD models, the soft computing (SC) approach has gained more attention in solving and predicting complicated and nonlinear hydrological and hydraulic phenomena. Several advantages of SC approaches are non-linearity structures, ability to handle big datasets, considering data with different scales, prediction of phenomena with complicated process and a robust predictor that can allow some incomplete or missing data. Prediction capability of SC approaches strongly depends on the size of the data set and especially data quality. Up to now, different SC models have been applied to predict C_d. for weirs. Artificial neural network (ANN) is the most widely used algorithm in the field of water resources engineering, while due to low convergence speed and low prediction power in the testing phase, especially, when range of test data is out of training data. Thus, ANN combined with fuzzy logic and adaptive neuro-fuzzy inference systems (ANFIS) developed. Azamathulla et al. (Azamathulla et al. 2016) compared prediction performance of ANN, support vector machine (SVM) and ANFIS for discharge coefficient of side weirs and stated that the SVM has a better performance than ANN and ANFIS algorithms. Parsaie et al. (Parsaie et al. 2019a) did a similar study to (Azamathulla et al. 2016) for combined weir-gate and reported similar results as them. Salazar and Crookston (Salazar and Crookston 2019) specifically considered C_d for arced trapezoidal labyrinth spillways using neural networks (NN) and random forests (RF) algorithms. Karami et al. (Karami et al. 2018) examined simulation power of ANN, genetic programming (GP) and extreme learning machine (ELM) for C_d. for of triangular labyrinth weir and reported that ELM outperforms other algorithms followed by ANN and GP. Norouzi et al. (Norouzi et al. 2019) stated that ANN has a higher prediction power than SVM. Bonakdari et al. (Bonakdari et al. 2020) predicted C_d using gene expression programming (GEP) and showed the superiority of GEP over nonlinear regression method (NLR). The group method of data handling (GMDH) approach was used by (Ebtehaj et al. 2015) to predict C_d. and result were compared with ANN and nonlinear regression equations. Their result showed the superiority of GMDH over ANN and NLR. Parsaie et al. (2019b) compared prediction performance of GMDH, GP and multivariate adaptive regression splines (MARS) to the mathematical modelling of discharge coefficient of nonlinear weirs with triangular plan. They revealed that MARS model has a higher computation power over GMDH and GP. ANFIS, SVM, GMDH and other similar algorithms have a weakness which lead to higher error when they are applied in a standalone framework. These algorithms must be optimized through metaheuristic algorithm to find the optimum operator values, especially weights in membership function. ELM also need a large dataset to have a high prediction capability, (unlike in this study). The SVM is a robust algorithm but it is susceptible to hyper-parameter selection (Ahmad et al. 2018). Thus, Zaji et al. (Zaji et al. 2016) developed firefly optimization-based support vector regression (SVR-FF) for C_d. for prediction and reported that firefly metaheuristic algorithm enhanced SVR model about 10%. Ebtehaj et al. (Ebtehaj et al. 2018) utilized genetic algorithm (GA) for the optimum selection of ANFIS membership functions and the evolutionary design of a GMDH model structure to achieve more accurate prediction of coefficient of discharge. Result revealed that the ANFIS-GA has a higher prediction power than GMDH-GA.

Recently, a new type of SC algorithms is being developed to overcome the weakness of the aforementioned more-traditional algorithms. Higher prediction capability of the SC algorithms over their counterparts were reported in literature. Specifically, (Akhbari et al. 2017) stated that M5 tree algorithm has a better performance than ANN algorithms. Hussain and Khan (Hussain and Khan 2020) declared random forest (RF) model outperforms of ANN and SVM for stream flow forecasting. (Khosravi et al. 2019b)Khosravi et al. (2019a) reported that optimized ANFIS hybrid algorithm with metaheuristic algorithms is an improvement over standalone decision trees algorithms (M5Prime (M5P), random tree (RT), RF and reduced error pruning tree (REPT) and thus the hybridized data mining algorithm may outperform optimized traditional algorithms.

Although not specific to weirs, this hybrid approach has been applied to other complex water-related problems. For example, Khosravi et al. (2018) applied standalone (i.e., REPT, M5P and instance-based learning (IBK)) and hybrid models (i.e., bagging-M5P, random committee-REPT (RC-REPT) and random subspace-REPT (RS-REPT)) as well as Salih et al. (2020) developed M5P, attribute selected classifier (ASC), M5Rule (M5R), and KStar (KS) for predicting suspended sediment load. Khosravi et al (2019b) used IBK and locally weighted learning (LWL) to predicted fluoride concentration in groundwater. Khosravi et al. (2020) hybridized decision tree algorithm using bagging algorithm for bed load sediment transport rate prediction and reported that bagging algorithm enhanced performance of standalone algorithms. Bui et al. (Bui et al. 2020) applied hybridized algorithms of cross-validation parameter selection (CVPS) and randomizable filtered classification (RFC) with decision tree algorithms for water quality index prediction. This, there is evidence that such an approach could be applied with success to labyrinth weir hydraulics.

Available conventional approaches for discharge coefficient computation were developed applying classic regression approach. They are mostly over-fitted models established on limited number of data. To this end, the main objective of the present study is to identify a robust, reliable and accurate method for coefficient of discharge prediction for the complex labyrinth weir. To accomplish this, the prediction power of eight novel standalone algorithms and eight hybrid algorithms was investigated. Of the standalone algorithms this study included: least median square (LMS), pace regression (PR), sequential minimal optimization (SMO), Kstar, decision table (DT), M5 Rule (M5R), M5 Prime (M5P) and random forest (RF). The eight new hybrid algorithms paired the staking algorithm (ST) with those standalone algorithms (i.e. ST-LMS, ST-Pace, ST-SMO, ST-Kstar, ST-DT, ST-M5R, ST-M5P, and ST-RF) for coefficient of discharge prediction at sharp-crested labyrinth weirs. To the best of the authors' knowledge, most of the developed algorithms have not been explored in geosciences.

2. Methodology

2.1. Identifying effective parameters

According to the relevant literature and considering the well-known head-discharge equation of $Q=(2/3)C_d\sqrt{2g}Lh^{1.5}$, C_d is depended on the vertex angle (θ), channel width (B), piezometric head over the crest of the weir (h), crest heights (W), crest length of the weir (L), gravitational acceleration (g), dynamic viscosity of fluid (μ), density of flow (ρ), surface tension (σ) and flow velocity (V) (Rehbock 1929; Kandaswamy and Rouse 1957; Kindsvater and RW Carter 1959; Kumar et al. 2011; Zaji et al. 2016; Bonakdari et al. 2020). Overall, these effective parameters can be described as follows:

$$C_d = f(\theta, B, h, W, L, g, \mu, \rho, \sigma, V) \tag{1}$$

Using classical dimensional analysis through Buckingham Π theorem to identify dimensionless parameters and to improve the modeling performance of the soft computing models and to directly compare datasets (Azamathulla et al. 2009; Pal et al. 2014). Using the Π theorem seven dimensionless parameters were extracted as follows:

$$C_d = f(h/W, L/h, L/W, B/W, L/B, Fr, \theta) \tag{2}$$

It is worthy to note that Reynolds (*Re*) and Weber numbers (*We*) are removed due to guideline of American Society of Civil Engineers (ASCE, 2000) committee (Manual 97), as We number is higher than100 and Re number shows fully turbulent flow.

2.2. Dataset collection

123 datasets measured and collected by (Kumar et al. 2011) are used to examine the effectiveness of the 16 algorithms considered herein. Kumar et al. (Kumar et al. 2011) experiments were carried out in a flume with 12 m length, 0.28 m width and 0.41 m depth. A triangular labyrinth weir made of a thin steel plate with six different vertex angles (θ = 30°, 60°, 90°, 120°, 150° and 180°) was located 11 m downstream of the channel entrance (Fig 1). Flow supplied to the flume was measured using a volumetric sump (located at the flume exit). A point-gauge with accuracy of ±0.1mm was used to measure the head of water over the crest of the weirs (*h*). More information about flume set-up and applied method can be found in (Kumar et al. 2011).

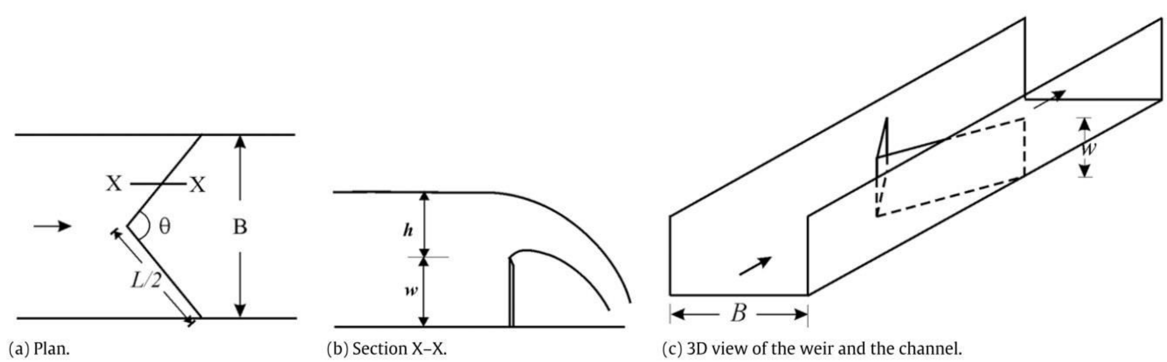


Fig 1. Sketch of sharp crested labyrinth weir (Kumar et al. 2011)

The Kumar et al. (Kumar et al. 2011) dataset was separated into two subgroups randomly in a ratio of 70:30, as 70% (86 set) of data as a training dataset were used for the model development while 30% (37 set) as a testing dataset for developed models validation. This approach is considered by the authors to be the most common method in modeling while there is not a universal guideline for preparation of training and testing dataset. Descriptive statistics of the training and testing dataset for input parameters are tabulated in Table 1.

Table 1. Descriptive statistics of the training and testing dataset

Parameters	Training					Testing				
	Max	*Min*	*Mean*	*STD*	*Skew*	*Max*	*Min*	*Mean*	*STD*	*Skew*
θ (degree)	180.00	30.00	103.45	50.69	180.00	180.00	30.00	100.00	50.20	180.00
h/w	0.72	0.09	0.38	0.16	0.72	0.67	0.12	0.36	0.17	0.67
L/B	3.86	1.00	1.75	1.00	3.86	3.86	1.00	1.78	1.01	3.86
L/h	135.25	3.89	19.61	24.22	135.25	98.36	4.18	20.44	22.00	98.36
Fr	3.21	0.61	1.18	0.71	3.21	3.26	0.62	1.22	0.73	3.26
B/W	3.04	2.59	2.76	0.14	3.04	3.04	2.59	2.76	0.14	3.04
L/W	11.76	2.69	4.95	3.16	11.76	11.76	2.69	5.06	3.20	11.76
C_d	0.91	0.54	0.72	0.07	0.91	0.86	0.57	0.72	0.07	0.86
Q (m^3/s)	0.01	0.00	0.01	0.00	0.07	0.01	0.00	0.01	0.00	0.23

2.3. Optimal input combination

Determination of the best input parameters have a significant effect on the result. To enhance a model's prediction power, based on the correlation coefficient between inputs and output parameters, seven input combinations was constructed to find the optimal or most effective scenario. At the first step, input parameters with the highest correlation coefficient (*r*) were used as a single input. The hypothesis is to identify the parameter with highest ability to accurately predict C_d. Next, the parameter with the second highest *r* value was added to the first input and to this end, input No. 2 was constructed. This method continued until the last of the seven parameters also with the lowest *r* was added (Table 2).

To find the most effective input combination, the model's default operator was applied. Efficiency of all constructed input combinations were examined in terms of the root mean square error (*RMSE*); the lower the *RMSE* the more effective the input parameter combination.

Table 2. Different input combinations

No.	Input variables	Output
1	h/w	C_d
2	h/w, L/h	C_d
3	h/w, L/h, Fr	C_d
4	h/w, L/h, Fr, L/W	C_d
5	h/w, L/h, Fr, L/W, θ	C_d
6	h/w, L/h, Fr, L/W, θ, B/W	C_d
7	h/w, L/h, Fr, L/W, θ, B/W, L/B	C_d

2.4. Model's parameter optimization

In addition to data quality, the length of the data set, the model's prediction power, and the effectiveness of input parameters and optimized value for each operator have significant effects on the modelling prediction accuracy. Optimum values for each model's operator vary from study to study and data to data, hence, there is not an optimum value for all cases. For this study on labyrinth weirs, the trial-and-error approach were applied to determine the optimum model operators via the Waikato Environment for Knowledge Analysis (WEKA 3.9) software. Default values were first applied to each developed model and their performance was checked through *RMSE*. Next, higher and lower values were applied, and their performances were checked again until from the range of values the results the optimum values were identified with lowest *RMSE*.

2.5. Model theory background

This section provided in a supplementary material.

2.6. Model evaluation and comparison

Efficiencies of each developed algorithm must be evaluated, as without the model's prediction power validation stage, modeling results would be inapplicable and do not have a scientific soundness (Chung and Fabbri 2003). Also, as training datasets are used for model building processes, the results of this section only show how well the developed algorithms fit corresponding dataset. Thus, testing datasets were applied for the model validation stage. Two of the most common approaches for model evaluation and comparison are visually and quantitatively based methods. Visually based methods are comprised of line graphs, scatter plots and box plots. These approaches benefit from fast, interesting and desirable comparison and can quickly provide more information about accuracy prediction of maximum, minimum, median, first and third quartiles, etc. which cannot be driven using quantitative metrics. But these metrics suffer from lack of information about models performance classification and their ranking. Therefore, different quantitative approaches including *RMSE*, mean absolute error (*MAE*), the Nash-Sutcliffe efficiency (*NSE*), and percentage of bias (*PBIAS*) were computed and applied as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left[C_d^{Obs} - C_d^{\mathrm{Pre}}\right]}, \qquad 0 \le \mathrm{RMSE} < \infty \tag{3}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|C_d^{Obs} - C_d^{\mathrm{Pre}}\right|, \qquad 0 \le \mathrm{MAE} < \infty \tag{4}$$

$$NSE = 1 - \frac{\sum_{i=1}^{N}\left[C_d^{Obs} - C_d^{\mathrm{Pre}}\right]^2}{\sum_{i=1}^{N}\left[C_d^{Obs} - \overline{C}_d^{Obs}\right]^2}, \qquad -\infty < \mathrm{NSE} < 1 \tag{5}$$

$$PBIAS = \frac{\sum_{i=1}^{N}\left[C_d^{Obs} - C_d^{\mathrm{Pre}}\right]}{\sum_{I=1}^{N} C_d^{Obs}} * 100, \qquad -\infty \le \mathrm{PBIAS} \le \infty \tag{6}$$

where C_d^{Obs} and C_d^{Pre}, are measured and predicted coefficient of discharge values and $\overline{C}_d^{Obs}$ is the mean of measured coefficients of discharge.

3. Result and analysis

3.1. Relative parameter importance

Each input parameters have a different relative effectiveness on the results. Seven dimensionless input parameters were considered for the modeling process based on the aforementioned literature review and theory of the discharge over weirs. Effectiveness of these parameters is evaluated using the Pearson correlation coefficient (r). As shown in Figure 2, the results demonstrated that h/W has the highest impact on the modeling of C_d (r = 0.713) followed by L/h (r = 0.537), Fr (r = 0.318), L/B (r = 0.122), L/W (r = 0.119), θ (r = 0.112) and B/W (r = 0.019).

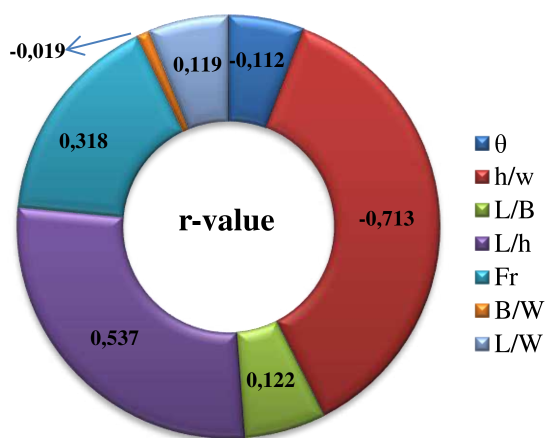


Fig 2. Pearson correlation coefficient between input parameters and output

3.2. Best input combination

To identify the best-input combination for C_d computations, seven scenarios were examined on eight stand-alone models of LMS, PR, SMO, Kstar, DT, M5R, M5P and RF, and their hybrid counterparts based on ST algorithm. The examined scenarios are given in Table 3, listed from one to seven combinations where the incorporated parameters in order of the presentation are *h/w, L/h, Fr, L/W, θ, B/W* and *L/B*. The models' performances in terms of accurate prediction are given in Table 4 as a heat-map. It is important to involve most significant parameters, as irrelevant parameters lead to a complex structure that may lower prediction accuracy.

Table 3. Heat map for determination of the best input combination based on RMSE

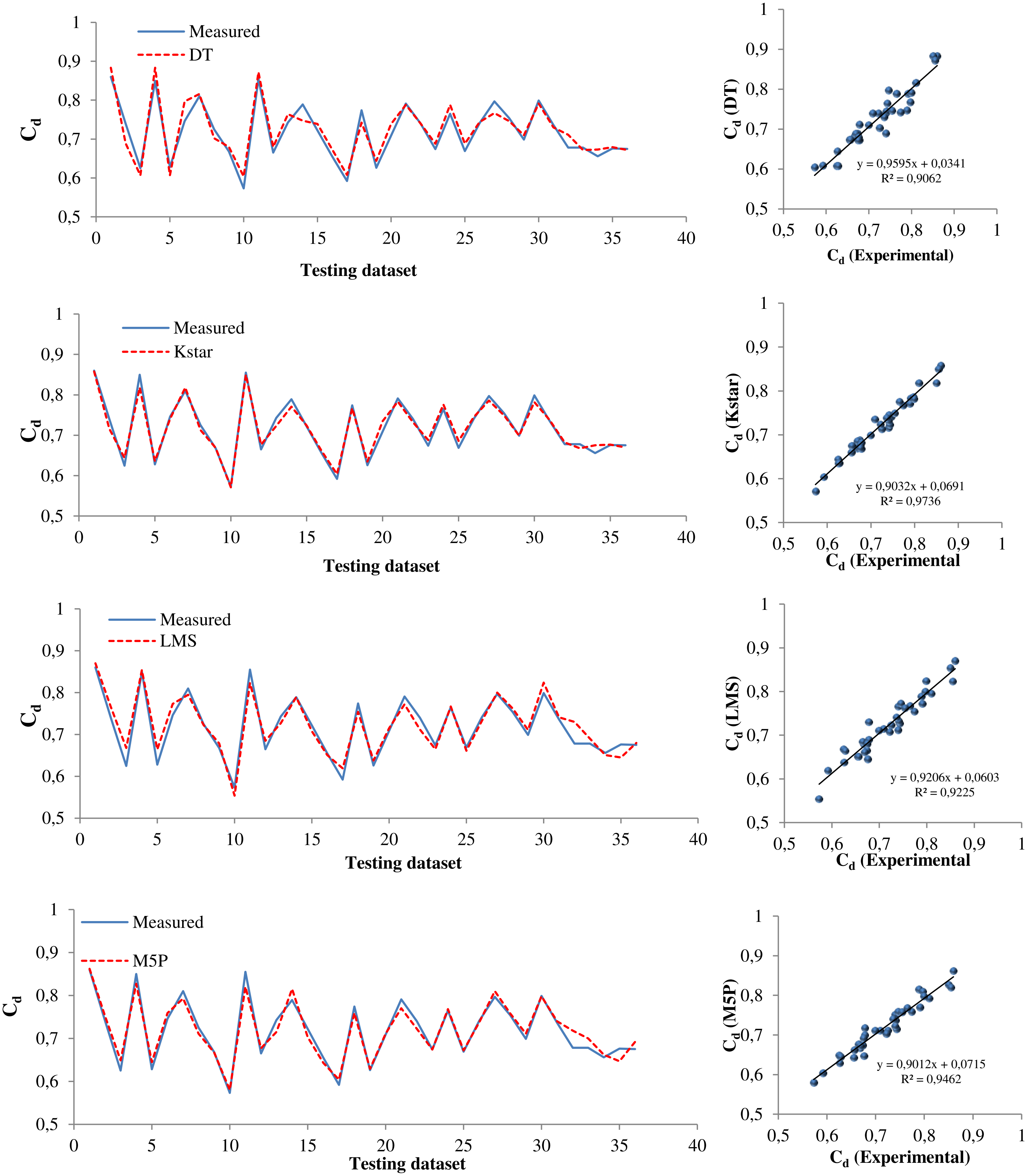
	Inputs No.						
	1	2	3	4	5	6	7
LMS	0.052	0.08	0.043	0.049	0.046	0.03	0.044
PR	0.049	0.049	0.039	0.024	0.021	0.019	0.019
SMO	0.052	0.052	0.041	0.03	0.031	0.025	0.024
Kstar	0.043	0.022	0.015	0.01	0.0088	0.0085	0.0084
DT	0.042	0.042	0.027	0.037	0.01	0.01	0.01
M5R	0.043	0.032	0.027	0.035	0.018	0.016	0.016
M5P	0.043	0.033	0.027	0.025	0.024	0.021	0.021
RF	0.022	0.021	0.01	0.01	0.01	0.01	0.01
ST-LMS	0.05	0.075	0.041	0.043	0.04	0.026	0.031
ST-Pace	0.048	0.048	0.039	0.023	0.022	0.019	0.019
ST-SMO	0.051	0.051	0.04	0.03	0.03	0.025	0.024
ST-Kstar	0.042	0.022	0.006	0.005	0.0047	0.0046	0.0046
ST-DT	0.041	0.038	0.025	0.026	0.01	0.01	0.01
ST-M5R	0.042	0.031	0.025	0.02	0.017	0.015	0.015
ST-M5P	0.042	0.033	0.025	0.025	0.024	0.019	0.019
ST-RF	0.022	0.021	0.015	0.0094	0.009	0.008	0.0074

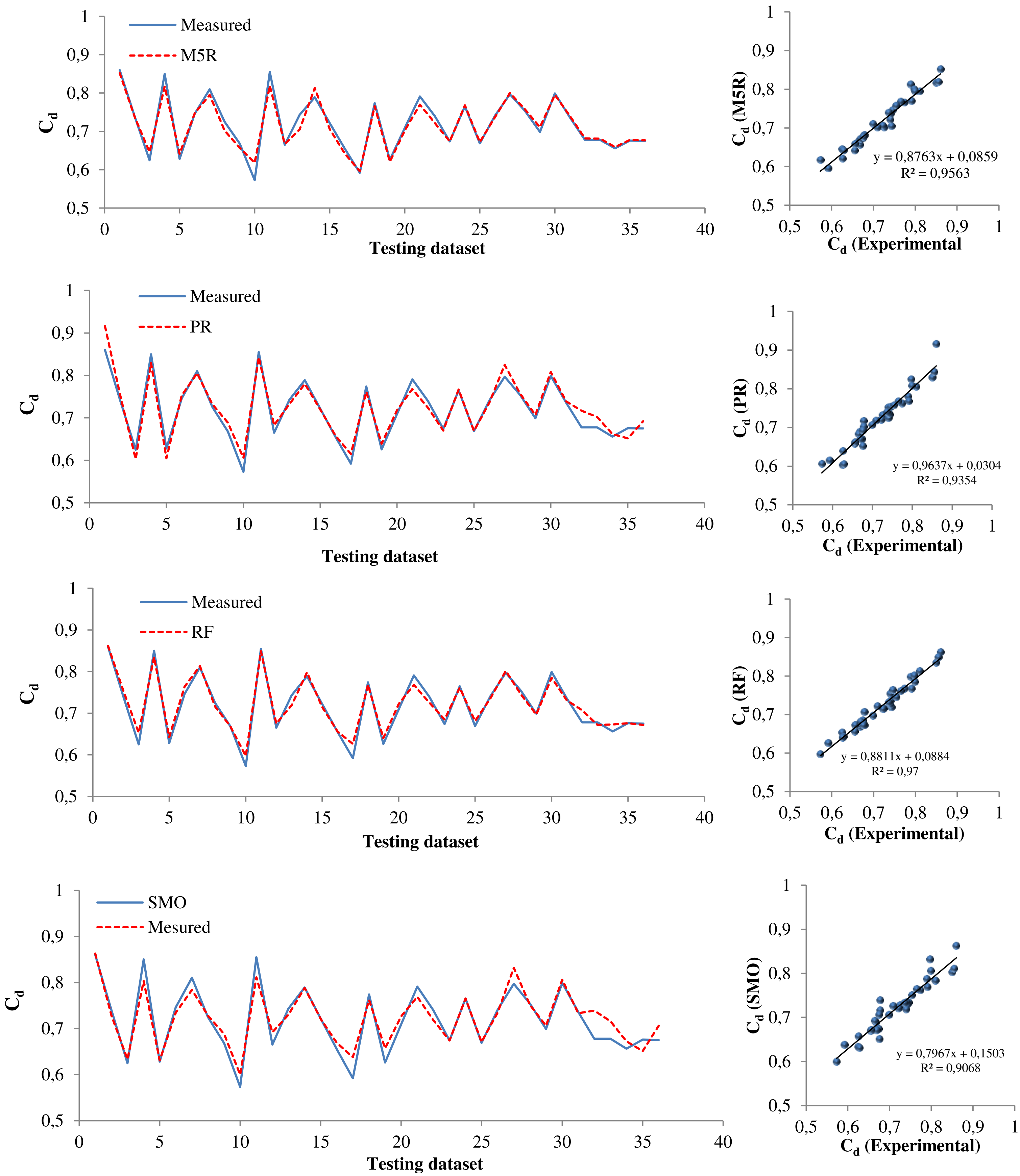
** Red light shows the worst input while the green colors illustrate the best inputs

Results obtained in Table 3 indicate that an increase in the number of incorporated parameters into the model improves the model's performance significantly. For instance, for the best stand-alone model of Kstar, it gives the *RMSE* of 0.043 for input No.1 (single input parameter), while it reaches the *RMSE* of 0.0085 and 0.0084 with six and seven input parameters, respectively. It shows 80% promotion in Kstar accuracy in C_d computation. Such an improvement is even more tangible in the hybrid models. The results indicate the ST-Kstar model as the most robust model (shown in Table 3), with *RMSE* of 0.042 and 0.0046 for one and six input variables, respectively. It indicates almost 90% improvement in its computation accuracy, due to incorporation of more input parameters into the model's structure.

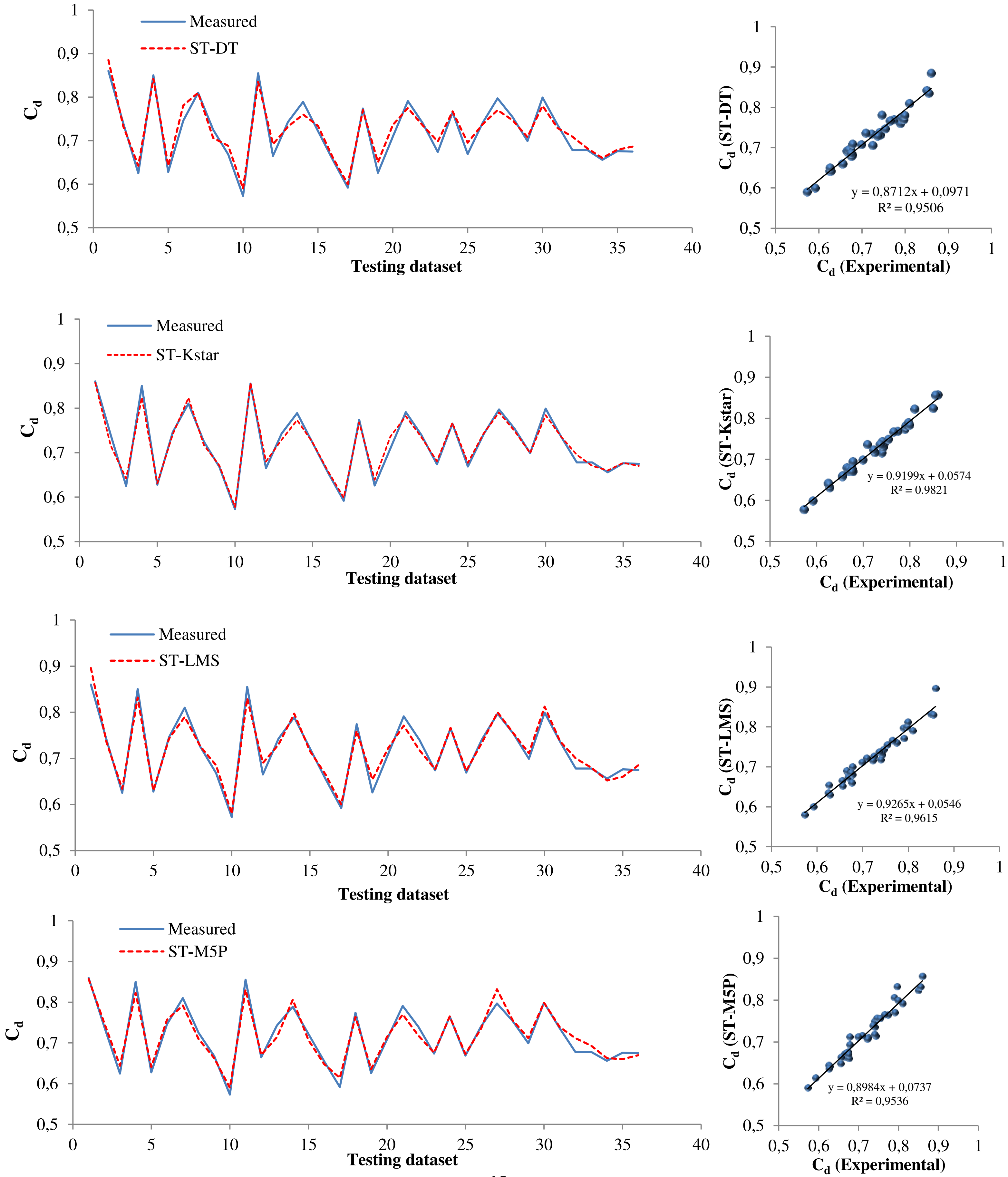
3.3. Comparison of models

The C_d values from experimental data and the values computed by the stand-alone models of LMS, PR, SMO, Kstar, DT, M5R, M5P and RF, and hybrid models of ST-LMS, ST-PR, ST-SMO, ST-Kstar, ST-DT, ST-M5R, ST-M5P and ST-RF are compared in terms of line graphs and scatter plots in Figure 3. As shown in Figure 3, although a few stand-alone models provide accurate performances, they generate large scatter as their results are not fitted to the best-fit line. For instance, DT and SMO models have significant over- and under-estimations, while Kstar and RF give more accurate computations. As shown in Figure 3, hybridization of the stand-alone models with ST ensemble algorithm improves model performances for the majority of cases. Hybrids models of ST-Kstar and ST-RF are superior predictors where most of the data remained on the best-fit line, thus showing their high performance in C_d computation. Also shown for the case ST-PR, ST-SMO and ST-DT models, the hybridization technique cannot significantly improve their performances as large scatter are still shown, thus demonstrating less accurate performances of these models.


Measured
DT
Cd
Testing dataset
Cd (DT)
Cd (Experimental)
y = 0,9595x + 0,0341
R² = 0,9062
Measured
Kstar
Cd
Testing dataset
Cd (Kstar)
Cd (Experimental
y = 0,9032x + 0,0691
R² = 0,9736
Measured
LMS
Cd
Testing dataset
Cd (LMS)
Cd (Experimental
y = 0,9206x + 0,0603
R² = 0,9225
Measured
M5P
Cd
Testing dataset
Cd (M5P)
Cd (Experimental)
y = 0,9012x + 0,0715
R² = 0,9462



Measured
M5R
Cd
Testing dataset
Cd (M5R)
y = 0,8763x + 0,0859
R² = 0,9563
Cd (Experimental)
Measured
PR
Cd
Testing dataset
Cd (PR)
y = 0,9637x + 0,0304
R² = 0,9354
Cd (Experimental)
Measured
RF
Cd
Testing dataset
Cd (RF)
y = 0,8811x + 0,0884
R² = 0,97
Cd (Experimental)
SMO
Mesured
Cd
Testing dataset
Cd (SMO)
y = 0,7967x + 0,1503
R² = 0,9068
Cd (Experimental)


Measured
ST-DT
Cd
Testing dataset
Cd (ST-DT)
Cd (Experimental)
y = 0,8712x + 0,0971
R² = 0,9506
Measured
ST-Kstar
Cd
Testing dataset
Cd (ST-Kstar)
Cd (Experimental)
y = 0.9199x + 0.0574
R² = 0.9821
Measured
ST-LMS
Cd
Testing dataset
Cd (ST-LMS)
Cd (Experimental)
y = 0,9265x + 0,0546
R² = 0,9615
Measured
ST-M5P
Cd
Testing dataset
Cd (ST-M5P)
Cd (Experimental)
y = 0,8984x + 0,0737
R² = 0,9536

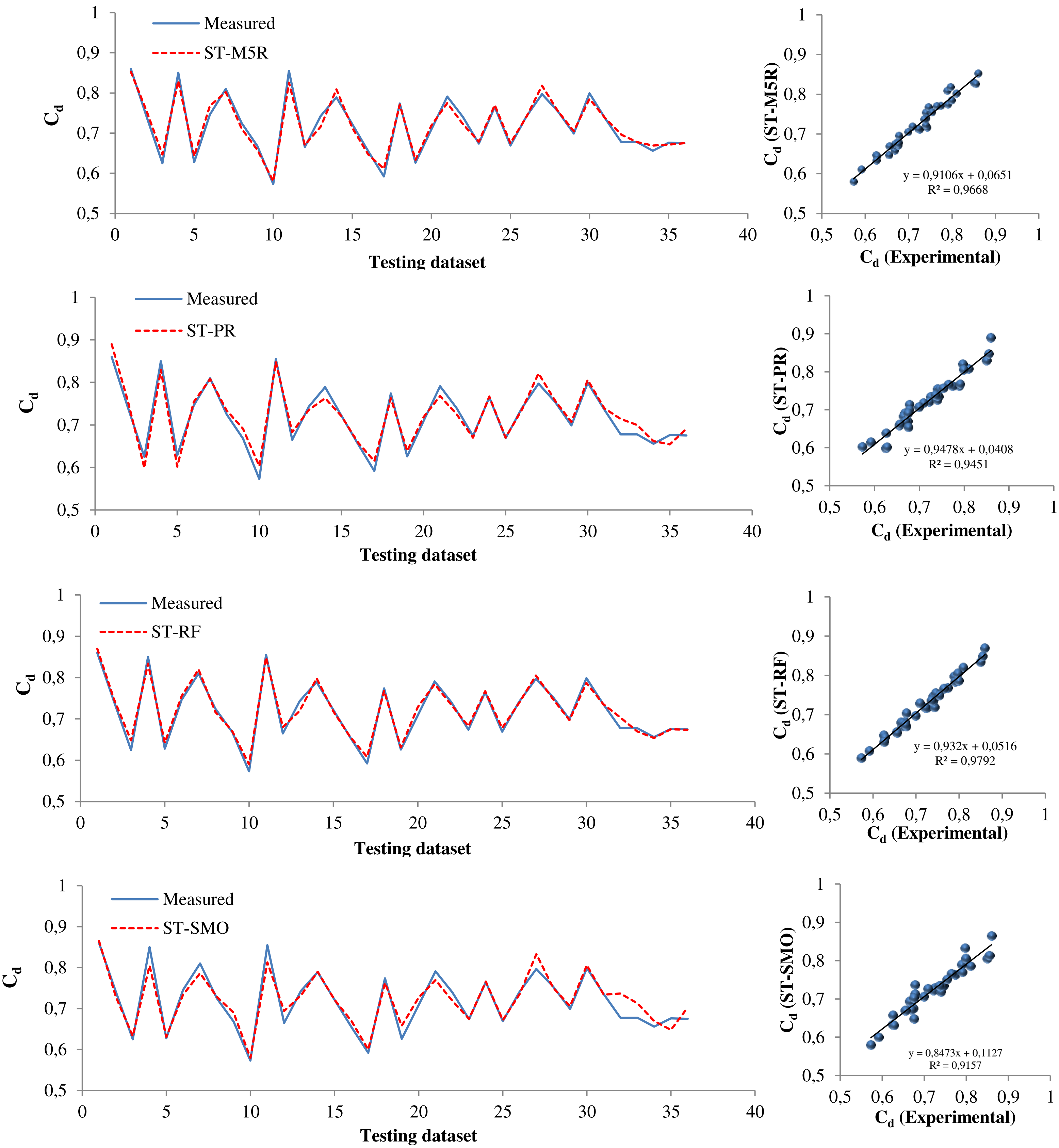


Fig 3. Line-graph and scatter plot of measured *Vs.* prediction C_d in testing phase

Comparison of the developed models in this study for C_d computation is shown via Figure 4. The use of violin plots is helpful to understand the distribution of the data in the studied models results. It uses density curves where their widths are attributed to the frequency of data in a specific region. To this end, a model which has most similar violin plot shape to the measured counterpart generates more accurate computations.

As shown in Figure 4, the ST-Kstar is in excellent agreement with the measured violin plot; the ST-RF models have approximately similar violin plot shapes to the measured one, although the ST-RF model has a wider distribution in the upper quartile. It shows that ST-RF is not as accurate for the higher C_d values. Generally, it can be concluded that hybrid models outperform their corresponding stand-alone models. The red dash line noted in Figure 4 shows the median of the data. For the hydride models, in most of the cases, the median line is located at the middle of the violin plot, while for some of the standalone models such as M5P, M5R, ST-M5P and ST-M5R the median lines are placed in a lower level, indicating their under-estimation of results. In terms of the maximum value, M5R, Kstar, ST-M5R, ST-Kstar were accurate predictors while only Kstar and ST-Kstar models had the ability to predict minimum C_d value in a high accuracy.

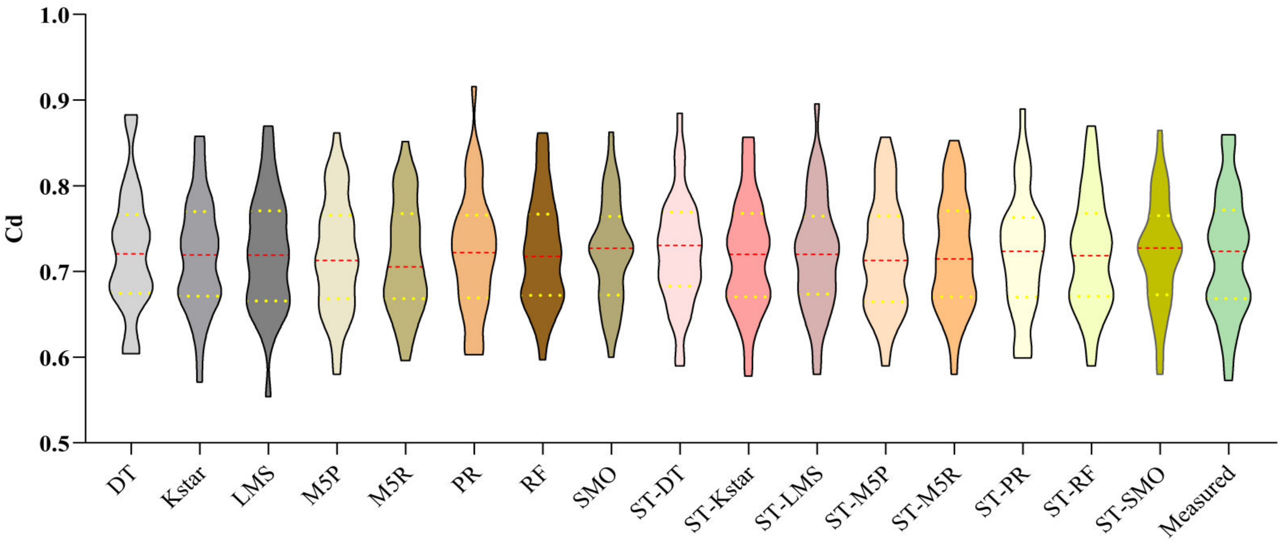


Fig 4. Violin plot used for model performance

Furthermore, comparison of the developed models for C_d computation is conducted in terms of four statistical performance indices of *RMSE*, *MAE*, *NSE* and *PBIAS*, which reports modeling performance quantitatively as shown in Figure 5. Among the standalone models, Kstar and RF provided much better results than the remaining models considered herein. Consistently their hybrid versions as ST-Kstar and ST-RF are found superior to their alternatives. In terms of *NSE*, all developed algorithms due to NSE score higher than 0.75, have a very good performance (Ayele et al. 2017), but ST-Kstar outperforms all other models with *RMSE*, *MAE*, *NSE* and *PBIAS* of 0.011, 0.008, 0.976 and 0.027, respectively. Indeed, the hybridization algorithm significantly improved the performance of some models yet for some cases hybridization has no considerable enhancement in the model's performance. For instance, a considerable improvement is seen in Figure 9 for DT and LMS models where their *RMSE* with 0.023 and 0.020 values are decreased to 0.016 and 0.014 in ST-DT and ST-LMS model, respectively. It shows 30% and 25% promotion in ST-DT and ST-LMS models accuracies in contrast to DT and LMS stand-alone models. This scenario is vice versa for M5P and SMO models as hybridization.

lesser increases their accuracies in ST-M5P and ST-SMO models with a factor of 5% and 8%, respectively. According to *PBIAS* result, Kstar, ST-Kstar and M5R algorithms under-estimated C_d values (negative values) while the remainder of the algorithms were over-estimators.

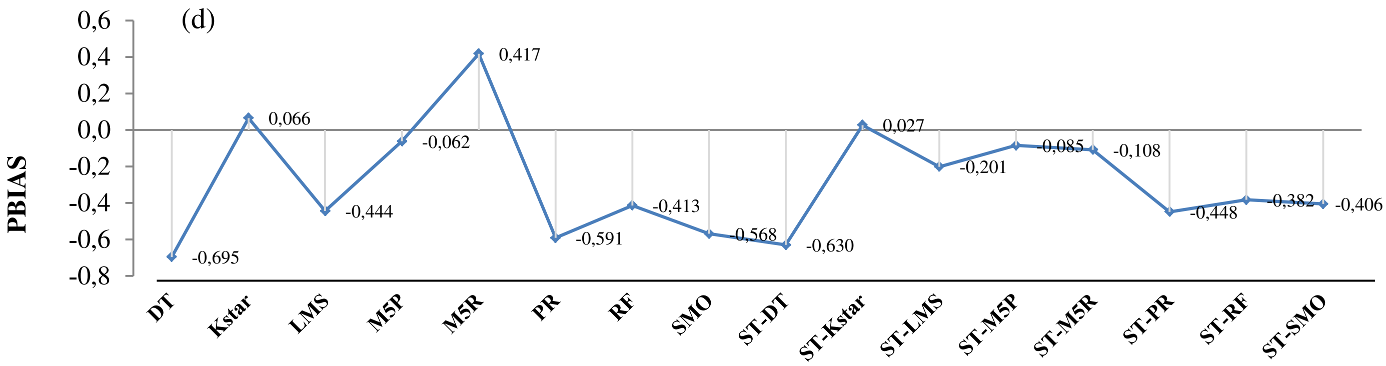
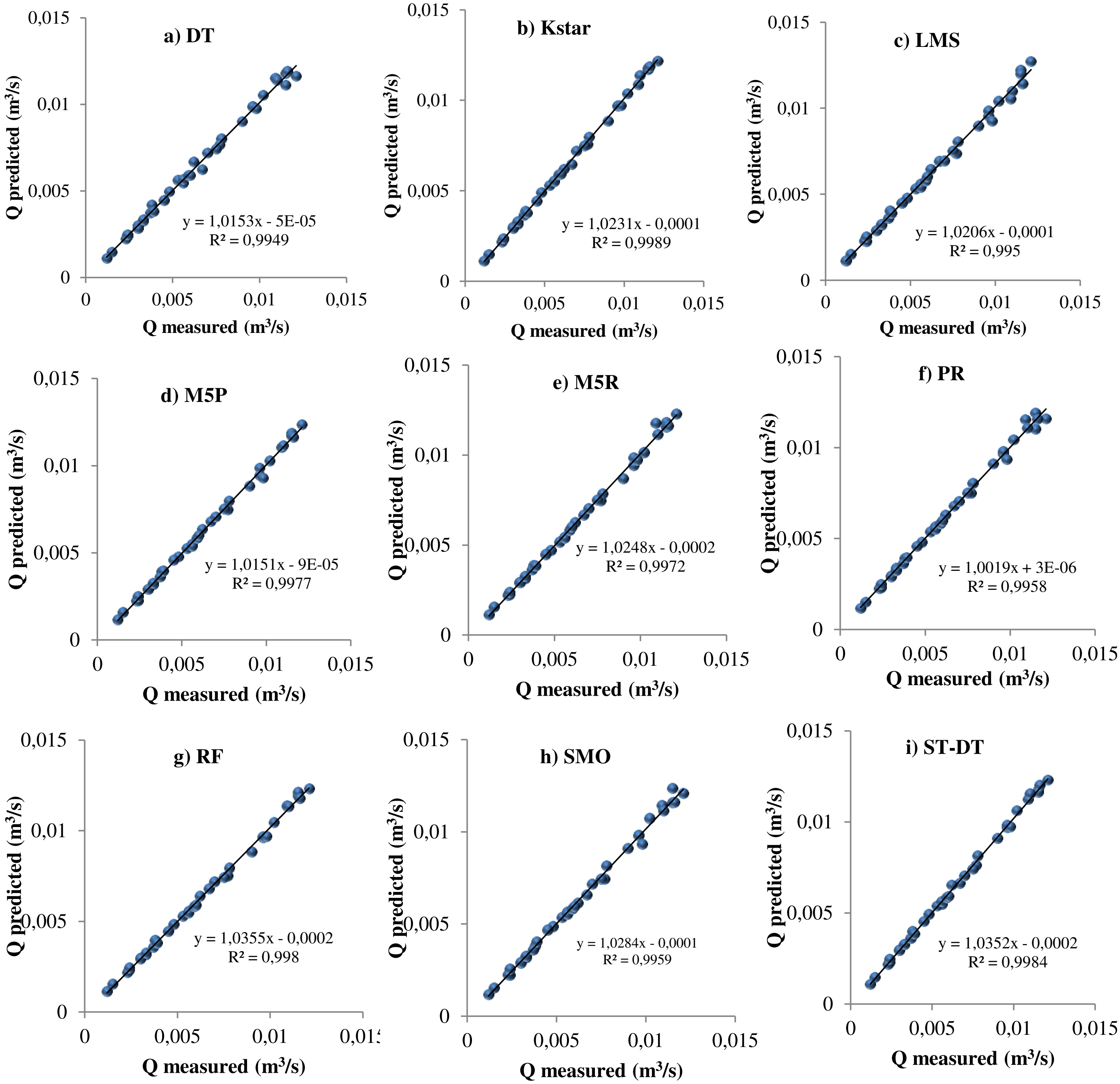


Fig 5. Model validation: (a) RMSE, (b) MAE, (c) NSE and (d) PBIAS

Additional insights can be gained by evaluating the models' performances in terms of accurate discharge computation based on the results obtained for C_d as shown in Figure 6. To this end, the predicted C_d values are incorporated into the $Q=(2/3)C_d\sqrt{2g}Lh^{1.5}$ to compute flow discharge passing the weir. From a first glance on Figure 10, it can be understood that, all machine learning models are successful for adjusting the C_d parameter for discharge computation. Although small scatter is seen for some models such as DT, LMS, M5R, PR and SMO, most of the models provide promising results where data are well-placed on the best fit line. Similar to results reported in the prior section, ST-Kstar and ST-RF models stay ahead in competition with other models in providing accurate results. To sum up, all developed algorithms predated C_d values accurately with corresponding coefficient of determination higher than 0.99 for whole the cases.


a) DT
y = 1,0153x - 5E-05
R² = 0,9949
b) Kstar
y = 1,0231x - 0,0001
R² = 0,9989
c) LMS
y = 1,0206x - 0,0001
R² = 0,995
d) M5P
y = 1,0151x - 9E-05
R² = 0,9977
e) M5R
y = 1,0248x - 0,0002
R² = 0,9972
f) PR
y = 1,0019x + 3E-06
R² = 0,9958
g) RF
y = 1,0355x - 0,0002
R² = 0,998
h) SMO
y = 1,0284x - 0,0001
R² = 0,9959
i) ST-DT
y = 1,0352x - 0,0002
R² = 0,9984
Q predicted (m³/s)
Q measured (m³/s)
0
0,005
0,01
0,015

361

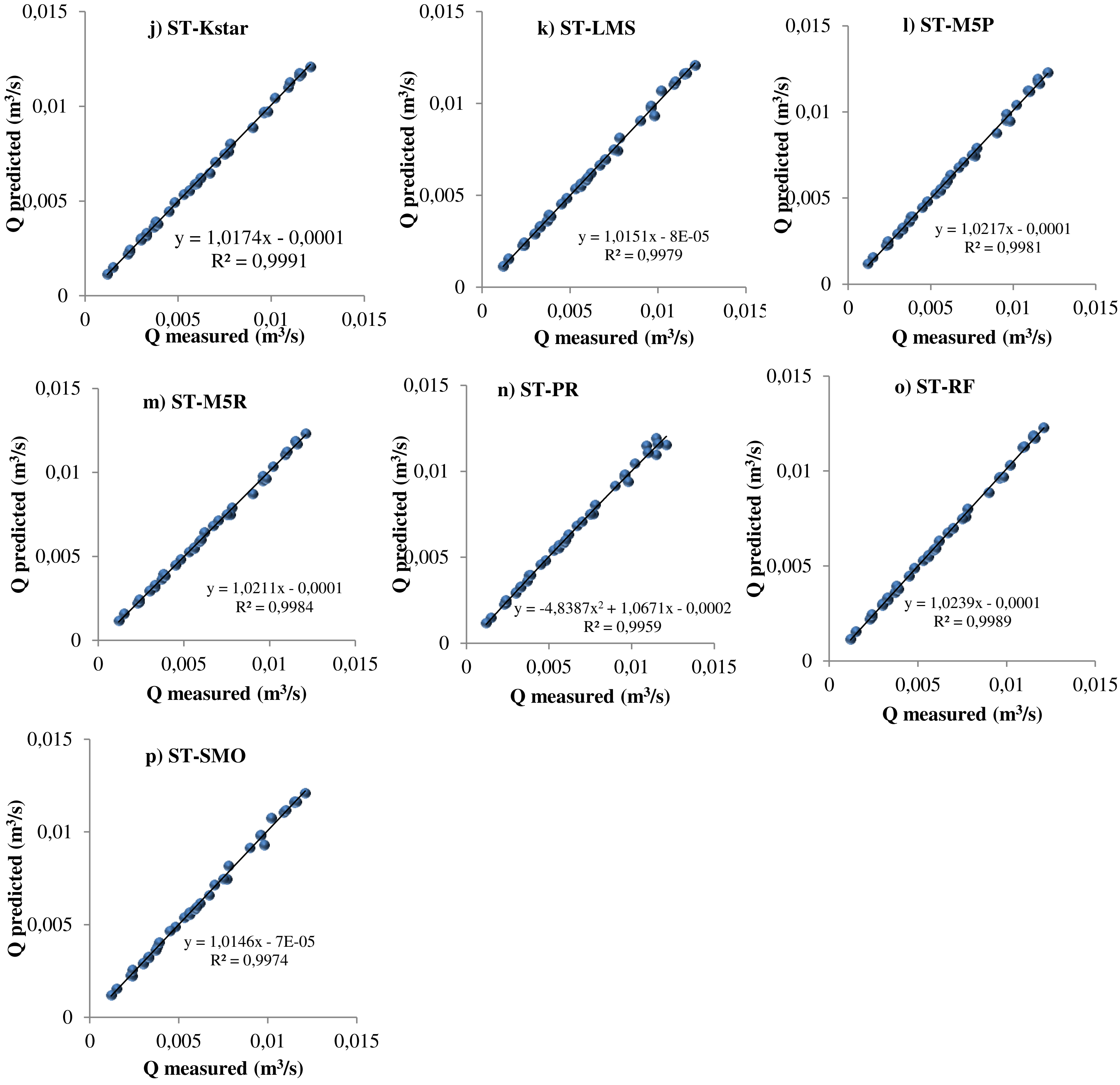


Fig 6. Measured and predicted flow discharge over weirs using adjusting C_d value

4. Discussion

Due to the topographical characteristics, site-specific constraints, project economics, and performance goals, it is often an essential issue to address discharge capacity. For many new and rehabilitation projects, enlargement of the weir crest length is a viable option to increase its discharge capacity. For the case of the conventional weirs, for greater discharges during the floods, water levels must also be greater and may cause unacceptable levels of upstream flooding and damage. In the case of flood infrastructure such as embankment dams and levees, this increased upstream elevation may result in overtopping, embankment erosion, breaching, and significant downstream flooding and corresponding consequences. To this end, implementation of labyrinth weir can be considered to overcome the afflux problem in conventional weirs. An important problem for application of the labyrinth weir comes from the determination of its discharge coefficient. Recommended approaches for computation of discharge coefficient in labyrinth weir were established from selected hydraulic and geometric variables. However, the existing benchmarks are generated on experimental data through developing a best fit relationship applying classical regression methods. Following the same methodology in published literature and through considering a variety of dimensionless parameters, robust machine learning algorithms are utilized in this study to develop rigorous models for discharge coefficient computation in sharp-crested labyrinth weirs.

This study applied eight stand-alone models of LMS, PR, SMO, Kstar, DT, M5R, M5P and RF, and their eight hybridized version constructed using the ST algorithm to develop ST-LMS, ST-PR, ST-SMO, ST-Kstar, ST-DT, ST-M5R, ST-M5P and ST-RF models. Results indicate that all models developed in this study have acceptable/very good performance for discharge coefficient computation. For the worst case in the models of DT and SMO, they provide errors less than 2%, while for the best models of ST-Kstar and ST-RF, 0.8% and 0.9% errors are found respectively for discharge coefficient computation showing the robustness of the models developed in this study. It can be asserted as a significant promotion in discharge coefficient computation in sharp-crested labyrinth weirs. This completely is resulting from different computation capability, flexibility and complexity of each algorithm, which gets back to different structure of each model that developed based on. Also, higher performance of hybridized algorithms maybe due to increasing in flexibility and non-linearity of each model (De'ath and Fabricius 2000). It has to be emphasized that, according to the(Kumar et al. 2011), ±5% error in discharge computation in sharp-crested labyrinth weirs is acceptable. The range of the error in discharge computation in this study for different models are found from 1.6% to 3%, where for the best models of ST-Kstar and ST-RF are 1.6% 1.8%, respectively (Fig. 7). This result also shows superiority of the present study over the approach proposed by (Kumar et al. 2011).

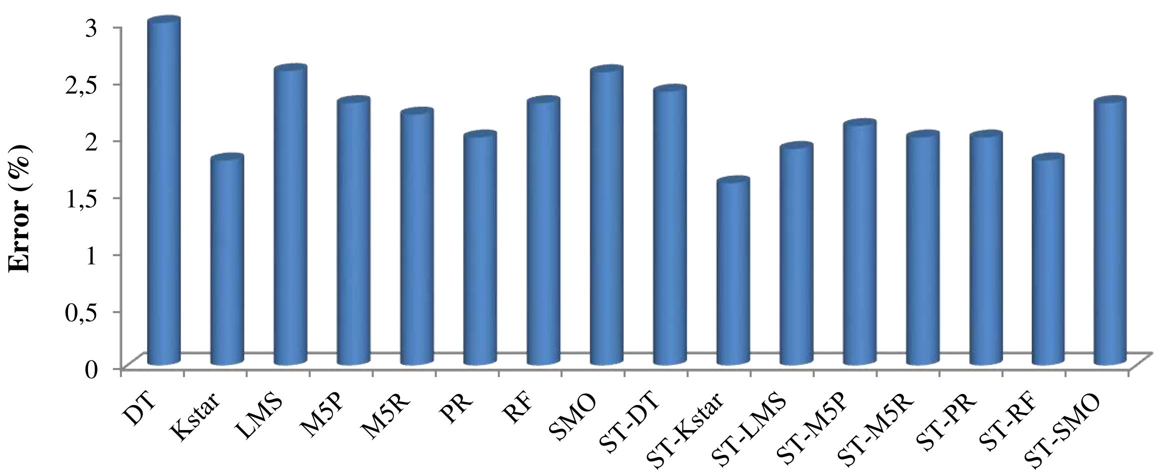


Fig 7. Average percentage error for discharge prediction

Although this is the first attempt that applied new data mining algorithms to predict C_d values it is difficult to make a direct comparison to traditional machine learning algorithms from other researchers with the same data of the present study. For example, (Bonakdari et al. 2020) used GEP and NLR algorithm and reported *RMSE* of 0.021 and 0.040 respectively. Our study shows 47.6% and 72.5% higher performance respectively using ST-Kstar algorithm. Also, (Akhbari et al. 2017) stated that M5 tree model with a $R^2 = 0.831$ has high prediction accuracy, which is in disagreement with the result of this study that showed 15% higher prediction capability than M5 tree model. These results show the successful application of the new machine learning algorithms proposed in the present study for discharge coefficient computation in sharp-crested labyrinth weirs. These discrepancies between prior studies may be linked to the details of training and implementation, which as shown herein are critical steps that can heavily influence results.

Our finding in determining relative importance of each input parameters on the result is in accordance with Roushangar et al. (Roushangar et al. 2018) who stated that h/W is the most influential parameter on C_d prediction. Akhbari et al. (Akhbari et al. 2017) stated that h/B and Fr are two most effective input parameters. Also, (Azimi et al. 2017) declared that Fr parameter, among single input parameters, has the highest effectiveness, which leads to lowest error. Bonakdari et al. (Bonakdari et al. 2020) stated that θ is the less effective parameter in C_d prediction. To sum up, parameter importance results vary from study to study and its importance depends on the conditions which control the experiments.

In terms of identifying the best input combination, except of prediction accuracy, the number of input parameters incorporated in the molding process is important, as sometimes, measuring many input parameters is time-consuming. Hence, a model which lead to a slightly lower accuracy with less input parameters, is preferable than a model with a slightly higher accuracy with greater number of inputs. For example, ST-Kstar with input No. 5 with *RMSE* of 0.0047, is preferable than input No.6 and 7 with *RMSE* of 0.0046.

It has been known that credibility of a hydraulic model is significantly attributed to the range of data used for the model development. On the other hand, there are a limited number of experimental studies on sharp-crested labyrinth weirs in the literature. Consequently, conducting experimental studies in large channels, adopting wide ranges of crest length, crest height and vertex angle needed, particularly at field scale, for further advancement of these models. Incorporation of the large number of parameters in the model structure arises a difficulty to use the model as a practical tool. To this end, future studies may consider the use of fewer parameters for simplifying the developed models and generating explicit models.

5. Conclusions

Weirs as a flow measurement structures are used for many purposes such as flood control, irrigation plan and controlling the flow discharge. Weirs are also widely implemented in the water management and hydro-system projects. Discharge capacity would be evaluated using coefficient of discharge, but accurate determination of this parameter can be a challenging task. The present study used different soft computing algorithms to predict coefficient of discharge using various readily available parameters as model inputs. The main findings of the present study can be summarized as follows:

1- All developed algorithms have a very good performance, while, ST-Kstar algorithm outperforms its alternatives.

2- Hybrid ST-Kstar model has improved prediction performance of standalone Kstar about 0.82% and provides almost 8.3% higher performance compared to the SMO, with lowest prediction power.

3- *h/W* has the highest impact on the modeling of C_d ($r = 0.713$) followed by *L/h* ($r = 0.537$), *Fr* ($r = 0.318$), *L/B* ($r = 0.122$), *L/W* ($r = 0.119$), θ ($r = 0.112$) and *B/W* ($r = 0.019$). Result shows 80% promotion in Kstar model accuracy in C_d computation when effective input combination was applied compared to the input No.1. This reaches up to 90% for ST-Kstar algorithm.

4- Relative importance of input parameters differs from study to study. While *L/h*, *Fr*, *L/B*, and *L/W* are the most important parameters in predicting the coefficient of discharge.

5- Best input combination is found as a model in which all input parameters involved except of *B/W* which its incorporation to the model, decreased modeling process performance.

6- Utilizing predicted C_d value by soft computing techniques, the computed discharges provide R^2 values higher than 0.99, near to the unity.

7- The novel approaches proposed in the present study outperform the traditional and non-linear regression models.

8- Kstar, ST-Kstar and M5R underestimated C_d values while rest of algorithms overestimated.

Current finding shows that both new standalone and hybrid algorithms are cost-effective tools not only for coefficient of discharge prediction. Relying on the promising results of this study, it is expected that the applied algorithms in this study can be implemented in variety of hydrology and hydraulic problems.

Conflict of interest statement

There is not any conflict of interest among authors.

Availability of Data and Materials

Available from the corresponding author upon reasonable request.

Declarations

Not applicable

Funding

There is not any funding for this paper

Contributions

KK: Conceptualization, methodology, software, writing – original draft, review and editing.

MJSS: Methodology, writing – original draft, review and editing

ZSK: Conceptualization, writing – original draft, data curation.

BC: Methodology, writing – original draft, review and editing.

AG: Conceptualization, Methodology, review and editing

Competing Interests

None.

Ethics Approval

Not applicable.

Consent to Participate

Not applicable.

Consent for Publication

Not applicable.

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