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THREE ARTIFICIAL INTELLIGENCE-BASED SOLUTIONS PREDICTING CONCRETE SLUMP

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This study evaluates the efficiency of adaptive neuro-fuzzy inference system (ANFIS), multi-layer perceptron (MLP), and radial basis function (RBF) models in concrete slump prediction. We considered the input parameters as cement, slag, water, fly ash, superplasticiser (SP), fine aggregate (FA), and coarse aggregate (CA), where the slump of was the output. Root mean square error (RMSE) and mean absolute error (MAE) were used to evaluate the efficiency of the applied models. It was shown that ANFIS (MAE_{test}=2.2599) presented the most accurate results followed by MLP (MAE_{test} = 3.1265) and RBF (MAE_{test} = 3.5585).

Keyword: concrete slump, ANFIS, RBF, MLP, artificial intelligence.

1. Introduction

Concrete is one of the most commonly used building materials in plenty of civil engineering projects. The main reason for utilizing concrete is its reasonable strength as well as the flowability which enables us to construct any desired form of structural elements [1]. Due to the different needs of human, he has invented various types of concrete. Among those, high-performance concrete (HPC) is a newly developed kind which is used for particular applications. There are many parameters such as early age strength, ease of placement, durability, etc. have made HPC a world-widely-used type of cement. Note that, HPC is known mostly for its workability (i.e., relevant to the portion of finer particles involved) [2]. Among various criteria which determine the workability of a concrete mixture, the slump is a well-known factor that directly indicates the workability of concrete. Also, when two mixtures of concrete are prepared with an equal amount of water, a slump can emerge as a comparative parameter between them [3]. As a matter of fact, the development of concrete specimens with the desirable slump is a crucial task which requires a lot of skill and experience. On the other hand, there are many parameters which affect the workability of concrete. Hence, having a

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reliable approximation method can effectively help us to save cost and time in the context of concrete slump measurement.

Up to now, many mathematical methods have been developed based on the experimental results to describe the behaviour of the materials used in concrete mixtures. However, these empirical relationships (regression equations for instance) have been broadly used for deriving the relationship between the dependent and independent parameters of concrete; they mostly fail to give reliable results when a large number of parameters are involved [4]. During the past few decades, the development of soft computing (SC) techniques has provided reliable solutions for modelling any complex real-world problem. Due to the high potential of such tools, they are able to map any non-linear relationship between the independent and dependent variables of a problem. Among diverse types of SC approaches, artificial neural networks (ANNs) [5] and adaptive neuro-fuzzy inference systems (ANFIS) [6] are known as powerful models.

Also, many engineers have successfully used intelligent models for concrete parameters modelling [7-12]. For the case of slump prediction, Öztaş et al. [13] successfully used ANN to predict the compressive strength and slump of high strength concrete (HSC). Based on their findings, the mean absolute percentage error of 5,782,223%, and also 99.34% accuracy proved the reliability of the proposed model for concrete slump estimation. Yeh [2] designed an ANN for forecasting the slump of concrete and compared its results with a regression model. He found that ANN outperforms the latter model due to the higher values of coefficient of determination (R^2) (0.860 and 0.302, respectively for the testing phase of ANN and regression model) and RMSE (41.2 and 108.0). Chandwani et al. [4] improved the usefulness of ANN by applying the genetic algorithm for estimation of the slump of ready-mix concrete.

This study explores and compares the capability of three well-known three well-known artificial intelligence tools including ANFIS, multi-layer perceptron neural network (MLP), and radial basis function (RBF) in the estimation of the concrete slump. To do so, we provided a proper dataset containing various slump effective parameters. The programming software of MATLAB version 14.0 was used in this study. After achieving the best structure of each model, they were implemented to estimate the slump. The results were evaluated and compared to introduce the most efficient model.

2. Methodology

2.1 Adaptive neuro-fuzzy inference system (ANFIS)

The ANFIS is a powerful predictive tool first introduced by Jang [6]. To remedy the shortcoming of the ANN, it was suggested to combine it with the fuzzy rules. It was revealed that ANFIS offers more compatible results compare to a typical fuzzy inference system (FIS). As Fig. 1 illustrates, the ANFIS network is composed of five layers. Similar to ANN, the training process is accomplished by some so-called computational units “neurons”. Note that, neurons are completely connected by directional links. In this model, based on the human knowledge and by synthesizing least-squares method and back-propagation gradient descent, FIS membership functions (MFs) map the non-linear relationships between a set of input-target samples.

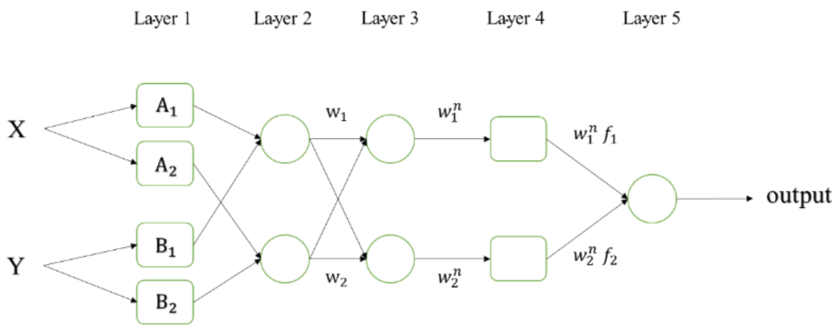


Fig. 1. Typical ANFIS structure

2.2 Multi-layer perceptron (MLP)

The MLP is one of the most commonly used soft computing approach which is satisfactorily employed in several fields of research. A typical MLP is structured in Fig. 2.

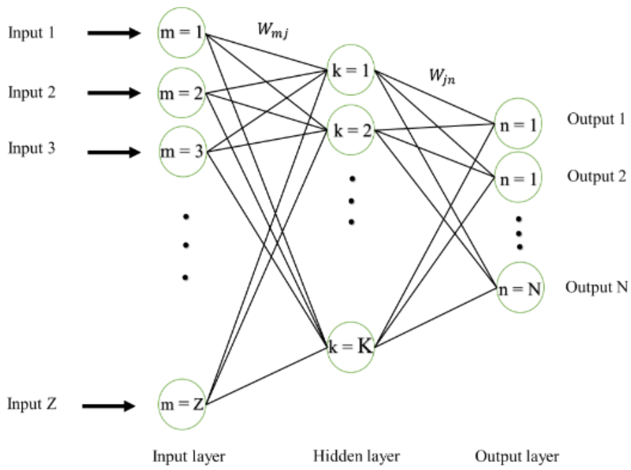


Fig. 2. The general structure of the MLP network

The name MLP is composed of a number of layers containing the computational nodes. However, an MLP can have more than one hidden layer; it has been demonstrated by various scholars that one hidden layer can give the suitable accuracy of MLP [14]. Each node aims to assign the best weights and bias to an input class. The activation function of the proposed node (AF) is then applied to the calculated value to release the local output. Equation 1 formulates the mentioned process:

$$Y_k = F\left(\sum_{m=1}^{z} T_m W_{mk} + b_k\right) \tag{1}$$

where T denotes the input value, W and b are the assigned weight and bias, respectively. Also, the term F symbolizes the activation function.

2.3 Radial basis function (RBF)

Similar to MLP, RBF denotes a feedforward ANN method which was first developed by Hardy in 1971 [15]. This model has been extensively used in many engineering simulations. Fig. 3 shows the overall structure of the RBF neural network. In this technique, the radial activated function [16] acts as the core function. The formulation of this function is expressed by Equation 2:

$$O_i = K\left(\frac{\left\| x - x_i \right\|}{\tau_i^2}\right) \tag{2}$$

in which Oi is the output of the neuron, and xi represents the centre of kernel K. Also, the term τ_i symbolizes the width of the ith RBF unit.

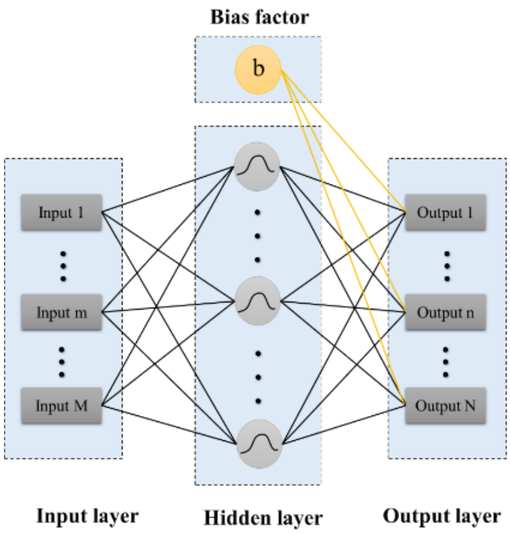


Fig. 3. Typical architecture of the RBF neural network

3. Results and discussion

This study addresses the application of three broadly used artificial intelligence tools, namely ANFIS, MLP, and RBF in concrete slump approximation. The required dataset was provided from (http://archive.ics.uci.edu/ml/datasets/Concrete+Slump+Test), based on research by Yeh [2]. Seven influential slump parameters (i.e., cement, slag, water, fly ash, superplasticiser (SP), fine aggregate (FA), and coarse aggregate (CA)) were considered as the inputs of the ANFIS, MLP, and RBF models to estimate the slump of the concrete. The statistical description of the used data is available in Table 1.

Table 1

Statistical description of the used dataset

	Slump (cm)	Cement (kg/m^3)	Slag (kg/m^3)	Water (kg/m^3)	Fly ash (kg/m^3)	SP (kg/m^3)	FA (kg/m^3)	CA (kg/m^3)
Minimum	0.0	137.0	0.0	160.0	0.0	4.4	640.6	708.0
Maximum	29.0	374.0	260.0	240.0	193.0	19.0	902.0	1049.9
Mean	18.0	229.9	149.0	197.2	78.0	8.5	739.6	884.0
Standard deviation	8.7	78.9	85.4	20.2	60.5	2.8	63.3	88.4

Remarkably, 80% of samples (82 rows) were used to train the methods, and the efficiency of each model was evaluated using the remaining 20% (21 rows). Moreover, two well-known statistical indices of root mean square error (RMSE) and mean absolute error (MAE) were defined to calculate the performance error of the employed tools. These indices are described as follows:

$$MAE = \frac{1}{N}\sum_{I=1}^{N} |Y_{i_{observed}} - Y_{i_{predicted}}| \tag{3}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} [(Y_{i_{observed}} - Y_{i_{predicted}})]^2} \tag{4}$$

where Yi observed, and Yi predicted denote the actual and predicted values of a concrete slump, respectively. Besides, the term N represents the number of instances

In the next step, based on the authors' experience, and also an extensive trial and error process, it was aimed to find the most proper structure of each predictive model. To this purpose, each model was coded in the programming language of MATLAB version 14.0. The results of this process are summarized in

Table 2, for ANFIS, MLP, and RBF. Next, each model was implemented with its optimal structure, and the results are presented and discussed later.

Table 2

The optimal parameters of ANFIS, MLP and RBF models

ANFIS	MLP	RBF
No. of MFs = 5 Input MF Type = Gaussmf Output MF Type = linear	No. of hidden neurons = 5 Activation function = Tansig Training algorithm = Train LM (Levenberg–Marquardt)	Spread = 20 Maximum no. of Neurons = 200

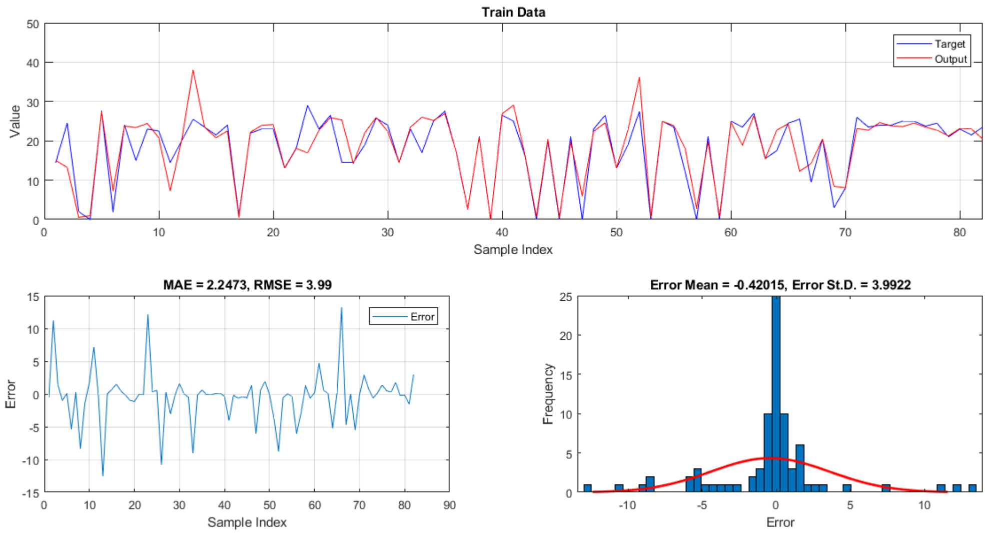
3.1 Assessment of the models

Table 3 summarizes the statistical report of the obtained results based on RMSE and MAE accuracy criteria. Moreover, Fig. 4 depicts a graphical description from the results of ANFIS, MLP, and RBF. In this regard, the measured and predicted values of the concrete slum are presented in the form of line charts for both training and testing samples. In addition, the error (i.e., the difference between the measured and modelled samples) is depicted in the form of a histogram chart showing the frequency of each error value.

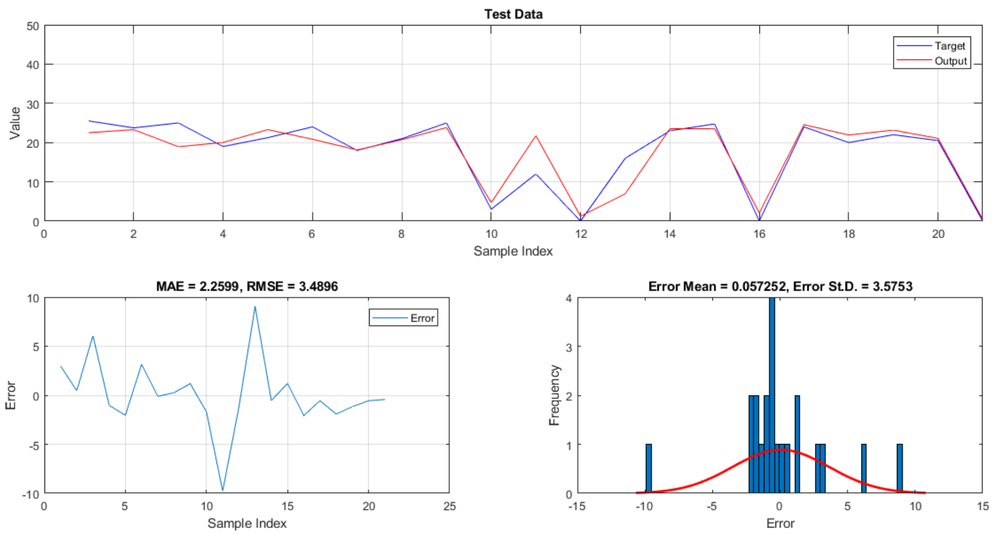
Table 3

Obtained MAE and RMSE for ANFIS, MLP, and RBF prediction

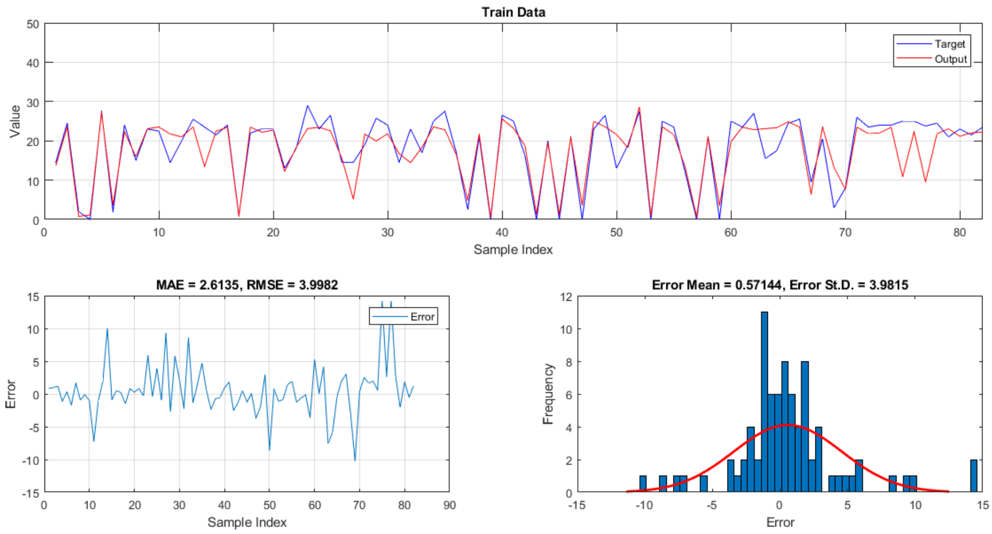
Model	Dataset			
	Training		Testing	
	RMSE	MAE	RMSE	MAE
ANFIS	3.9900	2.2473	3.4896	2.2599
MLP	3.9982	2.6135	4.9479	3.1265
RBF	4.1550	3.1451	4.7601	3.5585



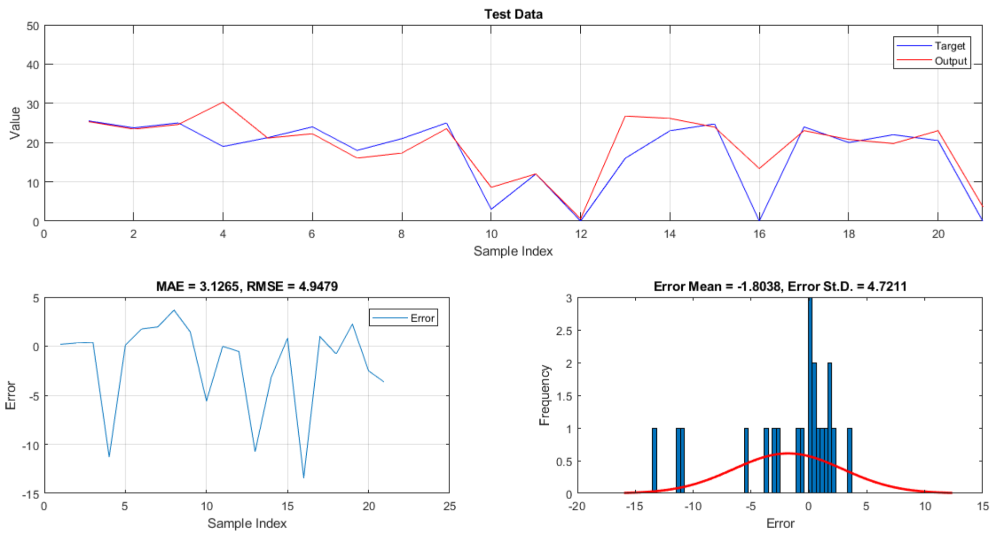
(a) ANFIS - Training



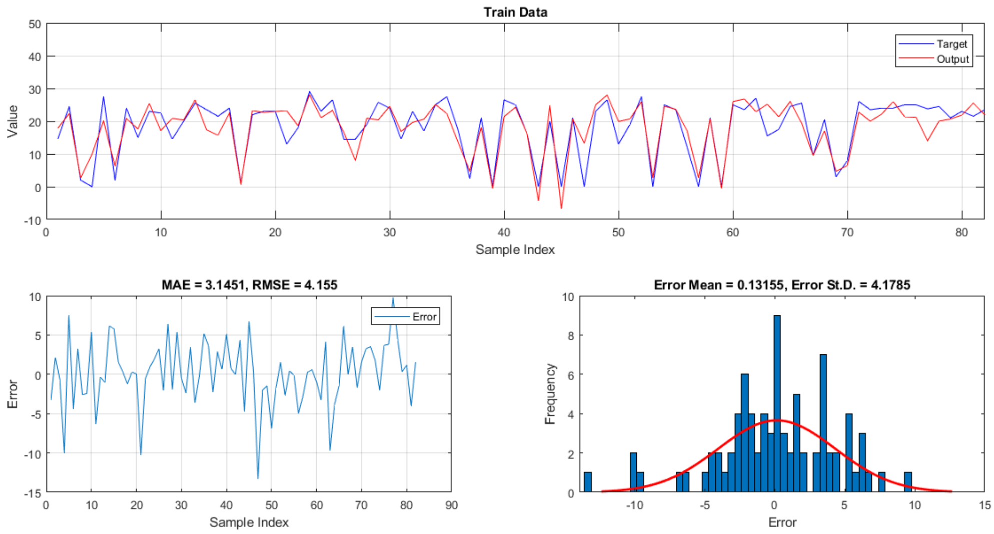
(b) ANFIS - Testing



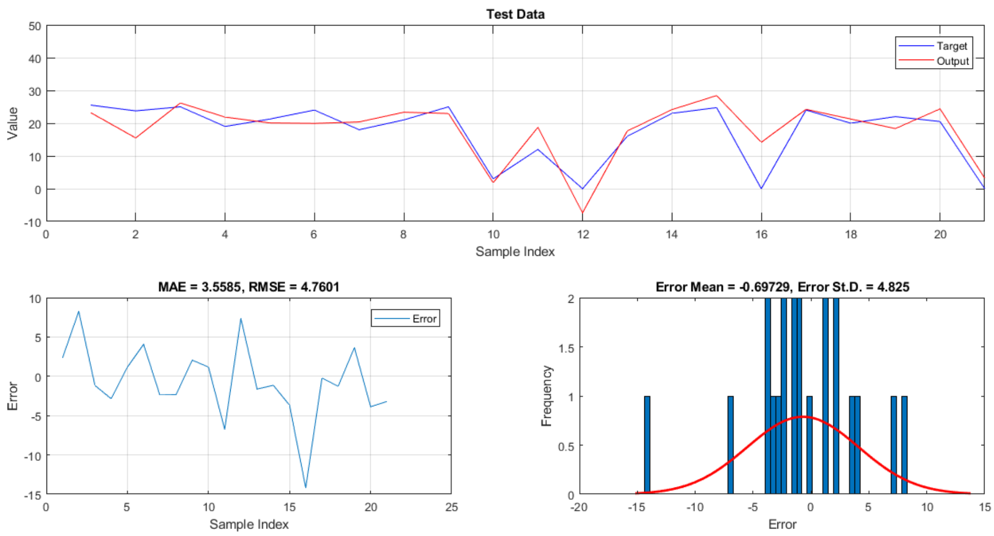
(c) MLP - Training



(d) MLP - Testing



(e) RBF - Training



(f) RBF - Testing

Fig. 4. A graphical view of the obtained results and the calculated errors for CL prediction based in (a and b) training and testing phases of ANFIS, (c and d) training and testing phases of MLP, and (e and f) training and testing phases of RBF, respectively.

As the first result, it can be concluded that all models performed efficiently, due to the low values of error calculated for all three models. From comparison viewpoint, referring to the computed RMSE in training (3.9900, 3.9982, and 4.1550, respectively for ANFIS, MLP, and RBF) and testing phases (3.4896, 4.9479, and 4.7601) it is revealed that ANFIS outperforms other models. In the case of MAE, the lowest error is obtained by ANFIS prediction for both datasets (MAE training = 2.2473 and MAE testing = 2.2599) followed by MLP (MAE training = 2.6135 and MAE testing = 3.1265) and RBF (MAE training = 3.1451 and MAE testing = 3.5585). All in all, ANFIS can be introduced as the most reliable model in this study. Likewise, however, RBF gave a lower RMSE than MLP in the testing phase, but the superiority of MLP can be deduced from the smaller error in training phase as well as both training and testing MAE criteria.

3.2 Comparison with previous studies

In this part, it was aimed to compare the results (in term of RMSE) of this study and some of the previously done researches that have used the same dataset. Note that, the results of the most efficient model (i.e., ANFIS) are considered in this part. Three related works that are presented in this part are Yeh [2], Yeh [17], and Yeh [18], which have employed an MLP neural network along with regression-based approaches for concrete slump simulation. Notably, since all of these networks have been developed using the same dataset, their input layer and output layer contains 7 and 1 computational neurons, respectively. As explained before, in Yeh [2] the superiority of the ANN was demonstrated compared to a second-order regression model. The ANN that was selected in that study had one hidden layer containing 7 hidden neurons. Yeh [17] proved the deficiency of the polynomial regression method for concrete slump prediction. This is while, an MLP with three hidden neurons in its hidden layer performed as a promising tool for the mentioned purpose. Also, Yeh [18] found that ANN results are much more accurate the non-linear regression outputs. The results are summarized in Table 4. As is seen, the ANFIS we developed in this work has achieved lower error (RMSE = 3.48) and higher correlation (0.8419) compared to the above-mentioned researches. It shows that the fuzzy-based rules surpass the neural computing in predicting the slump of concrete.

Table 4

A comparison between the results of the current study and other studies

Study	Used intelligent technique	Accuracy criteria	
		RMSE (Ideal value = 0.00)	Correlation (Ideal value = 1.00)
Yeh [2]	ANN (MLP)	8.51	0.7240
Yeh [17]	ANN (MLP)	4.12	0.816
Yeh [18]	ANN (MLP)	4.03	Not reported
This study	ANFIS	3.48	0.8419

Other than the higher potential of ANFIS that can be mentioned as a reason for this superiority, it should be noted that the distribution of data (i.e., for the training and testing sets) as well as the structure of the implemented model have a significant effect on the accuracy of the intelligent tools. Therefore, the authors suggest having an appropriate division of data and also a reliable technique for determining the optimal structure of the networks. Moreover, the optimization algorithms can be another effective was for improving the performance of such systems. Evaluating the effect of the suggested items can be a good subject for the future works.

4. Conclusions

Recent years have witnessed broad use of soft computing approaches to deal with various engineering problems. This study outlines the application of three well-known artificial intelligence tools, namely ANFIS, MLP, and RBF in concrete slump approximation. To achieve this aim, a dataset consisting of seven slump-related parameters including cement, slag, water, fly ash, super plasticizer SP, FA, and CA) were considered as the inputs of the ANFIS, MLP, and RBF models to estimate the slump of the concrete. 80% of data (82 samples) were used to train the methods, and the efficiency of each model was evaluated using the remaining 20% (21 samples). Also, we defined the accuracy criteria of RMSE and MAE to examine the efficiency of the applied models. Based on the obtained values of RMSE (3.99, 3.9982, and 4.1550, respectively for ANFIS, MLP, and RBF) and MAE (2.2473, 2.6135 and 3.1451) of the training phase, all three models performed satisfactorily in understanding the issue. Also, computed RMSE (3.4896, 4.9479, and 4.7601) and MAE (2.2599, 3.1265, and 3.5585) of the testing samples demonstrate that ANFIS outperformed other predictive methods. Based on the same reasons, MLP presents more accurate results compared to the RBF model.

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