DOI: 10.5604/01.3001.0014.8742
Volume 105 • Issue 1 • March 2021

Journal of Achievements in Materials and Manufacturing Engineering

International Scientific Journal published monthly by the World Academy of Materials and Manufacturing Engineering

Predictive models for estimation of labyrinth weir aeration efficiency

Aradhana [a], B. Singh [b,*], P. Sihag [c]
[a] Civil Engineering Department, National Institute of Technology, Kurukshetra, India
[b] Civil Engineering Department, Panipat Institute of Engineering and technology, Samalkha, India
[c] Civil Engineering Department, Shoolini University, Solan, India
* Corresponding e-mail address: balrajzinder@gmail.com
ORCID identifier: https://orcid.org/0000-0002-0381-4363 (B.S.)

ABSTRACT

Purpose: The purpose of the study is to estimate the aeration efficiency (E_{20}) of Labyrinth weir using artificial intelligent (AI)-based models.

Design/methodology/approach: The aeration efficiency (E_{20}) was collected by using the nine models of Labyrinth weir with different shapes and dimensions. A total of 180 observations were used out of which 126 used to train the AI-based models and the remaining used to test the model. This observation consists of input variables such as Fraud number (Fr), Reynolds number (Re), numbers of keys (N), the ratio of head to the width of the channel (H/W), the ratio of crest length to width of the channel (L/W), the ratio of drop height to width of the channel (D/W) and shape factor (SF) and E_{20} as the output variables. The AI-based models used were Fuzzy Logic, multi-linear regression (MLR), adaptive neuro-fuzzy interface system (ANFIS), and artificial neural network (ANN).

Findings: The main findings of this investigation are that ANN is the best AI-based model that can estimate the E_{20} accurately than MLR, ANFIS, and Fuzzy Logic. Sensitivity analysis depicts that drop height at labyrinth weir is the essential factors for the estimation of E_{20}; further, parametric studies have also been performed.

Research limitations/implications: The proposed AI-based models can be used in the estimation of E_{20} with different shapes of labyrinth weir but still it needs improvement for the different dimensions.

Practical implications: The best AI-based model can be used to calculate the E_{20} with the different values of input variables.

Originality/value: There are no such AI-based models such as ANN, ANFIS, and Fuzzy Logic, available in the literature which can estimate the values of E_{20} accurately.

Keywords: Labyrinth weir, Oxygen aeration efficiency, ANN, Fuzzy logic, ANFIS

Reference to this paper should be given in the following way:

Aradhana, B. Singh, P. Sihag, Predictive models for estimation of labyrinth weir aeration efficiency, Journal of Achievements in Materials and Manufacturing Engineering 105/1 (2021) 18-32. DOI: https://doi.org/10.5604/01.3001.0014.8742

ANALYSIS AND MODELLING

1. Introduction

Oxygen is imperative and vital for underwater life. It is significant to support and facilitate the survival of organisms, to endure species breeding, and for the growth of populaces. Oxygen is dissolved in water, and it is proportional to the pressure for the gaseous phase, but it declines as temperature declines. The entry of oxygen in the water from the atmosphere by absorption from the ambient or through the process of photosynthesis. It is taken away by organisms' respiration as well as by organic decay. Flora and fauna use dissolved oxygen during respiration, decomposition, and release CO_2 [1]. Aeration efficiency (E_{20}) is the process by which air is entrapped into the water from the surrounding ambient and used to improve the quality. The structures enhance the volume of DO in the water body, even though water is in touch with the hydraulic structure for just a brief spell. The same level of oxygen transfer would usually take place over various distances in a water body can take place at an individual structure. The principal cause attributed for this speed-up aeration is mainly oxygen-air is entrapped into the discharge by generating bubbles more significant in size and also more in numbers. These air bubbles significantly enhance the area of interface between ambient and flow surface for mass transfer [2]. A labyrinth weir is characterized as a non-linear weir for which the weir crest is not linear in plan-view unlike conventional linear weir as shown in Figure 1.

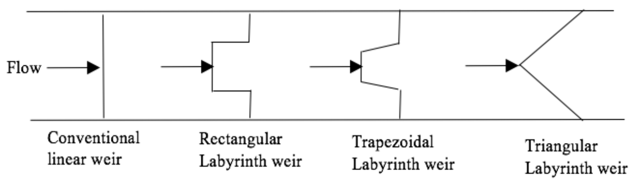

Fig. 1. General plan-view of rectangular, trapezoidal and triangular labyrinth weir

The enlarged crest length of labyrinth weirs provides them with a cutting edge of dropping upstream head for a specific flow rate. Cassidy et al. [3] demonstrated how these weirs could be effectively employed to enhance the spillway crest length. Further, Hay & Taylor [4] and Taylor [5] performed experiments and showed the advantages of these weirs in case of the limited width of the channel.

The flow rate over labyrinth weirs is exceeded than that of the corresponding conventional straight weir in the proportion of the weir crest lengths at low heads; however, it has been observed that as the head over the labyrinth weir reaches a certain threshold value depending on the shape and plan-form of the weir, the discharge ratio falls below that of the weir crest lengths because of collision and interference of the downstream over fall jets which ultimately tends to 'throttling' of the weir due to the spaces between the weir sections on the downstream side filled with water. It effectively becomes a conventional straight broad-crested weir.

Firstly, Gameson [6] reported on the aeration performance of linear weirs in rivers. After that, several researchers [7-12] examined the aeration potential of weirs. The Avery and Novak [9] model comes out from this comparison as slightly better for weir structures. Thus, a great deal of the work has been reported related to conventional linear weirs. Free overfalls amongst other structures and a very few works reported on non-linear labyrinth weirs which include Wormleaton & Soufiani [13], and Wormleaton & Tsang [14] showed that non-linear triangular and rectangular planform labyrinth weirs do have better oxygen aeration performance over conventional linear weirs respectively. But no modelling techniques have been employed to predict aeration performance of the non-linear labyrinth weirs using artificial intelligent (AI)-based techniques. Artificial intelligent-based techniques are used rapidly as problem-solving techniques in civil engineering and water resources projects. Many researchers used these techniques in the prediction of the output [15-25]. So, the main motto of the work is to evaluate and examine the suitability of labyrinth weir for measuring the aeration efficiency for the flow surface aeration in the laboratory, and further present work was also performed to investigate the potential of three modelling methods viz. ANN, Fuzzy logic, and ANFIS in generating models for estimating aeration efficiency as classical methods could not succeed due to the complicated flow characteristics and many geometric design variables involved there over, and above direct measurement of oxygen aeration efficiency is time-consuming and costly businesses either in the field or laboratory.

1.1. Oxygen aeration parameters

The oxygen aeration efficiency, E, at any temperature, T° C is outlined as [26].

$$E = 1 - \frac{1}{r} = \frac{C_{\frac{D}{S}} - C_{\frac{U}{S}}}{C_S - C_{\frac{U}{S}}} \tag{1}$$

where $\frac{D}{S}$ and $\frac{U}{S}$ are subscripts showing downstream and upstream locations, respectively & S subscript shows saturation. At the same time, C stands for the dissolved oxygen (DO) concentration (ML^3) while r denotes the oxygen deficit ratio. Further, E is aeration efficiency dependent on water temperature and generally oxygen aeration efficiency, E is normalized to 20°C which is denoted as $e_{20}$for the study and given by

$$1 - E_{20} = 1 - E^{\frac{1}{(1.0+0.02103(T-20)+8.261x10^{-5}(T-20)^2)}} \quad (2)$$

In which, T is the temperature in degree Celsius.

1.2. Aeration mechanism

The mechanisms through which aeration takes place and oxygen transferred into the water for the free-falling plunging jet are several and very complicated processes. Gameson [6] showed three stages of oxygen transfer. These are (a) during the fall (b) through the receiving free surface of water pool (c) in the water-ambient air biphasic interface, but one more additional step (d) was included and identified by Tsang [27] and which are depicted in Figure 2. The aeration mechanisms govern the interfacial area between water and ambient air& the residence time of the entrapped bubbles in the receiving water pool for mass transfer. Thereby, the mass transfer would be regulated by the aeration mechanism under the existing hydraulic conditions. At first, jets of water fell over the weirs and air entrapped mainly at receiving water pool surface as per category 'a' mechanism. As the height of drop became more lavish, the water jets' surface first got roughened, and after that, the water jet swung back forth during the plunge, entrapped air as discussed, respectively, by category 'b' & 'c' mechanisms. With further increase in the height of the drop, the water jet ultimately disintegrates into separate smaller droplets, and the category 'd' aeration mechanism succeeded. The breakup of the water jet caused a reduction in penetration depth into the water pool and hence also biphasic zone depth. This led to a significant decrease in the contact period between the bubbles and the receiving water pool. So aeration process by mechanism 'd' was perceived to be less efficient than by mechanisms 'b' and 'c'. This corroborated the aforesaid opinions of Gameson [6]. It is well known that the "breakup length" of the water plunging jet is not at all fully described and the water plunging jet disintegrates over a sizeable length. So, the transfer from mechanism 'b' or 'c' to mechanism 'd' is not abrupt and sudden but occurs gradually over a more considerable extent of drop heights. It does not bring down inefficient curtailment aeration, but a convincing drop in the pace of ineffective increase aeration with drop height.

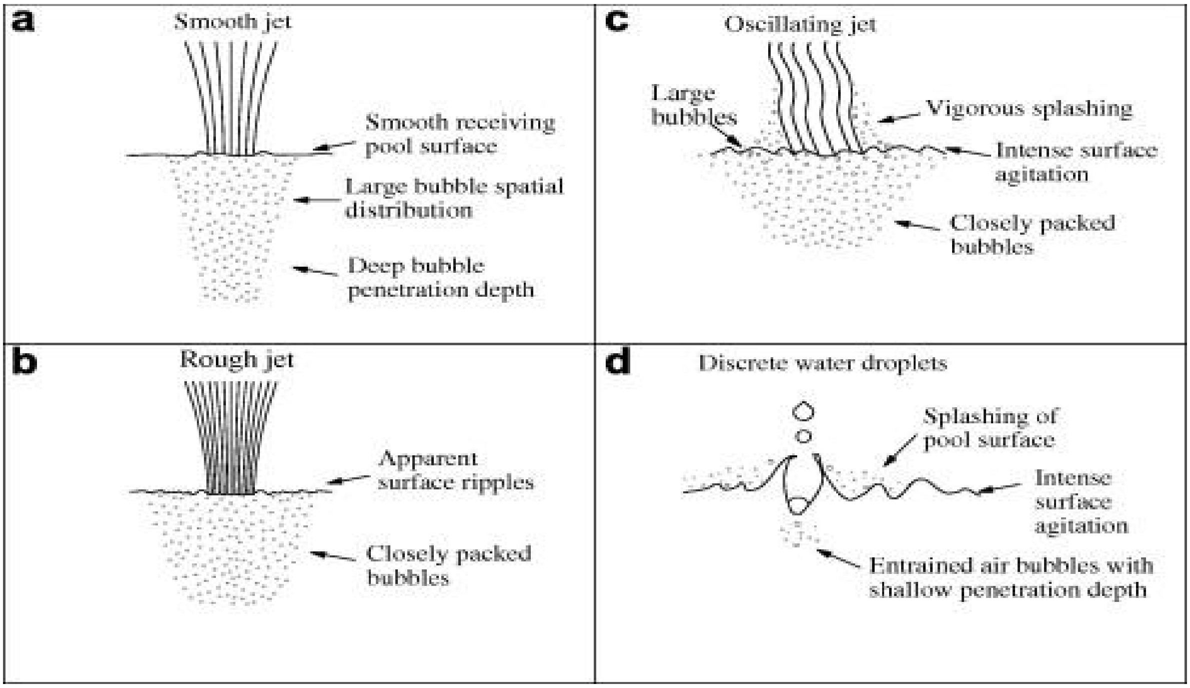

Fig. 2. Labyrinth weir aeration mechanisms [21]

Table 1.
Proposed existing classical predictive models for labyrinth weir aeration efficiency

Sr. No.	Equation source	Equation	Remarks
1	Avery and Novak [9]	$E_{15} = 1 - [1 + 0.627X10^{-4} F_r^{1.78} R_e^{0.53}]^{-1}$ $\frac{E_T\ (1 - E_{20})}{E_{20}(1 - E_T)} = [1 + 0.0355(T - 20)]$	Oxygen transfer at conventional rectangular weir
2	Tsang [21]	$E_{20} = 1 - [1 + 0.762X10^{-4} F_r^{1.78} R_e^{1.78}]^{-1}$	Aeration performance of Labyrinth weir
3	Wormleaton and Tsang [14]	$E_{20} = 1 - [1 + 0.385X10^{-6} F_r^{2.297} R_e^{0.684}]^{-1}$	Aeration assessment rectangular Labyrinth weir

where $F_r = (\frac{gD^3}{2q_j^2})^{\frac{1}{4}}$; $R_e = \frac{q_j}{\nu}$; q_j is discharged per unit perimeter of jet and E_T=Aeration efficiency at any temperature T°C.

1.3. Published relations in literature

Oxygen aeration efficiency of labyrinth weir is dependent on some relevant factors that contribute to the aeration process. Very few work on the estimation of oxygen aeration efficiency of labyrinth weir are available in the literature, and that too is based on traditional regression methods. These classical models are either overestimated or underestimated the labyrinth weir oxygen aeration efficiency. Thus, in this study, existing conventional models are evaluated and compared its performance by using test dataset collected from laboratory experiments and the relative performance of the existing conventional models is evaluated using the observed datasets. The performance of these conventional regression models is further compared to that of the more complex artificial intelligent based models which include MLR, Fuzzy Logic ANN and ANFIS. For the traditional models and equations developed by prior authors, the present study would assess the performance of three popular conventional relations, and these conventional predictive equations have been presented in Table 1.

2. Material and methods

2.1. Models of labyrinth weir

The present study consists of nine models of labyrinth weir prepared by varying planform and several keys whose dimensions and other details are shown in Table 2. All these laboratory-scale models were fabricated using a 5 mm thick good quality painted plywood sheet and a typical view having a single key model having three different plan-forms are shown in Figure 3.

2.2. Measurement of DO

Azide modification technique depending upon on the variables is used to compute the amount of DO in the storage cum aeration tank. Three representative samples of water to be tested are taken in a capacity of 300-ml BOD bottles where two sampling bottle consists of aerated water after running the experiments for 60-second [28,29] and other sampling bottles having the testing water before each experiment. The measurement technique is begun by pouring 1 millilitre of manganese sulphate succeeded by 1milliliter alkali-iodide-azide by employing a pipette keeping just over surfaces of the sample. Each sample is systematically blended and mixed up after winding up the bottles, and the precipitates are permitted to settle half the bottle volume. Sulfuric acid is after that poured to each of the samples and mixed thoroughly till proper dissolution. Thereafter, 200 millilitres of the original samples are titrated in a flask employing a burette having ± 0.1 ml least count comprising sodium thiosulfate solution ($Na_2S_2O_3$) after putting few drops of starch indicator to the testing samples. The volume of the thiosulfate solution used in titration is noted down in pursuance to compute the initial and final dissolved oxygen (DO) of the representative samples.

2.3. Experimental test program and procedure

The schematic test arrangement is depicted in Figure 4. Tests were conducted utilizing a tilting rigid steel flume of dimensions 0.26 m width X 0.30 m height X 4 m length in the hydraulic laboratory at Civil Engineering Department of National Institute Technology, Kurukshetra (India). The flume was fed by a 2-HP motor pump which delivers maximum discharge of 6 l/s, a flow regulating valve to control

Table 2.
Dimensions of the triangular, rectangular and trapezoidal labyrinth weir models

Type of weir	No. of key	Width, W	Crest length, L	Height, P
Triangular	1	26.3 cm	25 cm	12.5 cm
	2	26.3 cm	50 cm	12.5 cm
	3	26.3 cm	75 cm	12.5 cm
Rectangular	1	26.3 cm	51.3 cm	12.5 cm
	2	26.3 cm	76.4 cm	12.5 cm
	3	26.3 cm	100.8 cm	12.5 cm
Trapezoidal	1	26.3 cm	37.3cm	12.5 cm
	2	26.3 cm	70 cm	12.5 cm
	3	26.3 cm	90 cm	12.5 cm

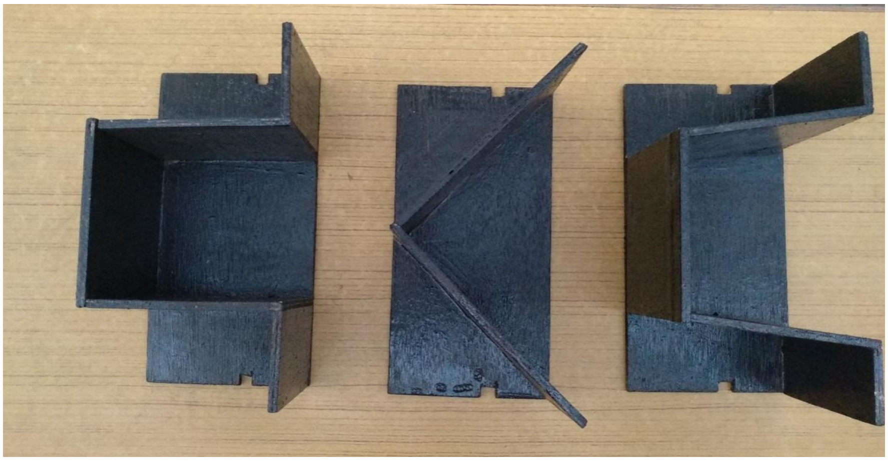

Fig. 3. Atypical view of 1-key different planform weir models

the discharge, a calibrated orifice meter to measure the discharge of water flowing through the flume, and a thermometer to measure the temperature of water in the aeration cum supply tank. Water entered the flume through the headbox, and the entry of the flume was equipped with a metal screen which was used to dampen the turbulence if any in the flow of the water. Flume was provided with the re-circulating closed device which was employed for continuously feeding the flume by redrawing water from supply cum aeration tank with dimension of 125 cm length, 60 cm width and 60 cm depth. A digital pointer gauge with 0.01 mm accuracy was used for measurement of water depth in the flume. The test model was put across the full width of the flume, and it was ensured that there could not be any leakage across the model and nine different shapes and keys of labyrinths were utilized in this study. For all the experiments, potable tap water was used, and it was ensured that the depth of water in aeration tank was consistently maintained greater than penetration depth for every test [9]. The water jet from the test labyrinth weir was allowed to be plunged into the aeration cum supply tank, whose height could be adjusted using the lifting jacks provided at both upstream and downstream of the flume. To obtain the quantity of oxygen transferred to water in the aeration cum supply tank, a fixed volume of drinking water was filled up in the tank. A suitable amount of sodium sulphite (Na_2SO_3), as well as cobalt chloride ($CoCl_2$) which acts as a catalyst, were added to bring down dissolved oxygen concentration of water in the supply tank around one-ppm [23] and water sample was collected for measurement of initial DO ($C_{U/S}$). Thereafter, the flume was allowed to run for a particular time such that DO in the tank does not acquire the saturation value at any tested temperature and the final value of DO ($C_{D/S}$) was computed. A thermometer calculated the water temperature in the tank with the least accuracy of ±0.1°C. The same steps were continued for various runs employing nine different labyrinth weirs having different shapes and number of keys, as mentioned in Table 2. The value of aeration efficiency (E_{20}) was then computed using equations 1 and 2.

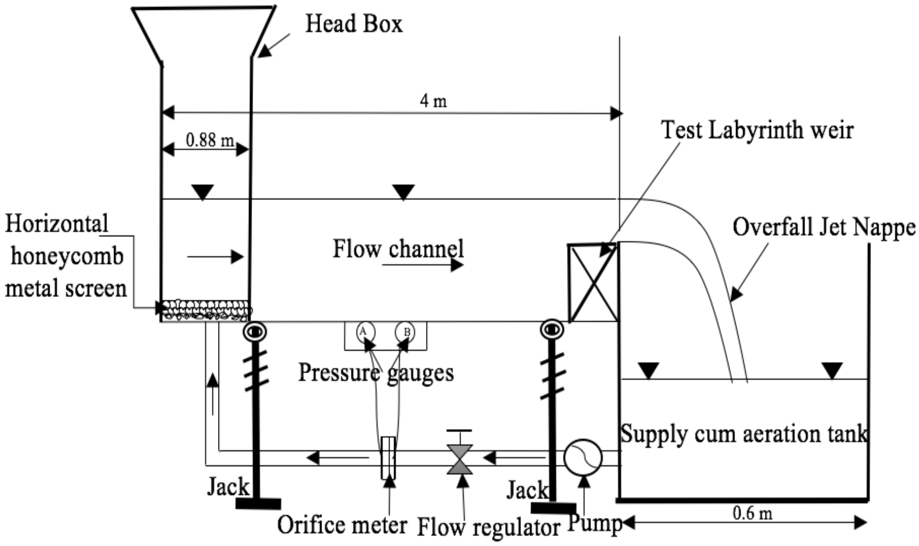

Fig. 4. The schematic view of the experimental setup

3. Data set

To evaluate the efficacy of ANN, Fuzzy Logic and ANFIS models to estimate the aeration efficiency at labyrinth weirs. Dataset used in this study was collected from laboratory experiments conducted on 1, 2 and 3-key triangular, rectangular and trapezoidal weirs. In the present study, the dataset comprises of 180 experimental test observations. Out of 180 readings, randomly selected 126 (70%) readings were selected for preparing, whereas rest 54 readings were chosen for testing the models [30]. To estimate the aeration efficiency at weirs, seven input parameters; Fraud number (Fr), Reynolds number (Re), numbers of keys (N), the ratio of head to the width of the channel (H/W), the ratio of crest length to width of the channel (L/W), the ratio of drop height to width of the channel (D/W) and shape factor (SF) were used whereas aeration efficiency (E_{20}) was output. Table 3 provides the characteristics of the training and testing data set.

Performance comparison of models

Two standard statistical parameters of the coefficient of correlation (CC) [31] and root mean squared error (RMSE) [32] were preferred to compare the performance of models, and the best among them was chosen.

$$CC = \frac{m(\sum j_i k_i) - (\sum j_i)(\sum k_i)}{\sqrt{m(\sum j_i^2) - (\sum j_i)^2}\sqrt{m(\sum k_i^2) - (\sum k_i^2)^2}} \quad (3)$$

$$RMSE = \sqrt{\frac{1}{M}(\sum_{I=1}^{M}(J_I - K_I)^2} \quad (4)$$

where j_i, k_i, and m are observed and estimated value of E_{20} and number of data respectively.

4. Proposed AI-based predictive models

4.1. Fuzzy logic (FL)

FL is a proficient and successful technique for implementing the curvilinear mapping between input and output parameters. It gives a lucid process of resolving where the exact condition is not given but merely the random parameters. Fuzzy set theory resolves the problems with the help of linguistic information and linguistic labels stimulated by membership functions (mfs). Although, FL was first coined and presented by Zadeh [33] and broadly, two kinds of rule base (I) Sugeno type and (II) Mamdani type. The present study deals with the Mamdani type of rule and prods process-based fuzzy model since estimation becomes more accurate. Further, for the defuzzification used in fuzzy logic, the weighted average process is applied. The typical features of FL are to allow an object to partial links with various subsets, which is only possible with membership functions. Partial belonging to a set is defined numerically by a membership function, whose range lies between 0 and 1. The advantages of FL is that it can easily be constructed. It is flexible and allow modification in the rules. Even imprecise, distorted and error input information is also accepted by the system.

Table 3.
Characteristics of the train and test data used in this study

Parameters	Minimum	Maximum	Mean	Standard Deviation	Kurtosis	Skewness
			Training			
Fr	8.90	22.64	13.63	4.22	-0.42	0.91
Re	2000	10000	6079.37	2855.46	-1.32	-0.02
N	1	3	2.02	0.81	-1.47	-0.03
H/W	0.168	0.76	0.50	0.20	-0.85	-0.51
L/W	1.32	3.94	2.54	0.79	-0.82	0.30
D/W	3.2	3.8	3.49	0.22	-1.33	0.03
SF	1	2	1.49	0.41	-1.51	0.03
E20	0.32	0.723	0.52	0.11	-1.23	0.15
			Testing			
Fr	8.90	22.64	14.05	4.40	-0.67	0.84
Re	2000	10000	5814.81	2808.84	-1.26	0.04
N	1	3	1.96	0.85	-1.61	0.07
H/W	0.168	0.76	0.49	0.20	-0.96	-0.48
L/W	1.32	3.94	2.52	0.76	-0.73	0.35
D/W	3.2	3.8	3.51	0.23	-1.45	-0.07
SF	1	2	1.52	0.41	-1.52	-0.07
E20	0.362	0.714	0.53	0.11	-1.42	0.09

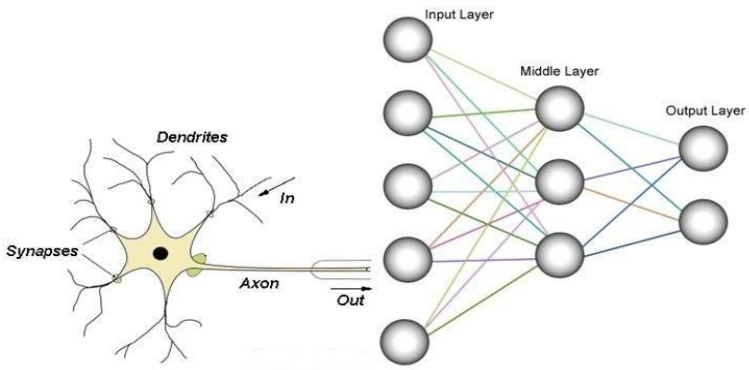

Fig. 5. A configuration of ANN

4.2. Artificial neural networks (ANN)

ANN is a powerful data mining techniques based on the nerve cell system of the intelligent brain like the human being (Fig. 5). It can identify and determine correlated patterns among input and output data sets. ANN can be expressed as a system of superficial processing nodes or neurons, interconnected to each other in a definite pattern, executing simple numerical manipulations. ANN, as a common structure, contains multiple layered networks. These networks include an input layer containing nodes showing various input variables, the hidden layer comprising of numerous hidden nodes, and the last layer (target) consisting of target/output variables [34]. The main advantages of ANN is its ability to learn and model non-linear and complex relationships, which is really important because in real-life, many of the relationships between inputs and outputs are non-linear as well as complex.

4.3. Adaptive neuro-fuzzy inference systems (ANFIS)

ANFIS is first coined and presented by Takagi and Sugeno [35]. ANFIS is a very dominant tool for solving the compound non-linear problem based on independent and dependent variables dataset. The ANFIS model is dependent

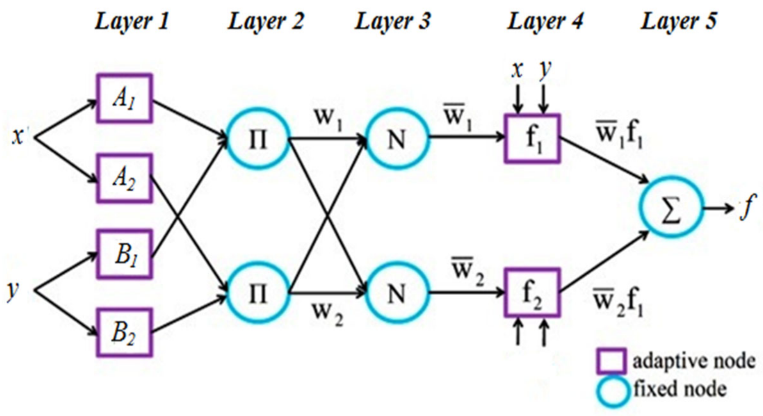

Fig. 6. Structure of the ANFIS model

on the combine arrangement of artificial neural network and fuzzy systems. This arrangement facilitates applying both numeric powers of intelligent systems. In fuzzy logic-based systems, different fuzzification and defuzzification approaches with different rules were selected for the independent parameter. ANFIS models should contain three phases. Phase one is the choice of membership function for every inputs variable. In this study, four shapes of membership functions (triangular, trapezoidal, generalized bell shape and Gaussian function) have been selected for each of the inputs variables. Figure 5 shows a fuzzy reasoning method. A fuzzy system with two inputs and one output variable was shown in Figure 6. The first order Sugeno type is implemented to develop two if-then rules as follows:

- Rule 1: If x is A_1 and y is B_1, then $f_1 = p_1 x + q_1 y + s_1$,
- Rule 2: If x is A_2 and y is B_2, then $f_2 = p_2 x + q_2 y + s_2$,

where A_1, A_2 and B_1, B_2 are mfs for inputs x and y, respectively; p_1, q_1, s_1 and p_2, q_2, and s_2 are parameters of the output function.

In the first layer, all inputs variables provided the class membership with MF, and in layer II, all membership classes will be multiplied together. In layer III, the entire classes of the member will be normalized, and in layer IV, the involvement of all rules will be calculated. And in the final layer (Layer V), the target variable will be calculated as the average weighted of class membership. It has the advantage of having both numerical and linguistic knowledge also having a transparent system to the user that causes less memorization errors.

4.4. Multi-Linear Regression (MLR)

Multi-linear regression (MLR) is applied on more than one estimator's parameters. XLSTAT software was used to develop the MLR equation. It works on least square technique and goal is to model the linear relationship between the explanatory (independent) variables and response (dependent) variable. The common structure of the MLR model is:

$$Z = c_0 {x_1}^{c_1} {x_2}^{c_2} {x_3}^{c_3} {x_4}^{c_4} \ldots\ldots\ldots\ldots\ldots\ldots {x_n}^{c_n} \tag{5}$$

$$E_{20} = \frac{0.00021 Fr^{0.8567} Re^{0.284} (\frac{H}{W})^{0.0441} (\frac{L}{W})^{0.548} (\frac{D}{W})^{2.349}}{N^{0.316} SF^{0.1259}} \tag{6}$$

5. Results and discussion

5.1. Fuzzy Logic results

In this study, two shapes of membership function (generalized bell shape and Gaussian) were used for the model development. Several trials were performed for the optimum number of membership function for various parameters (inputs and output). The optimum number of membership function for best model were F_r =9, R_e = 5, N =3, H/W =7, L/W =7, D/W =3, SF =3 and E_{20} =9. Figure 7 shows the scatter plot of the fuzzy logic-based model for both training and testing dataset, and Table 4 shows the CC and RMSE values of the Fuzzy logic-based models. Further, Table 4 suggests that generalized bell shape (gbellmf) based model performs better than Gaussian (gaussmf) based model in estimating the aeration efficiency (E_{20}) at Labyrinth weir with CC = 0.8482 and RMSE = 0.0640 for testing dataset. Figure 7 and Table 4 indicate that performances of Fuzzy Logic-based models are suitable for estimating the aeration efficiency (E_{20}) at Labyrinth weir.

Table 4.
Performance assessment parameters

Approaches	Training dataset		Testing dataset	
	CC	RMSE	CC	RMSE
Fuzzy_gbellmf	0.9327	0.0412	0.8492	0.0670
Fuzzy_gaussmf	0.9330	0.0403	0.8249	0.0647
ANN	0.9888	0.0167	0.9901	0.0156
ANFIS_gbellmf	0.9954	0.0106	0.9518	0.0345
ANFIS_gaussmf	0.9976	0.0077	0.9730	0.0259
MLR	0.9638	0.0294	0.9521	0.0338
Avery and Novak [9]	0.57834	0.1386	0.5856	0.1458
Tsang [21]	0.5783	0.1387	0.5856	0.1459
Wormleaton and Tsang [14]	0.8411	0.0985	0.8476	0.1031

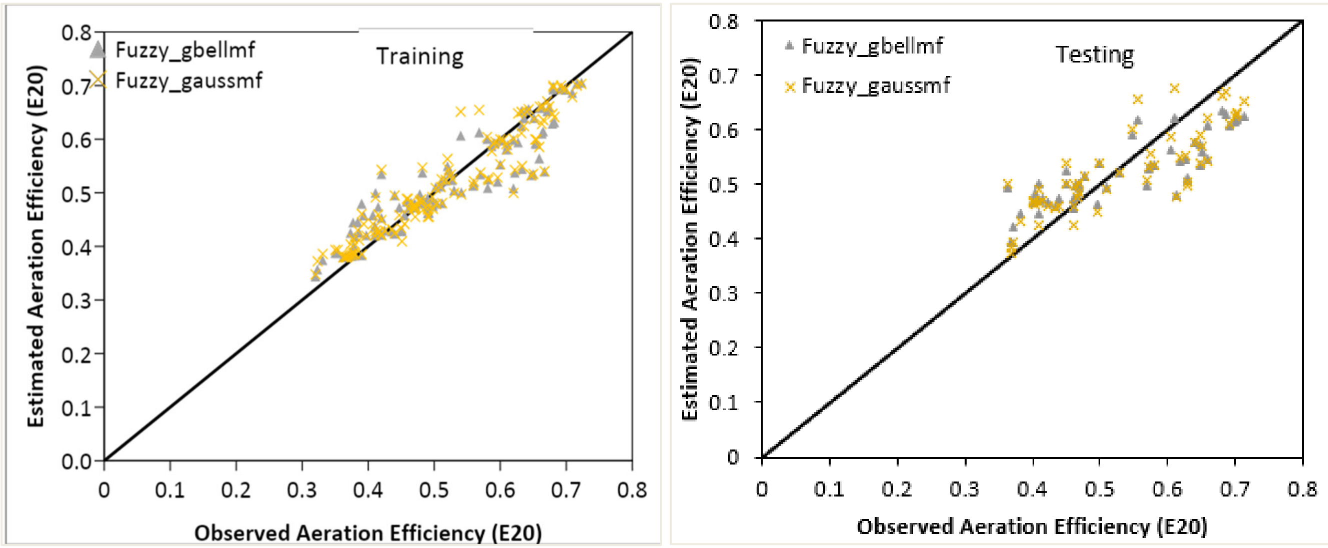

Fig. 7. Scatter plot of the Fuzzy Logic-based model for training and testing dataset

5.2. ANN results

In this study, several different networks were tested for development of ANN model Table 4 indicates the CC and RMSE for ANN best model. The best number of neurons in the hidden layer was found in 2 neurons. This result is in contrast to the proposal that was given by Kavzoglu and Mather [36]. They propose that the number of neurons in a hidden layer should be twice as the input nodes plus one. It endorses that the number of neurons in a hidden layer should be determined using a trial-and-error method. Figure 8 shows the scatter plot of the ANN model for both training and testing dataset. Figure 8 and Table 4 indicate that the performance of the ANN model is suitable for estimating the aeration efficiency (E_{20}) at Labyrinth weir.

5.3. ANFIS results

In this study, two shapes of membership function (generalized bell shape and Gaussian) were used for the model development. Development of the ANFIS model is a trial and error process. Table 4 indicates the value of CC and RMSE for ANFIS based models. Figure 9 shows the scatter plot of the ANFIS model for both training and testing dataset. Both Figure 9 and Table 4 indicate that the performance of Gaussian MFS based ANFIS model is better than generalized bell shape mfs based ANFIS model with CC= 0.9730 and RMSE = 0.0 259 for testing dataset. Overall performance of ANFIS based models is suitable for estimating the aeration efficiency (E_{20}) at Labyrinth weir.

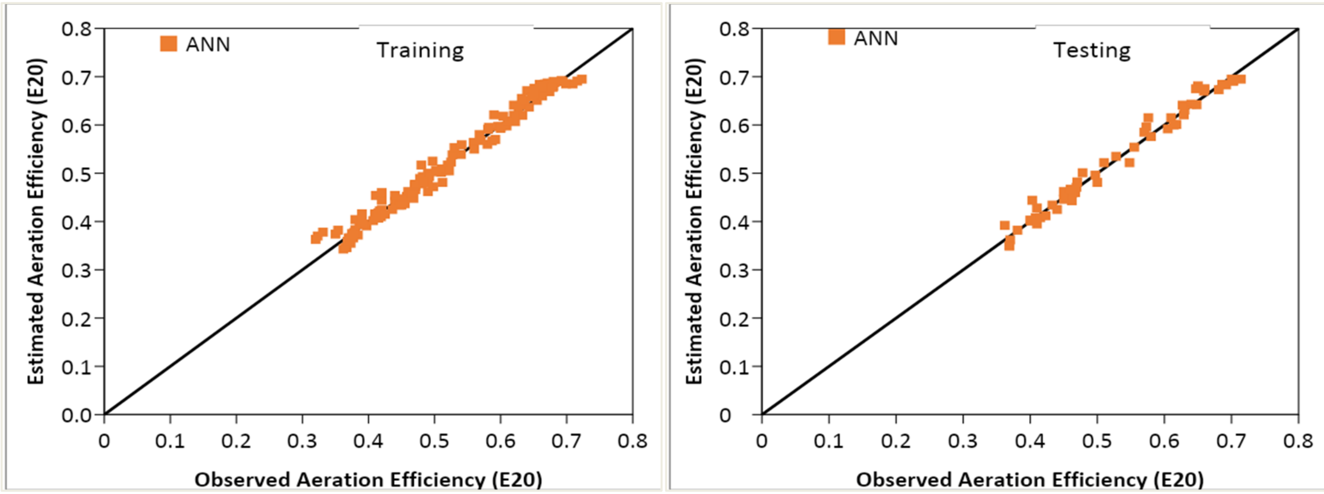

Fig. 8. Scatter Plot of ANN model for training and testing dataset

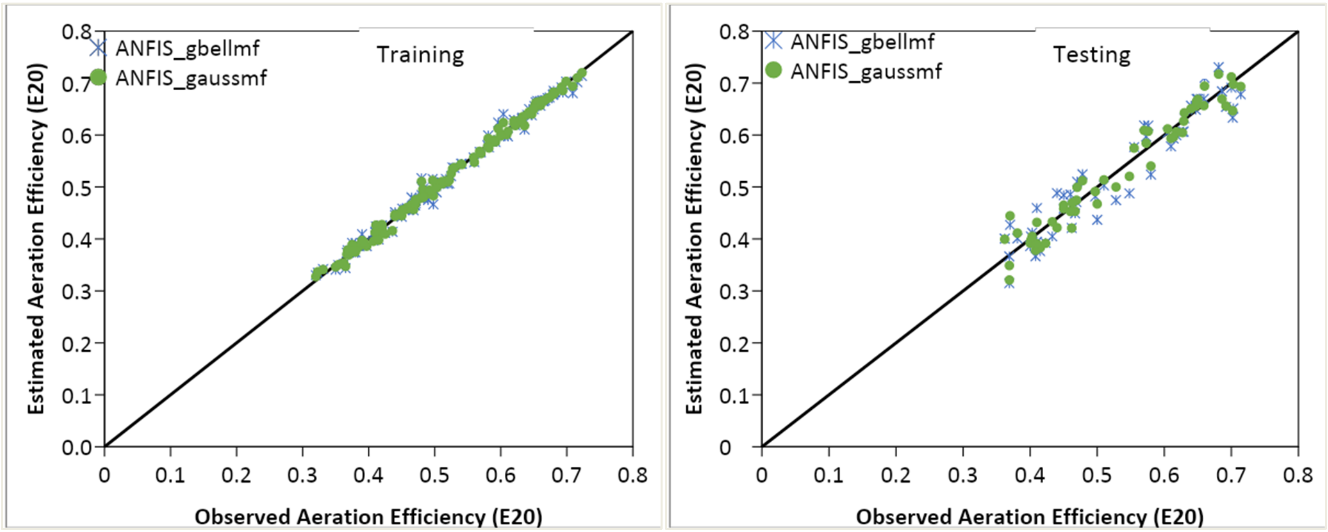

Fig. 9. Scatter Plot of ANFIS model for training and testing dataset

5.4. MLR results

MLR model development is based on the same data set used for ANFIS, ANN and Fuzzy logic model. A multi-linear regression equation was developed with the help of XSLSTAT software. Table 4 indicates the CC and RMSE values of the MLR model for training and testing stages. Figure 10 shows the scatter plot of the MLR model for both training and testing dataset. Figure 10 and Table 3 indicates that the MLR model is suitable for estimating the aeration efficiency (E_{20}) at Labyrinth weir with CC = 0.9521 and RMSE =0.0338 for testing dataset.

5.5. Comparison with the conventional model

Apart from for the Wormleaton and Tsang [14] equation, another conventional equation has a very high value of errors when it was used to estimate Labyrinth weir aeration efficiency (E_{20}) on the present dataset. Outcomes of every conventional equation were plotted against the observed aeration efficiency (E_{20}), which are shown in Figure 11. The standard error of indices having CC and RMSE were preferred to measure the exactness of conventional equations (see Tab. 4). As shown in Table 4 and Figure 10, the Wormleaton and Tsang [14] equation with CC = 0.8476

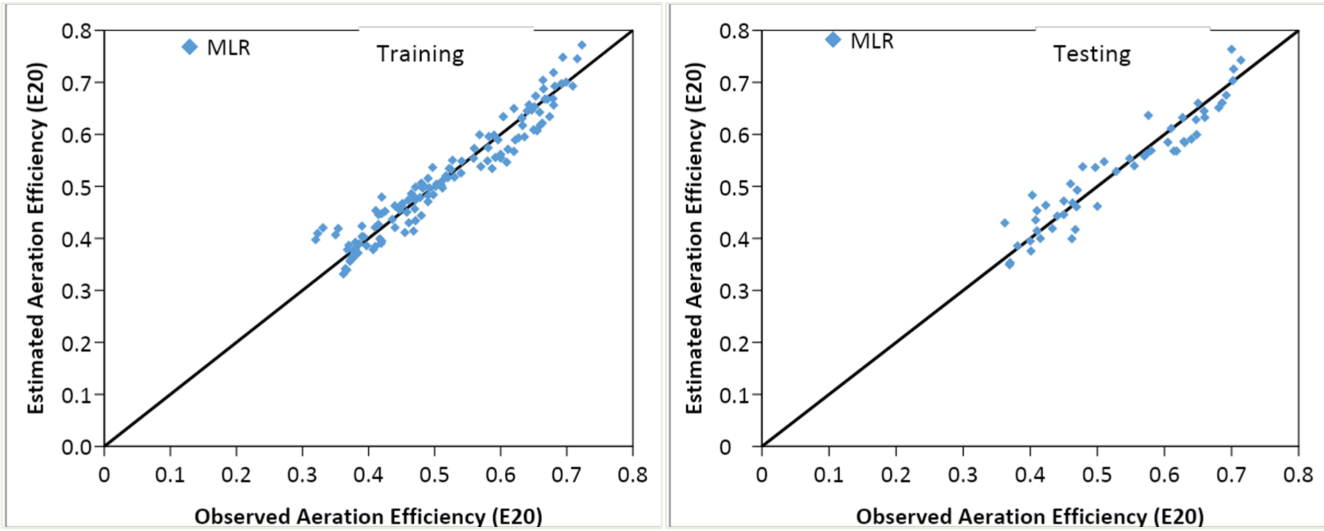

Fig. 10. Scatter Plot of the MLR model for training and testing dataset

and RMSE = 0.1031 is the most accurate one amid the conventional equation.

Performance of artificial intelligence techniques and conventional equation are presented in Table 4, which suggests that the performance of soft computing based model is better than conventional equations. Modern conventional MLR model works well than conventional/empirical equations with CC = 0.9521. ANN model is superior and outperforms the other considered conventional/empirical equations and soft computing based models with CC= 0.9901 and RMSE =0.0156 for the testing stage, which is shown in Table 4.

5.6. Sensitivity analysis

A sensitivity analysis was conducted to find the critical input parameter for the estimation of the aeration efficiency (E_{20}) at Labyrinth weir. The most significant parameters for assessment of aeration efficiency (E_{20}) are determined by the ANN method as it has been found the superior and outperforming model from the result. This method explains the consequences of every constraint on the model to estimate the aeration efficiency (E_{20}) at Labyrinth weir. At first, all the parameters concerning the Table 3 except E_{20} were considered as inputs for ANN, and then single input parameter eliminated, and the model was reconstructed with the same configuration. After adjusting the model structure, the sensitivity analysis of the models began to define the most useful parameters. Eliminating one of the input variables caused a change in model performance [37]. The performance of the models in the deficiency of every input parameter was examined using the estimation of indices comprising CC, and RMSE. The outcome of the sensitivity analysis of ANN is shown in Table 5. From its perusal, the ratio of drop height to the width of the flume is the most efficient parameter in the estimation of Labyrinth weir aeration efficiency (E_{20}).

5.7. Parametric investigation

From Table 4, it is clear that the ANN approach works superior for estimation the Labyrinth weir aeration efficiency (E_{20}) within the limit of input parameters and Table 5 further suggests that ratio of drop height of jet to the width of the channel (D/W) is the most influential parameter in the estimation of aeration efficiency (E_{20}). To examine the cause of the ratio of drop height of jet to the width of the channel (D/W) on the Labyrinth weir aeration efficiency (E_{20}), ANN-based parametric investigation was performed. In this investigation, an imaginary testing dataset was generated by varying the value of one input parameter [38] and keeping remaining input parameters as constant and considering this dataset as the test dataset for the ANN model.

Values of the ratio of drop height to the width of the channel (D/W) vary from 3.2 to 3.8, and other input parameters (Fr, Re, N, H/W, L/W and SF) were kept constant. Figure 12 suggests that labyrinth aeration efficiency (E_{20}) increases with increasing drop height to the width of the channel (D/W) ratio as per the expected line.

Besides, results also suggest that rectangular shape has higher aeration efficiency (E20) than the triangular and trapezoidal reason for this may be attributed as rectangular shape consists of more crest length than triangular and trapezoidal shapes for the same cross-sectional width.

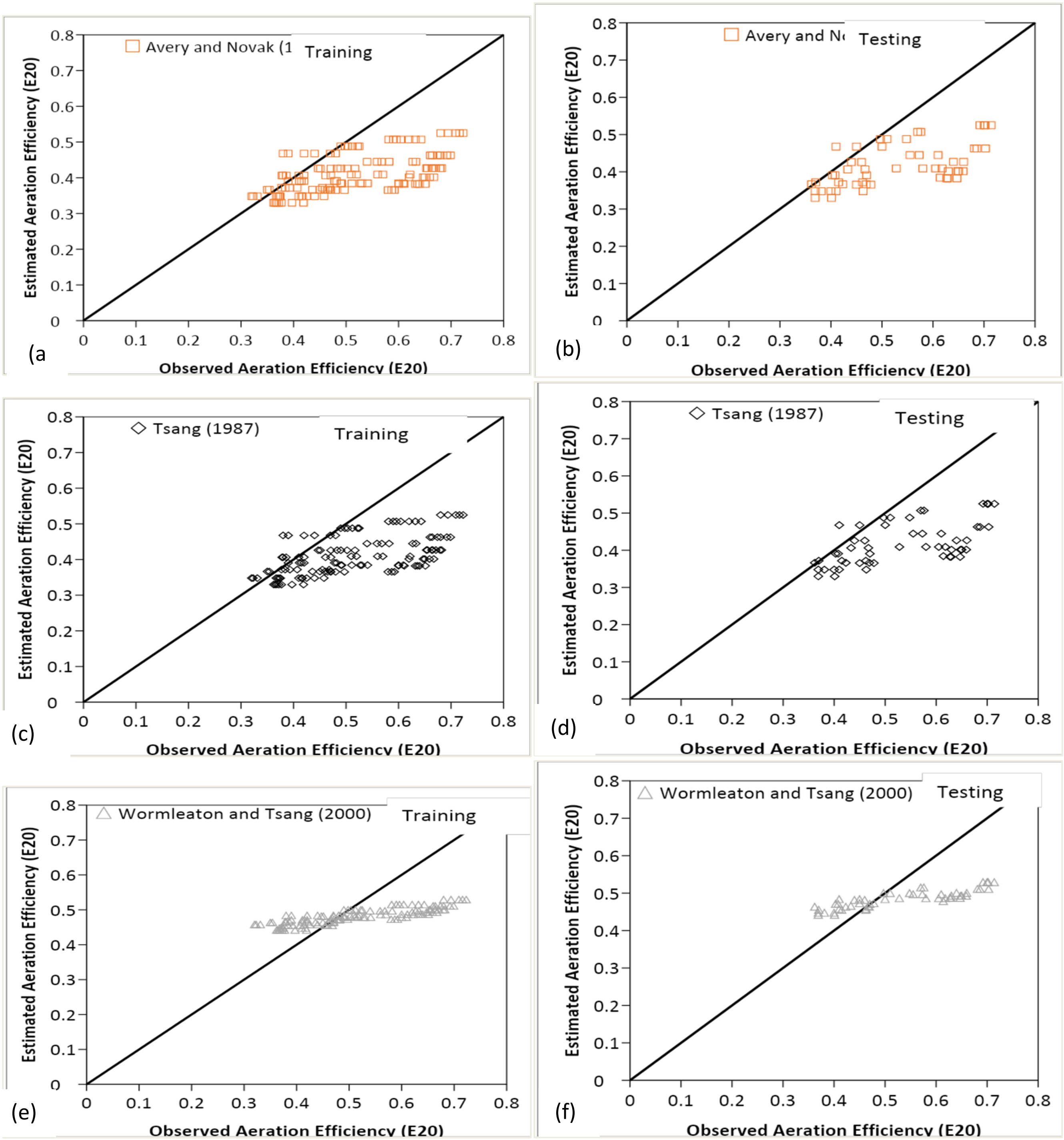

Fig. 11. Scatter Plot of conventional models

Table 5.
Performance of parameters for sensitivity analysis

Input Parameters	Removed Parameters	Target Parameter	ANN			
			Training		Testing	
			CC	RMSE	CC	RMSE
Fr, Re, N, H/W, L/W, D/W, SF		E_{20}	0.9888	0.0167	0.9902	0.0155
Re, N, H/W, L/W, D/W, SF	Fr	E_{20}	0.9882	0.0172	0.9899	0.0158
Fr, N, H/W, L/W, D/W, SF	Re	E_{20}	0.9875	0.0179	0.9885	0.0169
Fr, Re, H/W, L/W, D/W, SF	N	E_{20}	0.9886	0.0168	0.9894	0.016
Fr, Re, N, L/W, D/W, SF	H/W	E_{20}	0.9886	0.0173	0.9906	0.0155
Fr, Re, N, H/W, D/W, SF	L/W	E_{20}	0.9889	0.0168	0.9901	0.0157
Fr, Re, N, H/W, L/W, SF	D/W	E_{20}	0.7741	0.0857	0.805	0.0855
Fr, Re, N, H/W, L/W, D/W	SF	E_{20}	0.9857	0.019	0.9846	0.0198

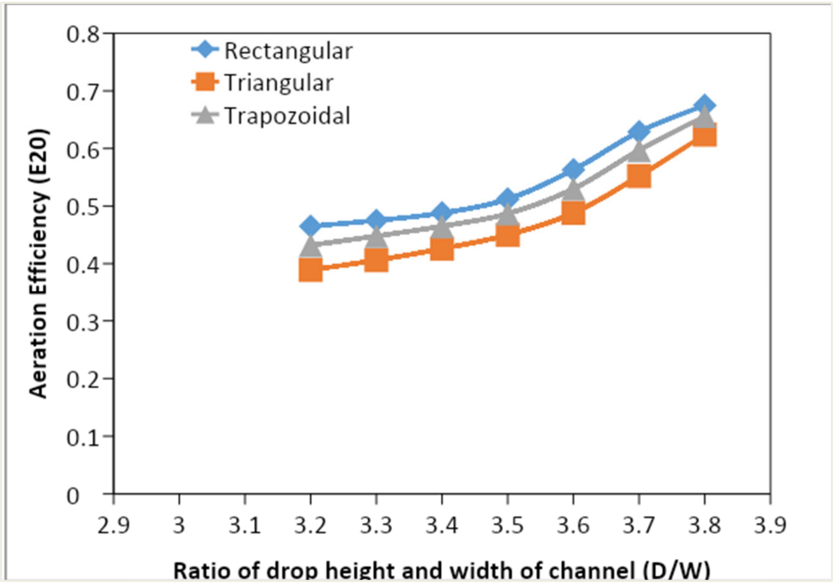

Fig. 12. Variation of Aeration Efficiency (E_{20}) at Labyrinth weir for different ratios of drop height to the width of the channel (D/W)

6. Conclusions

In an irrigation and drainage system, oxygen aeration occurs on the surface of the flow as farming water moves down the waterway and to manage that agriculture water, hydraulic structures like weirs, spillways, drops etc. Are used, which indirectly improves this oxygen aeration hugely. In this work, a sincere attempt has been made to decode oxygen aeration at labyrinth weirs, and it is concluded that

1. The ANN model was outperforming other aforesaid AI-based data-driven models as well as classical models in the estimation of the oxygen aeration efficiency of labyrinth weirs. Nevertheless, other AI-based models were also working well, and it could be used in the estimation of the labyrinth weir aeration efficiency.
2. Results of the work further showed that estimating labyrinth weir aeration efficiency with conventional models except modern conventional MLR model leads to apparently unexpected errors. However, Wormleaton and Tsang [14] were found to be giving comparatively good results.
3. Findings of the sensitivity analysis showed that drop height at labyrinth weirs was the most significant parameter for the estimation of oxygen aeration efficiency.

4. Parametric investigation suggests that labyrinth weir aeration efficiency increases with an increase of drop height and rectangular planform has higher aeration efficiency (E_{20}) than triangular and trapezoidal for the same cross-sectional weir width.

References

[1] A. Baylar, T. Bagatur, Study of aeration efficiency at weirs, Turkish Journal of Engineering and Environmental Sciences 24/4 (2000) 255-264.

[2] A. Baylar, D. Hanbay, M. Batan, Application of least square support vector machines in the prediction of aeration performance of plunging overfall jets from weirs, Expert Systems with Applications 36/4 (2009) 8368-8374. DOI: https://doi.org/10.1016/j.eswa.2008.10.061

[3] J. Cassidy, C.A. Gardner, R.T. Peacock, Labyrinth crest spillway planning, design and construction. Proceedings of the International Conference on Hydraulic Aspects of Floods and Flood Control, City University, London, 1983.

[4] N. Hay, G. Taylor, Performance and design of labyrinth weirs, Journal of the Hydraulics Division 96/11 (1970) 2337-2357.

[5] G. Taylor, The performance of labyrinth weirs, PhD Thesis, University of Nottingham, 1968.

[6] A.L.H. Gameson, Weirs and aeration of rivers, Journal of the Institution of Water Engineers 11/6 (1957) 477-490.

[7] G.T.N. Van der Kroon, A.H. Schram, Weir aeration – part I: Single free fall, H_2O 22 (1969) 528-537.

[8] H. Nakasone, Study of aeration at weirs and cascades, Journal of Environmental Engineering 113/1 (1987) 64-81. DOI: https://doi.org/10.1061/(ASCE)0733-9372(1987)113:1(64)

[9] S.T. Avery, P. Novak, Oxygen transfer at hydraulic structures, Journal of the Hydraulics Division 104/11 (1978) 1521-1540.

[10] J.S. Gulliver, A.J. Rindels, Measurement of air-water oxygen transfer at hydraulic structures, Journal of Hydraulic Engineering 119/3 (1993) 327-349. DOI: https://doi.org/10.1061/(ASCE)0733-9429(1993)119:3(327)

[11] S.C. Wilhelms, J.S. Gulliver, K. Parkhill, Reaeration at low-head hydraulic structures, Report No. WES/TR/W-93-2 prepared for Headquarters, U.S. Army Corps of Engineers, 1993.

[12] J.R. Thene, Gas transfer at weirs using the hydrocarbon gas tracer method with headspace analysis, MS Thesis, University of Minnesota, Minneapolis, 1988.

[13] P.R. Wormleaton, E. Soufiani, Aeration performance of triangular planform labyrinth weirs, Journal of Environmental Engineering 124/8 (1998) 709-719. DOI: https://doi.org/10.1061/(ASCE)0733-9372(1998)124:8(709)

[14] P.R. Wormleaton, C.C. Tsang, Aeration performance of rectangular planform labyrinth weirs, Journal of Environmental Engineering 126/5 (2000) 456-465. DOI: https://doi.org/10.1061/(ASCE)0733-9372(2000)126:5(456)

[15] B. Singh, P. Sihag, K. Singh, Modelling of impact of water quality on infiltration rate of soil by random forest regression, Modeling Earth Systems and Environment 3/3 (2017) 999-1004. DOI: https://doi.org/10.1007/s40808-017-0347-3

[16] P. Sihag, Prediction of unsaturated hydraulic conductivity using fuzzy logic and artificial neural network, Modeling Earth Systems and Environment 4/1 (2018) 189-198. DOI: https://doi.org/10.1007/s40808-018-0434-0

[17] P. Sihag, N.K. Tiwari, S. Ranjan, Modelling of infiltration of sandy soil using gaussian process regression, Modeling Earth Systems and Environment 3/3 (2017) 1091-1100. DOI: https://doi.org/10.1007/s40808-017-0357-1

[18] P. Sihag, P. Jain, M. Kumar, Modelling of impact of water quality on recharging rate of storm water filter system using various kernel function based regression, Modeling Earth Systems and Environment 4/1 (2018) 61-68. DOI: https://doi.org/10.1007/s40808-017-0410-0

[19] A. Mansour-Bahmani, A.H. Haghiabi, Z. Shamsi, A. Parsaie, Predictive modeling the discharge of urban wastewater using artificial intelligent models (case study: Kerman city), Modeling Earth Systems and Environment (2020). DOI: https://doi.org/10.1007/s40808-020-00900-z

[20] B. Singh, P. Sihag, S. Deswal, Modelling of the impact of water quality on the infiltration rate of the soil, Applied Water Science 9/1 (2019) 15. DOI: https://doi.org/10.1007/s13201-019-0892-1

[21] B. Singh, Prediction of the sodium absorption ratio using data-driven models: a case study in Iran, Geology, Ecology, and Landscapes 4/1 (2020) 1-10. DOI: https://doi.org/10.1080/24749508.2019.1568129

[22] B. Singh, P. Sihag, K. Singh, S. Kumar, Estimation of trapping efficiency of a vortex tube silt ejector, International Journal of River Basin Management (2018). DOI: https://doi.org/10.1080/15715124.2018.1476367

[23] P. Sihag, B. Singh, A. Sepah Vand, V. Mehdipour, Modeling the infiltration process with soft computing

techniques, ISH Journal of Hydraulic Engineering 26/2 (2020) 138-152.
DOI: https://doi.org/10.1080/09715010.2018.1464408

[24] S. Arora, B. Singh, B. Bhardwaj, Strength performance of recycled aggregate concretes containing mineral admixtures and their performance prediction through various modeling techniques, Journal of Building Engineering 24 (2019) 100741.
DOI: https://doi.org/10.1016/j.jobe.2019.100741

[25] A. Sepahvand, B. Singh, P. Sihag, A. Nazari Samani, H. Ahmadi, Nia Fiz, S. Assessment of the various soft computing techniques to predict sodium absorption ratio (SAR), ISH Journal of Hydraulic Engineering (2019).
DOI: https://doi.org/10.1080/09715010.2019.1595185

[26] J.S. Gulliver, J.R. Thene, A.J. Rindels, Indexing gas transfer in self-aerated flows, Journal of Environmental Engineering 116/3 (1990) 503-523.
DOI: https://doi.org/10.1061/(ASCE)0733-9372(1990)116:3(503)

[27] C.C. Tsang, Hydraulic and aeration performance of labyrinth weirs, PhD Thesis, University of London, London, 1987.

[28] N.K. Tiwari, P. Sihag, Prediction of oxygen transfer at modified Parshall flumes using regression models, ISH Journal of Hydraulic Engineering 26/2 (2020) 209-220.
DOI: https://doi.org/10.1080/09715010.2018.1473058

[29] M. Kumar, S. Ranjan, N.K. Tiwari, Oxygen transfer study and modeling of plunging hollow jets, Applied Water Science 8/5 (2018) 121.
DOI: https://doi.org/10.1007/s13201-018-0740-8

[30] B. Singh, P. Sihag, A. Parsaie, A. Angelaki, Comparative analysis of artificial intelligence techniques for the prediction of infiltration process, Geology, Ecology, and Landscapes (2020). DOI: https://doi.org/10.1080/24749508.2020.1833641

[31] A. Sepahvand, B. Singh, M. Ghobadi, P. Sihag, Estimation of infiltration rate using data-driven models, Arabian Journal of Geosciences 14/1 (2021) 42. DOI: https://doi.org/10.1007/s12517-020-06245-2

[32] P. Sihag, M. Kumar, B. Singh, Assessment of infiltration models developed using soft computing techniques, Geology, Ecology, and Landscapes (2020).
DOI: https://doi.org/10.1080/24749508.2020.1720475

[33] L.A. Zadeh, Information and control, Fuzzy Sets 8/3 (1965) 338-353.

[34] S. Haykin, Neural networks: a comprehensive foundation, Prentice Hall PTR, 1994.

[35] T. Takagi, M. Sugeno, Fuzzy identification of systems and its applications to modeling and control, IEEE Transactions on Systems, Man, and Cybernetics SMC-15/1 (1985) 116-132.
DOI: https://doi.org/10.1109/TSMC.1985.6313399

[36] T. Kavzoglu, P.M. Mather, The use of back propagating artificial neural networks in land cover classification, International Journal of Remote Sensing 24/23 (2003) 4907-4938.
DOI: https://doi.org/10.1080/0143116031000114851

[37] B. Singh, P. Sihag, S.M. Pandhiani, S. Debnath, S. Gautam, Estimation of permeability of soil using easy measured soil parameters: assessing the artificial intelligence-based models, ISH Journal of Hydraulic Engineering (2019).
DOI: https://doi.org/10.1080/09715010.2019.1574615

[38] P. Sihag, N.K. Tiwari, S. Ranjan, Prediction of cumulative infiltration of sandy soil using random forest approach, Journal of Applied Water Engineering and Research 7/2 (2019) 118-142. DOI: https://doi.org/10.1080/23249676.2018.1497557