CONCRETE STREGNTH PREDICITON MODEL BASED ON ARTIFICIAL INTELLIGENCE ALGORITHMS

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Abstract: A concrete strength prediction is done to measure the overall quality of the concrete. However, the quality of concrete is highly dependent on its ingredients, namely, cement, blast furnace slag, fly ash, water, superplasticizer, coarse aggregate, fine aggregate, and the number of days. Thus, in the literature, artificial intelligence algorithms are deployed to design concrete strength prediction models based on these ingredients. In this paper, we have considered the two artificial intelligence algorithms, namely, the artificial neural network (ANN) and termite alate optimization (TAO) algorithms, to design a concrete strength prediction model. In the proposed model, the TAO algorithm is utilized to determine the optimal weight of the ANN. The TAO algorithm is chosen over other optimization algorithms due to its better exploration and exploitation rates. In the proposed model, we have designed a multi-objective function. The parameters taken into consideration in the multi-objective function are the root mean square error, mean absolute error, and correlation coefficient. After determining the optimal weight, the ANN algorithm is trained and tested on the standard dataset. The dataset is available in the Kaggle database. The simulation result shows that the proposed model provides an overlap between the actual and predicted values. Thus, it provides a minimum error over the existing model based on ANN. Further, four performance metrics, RMSE, MAPE, NMAE, and SDE are measured for the proposed model and comparison purposes. The result shows that the proposed model achieves a lower error between actual and predicted values.

Keywords: AI, ANN, Civil Engineering, Concrete Strength, Prediction, TAO.

1. Introduction

Concrete, which consists of cement paste and aggregates, may be shaped and sized to suit almost any building need [1]. It is estimated that more than 10 billion metric tons of Portland cement concrete are produced annually across the world [2, 3]. An enormous quantity of primary resources are used in the manufacturing of concrete. Cement manufacturing, for example, consumes a lot of power and materials. To produce 1 tonne of cement, 4 GJ of energy, 1.7 tonne of raw materials, and 0.73 to 0.99 tonne of carbon dioxide are used and released [2, 4–6]. There is an annual aggregate demand of roughly 8–12 billion metric tons for Portland cement concrete manufacturing [6, 7]. Constantly increasing building needs have already begun depleting natural stone reserves, which has had and will have far-reaching ecological consequences [7–9]. As a result, the concrete sector is investigating new methods to reduce its negative effects on the environment and advance sustainable practices in the sector [10]. In an effort to reduce the cost of making concrete while also protecting the environment and minimizing waste [11–18], cement and aggregates made from construction and industrial wastes have been used as substitutes. Potential aggregate and cement alternatives include recycled asphalt pavement (RAP) and rice husk ash (RHA), both of which come from construction and agro-industrial wastes.

The basic components of concrete are cement, coarse aggregates, water, and fine aggregates [10]. Many factors, including aggregate type and amount, cement type, water content, and water-to-cement ratio [19], affect the final concrete product's performance. To simulate the influence of these variables on the mechanical characteristics of concrete, the conventional method begins with a made-up analytical equation [20]. When some of the components of the concrete are not typical materials and when the assumption is incorrect, this method fails to comprehend the real issue. When planning the construction of a concrete building, it is important to take into account the material's compressive and tensile splitting strengths [21]. The bulk of concrete's ultimate strength is reached after 28 days of curing, making that age a useful standard for calculating strength at subsequent ages.

Predicting the strength of concrete with a variety of elements has been the subject of several studies in recent years, with researchers utilizing techniques as diverse as mechanical modeling, analytical modeling, statistical approaches, and artificial intelligence [10, 22]. Artificial neural networks (ANNs) are a rapidly developing subfield of AI that has found widespread use in a variety of engineering applications [23–25]. In civil engineering, ANN has been used for a wide variety of tasks, including system identification, proportioning of concrete mix, damage detection, modeling of material behavior, prediction of foundation settling, groundwater monitoring, and prediction of concrete strength. The performance of the ANN algorithm is highly dependent on the weight values that connect the nodes. Thus, metaheuristic algorithms are deployed in the literature to find out the optimal weight values of ANN. In the literature, a number of metaheuristic algorithms are available. However, we have chosen the termite alate optimization algorithm because it provides better exploration and exploitation rates than the other optimization algorithms [26].

The main contribution of the proposed concrete strength prediction model is given below.

- The proposed model provides a minimum error between actual and predicted values over the existing model based on the ANN algorithm.
- In the proposed model, a multi-objective based objective function is designed in place of a single objective. Three performance metrics, such as RMSE, MAE, and correlation, are taken into consideration in the proposed model for multi-objective design.
- In the proposed model, the termite alate optimization algorithm is chosen for searching the optimal weight values of the ANN algorithm due to its better exploration and exploitation rate.

The paper is categorized into five sections. Section 2 shows the artificial intelligence algorithms deployed for the proposed concrete strength prediction model. Section 3 explains the proposed methodology, in which a detailed description of data collection, how artificial intelligence algorithms are deployed for the proposed model, and performance metrics are given. Section 4 shows the simulation results. Finally, a conclusion and future scope are drawn in Section 5.

2. Related Work

In this section, the artificial intelligence algorithms are explained that deployed for the proposed concrete strength prediction model.

- **Artificial Neural Network**

To make decisions in a network-like fashion, ANN takes its cue from the biological human brain, which may have as many as 60 trillion neurons. To build upon this foundational concept, artificial neural networks often start with a small number of extremely simply coupled neurons that function as a central processor. Using the neuron model developed by Mc Culloch and Pits, the notion of the perceptron was first established. The building blocks of an ANN are a single layer consisting of input, processing, and output components. Thus, ANN operates as a complicated mathematical formulation to get the best possible outcome for any datasets or issue segments, starting from the most fundamental idea of the information processing cycle. Both the feed-forward and backward algorithms should be used to evaluate a neuron as part of a network's cycle. Historically and now, backward algorithms and back propagation have received the most attention from scholars.

Initially, the number of layers is determined by the difficulty of the task. The four fundamental processes of a neural network are the "initialization," "activation," "weight training," and "iteration" in a classification job. The process, or the activation functions, are different, however, depending on the nature of the issue at present. Neurons, linked through connections, are the building blocks of a neural network and the basis for its ability to process information. Every neuron has many weights in addition to the adjusted weight, and each connection has its own weight. Connections will be radiating outward from the input neuron. This kind of network is called a feed-forward (FF) neural network. In the final result, each connection is represented by a weighted number. Perceptron is a collective noun for all of interconnected nodes. Each of the input connections will be assigned a weight, and then those weights will be added together to provide an activation function. At this point, the Conjugate gradient formulas were used to determine the optimal weight linked to the next layer, layer2 to layer3, and so on up to layer n. The complexity of the problem at hand determines the optimal number of layers for a given network. Using feedforward and backpropagate algorithms, the following figure depicts a simple NN process.

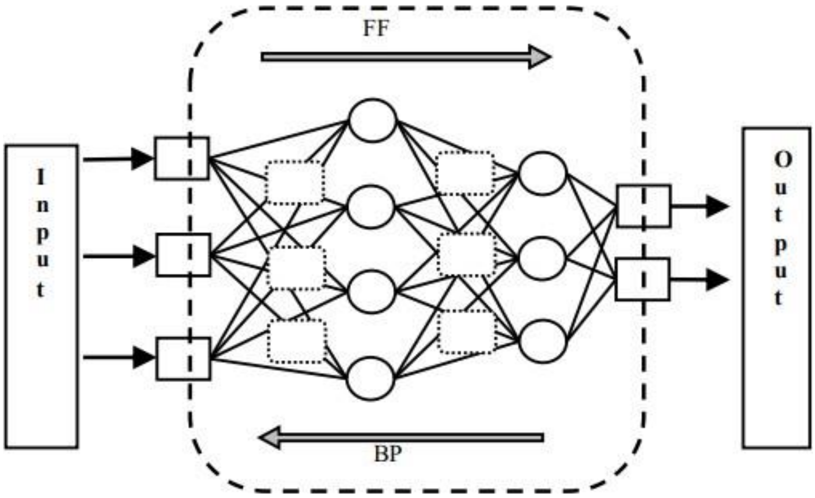

Figure 1 Block Diagram of FF and BP ANN [27]

- **Termite Alate Optimization Algorithm**

Optimization algorithms are crucial in the search for the best answer to any issue by identifying the objective function that best describes it. Due to their superior performance over conventional methods, metaheuristic algorithms have assumed a central position in the study of optimization problem-solving in the academic literature. Researchers have created and tested a wide variety of metaheuristic algorithms. The main drawbacks of these metaheuristic-based algorithms, however, are their complexity and the large number of input parameters that need tuning. In order to find the best possible settings for an artificial neural network's weights, they have implemented a novel metaheuristic method here known as the Termite Alate Optimisation method (TAOA). The termite alate group serves as the basis for this system's phototactic action. This algorithm's strengths lie in its efficient exploration and exploitation, as well as its quick convergence rate. The computational complexity and number of process parameters in this approach are both on the low side [26]. The TAO algorithm's two guiding principles are outlined below.

- The termites are drawn to the alate in the brightest position, while they are repulsed by the alate in the darkest location.
- The population of termite alates looking for the best light source remains stable. Birds eat the alates that live in the shadows, and the alates who can't fly to the light die before they get there. So, new alates are introduced into the more illuminated areas, while the old ones are removed.

The first rule lets TAOA start probing the search space. At the same time, it turns the last phase of convergence seeking into an exploitative activity. The second rule improves the convergence rate of TAOA by preventing termite alates from being stuck in local optima.

Each alate's location in the algorithm is determined by a vector whose length is equivalent to the number of variables (d) in the fitness function. Each area's fitness function value is indicative of its brightness. The intensity of the light is directly related to the value of the fitness function in maximization issues. In contrast, in minimization problems, the value of the fitness function has a negative correlation with how brilliant the solution is.

The TAO algorithm may be broken down into two distinct parts. At initially, all of the alates will go towards the one in the brightest area and away from the one in the darkest one. In the second stage, alates are separated into two groups: those that will survive the light, and those that will be eliminated. Any given alate in the population may be filtered out if its present location is too bright or too dark relative to the location of the newly chosen alate. The previous alate is removed and a new one is installed if the new alate is located in a more advantageous lighting situation.

3. Methodology

The main motive of the proposed model is designed a model which accurately predicts compressive strength of the concrete. Figure 2 shows the main steps of the proposed model, namely, data collection, pre-processing of the dataset, train and test the ANN, train and test the ANN with optimal weight value determination of it using Termite Alate Optimization Algorithm, and performance analysis. The detailed description of these steps is described below.

- **Data Collection:** In the proposed model, we have taken standard dataset to measure the concrete compressive strength. The dataset is publicly available on Kaggle [28]. The dataset contains total eight ingredients of concrete, namely, cement, blast furnace slag, fly ash, water, superplasticizer, coarse aggregate, fine aggregate and according to these ingredients' concrete compressive strength. Thus, total eight ingredients are used as input attributes and concrete compressive strength as the output attribute for train and test the proposed model. Further, dataset contains total 1030 observations.

- **Pre-Processing of the Dataset:** In this step, pre-processing of the dataset is done to extract the attributes from the dataset and classify into training and testing dataset. In the dataset, first eight attributes are classified into training dataset and nineth attribute is classified into testing dataset.

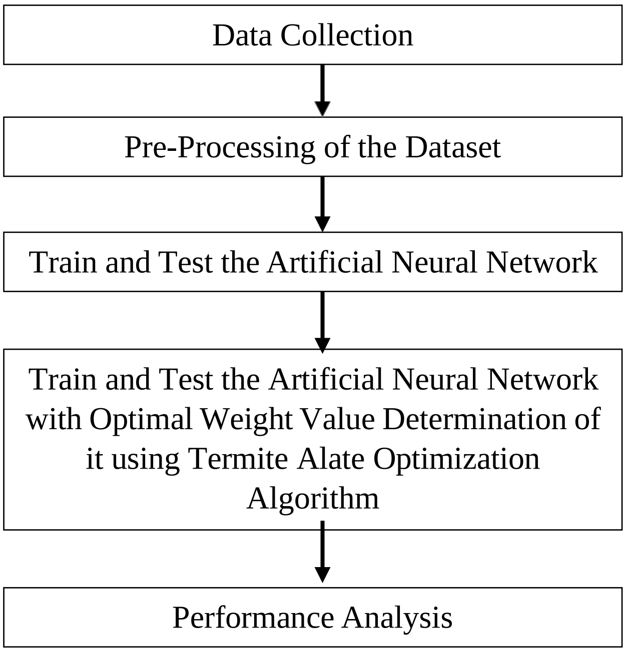

Figure 2 Steps of Concrete Strength Prediction Model

- **Train and Test the Artificial Neural Network:** In this step, the ANN algorithm is configured and prediction is done by giving the training and testing dataset to the network. In this step, the weight values of the ANN are randomly chosen.
- **Train and Test the Artificial Neural Network with Optimal Weight Value Determination of it using Termite Alate Optimization Algorithm:** In this step, optimal weight values of the ANN algorithm are determined using the TAO algorithm based on the multi-objective function. In the proposed model, objective function is designed based on the RMSE, MAE, and correlation coefficient, as shown in Eq. (1).

  $$MOF = RMSE + MAE + \frac{1}{CC} \quad (1)$$

  In Eq. (1), MOF denotes the multi-objective function whereas RMSE, MAE, and CC denotes the root mean square error, mean absolute error, and correlation coefficient, respectively. After determination of the optimal weight, the ANN algorithm is configured and prediction is done by giving the training and testing dataset to the network.
- **Performance Analysis:** The performance analysis of the proposed concrete strength prediction model is done using various performance metrics, such as RMSE, MAPE, NMAE, SDE, and convergence rate. Table 1 shows how these performance metrics are calculated.

Table 1 Performance Metrics

Parameter	**Equation**

Root Mean Square Error (RMSE)	$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(O_i - P_i)^2}$
Mean Absolute Percentage Error (MAPE)	$MAPE = \frac{100}{N}\sum_{i=1}^{N}\left\lvert\frac{O_i - P_i}{O_i}\right\rvert$
Normalized Mean Absolute Error (NMAE)	$NMAE = \frac{1}{N}\sum_{i=1}^{N}\left\lvert\frac{O_i - P_i}{O_{Peak}}\right\rvert$
Standard Deviation of Error (SDE)	$SDE = \frac{1}{N}\sum_{i=1}^{N} e_p - \overline{e}$
Convergence Rate	CR=Objective Function vs. Iterations

4. Simulation Results

This section shows the simulation results of the proposed concrete prediction model and comparative analysis with the existing models for validation purposes. MATLAB software is used for simulation purposes because it supports a number of inbuilt libraries, functions, and graphical support. The hardware configurations of the system are i7 processor, 64-bit operating system, window-10, 1TB hard disk, and operating at 2.70GHz. Further, Table 2 shows the setup configuration of artificial intelligence algorithms are deployed for the proposed model.

Table 2 Setup Configuration of the Artificial Intelligence Algorithms

Parameters	Values
Number of Iteration	50
Population Weight Value	5
beta	0.2
Pe	0.25

Figure 3-11 shows the number of samples vs. various components distribution to used to simulate the proposed model on the standard dataset.

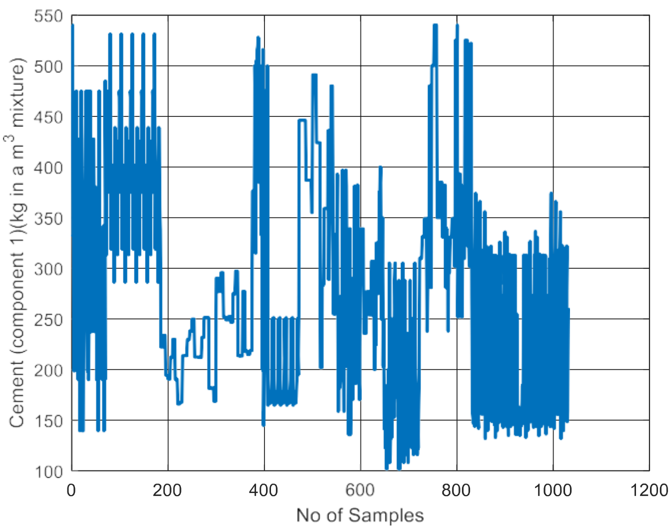

Figure 3 Number of Sample vs. Cement Distribution

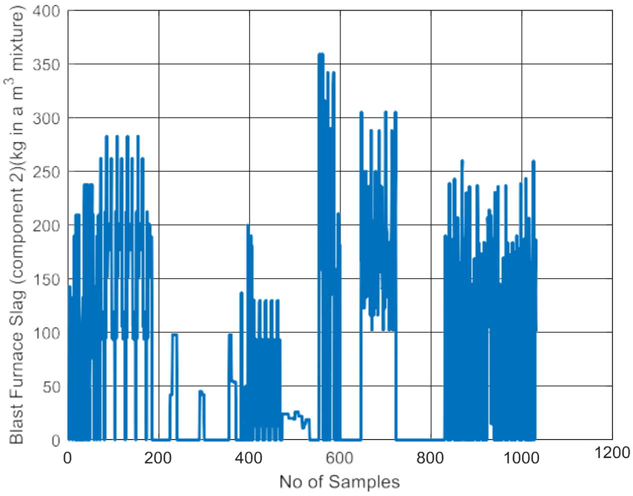

Figure 4 Number of Sample vs. Blast Furnace Slag Distribution

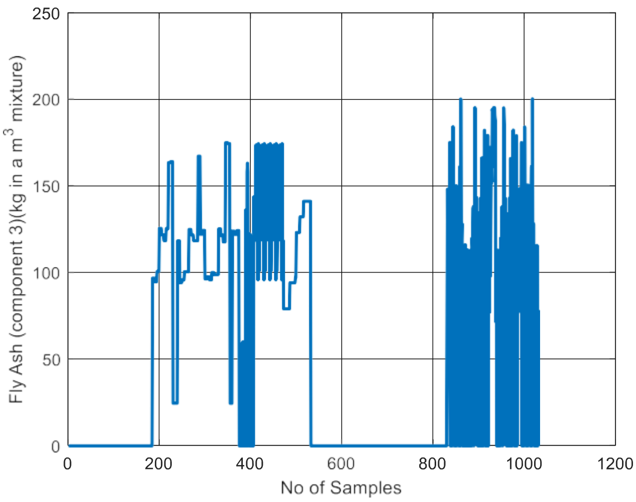

Figure 5 Number of Sample vs. Fly-Ash Distribution

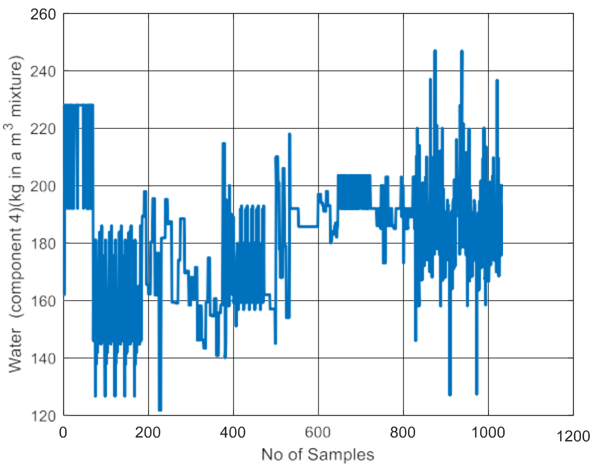

Figure 6 Number of Sample vs. Water Distribution

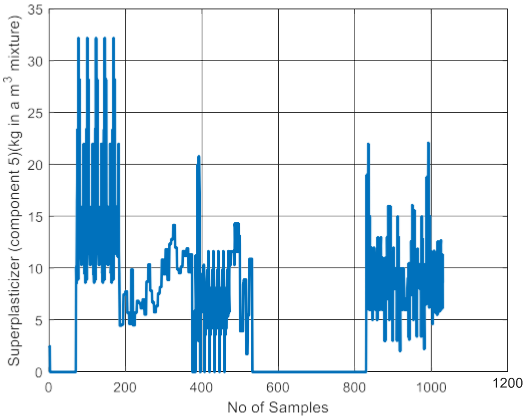

Figure 7 Number of Samples vs. Superplasticizer Distribution

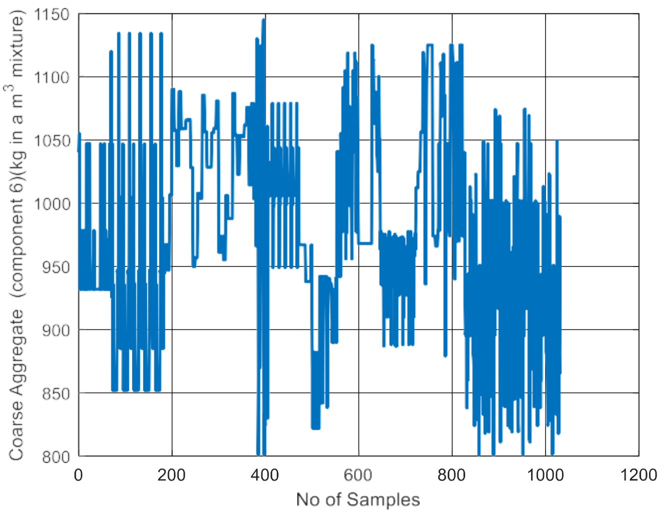

Figure 8 Number of Samples vs. Coarse Aggregate Distribution

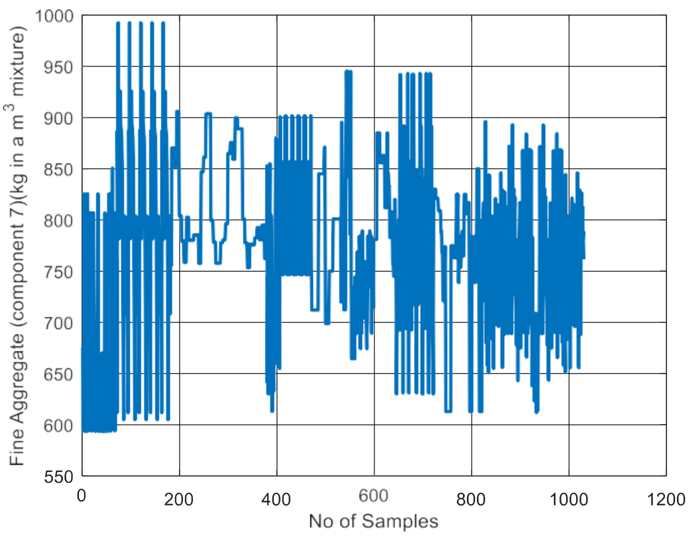

Figure 9 Number of Samples vs. Fine Aggregate Distribution

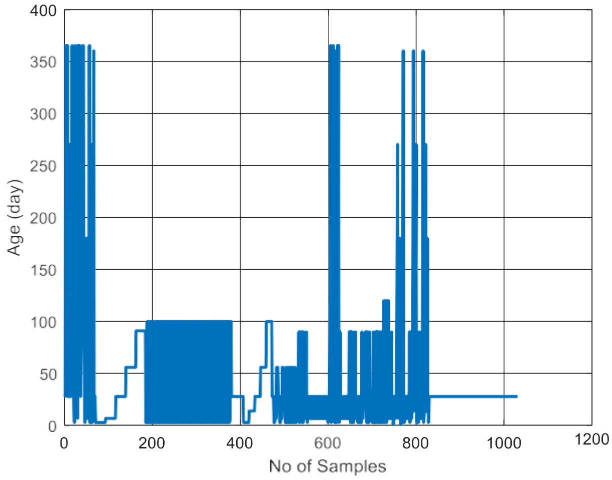

Figure 10 Number of Samples vs. Age (Day) Distribution

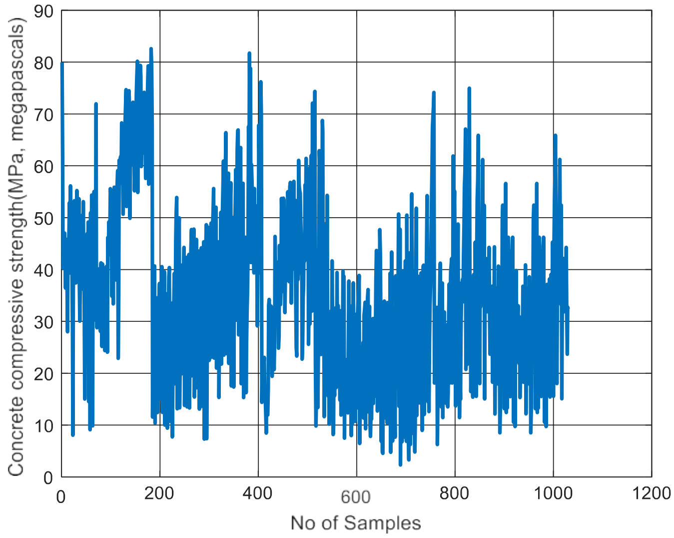

Figure 11 Number of Samples vs. Concrete Compressive Strength Distribution

Figure 12-13 shows the graph for number of samples vs. compressive strength for ANN and proposed model (ANN_TAO Algorithm). The result shows that there is huge difference between actual and predicted value for ANN algorithm, as shown in Figure 10. On the other hand, Figure 11 shows the actual and predicted values are overlapped and produces lesser error for the proposed model.

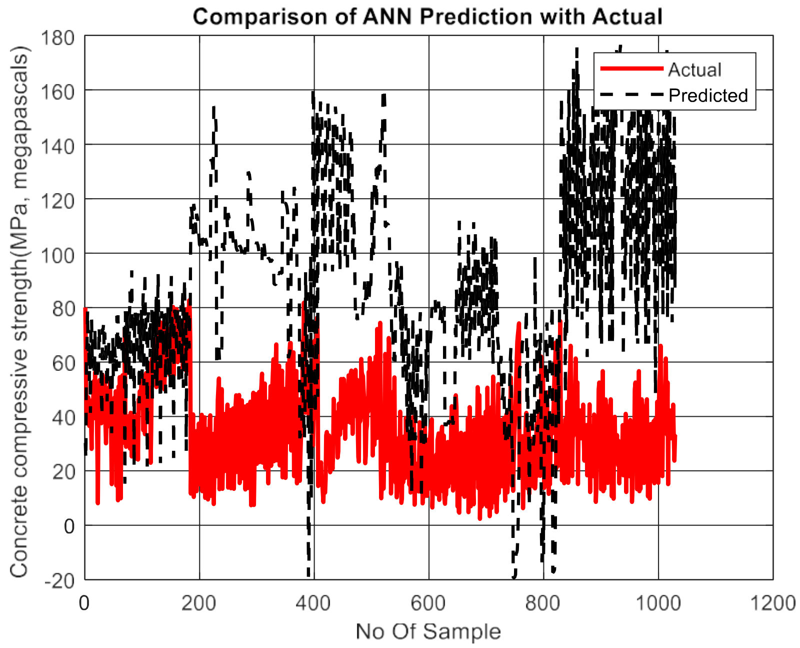

Figure 12 Number of Samples vs. Concrete Compressive Strength Prediction for ANN Algorithm

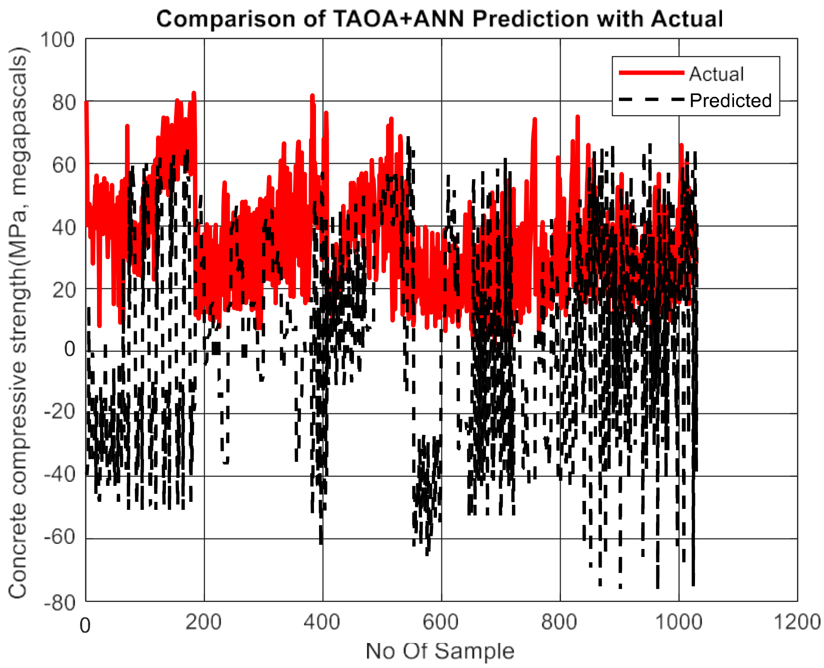

Figure 13 Number of Samples vs. Concrete Compressive Strength Prediction for Proposed Model (ANN_TAO Algorithm)

Table 3 shows the comparative analysis of FF-ANN and proposed model based on various performance metrics. The result shows the proposed model achieves lesser error between actual and predicted value over existing ANN algorithm in terms of RMSE, MAPE, NMAE, and SDE. Figure 14 shows the proposed model achieves RMSE=48.577 over 67.782, MAPE=131.01 over 251.23, NMAE=37.66 over 63.655, and SDE=38.781 over 56.648.

Table 3 Comparative Analysis based on Various Performance Metrics

Parameter	FF-ANN	Proposed Model (ANN_TAO Algorithm)
RMSE	67.782	48.577
MAPE	251.23	131.01
NMAE	63.655	37.66
SDE	56.648	38.781

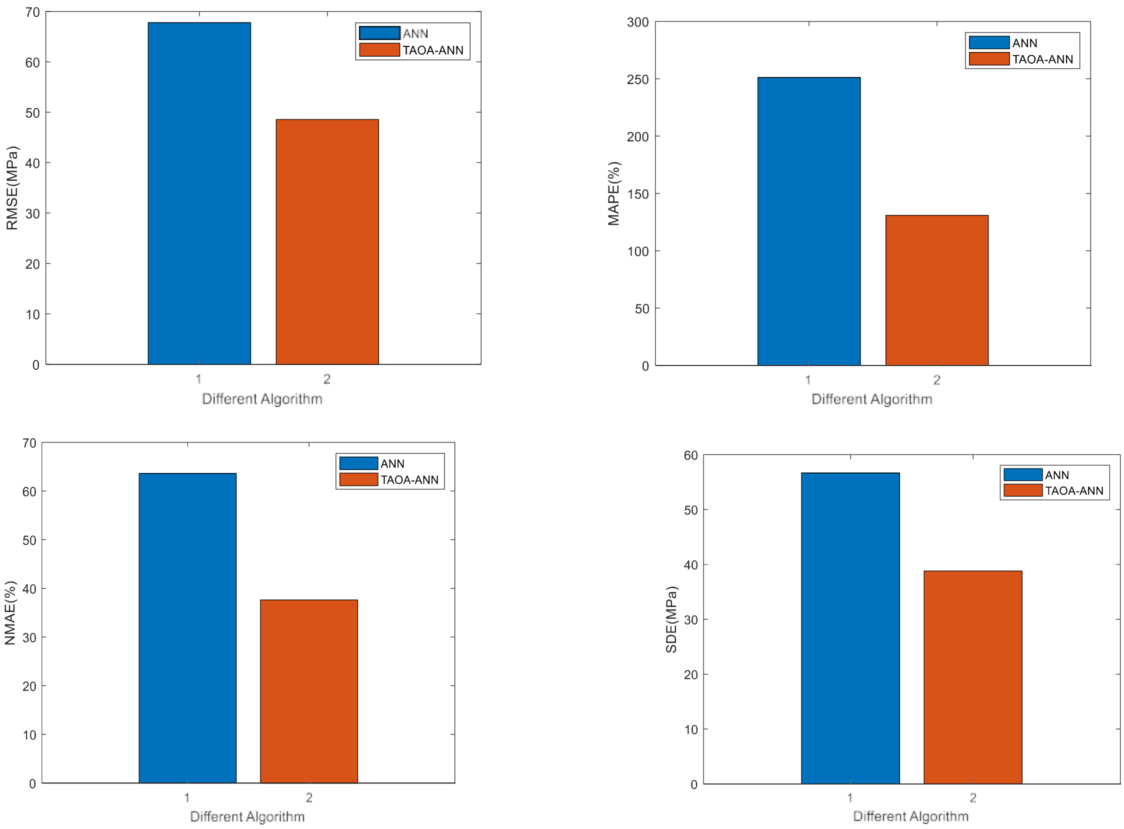

Figure 14 Comparative Analysis based on RMSE, MAPE, NMAE, and SDE Parameter

Figure 15 shows the convergence rate graph is plotted for termite alate optimization algorithm for search the optimal weight values of the artificial neural network. The result shows that the TAO algorithm searches the optimal solution in the 13th iteration.

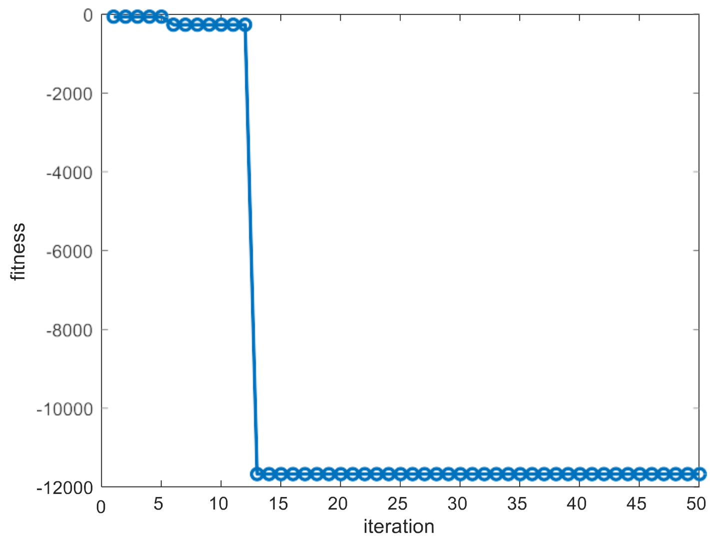

Figure 15 Convergence Rate Graph for TAO Algorithm for Search the Optimal Weight Values of the ANN Algorithm

5. Conclusion and Future Work

In this paper, we have proposed a concrete strength prediction model that is based on artificial intelligence algorithms. In the proposed model, an artificial neural network, and a termite alate optimization algorithm are taken into consideration. The main role of the ANN algorithm is to predict the compressive strength of the concrete based on the various ingredients, whereas the TAO algorithm is utilized to determine the optimal weight value of the ANN algorithm based on the objective function. Further, the main novelty of the proposed model is that, we have designed a multi-objective function by considering the RMSE, MAE, and correlation coefficient parameters. The simulation result shows that minimum parameters are required to initialize the TAO algorithm. Next, the proposed model achieves a minimum error between the actual and predicted values. Further, the proposed model achieves a low RMSE of 48.577, MAPE of 131.01, NMAE of 37.66, and SDE of 38.781. Moreover, the convergence rate graph shows the proposed model searches for the optimal value in the initial iterations. In the last section, the comparative analysis with the existing ANN model shows that the proposed model provides superior performance. In the future, we will explore other artificial intelligence algorithms to design the concrete strength prediction model that gives the minimum error between the actual and predicted values. Further, we will explore other metaheuristic algorithms that require no parameter tuning to search the solution space for optimal solutions, such as the JAYA, RAO algorithms.

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