REVISTA MATÉRIA
V.29 N.1
ISSN 1517-7076 articles e20230247, 2024

Prediction of autoclaved aerated cement block masonry prism strength under compression using machine learning tools

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ABSTRACT

When the only information available is the issue parameters, and the intended outwards, machine learning techniques like ANN (Artificial Neural Networks) and ANFIS (Adaptive neuro-fuzzy inference system) been proven to address the complex problems without duplicating the phenomena under investigation. The main prompting characteristics are the height-to-the-thicknesses ratio of prisms and the strength under compression of prisms and mortar were analyzed. As inputs, the prototypes are used as blocks and mortars. Both prototypes were accomplished and evaluated. Thirty-six data sets were gathered for testing in addition to verified technical and subsequently comparison with other empirical computation methods served to validate. The outwards show that the suggested prototypes have good forecast capabilities with negligible error rates. To assess and compare the structural behavior of structural completion of AAC block with the other types. At last, both the machine learning tools are good application and dependability.

Keywords: ANN; ANFIS; AAC block masonry prism; statistical model values.

1. INTRODUCTION

The strength under compression of brick masonry is considered one of the essential mechanical criteria in masonry construction design because it significantly impacts the structure's safety and economic evaluation [1, 2]. However, due to the complicated composite behaviour induced by the masonry components and their interfaces, measuring the compressive strength is a substantial issue.

Various elements influence the strength under compression of clay brick masonry walls linked together with mortar. In general, the masonry resistance system exposed to stresses under compression is primarily determined by the interaction of bricks and mortar. The material characteristics themselves change when they are operated separately as well as when they form part of a masonry wall. Masonry is an anisotropic material that is susceptible to building methods [3, 4]. The many available factors, some quantitative (e.g., brick strength under strength) and others more qualitative, substantially complicate the calculations and design of masonry structures.

Several theoretical studies [5] on the behaviour and strength of masonry prototypes under compression has been conducted during the last several decades. Multiple analytical models have been created. The strength under compression has been predicted by a forward set of assumptions about the process and establishing the equilibrium and deformation compatibility equations. In general, the forms of these models are complicated, requiring many factors to represent the masonry's failure characteristics. Furthermore, based on experimental findings [6, 7] strength under compression has been predicted using particular empirical models, including those used in design codes. Most of these empirical expressions rely heavily on the height-to-thickness ratio of the prisms and the strength under compression of hollow concrete blocks and mortars. However, the data utilized to build the empirical equations were restricted.

As new test results become available, these empirical models' predicted accuracy and dependability must be re-evaluated. The model with stochastic demand and cost variables was solved using an artificial neural network (ANN) model; the same issue was solved using an adaptive neuro-fuzzy inference system (ANFIS) with both variables being fuzzy with other robust AI models such as M5, GEP, MARS, SVM, ensemble learning, RF, RT and EPR. Interestingly, even a small number of datasets may be used to build these models during the training phase [8, 9]. In reality, by putting forward these models, many scientific and

Corresponding Author: Soundar Rajan Muthukumar Received on 23/08/2023 Accepted on 06/11/2023

DOI: https://doi.org/10.1590/1517-7076-RMAT-2023-0247

engineering problems will need less time-consuming and expensive trials. As a standard for AI approaches, artificial neural networks (ANNs) were established as clever meta-modeling tools in previous decades. These techniques have the capacity to tackle a wide range of issues in science and engineering, including material science. According to Alexandridis [10], ANNs may guess essential values without measuring them, which helps address the difficulties. The artificial neural network (ANN) and fuzzy inference system (FIS) are combined to create ANFIS. In reality, ANFIS may combine the best features of these two models to provide a cohesive solution for challenges in science and engineering.

2. EXPERIMENTAL INVESTIGATION AND DATA COLLECTION

Gathering enough information for practicing and examining samples, which were subsequently used to determine the models' assessment parameters, was the initial stage in constructing both the ANN and ANFIS models. To populate these models with empirical information, a database was built by aggregating data sets from experiments performed both in this work and in earlier investigations [11].

2.1. Materials

An AAC block of dimensions 200 × 100 × 100 mm is investigated for the experimental programme. The masonry prisms were made using regular cement mortar with ratio of 1:3. The strength under compression of the mortar was evaluated using mortar cube mould specimens (70.7 mm). For the current investigation, three different grades of mortar were used, with the mix proportions by weight being 1:6, 1:4.5, and 1:3 for cement and sand respectively [12]. During the fabrication of the masonry prisms, three examples were created for each mix percentage. Before testing, the mortar cubical specimens were cured.

2.2. Fabrication of masonry prism

Taking the height-to-thickness ratio (h/t), unit strength under compression (f_b), and mortar strength under compression into account. This work produced and tested one kind of masonry prism with three distinct block/mortar combinations for strength under compression (f_m). The masonry prototype dimensions were 200 mm × 100 mm × 430 mm [13], as shown in Figure 1. These specimens were built in a flowing bond with complete bedding. The vertical and horizontal joints were each 10 mm thick, and 36 AAC masonry prisms were manufactured. All the masonry prototypes were built and cured for 28 days before testing.

2.3. Experimental setup

The prisms were examined using fluid induced testing equipment (capacity of 5000 kN) under monotonically rising loads. An axial load of 0.5 kN/s was applied at a steady rate till failing and monitored by a force detector with a range of 2500 kN [14, 15]. The masonry protypes were capped with a strength board before testing to address the disparity of the pressure surface and guarantee that the axial force was distributed equally throughout

Figure 1: AAC block masonry prism.

the tests. The strength of the capping is greater than that of the mortar joints. The mean strength under compression of the blocks (f_{block}), mortar (f_{mortar}), and prisms (f_{prism}) for each group are summarised in Table 1.

2.4. Data collection

To supplement the practing and examing datasets, 90 test data sets comprising test results for more than 300 prototypes were collected [16, 17] and published literature [18]. The data were chosen according to the following criterion to guarantee conformity with specifications and building practices:

- The porous portion of the blocks should vary from 5% to 20%;
- The prototypes should be built with mortar capping;
- The prototypes built with higher than courses should be excluded.

As a result, more than hundred data sets were acquired to build the practing and examing datasets. Eighty data set value were chosen as practing sets, while the remaining were chosen as examing sets. These data set values were chosen randomly to eliminate human selection's impacts on the outwards. The height-to-thickness ratio (h/t) of the masonry prototype, unit compressive strength (f_{block}) of the masonry prototype, and mortar compressive strength (f_{mortar}) of the masonry prototype were chosen as the essential critical criteria for the strength under compression of the masonry prototypes based on the empirical models of the design standards [19, 20]. As a result, the model's input variables contained these three factors, and the intended output was the masonry's strength (f_{prism}). Table 2 shows the investigation's inward and outward variables.

3. MODELLING TECHNIQUES

3.1. Artificial neural networks

Artificial neural networks, often known as ANNs, are computer simulations that attempt to mimic the central nervous system's biological and neurological structure and its functional qualities. The structure of the central

Table 1: Properties of blocks, mortar and prism.

DESCRIPTION	HEIGHT TO THICKNESS RATIO	f_{block} (MPa)	f_{mortar} (MPa)	f_{prism} (MPa)
AACB1 M1	4.3	4.46	6.35	2.33
AACB2 M1	4.3	4.53	6.39	2.38
AACB3 M1	4.3	4.58	6.42	2.26
AACB1 M2	4.3	4.46	10.04	2.95
AACB2 M2	4.3	4.53	10.12	2.79
AACB3 M2	4.3	4.58	10.18	3.02
AACB1 M3	4.3	4.46	18.66	3.55
AACB2 M3	4.3	4.53	18.75	3.63
AACB3 M3	4.3	4.58	18.81	3.72

Table 2: Research data statistics.

VARIABLE	INFORMATION USED FOR DEVELOPING AND EVALUATING ANN AND ANFIS PROTOTYPES [21]			STANDARD DEVIATION	COV (%)
	LOWEST	HIGHEST	MEAN		
height to thickness ratio	2.00	5.00	3.00	4.58	0.50
f_{block} (MPa)	9.00	40.00	22.00	35.12	0.61
f_{mortar} (MPa)	4.00	27.00	13.00	12.77	0.90
f_{prism} (MPa)	6.00	30.00	18.00	27.65	0.83

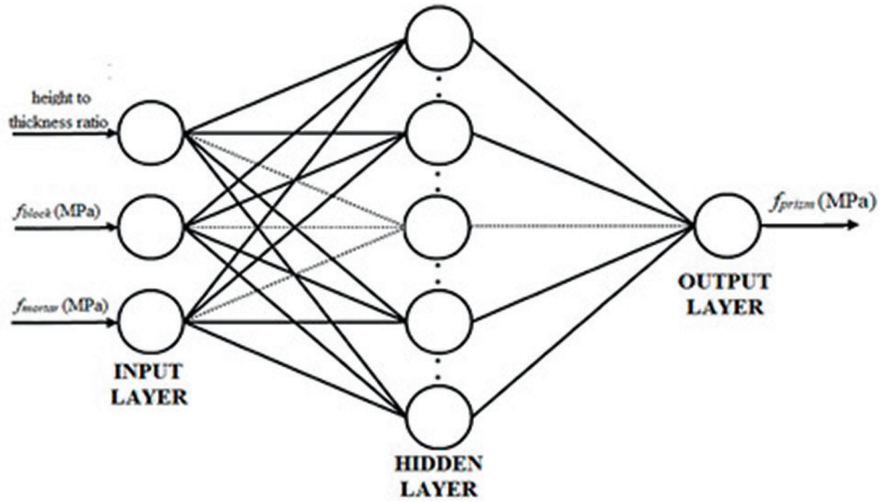

Figure 2: ANN architecture.

nervous system. An artificial neural network is a system that processes data by using the neurons' dynamic responses to a set of inputs from outside [22, 23]. An ANN is composed of several neurons that are intimately coupled to one another. The most common kind of artificial neural network architecture is the post multilayer perception network as shown in Figure 2. An input, hidden, and output layer are the three levels that make up this sort of network. The numerous neurons that make up this network are scattered throughout these layers. Regarding this kind of network, every event in every layer is related to every activity below it [24].

3.2. Neural network architecture

The backpropagation is one of the most basic and widely used algorithms for multi-layered feed-forward networks. It is a descent strategy that reduces mistakes for a specific practing pattern by modifying the weights in tiny increments every time [25, 26]. This concept network is divided into two stages: post stage and behind stage. The inward data is transmitted from the front layer to the concealed in the forward stage. Each event in the hidden layer computes a weighted addition of the inward data, then applies activation functions to the total and sends the decent result to the outward layer in Equation 1 [27, 28] is used to determine the weighted sum of the input components:

$$net_j = \sum_{i=1}^{n} w_{ij} x_i + b_j \tag{1}$$

where net_j is the weighted sum of the jth neuron received from the lower layer with 'n' neurons, w_{ij} is the connective weight between the ith neuron in the lower layer and the jth neuron in the higher layer, x_i is the lower layer's output, and b_j is the upper layer's bias value [29, 30]. Typically, the sigmoid function provided in Equation 2 is used to determine the output of the jth neuron, o_j:

$$O_j = f(net_j) = \frac{1}{(1+\exp(-net_j))} \tag{2}$$

The deviation of anticipated and experimental values is transmitted backwards from the output to the input layer in the behind stage, the values of the bias and weight being changed. This procedure is follow at the end of network, error has been reduced to an acceptable level. The past research, ANN model was developed using the LMBP rather than BP approach. LMBP is the quickest BP algorithm accessible, and it is a hybrid optimization strategy [31, 32]. Furthermore, the sigmoid function was utilised in the behind layer, and in the output layer, the linear function was used.

3.3. Development of neural network models

The BP network constructed in this study. The number of input and output units was determined by the geometry of the issue [33]. Unfortunately, no defined method exists for calculating the number of hidden levels and the number of units in each hidden layer. As a result, they must be found by trial and error. Following a series of trials, the parameters with the lowest mean squared error (MSE) of the training data were chosen as follows: Following a series of trials, the parameters with the lowest mean squared error (MSE) of the training data were chosen as follows:

The number of input layer units is three, several concealed layers are one, several hidden layer units is equal to 12a, several output layer units is one, the momentum rate is 0the .9, the learning rate is 0.3, learning error is 0.001 and learning toles up to 20000 [34].

3.4. ANFIS model

ANFIS is a well-known vigrant neuro-fuzzy technique for modelling large nonlinear tools [35] that effectively blends ANN's adaptive learning process with fuzzy inference systems' reasoning capacity. This was rule-based linguistic tool that have a set of if-then fuzzy rules.

They are considered universal approximators because they can accurately describe in the system [36]. They lack of self-adaptability-learning abilities required to scope with a modern external circumstances. Consequently, the learning parameters of networks were merged and produce ANFIS [37]. For the sake of simplicity, assume that two inward variables (x, y) and one outward variable (f) as shown in Figure 3. The different layer serves certain functions as listed in Table 3.

Where x is the input to node *i*, A_i is the fuzzy set associated with the node function, μ(x) is the membership function for the fuzzy set A_i, and O_{1i} is the membership grade of the fuzzy set [38, 39]. The triangle membership function was used in this investigation. A hybrid learning approach was used to update the event functional parameters in this proposed model [40, 41]. To identify the collection of preceding and following parameters, the proportion of these two strategies was able to minimise the complexity of the research process while also improving gathering the ideas proportion has a complete discussion of the ANFIS model as shown in Table 4.

3.5. Procedures for processing the data

It is suggested that the raw data should be put into a range that makes sense. So that training can be more effective and stable, Normalization is a way to improve a process and get more accurate. The standardisation of data

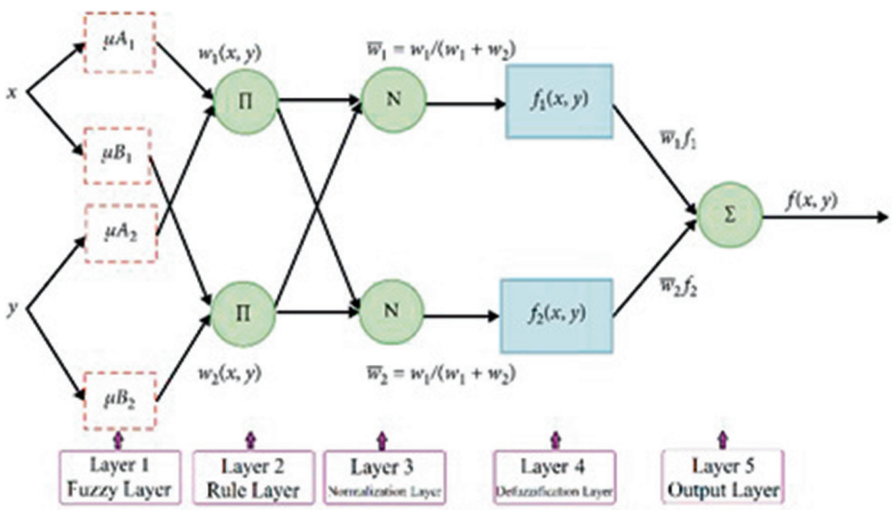

Figure 3: ANFIS architecture.

Table 3: Properties of Layers in ANFIS architecture [40].

ROLE OF LAYER	NAME OF THE LAYER	NODE EQUATION
Fuzzy Layer	I Layer	$O_i^1 = \mu_{Ai}(x)$
Rule Layer	II Layer	$O_i^2 = \mu_{Ai}(x) \times \mu_{Bi}(y)$
Normalization Layer	III Layer	$\bar{w}_i = \frac{w_i}{(w_1 + w_2)}$
Defuzzification Layer	IV Layer	$O_i^4 = \bar{w}_i f_i$
Output Layer	V Layer	$O_i^5 = \frac{\sum_i w_i f_i}{\sum_i w_i}$

Table 4: Suggested statistical model values.

EFFICIENCY MEASURES		MEAN SQUARE ERROR (MSE)	MEAN ABSOLUTE PERCENTAGE ERROR (MAPE)	INTEGRAL ABSOLUTE ERROR (IAE)	COEFFICIENTS (R^2)
ANN	Practice Set	0.4523	0.0842	4.12%	0.9547
	Examining Set	0.6622	0.0285	4.59%	0.9382
ANFIS	Practice Set	0.3287	0.0738	3.35%	0.9663
	Examining Set	0.4249	0.0256	3.66%	0.9536

could also speed up learning by many values in the area of the sigmoid activation function, where changes in the inputs have the most effect on the output [43, 44]. Most of the formulas for normalising are either linear or logarithmic functions. A simple linear normalising function was used in this work, as shown by Equation 3 was used to set the range of the data that was given of 0.1–0.9:

$$X_{i,ANN} = 0.1 + \left(0.8 \times \frac{X_i - X_{\min}}{X_{\max} - X_{\min}}\right) \tag{3}$$

where X_i is the original value, $X_{i, ANN}$ is the normalised version of that value, and X_{max} is the maximum value and minimum input values are denoted by X_{min} respectively. When this occurs, it's common practice to do an inverse normalisation, which is used in the final processing stage to generate the test values.

4. ANALYSIS AND DISCUSSION OF RESULTS

To measure how well each model did, we used four standards. These norms between the expected and experimental outwards are obtained and shown in Table 5. where p denotes the total number of patterns, t_j denotes the pattern's predicted value, o_j denotes its target value, and denotes the pattern's average target value.

4.1. Assessment of results

The strength of concrete masonry prisms was forecasted using the identified models used in this work. Figures 4–7 show assessment comparisons between the anticipated and actual findings values for each model's practicing and examining sets. The created models were effective in learning the nonlinear connection between the inward and outward variables since the predicted values of the practicing and examining sets are incredibly close to the goal values. As a result, both models have a fair chance of accurately forecasting the strength of masonry buildings.

Our suggested mathematical models are appropriate and have high-precision prediction capabilities. Additionally, the ANFIS model network outperformed the ANN model network with somewhat superior outcomes.

4.2. Comparison of the outwards of several calculating techniques

In this investigation, prototypes findings with three suggested empirical calculation techniques to examine the degree of fit between the value of the strength under compression of masonry assemblies determined by

Table 5: Computed performance models with different forms [42].

PERFORMANCE	NOTATIONS	COMPUTED EQUATIONS
Mean Square Error	*MSE*	$\frac{1}{p}\sum_j \left(o_j - t_j\right)^2$
Coefficient	R^2	$1 - \left(\frac{\sum_j (o_j - t_j)^2}{\sum_j (o_j - \bar{o})^2}\right)$
Mean Absolute Percentage Error	*MAPE*	$\frac{1}{p}\sum_j \left\lvert\frac{o_j - t_j}{o_j}\right\rvert$
Integral Absolute Percentage Error	*IAE*	$\frac{\sum_j \left[(o_j - t_j)^2\right]^{0.5}}{\sum_j o_j} \times 100\%$

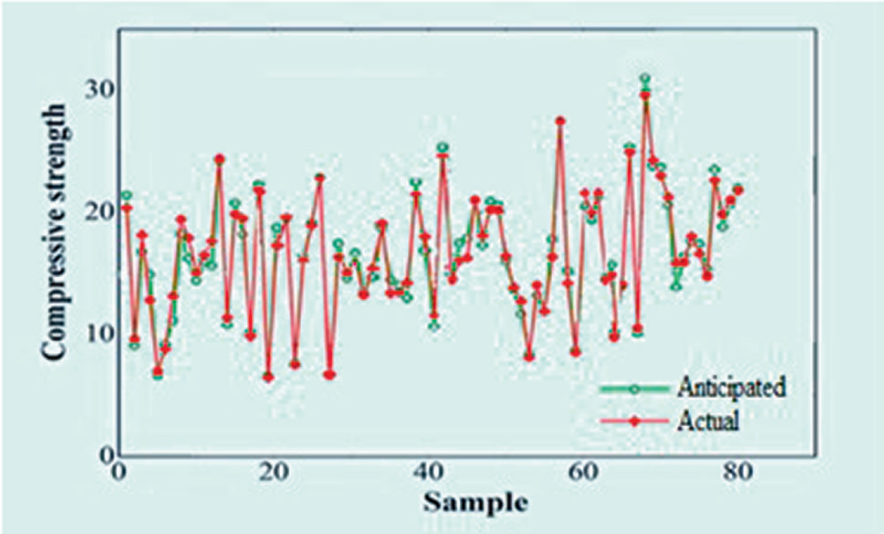

Figure 4: Assessment of ANN model anticipated values with actual experimental data – Practicing sets.

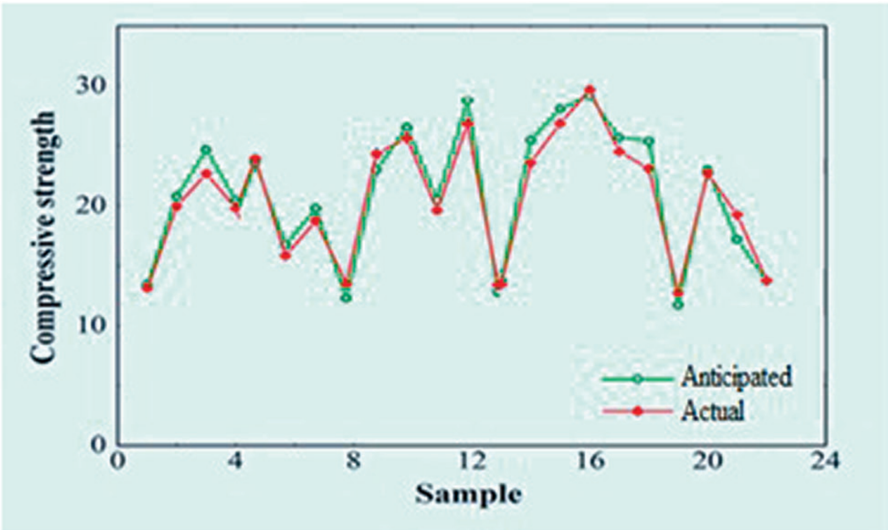

Figure 5: Assessment of ANN model anticipated values with actual experimental data – Examining sets.

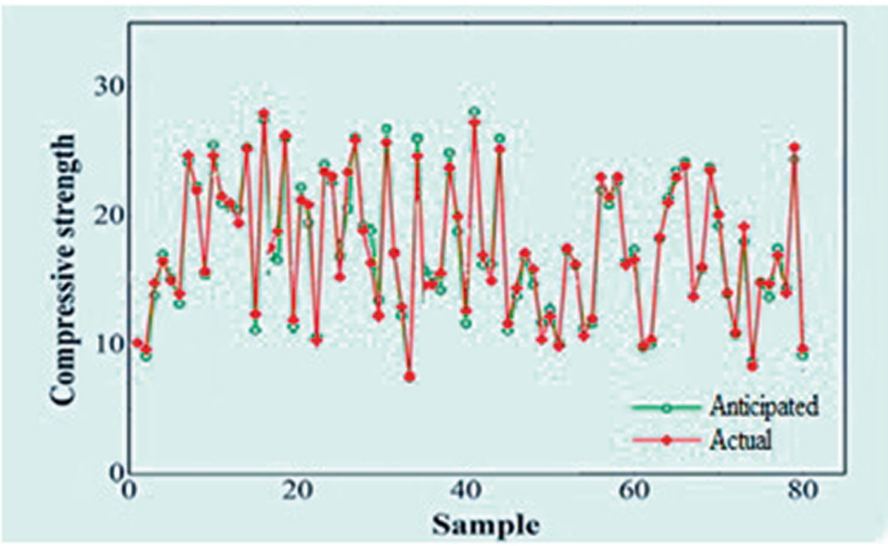

Figure 6: Assessment of ANFIS model anticipated values with actual experimental data – Practicing sets.

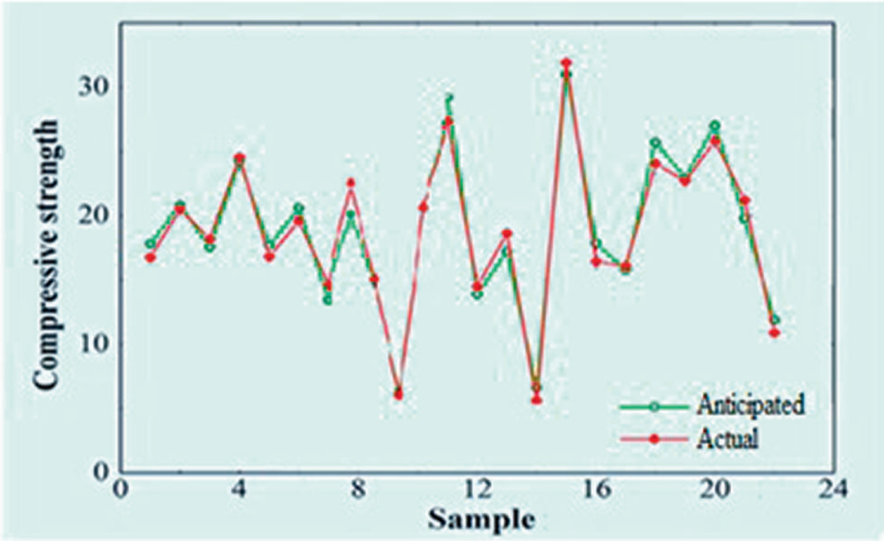

Figure 7: Assessment of ANFIS model anticipated values with actual experimental data – Examining sets.

Table 6: Empirical techniques for comparison of results.

PROPOSED REFERENCE	EXPRESSION	MEAN	STANDARD DEVIATION
MANN [44]	$f = 0.83 \times f_b^{0.67} \times f_m^{0.33}$	1.19	0.22
DAYARATNAM [45]	$f = 0.28 \times f_b^{0.50} \times f_m^{0.50}$	0.32	0.22
KAUSHIK *et al.* [46]	$f = 0.63 \times f_b^{0.49} \times f_m^{0.32}$	0.48	0.34
Eurocode 6 [34]	$f = K \times f_b^{0.65} \times f_m^{0.25}$	0.57	0.34
Design proposal	ANN Architecture	1.02	0.38
	ANFIS Architecture	1.11	0.42

mathematical logical tools compared to empirical methods as shown in Table 6. The results of the exception of Mann's and Kaushik *et al*., where the mean value of the $f_{proposed}/f_{real}$ ratio is more than 1, So all empirical formulations are on the safe side, with several having mean values less than 0.50. Except for Mann and Dayaratnam, the standard deviation values were not low, with a value of 0.3 in all instances [45].

Comparing practical suggestions with ANN and ANFIS outwards in this research reveals that our suggested technique improves with current expressions. The numerical approaches we utilised yielded a mean value close to one and a standard deviation compared to the empirical expressions. Finally, it can be concluded that our outcome is a significant improvement and thus can be safely recommended for use by researchers and practitioners interested in determining the strength of a masonry assemblies. Compared to empirical approaches, the suggested model's calculation in this work accurately anticipated masonry behaviour. As a result, the suggested models might be utilised to correctly forecast the strength and behaviour of masonry prototypes [46, 47].

5. FINAL CONCLUSION

The computational approaches of mathematical tools (ANN and ANFIS) were used in this study to calculate the strength under compression of AAC block masonry prisms. A trustworthy datas of published experimental findings was compiled to evaluate the suggested models. The ANN model performs well in prediction. In the created models, the predicted values are pretty near to the experimental data for both the practicing and examining sets. The projected values from the ANFIS model built were very accurate. Furthermore, a comparison of the performance indices revealed that the ANFIS model performed somewhat better than the ANN model [48].

The suggested models' findings were compared against past references. The comparison revealed that empirical approaches, on average, underestimate compressive strength by 18%, but the projected findings from the models produced in this work roughly coincide with the experimental values. In summary, the suggested ANN and ANFIS models estimate the compressive strength of AAC block masonry prisms with good application and dependability. Furthermore, the strength under compression may be determined quickly and with minimal error rates [49].

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