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Prediction of scour hole characteristics caused by water jets using metaheuristic artificial bee colony-optimized neural network and pre-processing techniques

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ABSTRACT

Preventing plunge pool scouring in hydraulic structures is crucial in hydraulic engineering. Although many studies have been conducted experimentally to determine relationship between the scour depth and water jets in several fields, available equations have deficiencies in calculating the exact scour due to complexity of scour process. This study investigated local scour depth in plunge pool using Metaheuristic Artificial Bee Colony-Optimized Feed Forward Neural Network (ABCFFNN), variational mode decomposition (VMD) and ensemble empirical mode decomposition (EEMD) techniques. To set modeling, the input parameters are impact angle, densimetric Froude number, impingement length, and nozzle diameter. The models' training and testing were conducted using data available in the literature. The models' performances were compared with experiments. The results demonstrate that scour depth, length, width, and ridge height can be calculated more accurately than available equations. A rank analysis was also applied to obtain the most critical parameter in predicting scour parameters in water jet scouring. ABC-FFNN, VMD-ABCFFNN and EEMD-VMD-FFNN hybrid models were performed to obtain scour parameters. As a result, ABC-FFNN algorithms produced the best solution to predict the scour due to circular water jets, with the values for training (R^2: 0.331 to 0.778) and testing (R^2: 0.495 to 0.863).

Key words: artificial bee colony optimization, artificial neural network, scour hole characteristics, signal process, water jet

HIGHLIGHTS

- This study analyzed the scour due to water jets using metaheuristic algorithms based on artificial bee colony ABC.
- Metaheuristics optimized feed forward neural network (ABC-FFNN) and pre-processing techniques were used to predict the scour characteristics.

LIST OF SYMBOLS

B	the plunge pool width of (m)
d	the circular nozzle diameter (m)
D_{50}	median diameter of the sediment particles (m)
F_0	densimetric Froude number (–) $\left(U_0/\left(\sqrt{g\left(\frac{\Delta\rho}{\rho}\right)D_{50}}\right)\right)$
g	acceleration due to gravity (m s^{-2})
t_d	tailwater depth (m)
H	impingement length (m)
t	time (s)
T	relative tailwater depth (t_d/d)
U_0	jet velocity at the circular nozzle (m s^{-1})
Δ_m	maximum ridge height (m)

$x_1 + x_2$ scour hole length (m)
ε_m maximum scour depth (m)
θ impact angle (angle of jet to the water surface) (°)

ABBREVIATIONS

ABC artificial bee colony
ANN artificial neural network
ANFIS adaptive neuron-fuzzy inference system
DWT discrete wavelet transform
EMD empirical mode decomposition
EEMD ensemble empirical mode decomposition
GEP gene expression programming
GMDH group method of data handling
GBM gradient boosting machines
GP genetic programming
LGP linear genetic programming
ML machine learning
PSO particle swarm optimization
REMD robust empirical mode decomposition
SVM support vector machines
VMD variational mode decomposition

1. INTRODUCTION

Water jets are commonly applied in engineering fields such as chemical, environmental, civil engineering, and other disciplines. In addition to this, water jets are involved in engineering projects such as liquid-fertilizer injection, agricultural irrigation, oxygen transfer, pond water aeration systems, aeration, wastewater–potable water treatment and storm drainage pipes, aquaculture, and outlets of culverts. Numerous studies on circular water jets have been conducted in order to examine the effects of nozzle type, impact angle, plunge pool depth, impact velocity, nozzle dimension, momentum flux of the jet and jet Reynolds number for aeration, flotation processes, and oxygen transfer (Cummings & Chanson 1997; Ervine 1998; Zhang & Zhu 2015).

Scour is a crucial subject in the application of hydraulic engineering. Scour is a common phenomenon that lowers the riverbed level due to sediment evacuation caused by the erosive activity of a moving stream (Karbasi & Azamathulla 2017). It happens when hydrodynamic shear forces surpass the critical shear stress of sediment. The process appears in cohesive materials such as clay and highly eroded rocks. In other words, scour starts at the plunge pool when the bed shear stress applied by the underwater jet surpasses the critical bed shear stress for bed sediments. Scour can gradually degrade a structure's foundation and cause a devastating threat by decreasing support. Because of this, the prediction of the local scour forming in hydraulic structures has great significance. The engineering treatment of hydraulic structures provided after scour formation is costly. As a result, reliable estimation of scour depth and scour hole slopes can reduce failure risks. Also, understanding the water jets that create local scour downstream is critical to maintaining the safety and integrity of the hydraulic structure.

Numerous studies were conducted (Sarkar & Dey 2004; Pagliara *et al.* 2006, 2008; Aderibigbe & Rajaratnam 2010; Bombardelli *et al.* 2018; Kartal 2018; Kartal & Emiroglu 2021, 2022, 2023; Palermo *et al.* 2021) on jet scours in downstream pools but, Rouse (1939) was the pioneer of the study of scour caused by water jets. Most studies were investigated with circular nozzles in literature; however, the square-shaped, rectangular, and elliptical outlet structures were also utilized in water resources engineering (Canepa & Hager 2003; Kartal & Emiroglu 2023). Kartal & Emiroglu (2021) investigated the water jets scour and found that the water jets scour reduces if the plates are used in the water jets. Kartal & Emiroglu (2022) studied the scour morphology of the impinging jets. They stated that the slope upstream and downstream of the scour hole are nearly equal.

The dimensions of a scour hole are often determined using empirical formulas whose validity is limited to experimental conditions. Since developing physical models are exhausting, the scour hole parameters were used in this paper with previously conducted experimental runs in the literature (Kartal 2018; Kartal & Emiroglu 2021, 2022, 2023) to validate and convince the results were obtained. The safety of the downstream apron is threatened by downstream scour induced by the scour of water jets which can result in the hydraulic structures' failure. Therefore, sufficient preventive measures can only be engineered with a full recognition, location and magnitude prediction or scour extent at downstream. The scour event downstream of a steady or unsteady apron is highly complex because of the change of flow characteristics in the sediment layer over time. The scour depth is a function of jet angle, flow velocity, impingement distance, tailwater depth, median diameter of sediment, operating time, nozzle diameter, and many other parameters.

The scour hole development in the vertical dimension is faster than longitudinal. At the initial stage, sediment suspension is usually the only sediment transport mode. However, when the vertical dimensions of the scour hole decrease, the sediment transport mode becomes a combination of suspended and bed loads. As the scour increment rate nears zero, the equilibrium scour conditions are achieved asymptotically. It is challenging to estimate scour due to turbulent flow in an open channel, irregular and time-varying geometry, and complex sediment transport (Dey & Sarkar 2006).

Estimating the maximum scour depth with reasonable accuracy is important for properly managing, designing, and planning hydraulic structures. Scour is a dynamic and complex event influenced by several parameters which are related and difficult to comprehend. Nevertheless, deterministic models with different complexity degrees have been utilized to model the scour process with varying degrees of accuracy. As stated above, several researchers have examined scour in the control structures and suggested empirical equations for estimating scour dependent on laboratory experiments under different conditions of time, flow, tailwater, and sediment, etc. They are mainly based on experimental runs to examine scour through physical modeling.

Pal & Goel (2006, 2007) implemented SVMs successfully for estimating the final depth ratio and discharge for trapezoidal, circular, and semi-circular channels and reported good performance compared to empirical relationships. Due to the scour complexity, the proposed empirical formulas based on experimental runs are not precise enough to estimate the scour depth. A new era of data mining approaches, such as machine learning (ML) models for modeling and simulating various hydrological phenomena, has evolved over the past several decades with the development of high-speed processors and novel soft computing techniques (Ikram *et al.* 2022; Mostafa *et al.* 2023) The use of hybrid models and artificial intelligence (AI) for engineering applications has also been the subject of a great deal of research with success (Ikram *et al.* 2023a, 2023b). Besides, AI model creation is fast due to its straightforward architecture and minimal requirements for experimental data collection (Adnan *et al.* 2023a). Several AI methods such as gene expression programming (GEP), artificial neural networks (ANNs), genetic programming (GP), group method of data handling (GMDH), and model tree (MT) were applied to calculate scour in the hydraulic structures (Lee *et al.* 2007; Azamathulla *et al.* 2011; Pal *et al.* 2012; Akib *et al.* 2014; Najafzadeh *et al.* 2016; Shakya *et al.* 2022). As hydraulic model studies must be undertaken, which takes time and money, there is not currently suitable alternative method except for some soft computing models (Lashkar-Ara *et al.* 2016). ANNs have the usefulness of being practicable to a wider range of hydraulic conditions than traditional empirical models, which eliminates the need for the designer to choose the appropriate equation for the expected hydraulic conditions. Therefore, this study represents a significant advancement in the field of soft computing. Numerous AI techniques, including as ANNs (Kaya 2010), adaptive neuron-fuzzy inference system (ANFIS) (Farhoudi *et al.* 2010), decision trees (Etemad-Shahidi & Ghaemi 2011), linear genetic programming (LGP) (Azamathulla *et al.* 2011), GEP (Moussa 2013) and ML methods have recently been used for modeling difficulties in scour prediction. Liriano & Day (2001) stated that using ANN in scour prediction could result in a miscellaneous tool for engineers. Karbasi & Azamathulla (2017) used GEP, support vector regression (SVM), ANFIS, grouping method of data handling (GMDH) neural network and to estimate maximum scour depth at the downstream for the sluice gates. Their findings revealed that the ANFIS, ANN, GEP, and SVR approaches agreed well with the observed data. Karaboga (2005) introduced the artificial bee colony (ABC) algorithm and used to simulate the foraging behavior of a bee colony and to optimize numerical problems. Although several studies are based on ABC, there is limited study in hydraulic engineering applications. Therefore, the ABC was studied to estimate scour characteristics formed by oblique circular water jets in this study. This approach was chosen to leverage the capabilities of the feed-forward neural network (FFNN), known for its ability to represent intricate and non-linear relationships precisely. Specifically, the model was used to depict the scour hole characteristics caused by water jets, which have been notoriously difficult to capture using traditional linear methods accurately. In order to improve the ability of a regular FFNN to predict water jets, the ABC nature-inspired optimization algorithm was utilized to optimize the parameters of the FFNN. The ABC-FFNN algorithm employed in the study was favored for its capability to handle noisy data, tackle non-linear and intricate problems, and flexibly model the correlation between various datasets. In addition, the ABC-FFNN hybrid model was combined with the VMD and EEMD signal decomposition approaches to evaluate the water jet prediction accuracy of the EEMD-ABC-FFNN and VMD-ABC-FFNN models. Local scour formed by circular water jets in the downstream pool were analyzed for high F_0 (densimetric Froude number) values (34.7–159.22). The impact angle (θ), relative tailwater ($T = t_d/d$), impingement distance (H), nozzle diameter (d) and densimetric Froude number ($F_0 = U_0/\sqrt{g\,D_{50}\frac{\rho_s-\rho}{\rho}}$) on scour characteristics were analyzed. To the best of our knowledge, numerous studies have introduced with the use of ABC in hydraulic engineering, but no study has conducted its use for water jet scour prediction. VMD and EEMD data pre-processing techniques can transform signals into intrinsic mode functions (IMFs) that reflect the raw data's local properties. Components representing the main dataset are obtained and data noise is removed. In addition, the trends and features in the data are modeled more comprehensively, allowing the prediction model to be developed. The effect of VMD and EEMD methods on the estimation performance of the established model varies according to the data set and data type. These methods can improve the performance of AI models by reducing residuals in the data and modeling each IMF separately, reducing noise and grouping different frequencies (Lei *et al.* 2019; Xie *et al.* 2020). The current study aimed to investigate the local scour depth using metaheuristic ABC-optimized feed-forward neural network (ABC-FFNN) and pre-processing techniques. In order to obtain this goal, the accuracy of the ABC and pre-processing techniques were compared with those of the scour depth obtained from the previous studies (Kartal 2018; Kartal & Emiroglu 2021, 2022, 2023).

2. MATERIALS AND METHODS

To analyze scour due to water jets, ABC, the FFNN metaheuristic logarithms, variational mode decomposition (VMD), ensemble empirical mode decomposition (EEMD), and Rank Analysis were applied.

2.1. Data used

The effectiveness of the Metaheuristic ABC-Optimized Neural Network and Pre-processing Techniques for modeling scour in water jets was evaluated using the experimental data sets conducted by (Kartal 2018; Kartal & Emiroglu 2021, 2022, 2023). Experimental data set has 144 runs with six nozzle diameter (10, 15, 20, 28, 34, 40 mm) and three impact angles (30°, 45°, 60°), four impingement distances (10, 15, 20, 30 cm) were get from the studies of them. Median diameter of sand and tailwater depth was kept constant. All experiments were conducted in unsubmerged flow conditions.

2.2. Artificial bee colony

The algorithm was introduced in 2005 by Karaboga (2005). It is modeled from the behavior of a honey bee colony. It can be used for smart system models due to its several features (communication, task selection, foraging, decision-making of the collection, etc). Every model for a particular task describes every behavior. By performing a series of movements referred to as a waggle dance, the bees communicate information about the location of food sources. The queen produces all the eggs in a bee honey colony. It is classified into three groups: employed bees, looker bees, and scouts. The utilized bees are located in the first colony part, whereas the on-lookers are in the second part. The employed bee's source of food consumed by the bees will be scouted to search for new food sources randomly (Karaboga & Basturk 2007, 2008).

2.3. Metaheuristic algorithms

Metaheuristic algorithms are applied techniques to various problems to obtain near-optimal solutions at a competitive computation cost-efficiently (Hemeida *et al.* 2020). They are intelligent approaches to handling various complex issues efficiently. Deterministic methods execute analyses based on their strong analytical capabilities. However, heuristic methods are typically more adaptable and less likely to produce generic or confusing solutions throughout the implementation phase (Adnan *et al.* 2023b). Such methods depend on distinct agents, ensure global population optimization, and avoid suboptimal local optimization. The most important key in designing meta-heuristics is the ability to conduct large-scale exploitation and exploration. Meta-heuristics fall into two categories: single solution-based methods and population-based methods. While single solution-based methods such as tabu search (Elhedhli *et al.* 2014), emulated annealing (Liu *et al.* 2017), etc., population-based methods contain evolutionary methods such as particle swarm optimization (PSO) (Rathore & Sharma 2017), ABC optimizations (Alatas 2010), cuckoo search algorithm (CS) (Shehab *et al.* 2017). PSO was introduced as a global optimization method in 1995 (Sharma & Pandey 2016; Morra *et al.* 2018). PSO employs to model the loose and unpredictable behavior of flocks of birds to get a solution for the optimization problem.

2.3.1. The FFNN

FFNN consists of hidden layers that are an input and output layer. The links with every neuron for a layer and all neurons for the following layer symbolize the weights (w). The weights symbolize how strong the link with neurons is. Any pattern in

$P = \{1, 2, 3, \ldots p\}$ is transmitted to the input layer in vector form. Every neuron gets inputs from other neurons, acquires aggregation of the weights, performs an activation function on the weighted sum, and produces outputs to other neurons in the network. The output of the neurons in the output layer constitutes the network output (Svozil *et al.* 1997; Ma & Khorasani 2003). The output for every neuron for the hidden layer is computed using the following formula:

$$s_h = \sum_{i=1}^{n} s_i \times w_{ih} \tag{1}$$

The output is computed below for a neuron L of the output layer:

$$o_L = \sum_{i=1}^{n} s_h \times w_{hL} \tag{2}$$

2.4. ML and decomposition models

The scour prediction performance of models is compared with ABC-FFNN, EEMD-ABC-FFNN, and VMD-ABC-FFNN hybrid algorithms. In the selection of ML algorithms, 80% of the data were utilized for training, while %20 of data was used for testing (Katipoğlu 2022). In addition, five parameters were used as an input.

2.4.1. Empirical mode decomposition

EMD presents adaptive instantaneous frequency-based IMFs, extensively deployed to flexibly analyze multichannel data with linear and non-stationary time series (Sarıgöl & Katipoğlu 2023). Every IMF is representative of a simple oscillation in the signal. The frequencies and amplitudes of IMFs are not steady but can vary with time. If $x(n)$ is stated as a time series:

The model adaptively decomposes a non-stationary signal into a series of IMFs from high frequencies to low frequencies, and the decomposed signal can be described as:

$$x_i = \sum_{i=1}^{N} C_i(t) + r_{N(t)} \tag{3}$$

Here, $r_N(t)$: residual of signal, $C_i(t)$: ith IMF $x(t)$ (Kedadouche *et al.* 2016).

2.4.2. Ensemble empirical mode decomposition

Even though EMD is extensively employed in non-stationary and/or non-linear signal analysis, its decomposition results are subject to various problems due to mode mixing. The EMD ensemble method was developed to eliminate this problem. When repeatedly decomposing the signal into IMFs with the EMD method, finite-amplitude white noise is injected into the original signal. The averages of the IMFs produced from each trial are denoted as the IMFs of the EEMD method. In this way, the mode mixing problem is canceled by EEMD (Wu *et al.* 2009; Zhang *et al.* 2010).

2.4.3. Variational mode decomposition

It recursively separates a real-valued multicomponent signal f into quasi-vertical band-limited sub-signals. In addition, all modes are compact around a center vibration. Therefore, the equation of the limited variational problem can be formulated the following:

$$\begin{cases} min\left\{\sum_{1}^{K}\left\|\partial t\left[\left(\delta(t)+\frac{i}{\pi t}\right)u_k(t)\right]e^{-jw_k t}\right\|_2^2\right\} \\ \qquad\qquad \{u_k\}, \{w_k\} \\ \qquad\qquad s.t \sum_{k=1}^{K} u_k = f \end{cases} \tag{4}$$

where w_k shows the frequency center of each IMF, $\{w_k\} = \{w_1, w_2, \ldots, w_k\}$; $\{u_k\} = \{u_1, u_2, \ldots, u_k\}$ u_k refers to decomposed band-limited IMF (Wang & Markert 2016).

2.5. Performance indices

This study used six statistical metrics, such as straightforward interpretation, robustness to outliers, direction of the erroneous bias, and quality of a model's fit to evaluate model performance. Thus, the predictive accuracy of the established models was assessed from various perspectives, and the model with the highest score was selected by rank analysis (Botchkarev 2018; Onyutha 2021). These metrics evaluate the estimation performance of water jet-induced scour hole features. The following equations were used to calculate these metrics.

$$\text{Coefficient of Determination } (R^2) \quad R^2 = \frac{\sum_{i=1}^{n}(o_i - o_{\text{mean}})^2 - \sum_{i=1}^{n}(o_i - p_i)^2}{\sum_{i=1}^{n}(o_i - o_{\text{mean}})^2} \tag{5}$$

$$\text{Bias factor } = \frac{1}{N}\sum_{i=1}^{n}\frac{p_i}{o_i} \tag{6}$$

$$\text{Mean square error(MSE)} \quad \text{MSE} = \frac{1}{N}\sum_{i=1}^{n}(p_i - o_i)^2 \tag{7}$$

$$\text{Mean absolute percentage error(MAPE)} \quad \text{MAPE} = \frac{1}{N}\sum_{i=1}^{n}\left|\frac{o_i - p_i}{o_i}\right| \tag{8}$$

$$\text{Mean absolute error(MAE)} \quad \text{MAE} = \frac{1}{N}\sum_{i=1}^{n}|(p_i - o_i)| \tag{9}$$

$$\text{Meanbiaserror(MBE)} \quad \text{MBE} = \frac{1}{N}\sum_{i=1}^{n}(p_i - o_i) \tag{10}$$

where o is the observed value and p is the predicted value, o_i and p_i are the observed and predicted ith value. Error-values close to 0, and R^2 and bias factor values close to 1 indicate the most accurate possible estimation results.

2.6. Rank analysis

Individual ranking values were calculated within this study to determine the best model from the models in which many statistical indicators were employed. A rank was assigned to each performance parameter, the best-performing model was placed third, and the lowest-performing model was given the first rank. While the model with the highest overall ranking value is considered the best, the model with the lowest is regarded as the worst (Zhang *et al.* 2020).

3. RESULTS AND DISCUSSIONS

In this section, the developed approaches for scour prediction are evaluated, and statistical parameters for accuracy assessment are given based on the scour characteristics in Figure 1.

The EEMD-ABC-FFNN, ABC-FFNN, and VMD-ABC-FFNN hybrid models were utilized to predict and analyze scour due to circular water jets. Figure 2 shows the various IMFs and residues obtained by Model 2's EEMD algorithm. Accordingly, each subcomponent (F_0, T, H/d, θ, d) was established as presented to the ABC-FFNN algorithm and the EEMD-ABC-FFNN hybrid model.

Figure 3 indicates the subcomponents of Model 2, which are separated into various IMF and residuals by the VMD algorithm. Accordingly, each subcomponent was presented to the ABC-FFNN algorithm and a VMD-ABC-FFNN hybrid approach was obtained.

The estimation success of the model results designed in Table 1 was evaluated according to various statistical parameters. The model with the smallest error coefficient, the Bias Factor and R^2 value closest to 1 was evaluated as the best. Accordingly, the AI predictions with Models 1, 2 and 3 are compared. As seen from Table 1, the ABC-FFNN model produced the most successful predictions. The EEMD-ABC-FFNN hybrid algorithm showed the weakest predictions in the M2 combination, while the VMD-ABC-FFNN hybrid algorithm showed the weakest predictions in the M1 and M2 combination. Furthermore,

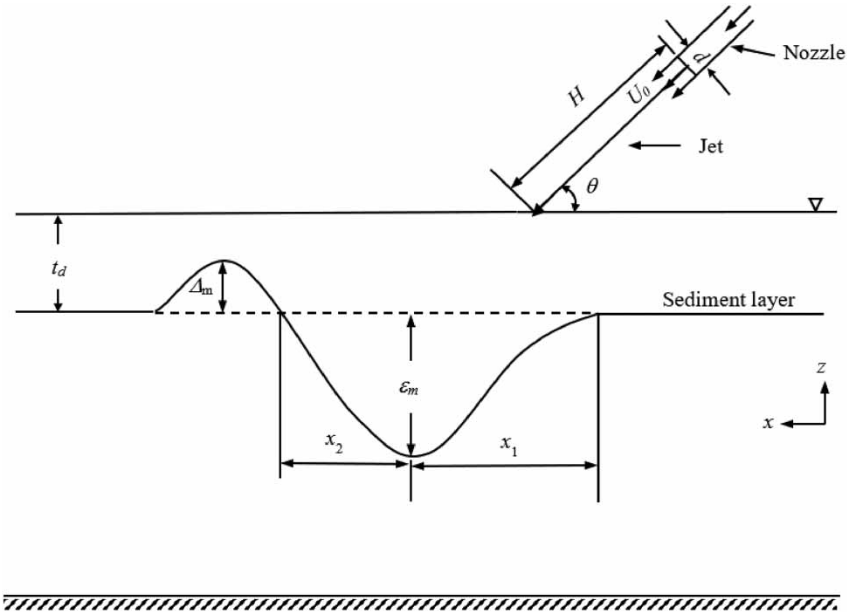

Figure 1 | Longitudinal section.

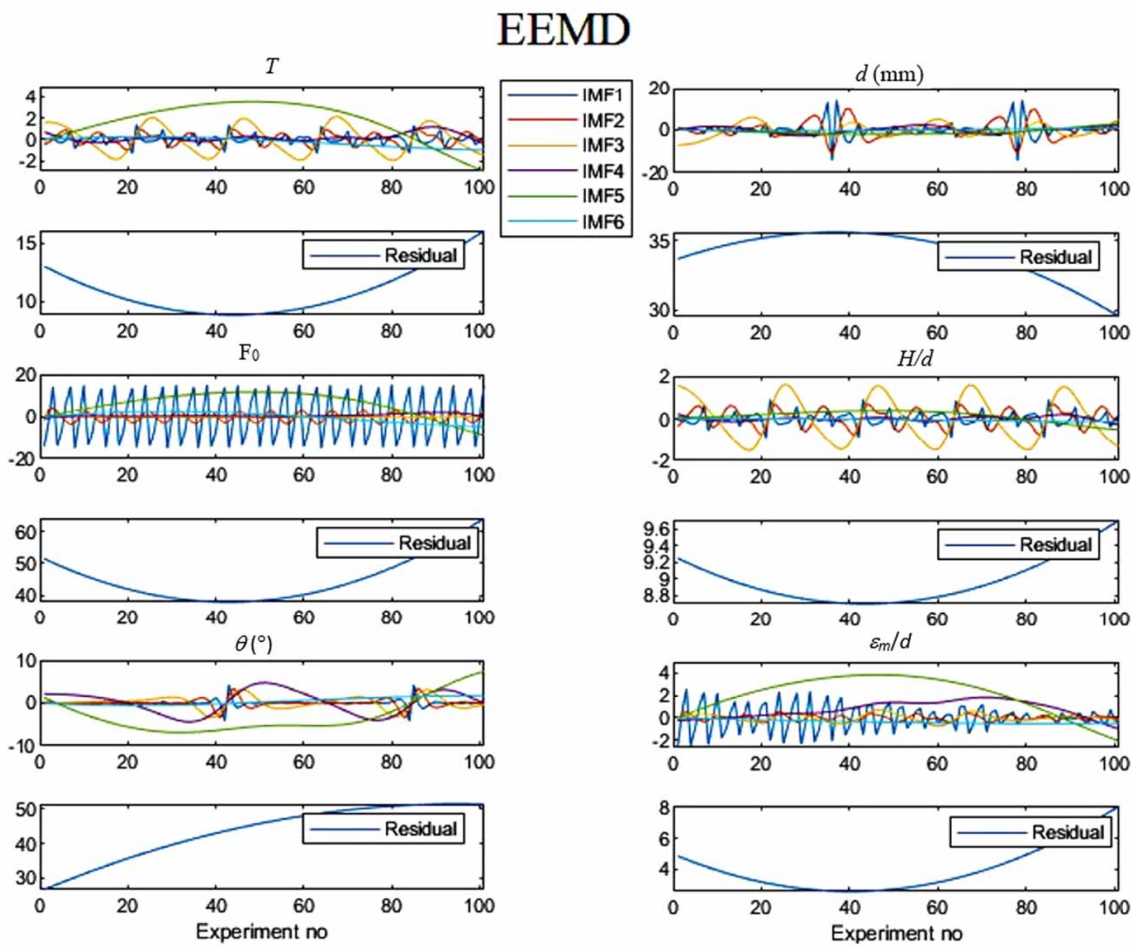

Figure 2 | Input variables separated into sub-bands by EEMD algorithm.

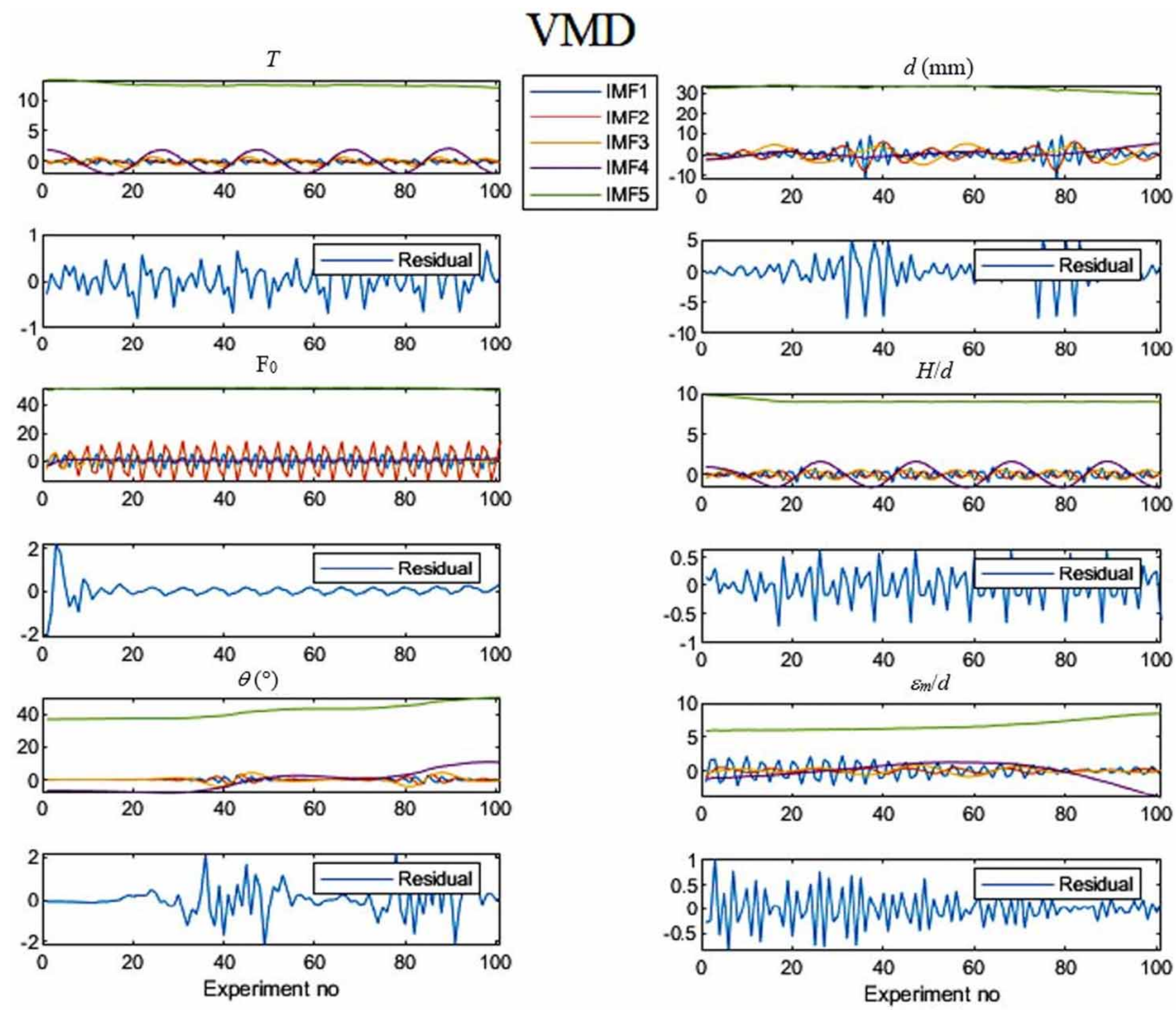

Figure 3 | Input variables separated into sub-bands by VMD algorithm.

out of all the input combinations, the ABC-FFNN algorithm with Model 1 structure yielded the most accurate predictions, with R^2 values of 0.778 for training and 0.680 for testing.

The prediction accuracies of the models created in Figure 4 were compared with the polar plot of various statistical indicators. Accordingly, it is seen that the ABC-FFNN model shows the most accurate results with the lowest error and the highest R^2 in the training phase of the M1 combination. However, in the testing phase, it can be said that the EEMD-ABC-FFNN model, which shows the lowest MAPE value and the MBE value closest to 0, gives the most accurate results. It is seen that the model showing the lowest MAPE and the highest R^2 value during the training and testing phase of the M2 combination is ABC-FFNN. EEMD-ABC-FFNN of the model showing the lowest MAPE and the highest R^2 value is seen in the training phase of the M3 combination. However, the lowest MAPE and the highest R^2 value are seen in the ABC-FFNN model.

The prediction successes of the models established in Figure 5 were evaluated according to the scatter plot. In these graphs, the actual and estimated values were compared, and the model with the regression line closest to a slope of 45 degrees was chosen as the most suitable model. Accordingly, the model that best represents the real values in all model combinations is seen as ABC-FFNN with a slight difference.

Table 1 | Statistical comparison of the established model

		MSE	MAE	MAPE	MBE	Bias Factor	R^2	Total Rank
	MODEL 1							
ABC-FFNN	Train	0.449	0.475	0.134	−0.012	1.058	0.778	**53**
	Rank	6	6	6	5	5	5	
	Test	19.389	2.653	0.239	−1.526	0.97	0.680	
	Rank	2	3	3	2	6	4	
EEMD-ABC-FFNN	Train	0.666	0.617	0.173	0.004	1.073	0.656	48
	Rank	5	5	5	6	4	3	
	Test	10.196	2.677	0.419	0.894	1.085	0.863	
	Rank	3	2	3	3	3	6	
VMD-ABC-FFNN	Train	1.290	0.831	0.242	0.015	1.121	0.331	24
	Rank	4	4	2	4	2	1	
	Test	34.354	5.161	0.883	−2.532	0.817	0.495	
	Rank	1	1	1	1	1	2	
	MODEL 2							
ABC-FFNN	Train	0.700	0.660	0.121	−0.026	1.021	0.757	**53**
	Rank	6	6	6	6	6	6	
	Test	20.572	3.236	0.38	−2.409	0.826	0.689	
	Rank	3	3	3	1	3	4	
EEMD-ABC-FFNN	Train	0.883	0.747	0.148	0.072	1.054	0.693	41
	Rank	5	5	5	5	5	5	
	Test	26.005	4.288	0.664	0.471	1.403	0.457	
	Rank	2	2	2	2	1	2	
VMD-ABC-FFNN	Train	1.579	0.961	0.201	0.141	1.095	0.458	32
	Rank	4	4	4	3	4	3	
	Test	42.117	5.847	0.852	−0.136	1.397	0.148	
	Rank	1	1	1	4	2	1	
	MODEL 3							
ABC-FFNN	Train	6.238	1.917	0.060	0.070	1.010	0.875	**51**
	Rank	6	6	6	6	6	5	
	Test	165.891	11.703	0.325	−4.118	0.787	0.904	
	Rank	3	2	2	2	1	6	
EEMD-ABC-FFNN	Train	8.919	2.343	0.073	−1.342	0.963	0.855	40
	Rank	5	5	5	4	4	4	
	Test	365.637	15.915	0.406	−3.975	0.965	0.646	
	Rank	1	1	1	3	5	2	
VMD-ABC-FFNN	Train	32.168	4.194	0.130	0.426	1.039	0.353	35
	Rank	4	4	4	5	3	1	
	Test	213.109	10.972	0.272	−5.206	0.908	0.798	
	Rank	2	3	3	1	2	3	

Note: Bold characters represent the optimum model.

In Figure 6, a comparison of the potential of estimation models with Boxplot is made. Boxplots provide visual information about data distribution, spread and quarterly slices. It was deduced that among the models established with the M1 combination, the ABC-FFNN algorithm showed the best results since the boxplot structure showed the highest similarity with the real data. In the prediction model built with the M2 model combination, it is seen that the box structure of the prediction results of the EEMD-ABC-FFNN algorithm in the training phase and the ABC-FFNN algorithms in the testing phase is the closest to the real data. In M3 model combination predictions, the ABC-FFNN algorithm in the training phase and the VMD-ABC-FFNN algorithm in the test phase show the best results.

Taylor diagrams of the waterjet prediction models set up are shown in Figure 7. Taylor diagrams are used to visualize the relationship between actual data and predicted data, standard deviation and error level. The estimation results with the lowest

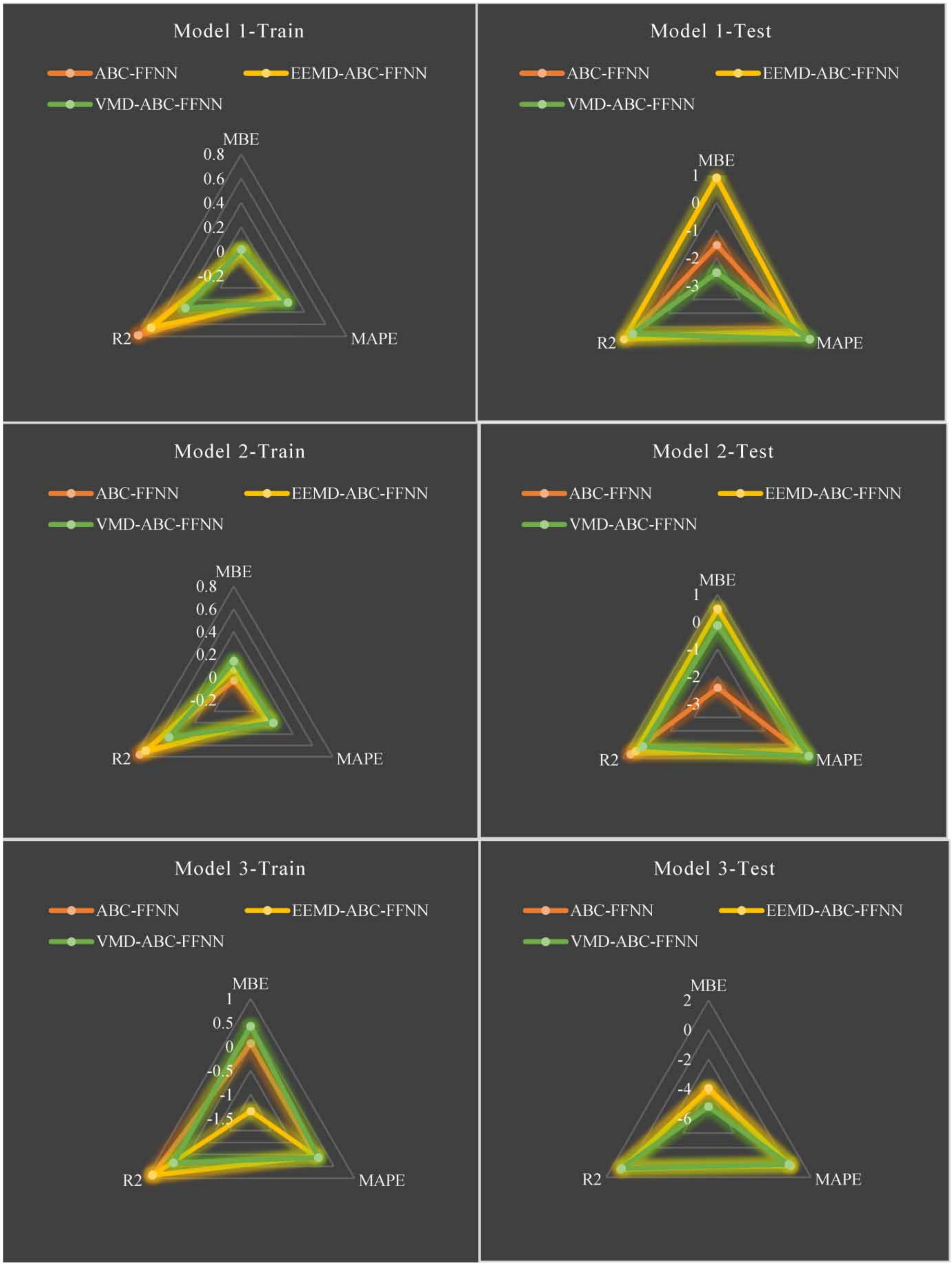

Figure 4 | Performance evaluation of established model results with Polar plot.

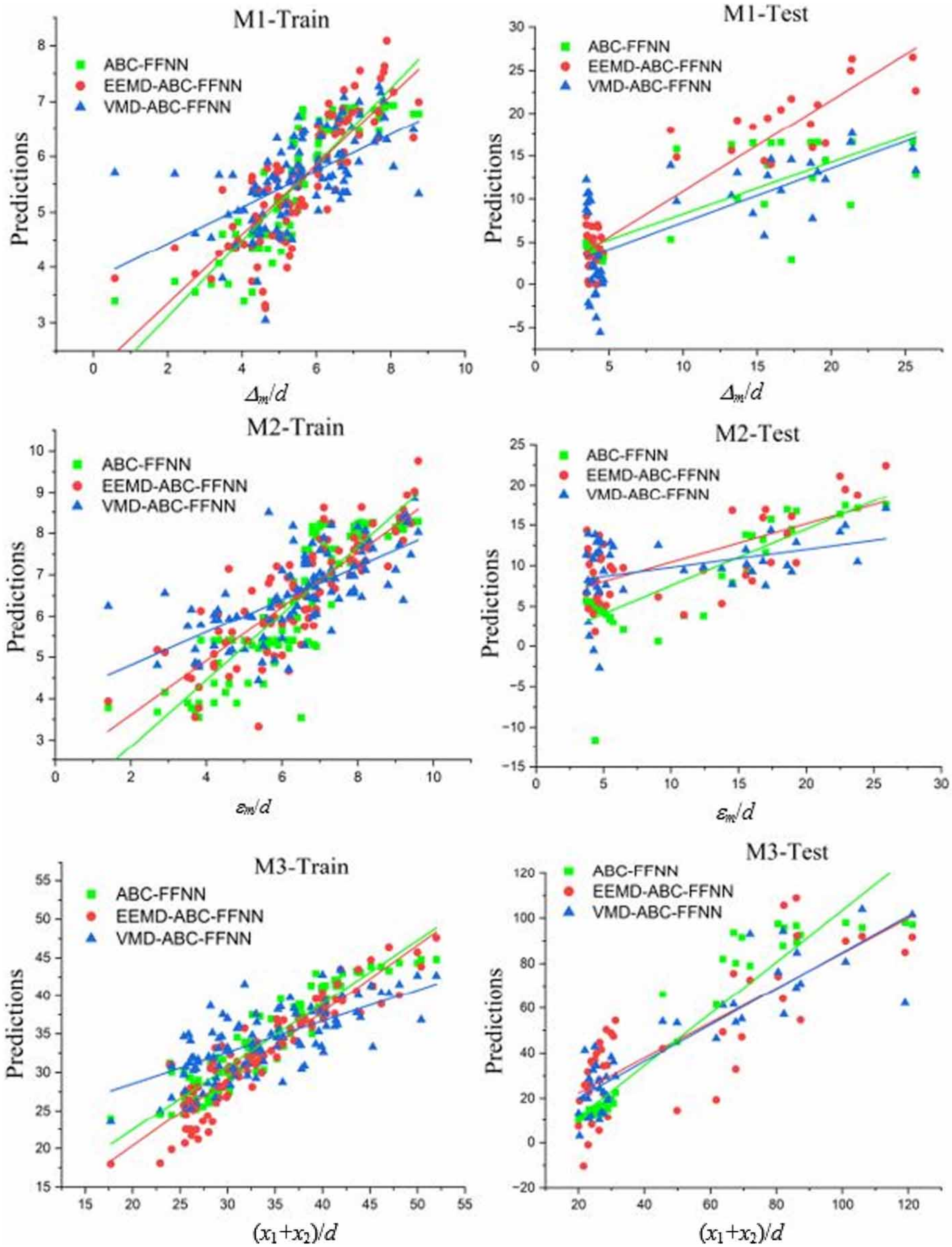

Figure 5 | Scatter plots of model predictions.

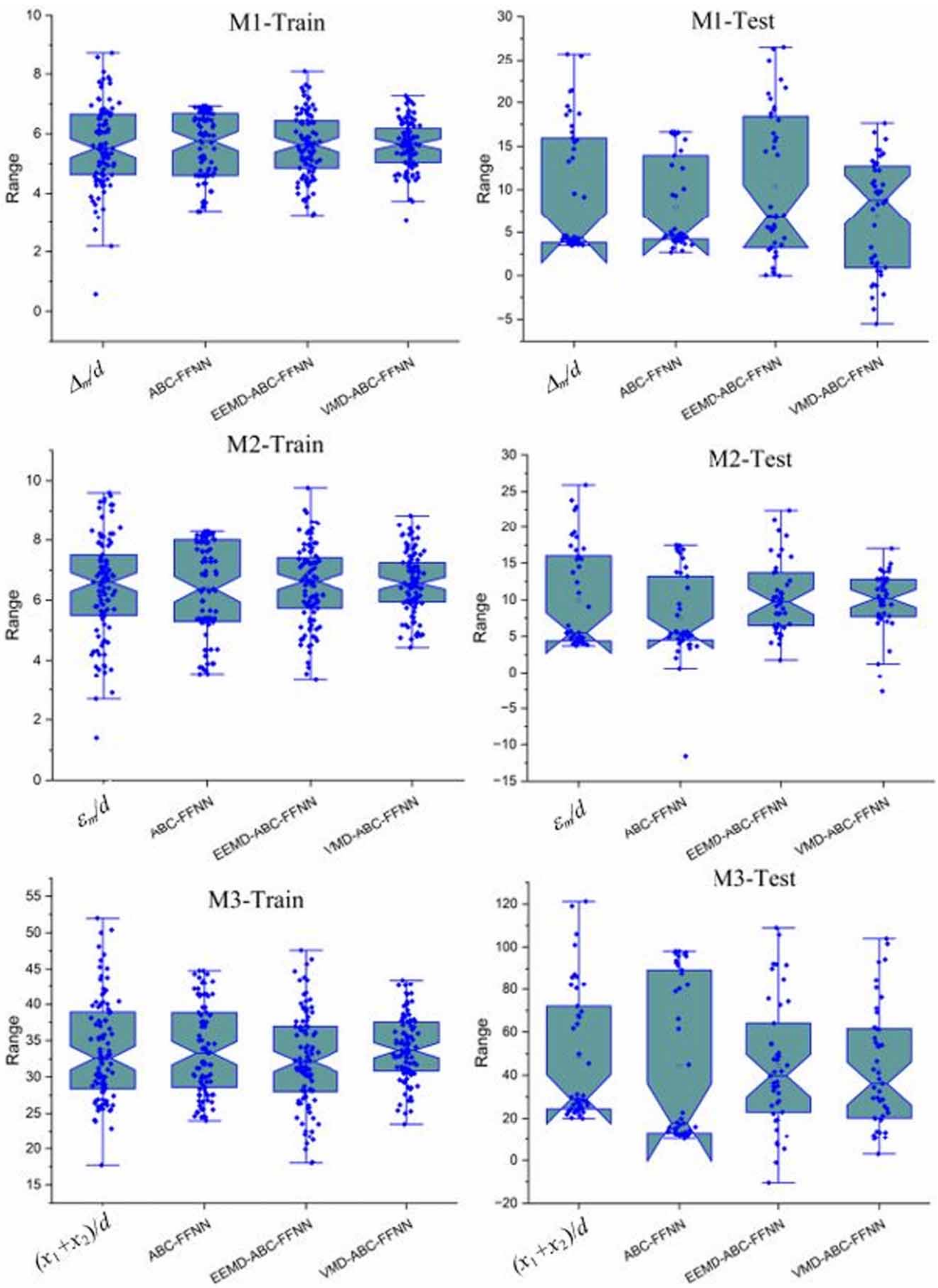

Figure 6 | Comparison of model performances with Boxplot.

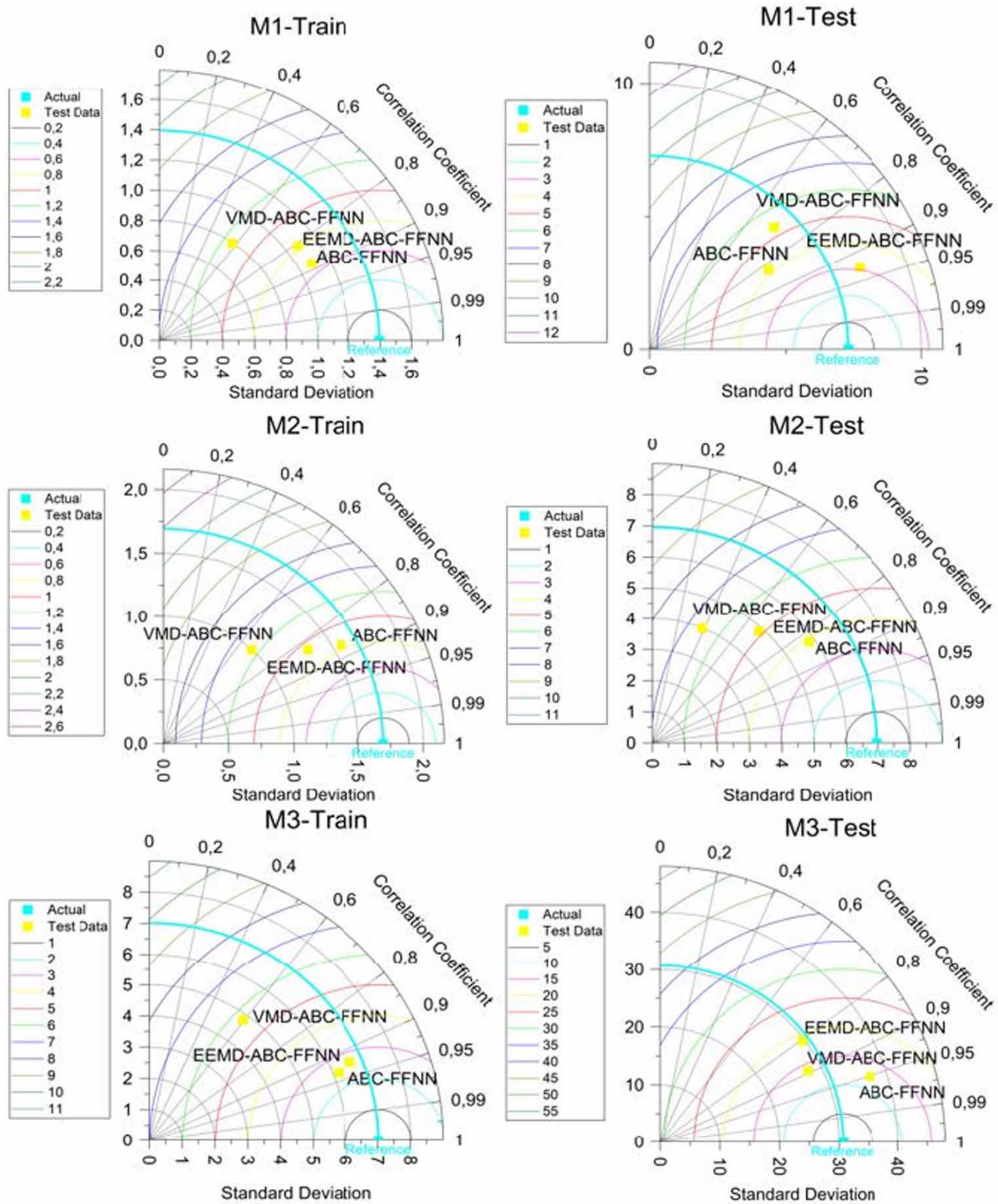

Figure 7 | Evaluation of model performances according to Taylor diagrams.

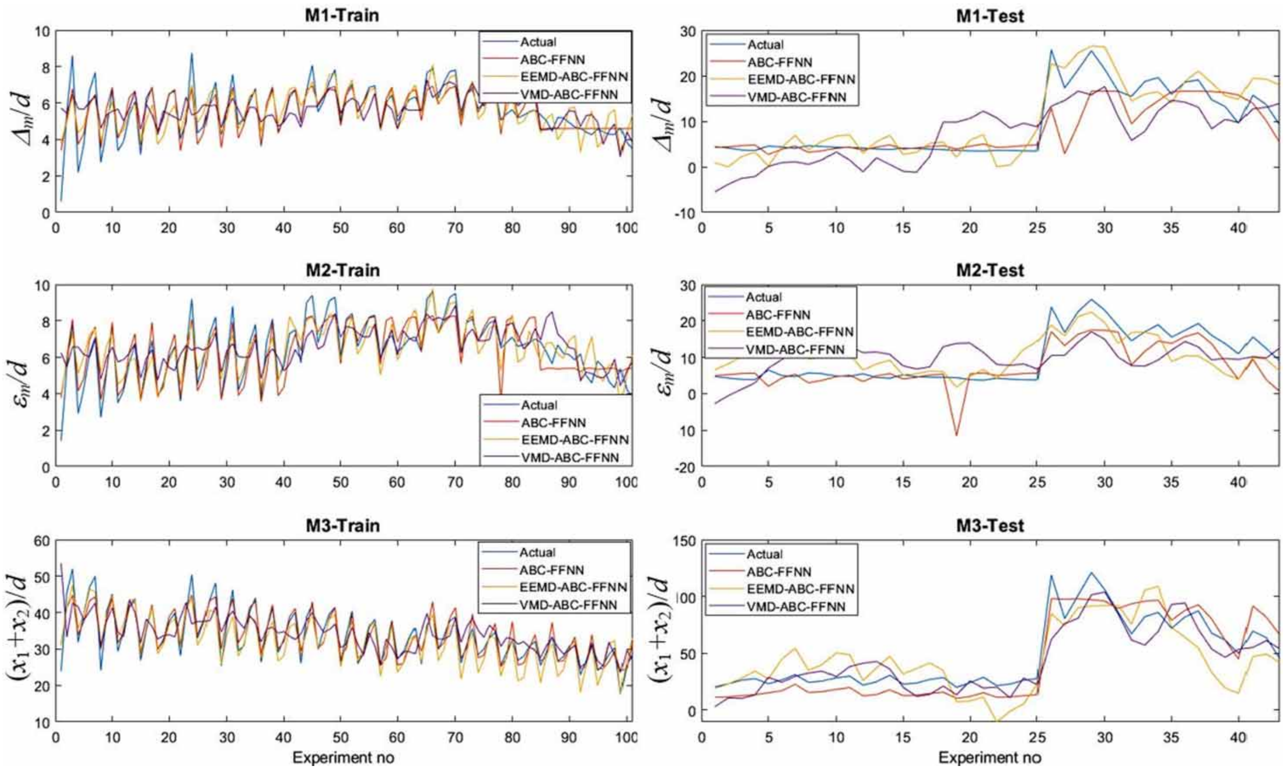

Figure 8 | Time series variation of prediction models.

model error, the highest R-value, and the closest standard deviation and position to the real data show the optimal result. Accordingly, while the ABC-FFNN algorithm gives the most accurate results in the training phase of the M1 model, it is the EEMD-ABC-FFNN algorithm in the test phase. In the training and testing phase of the M2 model, the most accurate predictions were produced with the ABC-FFNN model. In addition, the more precise prediction results in the training and testing phase of the M3 model were obtained with ABC-FFNN hybrid approaches.

In Figure 8, the potential of estimation models is evaluated with temporal variation graphs. Accordingly, among the models established with the M1 combination, in the ABC-FFNN algorithm training phase, the EEMD-ABC-FFNN algorithm, on the other hand, overlaps with the real time series during the testing phase. The prediction model built with the M2 model combination overlaps with the real time series of ABC-FFNN algorithms in the training and testing phase. In the M3 model combination predictions, ABC-FFNN in the training and testing phase showed similar oscillations with the real data. As a result, it is seen that the prediction performance of all models is satisfactory. However, the ABC-FFNN algorithm showed more accurate results, albeit slightly. There are several studies with soft computing techniques to estimate the scour (Karbasi & Azamathulla 2017; Lashkar-Ara *et al.* 2016), however the ABC algorithm with the combined hybrid model (EEMD-ABC-FFNN and VMD-ABC-FFNN) used in this study. These techniques can help AI models perform better with the help of reduced residuals in the data. These model types and estimating strategy that are suggested make a substantial contribution to the literature.

4. CONCLUSIONS

The study presents the results of scour prediction in non-cohesive sediments by oblique circular jets through experimental observations and modeling analysis. The present study was carried out to Metaheuristic ABC-FFNN and pre-processing techniques in scour prediction due to water jets using experimental data sets. The Metaheuristic ABC-FFNN and pre-processing techniques produced satisfactory results compared to backpropagation with experimental data for Kartal & Emiroglu (2021, 2022, 2023) data sets. Furthermore, significant differences in scour depth can affect the estimation of scale-up, flow, geometry, and material conditions. Nevertheless, the results of this study may encourage the use of EMD, EEMD, FFNN, VMD, ABC and pre-processing techniques in predicting the scour in water jets. It is seen that the prediction performance of all models is satisfactory. However, the ABC-FFNN algorithm showed more accurate results, the albeit slightly. It is also seen that the box structure of the prediction results of the EEMD-ABC-FFNN algorithm in the training phase and the ABC-FFNN algorithms in the testing phase is the closest to the real data. In M3 model combination predictions, the ABC-FFNN algorithm in training phase and the VMD-ABC-FFNN algorithm in the test phase showed the best results the ABC-FFNN model produced the most successful predictions, while the EEMD-ABC-FFNN model showed the weakest predictions. In addition, among all input combinations, the ABC-FFNN algorithm with Model 1 structure with training: 0.778 and testing: 0.680 produced the most accurate predictions. Although the model produced good estimation, it has some drawbacks including being a complex and have need of more parameters for training. In order to train the network and verify its efficacy, a comprehensive data set must be provided in further investigation.

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AUTHOR CONTRIBUTIONS

Each author participated in the concept and design of the study and contributed the draft of manuscript. V.K. and M.E.E. prepared the material, collected, and analyzed the data. E.K. drafted and edited the manuscript. O.M.K. conducted the analysis. All authors read and approved the final manuscript.

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DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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