A Neuro-Fuzzy Predictor Trained by an Elitism Artificial Electric Field Algorithm for Estimation of Compressive Strength of Concrete Structures

Ch. Sanjeev Kumar Dash[1], Sarat Chandra Nayak[2], Ajit Kumar Behera[1], Satchidananda Dehuri*[3]
[1]Department of Computer Science and Engineering, Silicon Institute of Technology, Silicon Hills, Patia, Bhubaneswar – 751024, India
[2]Department of Artificial Intelligence Engineering & Machine Learning, CMR College of Engineering & Technology, Hyderabad-501401, India
[3]Department of Information and Communication Technology, Fakir Mohan University, Vyasa Vihar, Balasore-756019, Odisha, India.
E-mails: sanjeev_dash@yahoo.com, saratnayk234@gmail.com, ajit_behera@hotmail.com, satchi.lapa@gmail.com

Keywords: metaheuristics, compressive strength of concrete, artificial neural network, artificial electric field algorithm, neuro-fuzzy systems, predictive systems, elitism

Received: Januar 30, 2022

Meta-heuristic learning-based forecasting is widely acceptable vis-à-vis manual and statistical methods in estimating the compressive strength of concrete structures. However, there is always a scope for exploring an effective, automated, and accurate predictor for this domain. This article proposes an elitism artificial electric field algorithm-based neuro-fuzzy network (eAEFA+NFN) for the prediction of compressive strength of concrete structures. The elitism method helps AEFA preserve the best individuals from iteration to iteration, by directly placing best fit particles into the population for the next generation and thus strengthening the optimization capacity of AEFA. A single hidden layer neural network (SHNN) is used as the base model and its inputs are fuzzified using the Gaussian triangular membership function with a degree of membership to different classes. The optimal number of input data, hidden neurons, bias, and weights for the hidden layer are decided by eAEFA. The model is evaluated on samples from a publicly available dataset with curing ages at 3, 7, 14, and 28 days. Considering four sample series, the eAEFA+NFN produced an average MAPE of 0.092073 and ARV of 0.139731 which are better compared to others. The experimental outcomes and analysis are in favor of the eAEFA+NFN-based forecasting.

Povzetek: Predlagana je meta-hevristična metoda eAEFA+NFN za napovedovanje moči betonskih struktur, ki temelji na elitistični AEFTA in nevro-mehkih mrežah z Gaussovo triangulacijo.

1 Introduction

Estimation of compressive strength (CS) [1] of concrete structures is a contemporary research area in the domain of manufacturing and construction engineering. The manual approach to solving this is very costly and time-consuming. Despite the availability of a large number of analytical and statistical models, the prediction preciseness is not quite satisfactory. In the last twenty years or so, multiple machine learning (ML) approaches to solve this problem have gained momentum, due to the availability of simulated datasets. The above-mentioned models are proven to be good in extrapolating data and predicting input-output relationships. Artificial neural networks (ANNs) are the most popularly used approach for concrete structure-property prediction. ANN-based [2] methods for compression strength prediction were also proposed where ANN trained with gradient descent method is found generating superior results compared to multiple regression analysis. Gradient-based learning methods are common approaches for ANN training. The pitfalls associated with ANN include imprecise learning, lethargic convergence rate, and inclination to local minima. Some other difficulties associated with ANN are appropriate learning mechanisms, optimal network structure, computation of the model, etc. However, there is no proper way of finding an optimal ANN and it is still a challenging task for researchers. Alongside, the fuzzy logic system (FLS) which is capable of handling uncertainties and incompleteness associated with real-life datasets. ANNs are suitable for dealing with quantitative and numeric data, while FLS are capable of handling qualitative and symbolic data. Individually both have reached a degree of maturity and excelled in solving real-world problems. Integration of ANN [3] and FL gives a synergetic effect as compared to an individual. The advantage of ANN [4] learning and fuzzy if-then rules with suitable membership functions are hybridized to obtain a high degree of accuracy in generating nonlinear input-output relationships. The hybrid systems combine the learning and connectedness architecture of neural networks with the human-like logical reasoning capability of fuzzy systems and take advantage of both.

Newly, AEFA [5] has been anticipated as an optimization method inspired by the principle of electrostatic force. AEFA is based on the strong theoretical concept of charged particles, electric field, and force of attraction/repulsion between two charged particles in an electric field. The learning capacity, convergence rate, and acceleration updates of AEFA have been established through solving some benchmark optimization problems. AEFA starts with random solutions, fitness evaluation, reproduction, and updating the velocity and position of the particles in the search space. The updated solution is then compared with the previous one, and the better-fit one is retained.

The objective of this article is to design a robust data-driven ML-based forecasting technique for modeling and forecasting the compressive strength of concrete structures. The forecast capitalizes on the approximation ability of ANN and the reasoning capability of FLS to generate a neuro-fuzzy network (NFN). The proposed eAEFA is used to design the optimal parameters of NFN as well as the size of the input and the hidden layers, thus producing a hybrid forecast, i.e., eAEFA+NFN. The proposed forecast is then used to reveal the hidden nonlinear pattern associated with the samples in the dataset and evaluated through different error metrics. The new answer is then compared to the old one, and the one that fits better is kept. However, in the preceding level, known as elite solutions, there may be a few good options. These elite answers are passed down to the next generation without alteration in the elitism mechanism. The worst answers are phased out in favour of elite ones. The worst solutions are replaced by the elite solutions discovered in the preceding generation of any generation. With many swarms and evolutionary algorithms, the elitism process of replacing the poorest answers with elite ones is implemented. The elitism approach aids AEFA in preserving the finest individuals from iteration to iteration by immediately introducing the best-suited particles into the population for the following generation, hence enhancing AEFA's optimization capability.

The rest of the article is organized into four sections. Section 2 discusses related works, Section 3 briefs about the methods and dataset, Section 4 summarizes the experimental outcomes and discussion, followed by concluding remarks in Section 5.

2 Related work

The background of the research work is presented in this Section. In Subsections 2.1 and 2.2, literatures study of FLANN as a classifier and predictor is discussed. Feature selection and its importance are the focus of Subsection 2.3. Differential evolution, a meta-heuristic computing paradigm is discussed in Subsection 2.4. Feng et al. [6] have used the adaptive boosting technique for predicting the compressive strength of concrete. By taking 1030 sets of data, they have compared their model with other individual machine learning techniques like artificial neural network (ANN) and support vector machine (SVM). The proposed approach is superior to other models. Deng et al. [7] have used a deep learning technique, namely convolution neural networks, for the prediction of compressive strength of recycled aggregate concrete. After that, the model is developed by softmax regression. Finally, their model is considered a new method for calculating the strength of recycled concrete. Salami et al. [8] have proposed a model by using the least square support vector machine (LSSVM) to predict the compressive strength of ternary-blend concrete. They have also applied Coupled simulated annealing (CSA) to LSSVM model for better performance. Kumar et al. [9] have applied different machine learning algorithms, such as Ensemble Learning (EL), Gaussian Progress Regression (GPR), Support Vector Machine Regression (SVMR), optimized GPR, SVMR, and EL, to predict the compressive strength of Lightweight Concrete (LWC). Khursheed et al. [10] have used different machine learning techniques such as extreme learning machine (ELM), emotional neural network, genetic programming, relevance vector machine, and min-max probability machine regression to forecast the 28-day compressive strength of fly ash concrete. Latif [11] has developed an LSTM model to predict concrete compressive strength. In his model, three statistical indices were used, namely the coefficient of determination (R2), mean absolute error (MAE), and root mean square error (RMSE). Asteris et al. [12] have proposed a hybrid ensemble surrogate machine learning technique to predict the compressive strength of concrete. Their HENSM model gives a very high predictive accuracy compared with other models.

Güçlüer et al. [13] have used Linear Regression (LR) algorithms, Decision Tree (DT), Artificial Neural Network (ANN), and Support Vector Machine (SVM) to measure concrete compressive strength. They found the DT algorithm had the least amount of error and is most suitable for use in concrete compressive strength estimation.

Abuodeh et al. [14] have attempted to address the ambiguity by applying two deep learning techniques to identify the critical material constituents that affect ANN.

Sevim et al. [15] have proposed a prediction model to predict the compressive strength of mortar samples. For model construction, they have used adaptive-network-based fuzzy inference systems and artificial neural networks (ANN). Finally, they compared the results with Multi-Linear Regression. Table 1 shows a few popular research results.

Table 1: Brief discussion of use of AEFA and ANN and prediction of concrete structure.

Ref. No.	Author	Model	Purpose	Outcome
[5]	Yadav et al.	AEFA	Proving of AEFA	AEFA is the best

			algorithm	optimization algorithm
[6]	Feng et al.	Adaptive boosting	Compressive strength test of the concrete structure	ANN and SVM give better result
[7]	Deng et al.	Deep learning method	To find the strength of recycled concrete.	Gives higher precision, high efficiency, and high generalization.
[8]	Salami et al.	LSSVM, LSSVM-CSA	To find the strength of ternary-blend concrete	LSSVM-CSA model works fine than another model with R^2 a value is 0.954
[9]	Kumar et al.	GPR, SVMR, EL, LWC	To predict the compressive strength of Lightweight Concrete	GPR gives the highest accuracy
[10]	Khurshed al.	MPMR, RVM, GP, ENN and ELM models.	To predict the compressive strength of concrete	MPMR gives better results than other models.
[11]	Latif	LSTM	To predict concrete compressive strength	LSTM model works fine than other models.
[12]	Asteris et al.	Hybrid HENSM model	To predict compressive strength (CS) of concrete structure	HENSM model better than CML model.
[13]	Güçlüer et al.	(ANN), (DT), (SVM) and (LR) algorithms.	To predict the concrete compressive strength	Best correlation coefficient and best absolute error using DT algorithm
[14]	Abuodeh et al.	SFS and NID	To find critical material constituents that affect the ANN	ANN with SFS and NID gives improved accuracy than other models.
[15]	Sevim et al.	ANN, ANFIS	To estimate compressive strength using the chemical composition of fly	GA-based ANFIS gives better result
[17]	Priyadarshee et al.	ANN	Compressive Strength (UCS) of Kaolin clay	ANN model gives better results than the MRA model
[18]	Cao et al.	MOMEM	Estimation of the ultimate shear strength of the soil	MOMEM is significantly superior to other AI-based methods
[19]	Dash et al.	QORA-ANN	Prediction of cryptocurrency	QORA-ANN is better than ANN-GA, ANN-DE, ANN-PSO
[20]	Sharifi et al.	ANN	Compressive strength of the mortars	ANN-based model gives better results for finding compressive strength of the mortars
[22]	Anita et al.	*AEFA with CSS, MOA, PSO, and GSA*	Stability condition checking of AEFA	AEFA works fine for stability condition checking
[23]	Nayak et al.	*Extreme learning-AEFA*	For optimizing the parameters of a neural network with a single hidden layer.	Generates the lowest mean absolute percentage of error (MAPE)
[24]	Anita et al.	*AEFA compared with PSO, GA, ABC, and GSA.*	AEFA is tested for two benchmark problem that is six and fifteen generator power plant systems.	The convergence rate is fast in case of AEFA
[25]	Behera et al.	*AEFA+ANN*	AEFA + ANN model used to predict software reliability datasets	The proposed model is best suitable for forecasting
[26]	AL-Dmour et al.	*AEFA*	Placement of phasor measurement units using an optimization algorithm	AEFA is best suitable for OPP problem

3 Methods and our model

This section presents methods like eAEFA and NFN in a nutshell and the development of the proposed eAEFA+NFN in detail.

3.1 *eAEFA*

AEFA simulates the charged particles as agents and measures their strength in terms of their charges [5]. The particles are moveable in the search domain through electrostatic force of attraction/repulsion among them. The charges possessed by the particles are used for interaction and the positions of the charges are considered the potential solutions to the problem. According to AEFA, the particle having the highest charge is measured as the best individual, and it attracts other particles having inferior charge and moves in the search domain. The mathematical justification of AEFA is illustrated in [5]. The velocity and position of a particle at time instant ‘t’ are updated as per Eqs. (1) and (2), respectively.

$$Velocity_i^d(t+1) = rand_i * Velocity_i^d(t) + acceleration_i^d(t) \tag{1}$$

$$Position_i^d(t+1) = Position_i^d(t) + V_i^d(t+1) \tag{2}$$

Elitism, as previously said, is a technique for passing down the greatest persons from generation to generation. The system never loses the best individuals discovered during the optimization process in this manner. Elitism can be achieved by inserting several of the best individuals into the next generation's population. Here, we simulate a potential solution of SHNN as a charged particle and its fitness function as the quantity of charge associated with that element.

3.2 NFN

The proposed method uses an SHNN as the base model depicted in Figure 1. An input undergoes a fuzzification process using the Gaussian triangular membership function as shown in Eq.3. The expanded vector intensifies the dimensionality of the input vector thus, generates a hyperplane that affords larger discrimination ability in the input pattern space.

$$Gaussian(x;c,\sigma)=e^{-\frac{1}{2}\left(\frac{x_i-small_i}{width_i}\right)^2}, \quad (3)$$

where x = input, c = center of the pattern, and σ = width of the input pattern. Considering smallest, medium, and biggest values as the center of the input pattern, a unit in the input pattern has a triangular membership function as in Eqs. (4) – (6).

$$O_{i,1}(x_i, small_i, width_i)=e^{-\frac{1}{2}\left(\frac{x_i-small_i}{width_i}\right)^2}, \quad (4)$$

$$O_{i,2}(x_i, \mathrm{medium}_i, width_i)=e^{-\frac{1}{2}\left(\frac{x_i-medium_i}{width_i}\right)^2}, \text{ and} \quad (5)$$

$$O_{i,3}(x_i, \mathrm{big}_i, width_i)=e^{-\frac{1}{2}\left(\frac{x_i-big_i}{width_i}\right)^2}. \quad (6)$$

The medium value of the i^{th} input vector $=(big_i-small_i)/sizeofinputpattern$. Each data is used as the input of these membership functions (low, medium, high) and the outputs $O_{ij}(i=1...N, j=1,2,3)$ are the grades of membership. For an input vector $X=[x1,x2,...,x_N]^T$ and membership of i^{th} the input pattern as $mf_{i,j}(x_i)$,the $N\times M$ membership matrix after fuzzification process is shown in Eq.7. This matrix is supplied to the SHNN as input.

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_N \end{bmatrix}^T = \begin{bmatrix} mf_{1,1}(x_1) & mf_{1,2}(x_1) & mf_{1,3}(x_1) \\ mf_{2,1}(x_2) & mf_{2,2}(x_2) & mf_{2,3}(x_2) \\ mf_{3,1}(x_3) & mf_{3,2}(x_3) & mf_{3,3}(x_3) \\ \cdots & \cdots & \cdots \\ mf_{N,1}(x_N) & mf_{N,2}(x_N) & mf_{N,3}(x_N) \end{bmatrix} \quad (7)$$

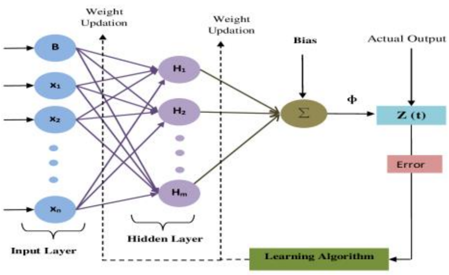

Figure 1: Single hidden layer neural network.

To increase its optimization potential, the recently created AEFA [21, 24] has been infused with the idea of elitism. The elitism approach assists AEFA in preserving the greatest individuals from generation to generation by immediately inserting the best-fit particles into the population for the following generation. The architecture of the proposed eAEFA+NFN model is presented in Figure 2.

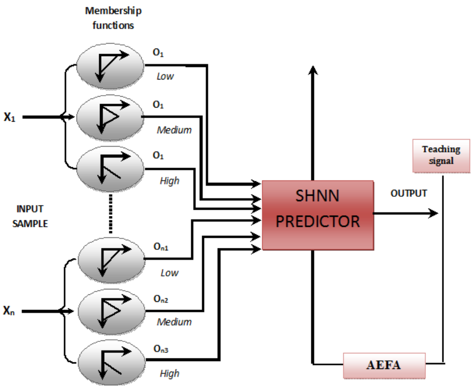

Figure 2: Architecture of eAEFA+NFN.

Output at j^{th} hidden neuron is calculated using Eq. 8 and that of output neuron is calculated using Eq. 9.

$$Z=f(Bias_j+\sum_{i=1}^{n}Weight_{ij}*O_i) \quad (8)$$

$$Z=f(Bias_o\sum_{i=1}^{m}Weight_j*Z) \quad (9)$$

This output is compared to the target output and the error is calculated as $Error_i=|Target_i-Estimated_i|$. We simulate a potential solution of SHNN as a charged particle and its fitness function (i.e., error) as the quantity of charge associated with that element. The velocity and position of a particle are updated as per Eq. 1 and 2.

3.3 eAEFA+NFN

This section describes the design of eAEFA+NFN [21,22,27] model and then the CS forecasting process. As discussed earlier, elitism is a mechanism to retain the finest entities from generation to generation. By this method, the system never misses the finest individuals initiated throughout the optimization procedure. Elitism can be done by inserting one or more best individuals directly into the population for the subsequent generation. The overall eAEFA+NFN process is depicted in Figure 3. The process starts with a random initial population of solutions. An individual of the population represents a potential initial weight and bias of NFN. This population and the input samples are fed to the NFN model and the fitness is evaluated. Based on the fitness, a set of elite solutions are selected. The remainder of the population is subject to the regular operators of AEFA. At the end of the current generation, the updated and original solutions are compared and the better one is carried over. Here, the worst solutions are substituted by the elite solutions and the process passes into the subsequent generation. In this way, the elite solutions are carried forward through successive generations. Finally, the best solution is preserved and used for testing. The high-level eAEFA+NFN process is presented by Algorithm 1 and depicted in Figure 3.

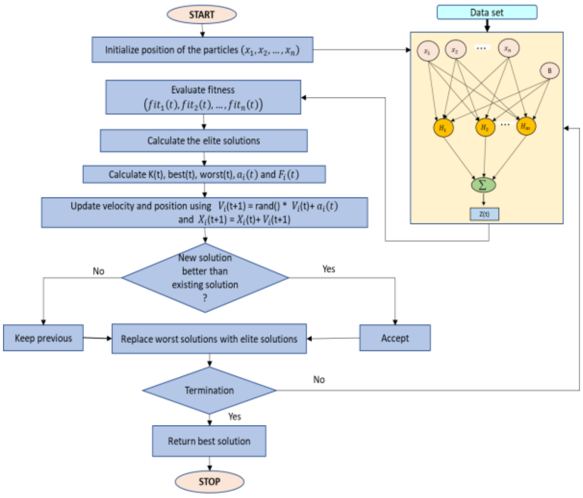

Figure 3: The eAEFA+NFN-based forecasting process.

Algorithm 1: eAEFA+NFN Training

1. Initialization of population
2. Setting Input data
3. Fuzzification of input data using Eq. 4-6
4. Normalization of fuzzified data
5. Supply input data and population to the NFN
6. Apply eAEFA for search updating
7. Supply test data and the best particle to the NFN and preserve the estimated CS value

4 Experimental data

The experimental data collected from an open repository contains 1030 samples each of which has 9 real attributes [28]. The attributes 1 – 8 are used as input features and the last one as the response variable. All instances are quantitative and have numeric values only. From the dataset samples curing ages at 3, 7, 14, and 28 days only are extracted and used for modeling. A statistical summary of the dataset is given in Table 2.

Table 2: Summary statistics from the dataset.

Component	**Mean**	**Std**	**Min**	**25%**	**50%**	**75%**	**Max**
Cement (kg/m3)	281.167	104.51	102.0	192.3	272.9	350.0	540
Blast furnace slag (kg/m3)	73.8958	86.279	0.000	0.000	22.0	142.95	359.4
Fly ash (kg/m3)	54.1883	63.997	0.000	0.000	0.0	118.30	200.1
Water (kg/m3)	181.567	21.354	121.8	164.9	185	192.0	247
Super plasticizer (kg/m3)	6.2046	5.9738	0.000	0.000	6.40	10.20	32.20
Coarse Agg. (kg/m3)	972.918	77.754	801.0	932.0	968	1029.4	1145
Fine Agg. (kg/m3)	773.580	80.176	594.0	730.9	779.5	824.0	992.6
Age (numeric)	45.6621	63.167	1.000	7.00	28.0	56.0	365
Compressive Strength (MPa)	35.8179	16.706	2.330	23.71	34.44	46.135	82.6

Table 3: Error statistics from four sample series and seven forecast.

Forecast	**Sample series**							
	3-days		**7-days**		**14-days**		**28-days**	
	MAPE	ARV	MAPE	ARV	MAPE	ARV	MAPE	ARV
eAEFA+NFN	0.062755	0.051725	0.065275	0.05268	0.07753	0.27205	0.16273	0.18247
AEFA+NFN	0.065302	0.082204	0.152847	0.058725	0.079201	0.445177	0.30066	0.18273
GD+NFN	0.088453	0.274423	0.367377	0.29872	0.16439	0.46283	0.32005	0.18725
ANFIS	0.087157	0.297405	0.096357	0.29953	0.09556	0.25293	0.33165	0.20116
MLP	0.454400	0.389472	0.406548	1.00523	0.20604	0.55729	0.35207	0.33023
SVM	0.488452	0.597655	0.686450	1.10308	0.76583	1.02734	0.72005	0.63047
MLR	0.892991	0.932005	0.972035	1.34125	0.92884	1.27026	1.35266	0.93820

4.1 Experimental outcomes and model evaluation

As stated earlier, we considered only the samples with curing ages of 3, 7, 14, and 28 days. The time-series approach is used for modeling the data. Model inputs are selected using a rolling window method from a sample series and normalized using the sigmoid method [29, 30]. Two error metrics, mean absolute percentage of error (MAPE) and average relative variance (ARV) are used for model evaluation and are shown in Eq. 10 -11.

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{|x_i - \hat{x}_i|}{x_i}\times 100\% \tag{10}$$

$$ARV = \frac{\sum_{i=1}^{N}(\hat{x}_i - x_i)^2}{\sum_{i=1}^{N}(\hat{x}_i - \overline{x})^2} \tag{11}$$

To ensure the performance of the eAEFA+NFN forecast, four comparative models as NFN with gradient descent-based training (GD+NFN), NFN with AEFA (AEFA+NFN) adaptive neuro-fuzzy inference system (ANFIS), multilayer perceptron (MLP), support vector machine (SVM), and multiple linear regression (MLR) are also implemented and evaluated with the same input patterns. Error statistics from different data series using different models are summarized in Table 3.

The best statistics are highlighted in boldface. From Table 3, the proposed eAEFA+NFN is found to be the best performing and MLR is the least performing forecast among all. For the 3-day sample set, eAEFA+NFN produced 0.062755 MAPE and 0.051725 ARV. In the case of the 7-day sample, it achieved 0.065275 MAPE and 0.05268 ARV. For 14-day samples, the MAPE and ARV by eAEFA+NFN are 0.07753 and 0.27205 respectively. Similarly, in the case of a 28-day sample, the proposed model generated the lowest MAPE of 0.16273 and ARV of 0.18247. GD+NFN and ANFIS are found to be similar in performance. Similarly, the performance of MLP and SVM are found closer to each other. Overall, the eAEFA+NFN model produced the lowest error metric values, offering consistent and satisfactory results compared to others. The forecast plots shown in Figures 4–7 reflect the accuracy of eAEFA+NFN. The model estimations are closer to the actuals.

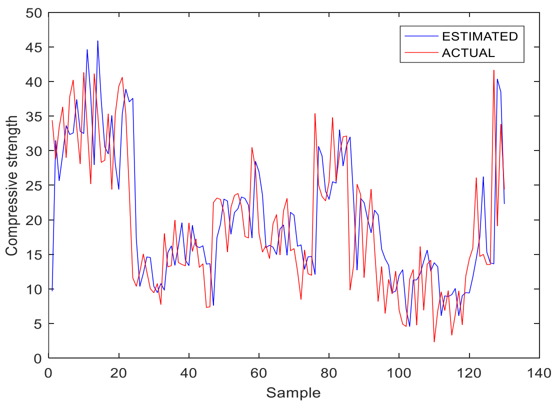

Figure 4: eAEFA+NFN forecast vs actual compressive strength values from the 3-day sample series

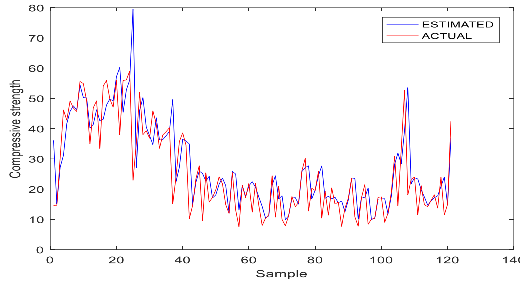

Figure 5: eAEFA+NFN forecast vs actual compressive strength values from the 7-day sample series.

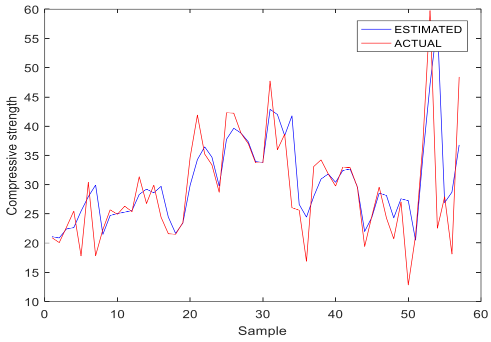

Figure 6: eAEFA+NFN forecast vs actual compressive strength values from the 14-day sample series.

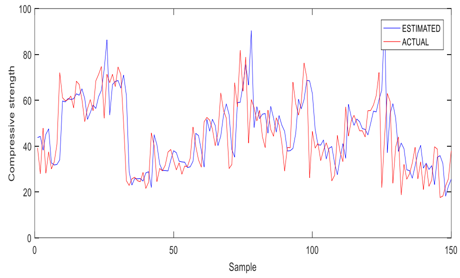

Figure 7: eAEFA+NFN forecast vs actual compressive strength values from the 28-day sample series.

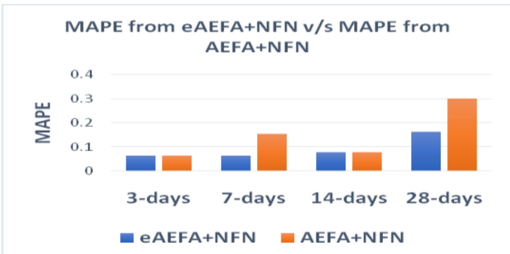

Figure 8: MAPE comparison of eAEFA+NFN and AEFA+NFN.

Further, to realize the benefit of elitism, we compared the MAPE from eAEFA+NFN and that of AEFA+NFN. The outcome of the comparative studies is depicted in Figure 8. It is observed that in the case of 3-days and 14-day time series data the performances of both models differ slightly from each other while there is a significant difference in the case of 7-days and 28-day datasets. Similar observations are inferred while comparing ARV from both methods. These shreds of evidence are in support of the elitism concept and thus eAEFA is found better in training NFN.

5 Conclusions

A robust hybrid forecast called eAEFA+NFN is proposed in this article for accurate and effective modeling of compressive strength of concrete cement data and forecasting the CS values of unseen samples. NFN inputs are fuzzified using the Gaussian triangular membership function with a degree of membership to different classes. The fuzzified input vectors intensified the dimensionality of the input thus, generated a hyperplane that affords a larger discrimination ability in the input pattern space. The model parameters are fine-tuned by eAEFA. The enhanced search ability of eAEFA and improved approximation ability of NFN combined to make the model robust helped in capturing the nonlinearity associated with the data. Considering four sample series, the eAEFA+NFN produced an average MAPE of 0.092073 and ARV of 0.139731 which are better compared to others. From comparative studies, it is found that the proposed eAEFA+NFN outperformed others. Further, the efficiency of the proposed approach may be evaluated in other areas of the predictive system. The current work may be extended using similar datasets from the manufacturing engineering domain.

Acknowledgment: This work is partly supported by TARE Fellowship awarded to Prof. Satchidananda Dehuri, Department of Computer Science, F. M. University, Balasore by SERB, Govt. India vide Sanction Order No. TAR/2021/000065.

References

[1] Asteris, P. G., & Mokos, V. G. (2019). Concrete compressive strength using artificial neural networks. Neural Computing and Applications, pp.1-20.

[2] Pandey, S., Kumar, V., & Kumar, P. (2021). Application and Analysis of Machine Learning Algorithms for Design of Concrete Mix with Plasticizer and without Plasticizer. Journal of Soft Computing in Civil Engineering, 5(1), 19-37.

[3] Nayak, S. C., Nayak, S. K., & Panda, S. K. (2021). Assessing Compressive Strength of Concrete with Extreme Learning Machine. Journal of Soft Computing in Civil Engineering, 5(2), 68-85.

[4] Nayak, S. C., & Misra, B. B. (2019). A chemical-reaction-optimization-based neuro-fuzzy hybrid network for stock closing price prediction. Financial Innovation, 5(1), 1-34.

[5] Yadav, A. (2019). AEFA: Artificial electric field algorithm for global optimization. Swarm and Evolutionary Computation, 48, 93-108.

[6] Feng, D. C., Liu, Z. T., Wang, X. D., Chen, Y., Chang, J. Q., Wei, D. F., & Jiang, Z. M. (2020). Machine learning-based compressive strength prediction for concrete: An adaptive boosting approach. Construction and Building Materials, 230, 117000.

[7] Deng, F., He, Y., Zhou, S., Yu, Y., Cheng, H., & Wu, X. (2018). Compressive strength prediction of recycled concrete based on deep learning. Construction and Building Materials, 175, 562-569.

[8] Salami, B. A., Olayiwola, T., Oyehan, T. A., & Raji, I. A. (2021). Data-driven model for ternary-blend concrete compressive strength prediction using machine learning approach. Construction and Building Materials, 301, 124152.

[9] Kumar, A., Arora, H. C., Kapoor, N. R., Mohammed, M. A., Kumar, K., Majumdar, A., & Thinnukool, O. (2022). Compressive strength prediction of lightweight concrete: machine learning models. Sustainability, 14(4), 2404.

[10] Khursheed, S., Jagan, J., Samui, P., & Kumar, S. (2021). Compressive strength prediction of fly ash concrete by using machine learning techniques. Innovative Infrastructure Solutions, 6(3), 1-21.

[11] Latif, S. D. (2021). Concrete compressive strength prediction modeling utilizing deep learning long short-term memory algorithm for a sustainable environment. Environmental Science and Pollution Research, 28(23), 30294-30302.

[12] Asteris, P. G., Skentou, A. D., Bardhan, A., Samui, P., & Pilakoutas, K. (2021). Predicting concrete compressive strength using hybrid ensembling of surrogate machine learning models. Cement and Concrete Research, 145, 106449.

[13] Güçlüer, K., Özbeyaz, A., Göymen, S., & Günaydın, O. (2021). A comparative investigation using machine learning methods for concrete compressive strength estimation. Materials Today Communications, 27, 102278.

[14] Abuodeh, O. R., Abdalla, J. A., & Hawileh, R. A. (2020). Assessment of compressive strength of Ultra-high-performance concrete using deep machine learning techniques. Applied Soft Computing, 95, 106552.

[15] Sevim, U. K., Bilgic, H. H., Cansiz, O. F., Ozturk, M., & Atis, C. D. (2021). Compressive strength prediction models for cementitious composites with fly ash using machine learning techniques. Construction and Building Materials, 271, 121584.

[16] Haykin, S. (2010). Neural networks and learning machines, 3/E. Pearson Education India.

[17] Priyadarshee, A., Chandra, S., Gupta, D., & Kumar, V. (2020). Neural Models for Unconfined Compressive Strength of Kaolin clay mixed with pond ash, rice husk ash and cement. Journal of Soft Computing in Civil Engineering, 4(2), 85-102.

[18] Cao, M. T., Hoang, N. D., Nhu, V. H., & Bui, D. T. (2020). An advanced meta-learner based on artificial electric field algorithm optimized stacking ensemble techniques for enhancing prediction accuracy of soil shear strength. Engineering with Computers, 1-23.

[19] Dash, C. S. K., Behera, A. K., Nayak, S. C., & Dehuri, S. (2021, April). QORA-ANN: Quasi Opposition Based Rao Algorithm and Artificial Neural Network for Cryptocurrency Prediction. In

2021 6th International Conference for Convergence in Technology (I2CT) (pp. 1-5). IEEE.

[20] Sharifi, Y., & Hosainpoor, M. (2020). A predictive model-based ANN for compressive strength assessment of the mortars containing metakaolin. Journal of Soft Computing in Civil Engineering, 4(2), 1-12.

[21] Yadav, A., & Kumar, N. (2019, December). Application of artificial electric field algorithm for economic load dispatch problem. In International Conference on Soft Computing and Pattern Recognition (pp. 71-79). Springer, Cham.

[22] Yadav, A. (2019). AEFA: Artificial electric field algorithm for global optimization. Swarm and Evolutionary Computation, 48, 93-108.

[23] Nayak, S. C., Nayak, S. K., & Dash, A. (2021, November). Extreme learning with Artifical Electric Field Algorithm (EL-AEFA) for estimation of Short-term Vehicular Traffic System. In 2021 IEEE 8th Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON) (pp. 1-4). IEEE.

[24] Yadav, A., & Kumar, N. (2020). Artificial electric field algorithm for engineering optimization problems. Expert Systems with Applications, 149, 113308.

[25] Behera, A. K., Panda, M., Nayak, S. C., Dash, C., & Kumar, S. (2022). An Artificial Electric Field Algorithm and Artificial Neural Network-Based Hybrid Model for Software Reliability Prediction. In Computational Intelligence in Data Mining (pp. 271-279). Springer, Singapore.

[26] Al-Khraisat, B., AL-Dmour, A. S., & Al-Maitah, K. (2021, November). Artificial Electric Field Algorithm for Optimum PMU Placement. In 2021 IEEE Green Energy and Smart Systems Conference (IGESSC) (pp. 1-6). IEEE.

[27] Nayak, S. C., Dash, C. S. K., Behera, A. K., & Mishra, B. B. (2021, December). A machine learning approach for estimating compressive strength of concrete structures using an artificial electric field algorithm-based neuro-fuzzy predictor. In 2021 19th OITS International Conference on Information Technology (OCIT) (pp. 229-233). IEEE.

[28] http://archive.ics.uci.edu/ml/datasets/Concrete+Compressive+Strength.

[29] Nayak, S. C., Misra, B. B., & Behera, H. S. (2019). ACFLN: artificial chemical functional link network for prediction of stock market index. Evolving Systems, 10(4), 567-592.

[30] Nayak, S. C., Misra, B. B., & Behera, H. S. (2014). Impact of data normalization on stock index forecasting. International Journal of Computer Information Systems and Industrial Management Applications, 6(2014), 257-269.