Research Article

Neural-network-based approach to predict the deflection of plain, steel-reinforced, and bamboo-reinforced concrete beams from experimental data

Mayank Mishra[1] · Atul Agarwal[1] · Damodar Maity[1]

Abstract
The necessity of providing low-cost housing to economically weaker sections of society has been recognised by the national government of India. In mountainous areas, the use of locally available construction material, such as bamboo, as concrete reinforcement has increased due its easy availability and economic benefit. However, due to the inadequate codal provisions for the design and detailing of bamboo-reinforced structures, evaluating the serviceability criteria for their deflection behaviour under different loads is difficult. Furthermore, factors such as bond failure between reinforcement and concrete, shrinkage and corrosion of reinforcing material, and uncertainty in material strength make the prediction of deflection even more cumbersome. This study presents an artificial neural network (ANN)-based method modelled using MATLAB for predicting the deflection behaviour of three types of beams, namely plain, steel-reinforced, and bamboo-reinforced beams. Experimental investigation is conducted to record data at regular load increments for the aforementioned three beam typologies fabricated in the laboratory under two-point loading for 28 days. A total of 122 laboratory test data are recorded for modelling the ANN. The used approach involves predicting the relationship among the applied load, tensile strength of the reinforcement, percentage (amount) of reinforcement (taken as input), and deflection of the beam (obtained as output). The present ANN approach exhibits gives satisfactory performance (coefficient of determination (R^2) = 0.9983 and mean square error = 0.00049) in predicting the deflection behaviour of beams. Hence, the ANN approach can be used as an efficient and robust tool in predicting serviceability behavior of different types of reinforced concrete beams.

Keywords Artificial neural network · Bamboo reinforced concrete · Low cost housing · Deflection · Sustainability

1 Introduction

Providing cost-effective, durable, sustainable, renewable, and eco-friendly housing is one the priorities of the civil engineering community [1]. Researchers and housing corporations worldwide are working to provide affordable housing and to ensure the safety of occupants in the long run. In this regard, bamboo is a viable alternative construction material [2, 3] for expensive steel inside reinforced concrete. Bamboo is a sustainable material with low energy consumption. It can resist earthquakes due to its flexible nature and shock absorbing capacity. Bamboo is primarily used in scaffolding for supporting buildings during construction and maintenance; however, its utility as concrete reinforcement is currently being examined. Various studies have provided promising results with regard to the use bamboo strips as reinforcing material in the construction of houses. When used as a reinforcing material in concrete beams, the tension carrying capacity of the structural member increases. The use of bamboo in reinforcing structures for upgrading their load-bearing ability and ductility has

✉ Mayank Mishra, mayank.mishra@civil.iitkgp.ac.in; mayank.mishra@unibas.it; Atul Agarwal, glfrs.76@gmail.com; Damodar Maity, dmaity@civil.iitkgp.ac.in | [1]Department of Civil Engineering, Indian Institute of Technology, Kharagpur 721302, India.

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been widely investigated for decades [4–9]. Although steel rebars are the most extensively used reinforcing material in the building industry worldwide, this material is sometimes not available locally. In these situations, bamboo serves as a suitable alternative, especially in hilly regions. Engineered bamboo is an ecologically friendly and nonpolluting material [10] that can contribute to the mitigation of climate change [11]. Yu et al. [12] analysed a residential building made of bamboo with a brick–concrete structure and reported that the bamboo structure can reduce the embodied energy by 11% and the embodied carbon by 18.5%. Figure 1a, b displays column members with bamboo strips as a reinforcing material and a house constructed using bamboo-reinforced concrete. Thus, bamboo-reinforced concrete can offer a promising solution to the building industry for meeting the ever increasing demand for accommodation.

The limitations and concerns of civil engineers when using bamboo as a reinforcement material include the high deflection [13] of structural members. Hence, the deflection behaviour of bamboo with different magnitudes of applied loads must be understood and estimated in advance for civil engineering applications. The prediction of deflection is a key aspect for builders, civil engineers, and researchers because it governs the serviceability criteria. Therefore, predicting the deflection behaviour is crucial for the safety of building occupants and for judging the design of bamboo-reinforced structures. The level of deflection mainly depends on three factors, two of which are controllable and one of which is uncontrollable. The controllable factors include the percentage of reinforcement used and the tensile strength of the bamboo material, whereas the uncontrollable factor is the load acting on the bamboo structure. Moreover, bamboo material has a large range of varieties, shapes, sizes, density, strength, and other parameters. Therefore, due to a wide range of input variables, estimating a reliable deflection value for concrete beams in real-world engineering structures is challenging.

Several design codes based on empirical relations cannot be used to estimate the deflection because bamboo material is not homogeneous and no industry standard exists. Hence, the conventional approach for deriving a mathematical relationship between the load and deflection has not been very successful in the field due to the presence of many uncertainties, which make the modelling process difficult. Furthermore, the load-carrying ability and deflection of bamboo-reinforced members is compromised by the water absorption capacity and premature bond failure of bamboo strips [14]. In reality, the field testing data must be trained so that it can be practically used. There exist some empirical equations for predicting the deformation and loading behaviour of bamboo in a similar manner to that of steel-reinforced members. Numerical tools, such as the finite element method, are unable to predict the relationship between the load and deflection due to the aforementioned uncertainties in bamboo material. Moreover, finite-element-simulations are found to be marginally stiffer [15] than in modelling the load-deflection characteristics of bamboo-reinforced concrete beams, and these methods are computationally expensive. Currently, artificial-intelligence-based techniques are used in such types of applications.

Artificial neural networks (ANNs) and various soft computing tools have been widely adopted in civil engineering applications due to their excellent estimation capacity. Studies have predicted the output variable from the training data in cases where a mathematical relationship is not evident. Most studies in civil engineering use ANNs for predicting the concrete compressive strength [16–24]. Other applications of ANNs include damage detection in beams by utilising vibration measurements [25–29] and the assessment of shear resistance in concrete beams [30–34]. Several researchers have used ANNs to predict

Fig. 1 **a** A bamboo strip used as reinforcement in a column after chemical treatment, coating, and sand spraying and **b** a model dwelling in Salua, India, constructed using bamboo-reinforced members

the deflection of structures and their members. Hegazy et al. [35] used an ANN for modelling the load–deflection characteristics of concrete slabs. Tadesse et al. [36] applied an ANN for anticipating the middle-span displacements of six composite bridges by using data generated from finite element modelling and experimental results. Sakr et al. [37] estimated the transient and longstanding displacements of composite beams, and Flood et al. [38] examined externally reinforced RC beams by using ANNs. Ud Darain et al. [39] evaluated the deflection and cracking behaviour of beams strengthened with various materials by using an adaptive neuro-fuzzy system. They used strengthening materials with variable bond lengths. The variable load is used as the input, whereas the crack width and deflection are the output. Nguyen et al. [40, 41] used an ANN model combined with the hierarchical k-means clustering algorithm [42, 43] to evaluate blast-triggered ground vibration in a coalmine situated in Vietnam. To estimate the blast-induced ground vibration, Bui et al. [44] used approaches such as random forest (RF), Bayesian additive regression trees, the Gaussian process, support vector regression, boosted regression trees, and k-nearest neighbours. Furthermore artificial intelligent tools are widely used in real world applications in various in different fields such as combination of ANN with random forest for estimating blast-induced air overpressure [45], ultimate bearing capacity of shallow footings [46]. In a previous study, a hybrid evolutionary-based algorithm was used to estimate the heating load of an energy-efficient building [47]. In [48], an ANN optimised with the particle swarm optimisation algorithm was used to predict the energy performance of a building. A literature review indicates that no studies have evaluated the serviceability behaviour of bamboo-reinforced beams by predicting the deflection through artificial intelligence techniques. The deflection behaviour governs the serviceability criteria on whether the structure would suffer damages due to cracks and excessive deformations. Thus, the current study aimed to fill this literature gap by determining the nonlinear correlation between the selected inputs in predicting the deflection of concrete beams through the application of an ANN.

This study used the tensile strength of the reinforcement member, percentage of reinforcement, and applied load as variables in the ANN for evaluating the deflection of reinforced concrete beams. The experimental study incorporated three different concrete beams (three in each typology) cast using M20 grade concrete. The nine beams are then tested as flexural elements. The concrete beam specimens are tested in the laboratory for deflection by using two-point bending tests. The loads are increased at regular increments until the specimens collapsed. This study focused on analysing the deflection at the central span of the beam because the maximum bending moment, deflections, and strains occur at that location. A database comprising 122 data points is prepared by recording the actual beam behaviour under loading.

2 Data acquisition and experimental setup

In this study, data is obtained from the experimental testing of rectangular concrete beams (three in each category) made of only plain concrete (PC), reinforced with steel (RC) and reinforced with bamboo (bamboo-reinforced concrete BRC). The bamboo strips used are made of Muli bamboo, which is locally procured. Before conducting experiments on BRC, tensile tests are performed on the bamboo specimen for evaluating its ultimate strength and engineering properties. The tensile test included the preparation of bamboo samples and the gripping arrangement for the specimen (Fig. 2a, b), for testing in the Universal Testing Machine (UTM). Normal bamboo consists of a round surface. Therefore, an aluminium tab is required to make a flat surface for attachment to the bamboo. First, the bamboo specimens were cut to the appropriate dimensions. The samples were between 9 and 12 inches long, and their widths were also suitably reduced. The bamboo used in the tensile test should have a strong grip, without which the bamboo tends to shift. The bamboo samples were loaded gradually with a moderate loading rate of 1 mm/min in the 60-tonne UTM machine until the bamboo strips broke (Fig. 2c). The average tensile strength of the three tested bamboo specimens was 186 N/mm^2, and their average modulus of elasticity was 24.5 GPa. The experimental tests indicated that the failure points of the specimens consisted of nodes.

A two-point load is applied to beams with a length of 1 m and cross-sectional area of 75 mm × 150mm (Fig. 3a, b) for studying their behaviour under bending and deflection. The clear cover provided is 25 mm, with a depth-to-width ratio of 2. The reinforced concrete beams are constructed as under-reinforced members. For steel reinforcement, Fe 250 grade bars having a tensile strength of 250 N/mm^2 are used. The variable parameters identified for the ANN of the aforementioned beams are the percentage of reinforcement, tensile strength of longitudinal reinforcement, and load applied when the displacement is the output.

M20 grade concrete is used, and the beams are tested after 28 days of curing (Fig. 4b). The bamboo-reinforced beams are treated with Sikadur 32 gel as an adhesive to enhance the adhesion capacity of the bamboo–concrete composite (Fig. 4a). As per the reinforcement, two bamboo strips with a total area of 140 mm^2 (reinforcement percentage (ρ) = 1.49) and two 8-mm-diameter rebars with a total area of 100.5 mm^2 (reinforcement percentage

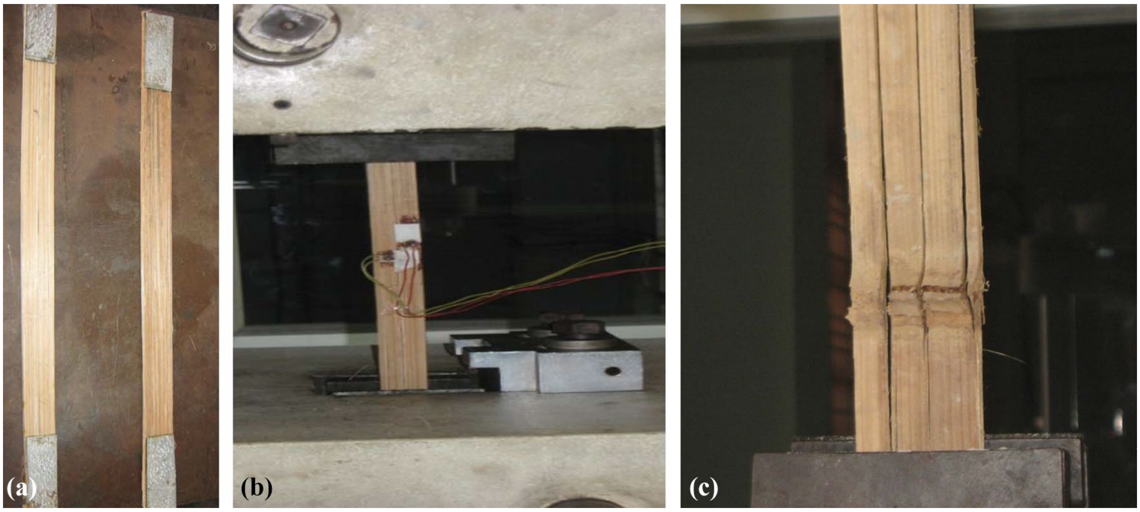
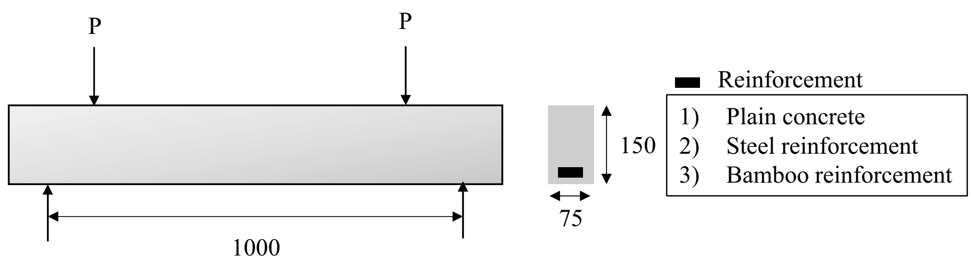


Fig. 2 **a** Bamboo specimens with aluminium end tabs for the tensile test, **b** tensile test conducted on the bamboo samples, and **c** failure of the bamboo samples

Fig. 3 Single reinforced concrete beam under two-point loading



(ρ) = 1.07) are used. The tensile test is conducted using a 10-ton (98 kN) proving ring having a manual jack. The ring has a lowest count value of 149.1 N (15.2 kg). The dial gauge to measure deformations is fixed at the centre of the beam (Fig. 4c). However, due to the unavailability of a sufficiently fine proving ring, capturing the deflection just prior to collapse is difficult. Consequently, the deflection corresponding to the collapse load could not be captured. Moreover, bamboo-reinforced concrete beams exhibited a ductile mechanism, wherein cracks first became noticeable at the beam surfaces at 80% of the limit load. Finally, failure was followed by the development of cracks and concrete spalling, as displayed in Fig. 4d.

Table 1 presents the dataset obtained from the experimental testing. The three input parameters (ρ, f_y, and the applied load) are employed as input vectors of the ANN. The load-displacement behaviour of all the beams is then compared. The selection of parameters is crucial because it has a direct influence on the evaluation of the deflection of the structural member. The load-displacement behaviour of all the beams was then compared. The output was selected as the member deflection governing the serviceability criteria. In addition to the selected three inputs, other factors such as the compressive strength of concrete; dimensions of the structural member; corrosion of rebars; clear cover remaining in the beam; aggregate type; and degradation of the bond between the reinforcement, water–cement ratio, and concrete [49, 50] also affect the long-term deflection of the structural member. The long-term effects of creep, shrinkage, and the environmental conditions on the deflection were also not considered in the experimentation. Paulson et al. [49] investigated the behaviour of reinforced concrete beams by examining the deflection over 12 months. Val and Chernin [50] considered the effect of rebar corrosion on the deflections of steel-reinforced beams by modelling the uncertainties in material properties, loads, and the bond between the reinforcing member and concrete. The dataset in this study indicates that the bamboo-reinforced beams can sustain larger deflections than the PC and steel-reinforced beams. Hence, in contrast to plain reinforced beams, bamboo-reinforced beams exhibit ductile failure.

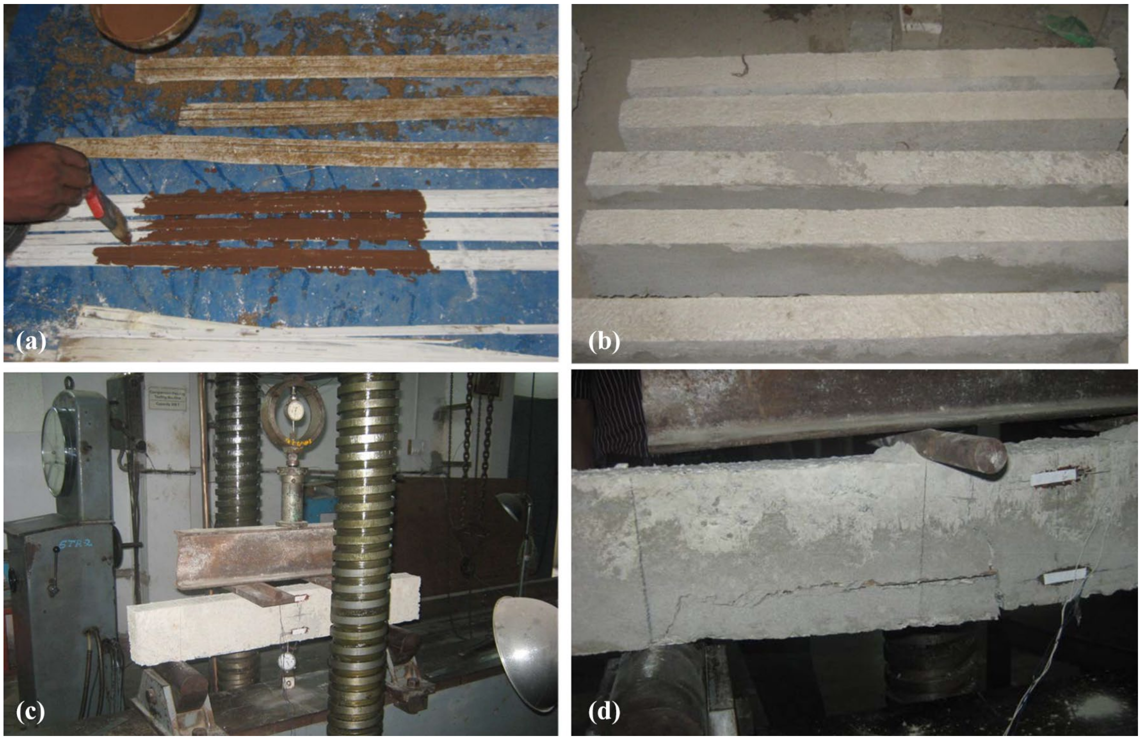


Fig. 4 **a** Adhesive being applied onto the bamboo strips, **b** casting of various beams, **c** two-point loading test of various beams, and **d** cracking pattern of bamboo-reinforced beams

3 ANNs

ANNs are one of the most commonly used artificial intelligence systems. ANNs use computing elements for processing known data as neurons that have the capability to match patterns in data and provide output for testing data. The applications of ANNs for solving various problems related to civil engineering are briefly explained in Sect. 1. Training is performed using the dataset with known outcomes. The training data can then be tested using datasets with similar input parameters. The ANN adjusts itself to the outcome by updating the neural weights accordingly. The weight of each node (Eq. 1) is adjusted according to each trained dataset by some algorithm specified in the neural network system. ANNs have applicability in areas where specifying an equation or a model to understand the phenomena is difficult. Each node in the ANN layer can act as a unit to process the weighted sum of the input data. The output signal is expressed as follows:

$$O = f\left(\sum w_i I_i\right) \quad (1)$$

where O is the output linked with ith input node, w_i is the weight linked with the ith input node, and I_i is the input at node i.

Three main input parameters, namely the type of reinforcement (PC beams with no reinforcement, steel-reinforced beams, and bamboo-reinforced beams), percentage of reinforcement (0, 1.07%, and 1.49%) at three levels, and load at regular intervals (0.30 kN) [51], are considered for designing the ANN model. The value of the output layer is the predicted deflection value. Before training the ANN, the datsets are pre-processed with min-max normalisation method [52, 53] to increase the efficiency of the model. Accordingly, the neural network model is trained, validated, and tested. The ANN toolbox available in the MATLAB package [54] is employed for the neural network model. Figure 5 displays the ANN architecture utilised in this study, which comprised three input nodes, one hidden layer with five neurons, and one output node (3-5-1). If few neurons are selected, the input–output relationship is not suitably reflected, whereas the selection of too many neurons leads to overfitting of the data [40]. A model with two hidden layers is utilised in complex problems [40]. The ANN model is trained using the Levenberg–Marquardt algorithm [55]. To decrease the error, the initial weights and biases were regulated after computing the performance of the ANN. In this study, the nonlinear logistic-sigmoid transfer function was selected for the hidden layer of the ANN model, whereas the purelin transfer function was selected for the output layer.. A learning rate of 0.9 and momentum factor of 0.3

Table 1 Experimental load-deflection dataset used for ANN training

S.No.	Beam type	ρ %	Load (kN)	Disp. (mm)	S.No.	Beam type	ρ %	Load (kN)	Disp. (mm)
1	PC	0	0.00	0	62	RC	1.07	7.75	0.82
2	PC	0	0.30	0	63	RC	1.07	8.04	0.86
3	PC	0	0.60	0.01	64	RC	1.07	8.34	0.94
4	PC	0	0.89	0.02	65	RC	1.07	8.64	1.01
5	PC	0	1.19	0.03	66	RC	1.07	8.94	1.04
6	PC	0	1.49	0.04	67	RC	1.07	9.24	1.10
7	PC	0	1.79	0.05	68	RC	1.07	9.53	1.16
8	PC	0	2.09	0.06	69	RC	1.07	9.83	1.22
9	PC	0	2.38	0.07	70	RC	1.07	10.13	1.30
10	PC	0	2.68	0.08	71	RC	1.07	10.43	1.33
11	PC	0	2.98	0.09	72	RC	1.07	10.73	1.39
12	PC	0	3.28	0.1	73	RC	1.07	11.02	1.46
13	PC	0	3.58	0.11	74	RC	1.07	11.32	1.53
14	PC	0	3.87	0.12	75	RC	1.07	11.62	1.66
15	PC	0	4.17	0.13	76	RC	1.07	11.92	1.74
16	PC	0	4.47	0.14	77	RC	1.07	12.21	1.83
17	PC	0	4.77	0.15	78	BRC	1.49	0.00	0.00
18	PC	0	5.06	0.17	79	BRC	1.49	0.30	0.01
19	PC	0	5.36	0.18	80	BRC	1.49	0.60	0.03
20	PC	0	5.66	0.18	81	BRC	1.49	0.89	0.04
21	PC	0	5.96	0.2	82	BRC	1.49	1.19	0.05
22	PC	0	6.26	0.22	83	BRC	1.49	1.49	0.06
23	PC	0	6.55	0.22	84	BRC	1.49	1.79	0.07
24	PC	0	6.85	0.24	85	BRC	1.49	2.09	0.08
25	PC	0	7.15	0.25	86	BRC	1.49	2.38	0.11
26	PC	0	7.45	0.25	87	BRC	1.49	2.68	0.11
27	PC	0	7.75	0.27	88	BRC	1.49	2.98	0.12
28	PC	0	8.04	0.28	89	BRC	1.49	3.28	0.14
29	PC	0	8.34	0.3	90	BRC	1.49	3.58	0.15
30	PC	0	8.64	0.3	91	BRC	1.49	3.87	0.18
31	PC	0	8.94	0.31	92	BRC	1.49	4.17	0.20
32	PC	0	9.24	0.33	93	BRC	1.49	4.47	0.22
33	PC	0	9.53	0.34	94	BRC	1.49	4.77	0.25
34	PC	0	9.83	0.35	95	BRC	1.49	5.06	0.26
35	PC	0	10.13	0.36	96	BRC	1.49	5.36	0.32
36	RC	1.07	0.00	0.00	97	BRC	1.49	5.66	0.35
37	RC	1.07	0.30	0.03	98	BRC	1.49	5.96	0.38
38	RC	1.07	0.60	0.05	99	BRC	1.49	6.26	0.42
39	RC	1.07	0.89	0.07	100	BRC	1.49	6.55	0.45
40	RC	1.07	1.19	0.08	101	BRC	1.49	6.85	0.49
41	RC	1.07	1.49	0.09	102	BRC	1.49	7.15	0.52
42	RC	1.07	1.79	0.10	103	BRC	1.49	7.45	0.56
43	RC	1.07	2.09	0.12	104	BRC	1.49	7.75	0.61
44	RC	1.07	2.38	0.15	105	BRC	1.49	8.04	0.63
45	RC	1.07	2.68	0.15	106	BRC	1.49	8.34	0.70
46	RC	1.07	2.98	0.17	107	BRC	1.49	8.64	0.75
47	RC	1.07	3.28	0.19	108	BRC	1.49	8.94	0.78
48	RC	1.07	3.58	0.21	109	BRC	1.49	9.24	0.82
49	RC	1.07	3.87	0.25	110	BRC	1.49	9.53	0.86
50	RC	1.07	4.17	0.28	111	BRC	1.49	9.83	0.91
51	RC	1.07	4.47	0.30	112	BRC	1.49	10.13	0.97

Table 1 (continued)

S.No.	Beam type	ρ %	Load (kN)	Disp. (mm)	S.No.	Beam type	ρ %	Load (kN)	Disp. (mm)
52	RC	1.07	4.77	0.34	113	BRC	1.49	10.43	1.00
53	RC	1.07	5.06	0.36	114	BRC	1.49	10.73	1.03
54	RC	1.07	5.36	0.43	115	BRC	1.49	11.02	1.09
55	RC	1.07	5.66	0.47	116	BRC	1.49	11.32	1.14
56	RC	1.07	5.96	0.52	117	BRC	1.49	11.62	1.24
57	RC	1.07	6.26	0.56	118	BRC	1.49	11.92	1.30
58	RC	1.07	6.55	0.60	119	BRC	1.49	12.21	1.38
59	RC	1.07	6.85	0.65	120	BRC	1.49	12.51	1.48
60	RC	1.07	7.15	0.70	121	BRC	1.49	12.81	1.70
61	RC	1.07	7.45	0.75	122	BRC	1.49	13.11	2.05

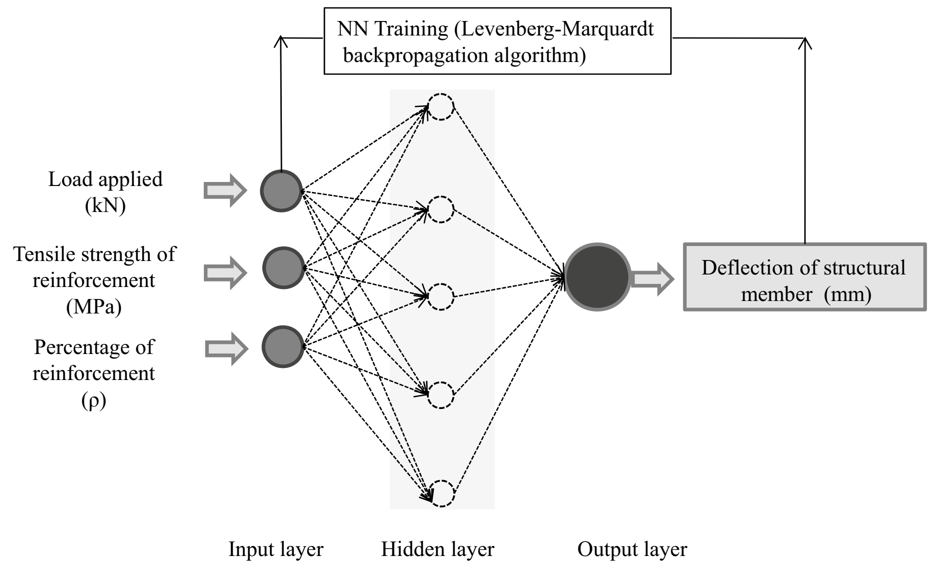


Fig. 5 Architecture of the ANN used in this study for predicting the beam deflection

are selected for the ANN. The model is terminated when the error reached below its predefined tolerance value or when the maximum number of cycles (epochs = 100) is completed. Moreover, for high reliability, the proposed ANN (3-5-1) architecture was run five times and the best result was selected. The performance of the ANN is generally assessed through the mean square error (MSE), root mean square error (RMSE), and coefficient of determination (R^2). The MSE is expressed as follows:

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}[E(x_i) - O(x_i)]^2 \tag{2}$$

where $E(x_i)$, $O(x_i)$ and N denote the estimated value of observation i, observed value of observation i, and total number of datasets, respectively. The RMSE is defined as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}[E(x_i) - O(x_i)]^2} \tag{3}$$

The coefficient of determination (R^2) is expressed as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}[E(x_i) - O(x_i)]^2}{\sum_{i=1}^{N}[E(x_i) - \overline{E(x_i)}]^2} \tag{4}$$

where $\overline{E(x)}$ denotes the mean value of $E(x)$ taken over N datasets. The ANN data were divided into three datasets for training, testing, and validating the model.

4 Results and discussion

Convergence analysis was conducted to designate the optimal count of neurons in the hidden layer of the ANN. Excessive neurons reduce the computational performance of the ANN, whereas a lack of neurons induces difficulty in characterising the input–output relationship. As proposed by Caudill [56], the upper limit of the number of neurons in the hidden layer was twice the number of inputs plus 1 (i.e., 7). After the count of neurons in the hidden layer reached 5, no significant improvement was observed in the MSE, the implied RMSE, and R^2. The ANN configuration with a minimum error (MSE and RMSE) and an R^2 value close to unity was selected. Among the 122 data points, 74 data points (about 60% of the total data) were randomly selected as the training dataset, whereas the other 24 data points (about 20% of the total data) were used as the testing and validation datasets. Figure 6 displays the MSE and number of epochs for all the datasets. When the MSE reached a minimum value in the validation dataset, the ANN training was stopped. At this point, the weights of the ANN were memorised and used for predicting the data outside the training sample. This approach enables the avoidance of overfitting and underfitting, which are common problems faced by many machine learning techniques. Table 2 presents the performance of the proposed ANN architecture over five simulation runs. The run having the lowest MSE was selected for comparison with the experimental data.

Figures 6 and 7 illustrate the summary of the ANN training. Figure 6 displays a converging MSE, which is indicative of a well-trained ANN. The plot illustrates three lines because the 122 datasets were randomly divided into three datasets. Figure 8 a–d illustrate the comparison of the magnitude of deflection obtained when using the ANN model after training and when using the experimentally obtained data for the training data, validation data, testing data, and all the data. The coefficient of the correlation was 0.9983, which indicates that the two results were consistent. Figure 9 illustrates a comparison between the load-deflection curve for all the typologies

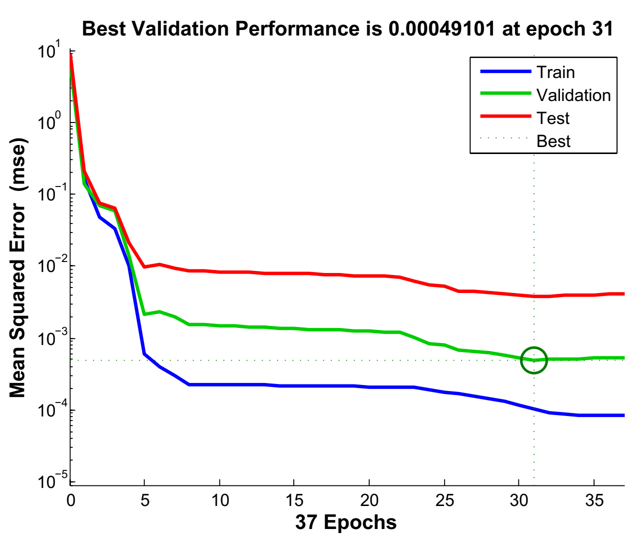


Fig. 6 MSE over ANN training for the 3-5-1 configuration

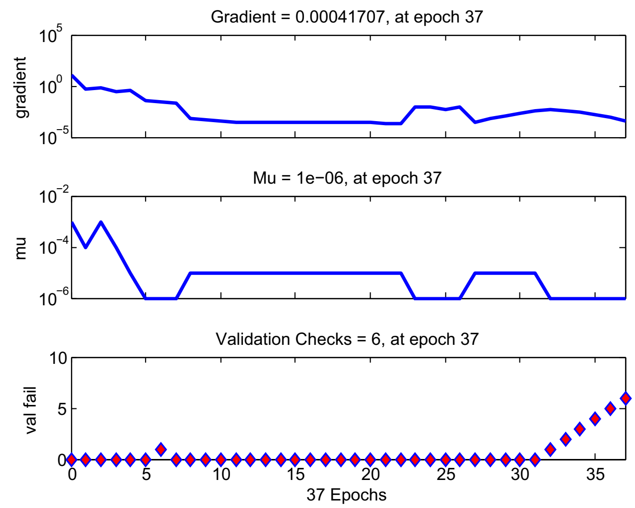


Fig. 7 Training state of the neural network with the 3-5-1 configuration

of beams in this study. The curve was consistent with the values simulated using the ANN model. Thus, the load-deflection curve indicates that the ANN model predicted the experimentally obtained data with high accuracy and precision. The concrete beams with no reinforcement failed in a brittle manner compared with the beams having reinforcements. The considered reinforced beam with bamboo strips exhibited a marginally more ductile behaviour than the steel-reinforced beam. Furthermore, the collapse load of the plain beam (10.13 kN) was significantly lower than that of the treated bamboo-reinforced beams (13.11 kN). Thus, bamboo material has the capability of replacing steel as a possible reinforcement in a limited and controlled manner. The performance of bamboo-reinforced beams is significantly better than that of beams with no reinforcement.

Table 2 Results of statistical analyses of the 3-5-1 ANN architecture over five sample runs

R^2				MSE	Rank
Training	Validation	Testing	All		
0.99977	0.99913	0.99505	0.9983	0.000417	1
0.99985	0.99482	0.99903	0.99821	0.001002	2
0.99863	0.99173	0.99857	0.99652	0.005964	3
0.99754	0.98426	0.99487	0.99378	0.006271	4
0.99815	0.9909	0.99893	0.99584	0.006883	5

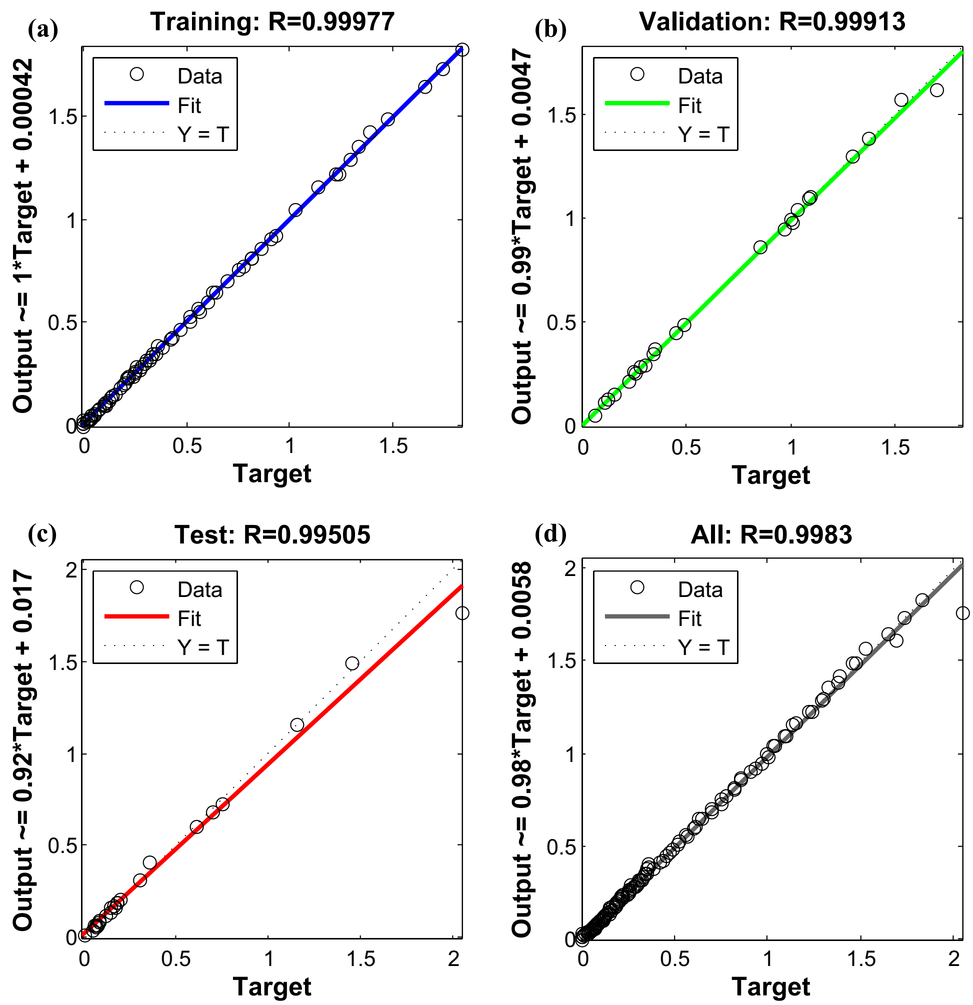


Fig. 8 Comparison of the deflection predicted using the ANN and using experimental observation for the **a** training dataset, **b** validation dataset, **c** testing dataset and **d** all datasets

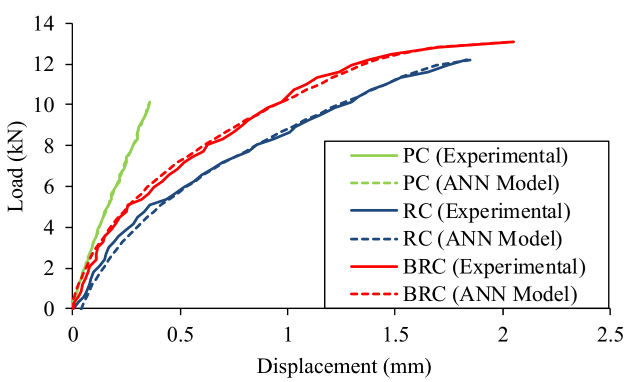


Fig. 9 Comparison of the load-deflection curve obtained with the ANN model and the experimental data for the PC (green), steel-reinforced concrete (blue), and BRC (red) beams

5 Conclusions

In this research, the deflection of several concrete beams is predicted under varying loads in short term, different types of reinforcement material, and different percentages of reinforcement by using an ANN. A sequence of experimental tests are performed to validate the usage of bamboo as a potential reinforcement material for concrete beams. The ANN results closely matched with the experimental values of deflection for the different beam typologies tested. The regression values of the ANN for training, validation and testing are 0.9997, 0.9991 and 0.9950 respectively with the best validation performance being obtained at epoch 31. The results indicate that the ANN can be utilised as a powerful and reliable tool for estimating the deflection behaviour of concrete beams in the considered loading conditions. It can be applied in civil engineering structures by engineers to quickly estimate the deflection of reinforced concrete beams without performing any complex analysis. The ANN and experimental results indicate that bamboo-reinforced beams can be used a substitute in place of traditionally used steel rebars. The ultimate load and maximum deflection are comparable for the two typologies of reinforced beams tested in this study. The bamboo-reinforced beam exhibited a 30% increase in the load-carrying capacity compared with the plain reinforced concrete beam for a 1.5% area of reinforcement. For a 1.1% area of steel reinforcement, the bamboo-reinforced beam exhibited an 8% increase in the load-carrying capacity.

In future studies, the database can be expanded by using different percentages of reinforcement and different varieties of bamboo. Furthermore, experimental data can be obtained for large-scale beams and columns to determine the actual site conditions. The present study evaluated the deflection of beams under loading only for predicting the short-term service life. Hence the time-dependent behaviour of reinforcing material, which affects the long-term serviceability, can also be investigated by performing further experimentation. Experimental studies can also be performed on other structural elements (i.e., concrete columns and slabs) that use bamboo strips as inherent reinforcement

Compliance with ethical standards

Conflict of interest The Authors declare that they have no conflict of interest.

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