Journal of Soft Computing in Civil Engineering 5-3 (2021) 88-100

Contents lists available at SCCE

Journal of Soft Computing in Civil Engineering

Journal homepage: www.jsoftcivil.com

Deep Neural Network-Based Storey Drift Modelling of Precast Concrete Structures Using RStudio

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https://doi.org/10.22115/SCCE.2021.289034.1329

ARTICLE INFO

Article history:
Received: 03 June 2021
Revised: 29 September 2021
Accepted: 29 October 2021

Keywords:
Deep neural network;
Modelling;
Storey drift;
Machine-learning;
Computer programming.

ABSTRACT

In this research, storey drift has been determined using Deep neural networks (DNN Keras). DNN Keras has various hyper tuning parameters (hidden layer, drop out layer, epochs, batch size and activation function) that make it capable to model complex problems. Building height, number of bays, number of storeys, time period, storey displacement, and storey acceleration were the input parameters while storey drift was the output parameter. The dataset consists of 288 models, out of 197 were used as training data and the remaining 91 were used as test data. 0.9598 correlation coefficient was observed for DNN Keras as compared to 0.8905 by resilient back-propagation neural networks (BPNN), indicating that DNN Keras has about 8 per cent improved efficiency in predicting storey drift. Wilcoxon signed-rank test (non-parametric test) was used to compare and validate the performance of DNN Keras and resilient BPNN algorithms. The positive results of this study point to the need for further research into the use of DNN Keras in structural and civil engineering.

How to cite this article: Dahiya N, Saini, B, Chalak H. Deep neural network-based storey drift modelling of precast concrete structures using RStudio. J Soft Comput Civ Eng 2021;5(3):88–100. https://doi.org/10.22115/scce.2021.289034.1329.

1. Introduction

Over the last decade, machine learning approaches have become an effective tool to solve complex engineering problems. Neural networks, support vector machines, decision trees and nature-inspired algorithm-based learning are the most popular machine learning techniques for structural and earthquake engineering problems. A brief and extensive literature review on the application of machine learning in structural engineering can be found in [1–6]. In precast concrete structures, seismic response of the structure is an important parameter that includes storey drift, displacement, story acceleration, storey forces and seismic reaction is of greater concern to structural engineers.

Storey drift should be reasonably reliably measured during the seismic design of a precast building, as they can be specifically connected to the financial harm and life-safety risks caused by seismic events. Storey drift was defined as the relative lateral displacement between two successive building floors. To avoid significant damage to structural and non-structural members of the building, storey drift should be restricted to particular values. Analysis on estimating drift has concentrated primarily on SDOF systems. Two methods (FEMA440 - 2004) are commonly used to estimate the maximum response of SDOF systems. The first method is based on the early concepts of Veletsos and Newmark [7], who explored the relationship between elastic and inelastic systems for displacement and developed the equal-displacement rule. The second method is based on the idea of reciprocal linearization. The maximum displacement of the inelastic SDOF system is observed by Jacobsen [8] and Iwan [9]. The maximum displacement of the SDOF elastic system with stiffness lower than the initial stiffness of the inelastic system and damping greater than the inelastic system approximates the SDOF system. The current practice (IS 1893. ATC, FEMA440, Eurocode 8) adopts procedures that are based on similar SDOF systems to estimate maximum deformations of buildings.

Under pseudo-static cyclic loads, the behaviour of a full-scale two-story reinforced precast concrete structure connected utilising three-way wet joints with poorly designed and detailed steel connectors was investigated. Steel connectors failed due to permanent bending mechanisms at relatively modest storey drift, with friction/sliding and connection behaviour dominating the structure's response [10].

Menegon et al. [11] and Seifi et al. [12] studied the behaviour of precast concrete structures in seismic regions. Building walls and cores made of precast concrete have become increasingly popular over the last 10 to 20 years, both in regions with low seismicities, such as Australia and in regions with high seismicities, such as New Zealand. On-site time frames are shorter with precast construction, and high quality of construction can be achieved in the precast yard, which is more efficient than traditional cast in situ building techniques. To develop new innovative precast wall systems, various research studies have been conducted [13,14]. Precast concrete structures were evaluated for their in-plane lateral drift behaviour and ductility.

Machine learning techniques, such as BPNN are used in predicting the structural reliability evaluation and seismic response of structure [15]. Deep learning has been used in various civil and structural engineering problems over the last 5 years, and it has been found to perform well in contrast to conventional modelling approaches [16,17]. Storey drift of structure erected using precast concrete members using deep neural networks was carried out. Input parameters consisted of building height, number of bays, number of storey, time period, storey displacement, and storey acceleration on the seismic drift of precast concrete structures.

It was reported in recent years that deep learning was being used to solve civil engineering problems with excellent results when compared to existing modelling approaches [18–21]. Detailed literature reviews indicate that deep learning has not yet been used to predict storey drift. While keeping this in mind, as well as the enhanced performance of deep learning-based regression models, this research explores its potential for predicting storey drift in precast concrete structures.

2. Deep learning

The Neural Network (or the Artificial Neural Network) has the potential to learn from instances. ANN is an information retrieval model focused on a biological neuron network. To solve problems, this is made up of a large number of highly interconnected computing modules known as neurons or nodes. This takes the non-linear direction and processes information in parallel across the nodes. A neural network is a dynamic mechanism of adaptation. Adaptive means that it can shift the weight of the inputs to change the internal structure [21].

A deep neural network (DNN) is based on ANN, but the difference is in the number of layers. An ANN has 3 layers i.e input layer, hidden layer and output layer. DNN has also 3 layers that are input layer, hidden layers and output layer, but DNN can have n numbers of hidden layers for accurate prediction. The input layer is the layer that is connected to the input data and no processing is done in the input layer. In the hidden layer, the activation function is used to transform and transfer the data to the output layer. The output of the hidden layer activation function is transferred to the output layer which is responsible for calculating the predicted output. The final layer is called as output layer.

Each node has its associated weight and bias, weight is a factor inside a neural network that converts input data into hidden layers of the network. Each node is a set of inputs, weight and bias given by equation 1 [21].

$$\mathrm{y} = \mathrm{Wx} + \mathrm{b} \tag{1}$$

Where y is the output, x is the input, W is the weight and b is bias. Without activation function ANN model is like a linear regression model, the activation function is a code that gives DNN a non-linearity that allows it to understand the complexity of the model. There are a variety of activation functions, such as identity, sigmoid, hyperbolic tangent (tanh) and rectified linear unit (ReLU). Epochs, batch size and learning rate are the critical hyper tuning parameters to train the data set. A deep neural network generally overfits the test data in case of limited training data. To avoid the problem of overfitting, the dropout layer can be introduced after the hidden layer in

DNN. Dropout is a regularization method that approaches parallel training of many neural networks with various architectures. Dropout can be implemented on the hidden layer but this should not be used on the output layer.

Several hyper tuning parameters require computational analysis. These parameters include number and nodes of the hidden layer, dropout layer and dropout rate, activation function, number of epochs, batch size and optimizer. To implement DNN, Keras [22] was used in RStudio [23].

3. Methodology for modelling

288 frame models of building having precast member for various ground floor height, bays number, storey displacement, time period, storey acceleration and material properties were analysed as shown in table 1.All these parameters were feed in various models based on deep learning. A total of 288 were analyzed to understand the effect of all the input parameters on the storey drift of structures. A live load of 3 kN/m^2 and a superimposed dead load of 1 kN/m^2 was considered for analysis. For analysis purpose, ETABS [24] software was used since it is a reliable software for structural design and analysis as the same software is used in analyzing the iconic Burj khalifa in Dubai [25]. The non–linear ground motion data has been adopted from the PEER database. An ensemble of 100 different ground motion data has been used for analytical study. These ground motions are combined using Bispec software. In the adopted ground motion records, only near-fault data has been adopted to obtain effective variation in the seismic response parameters. Figure 1 depicts the 3D modeling and plan of a 12 storey structure having 4 bays.

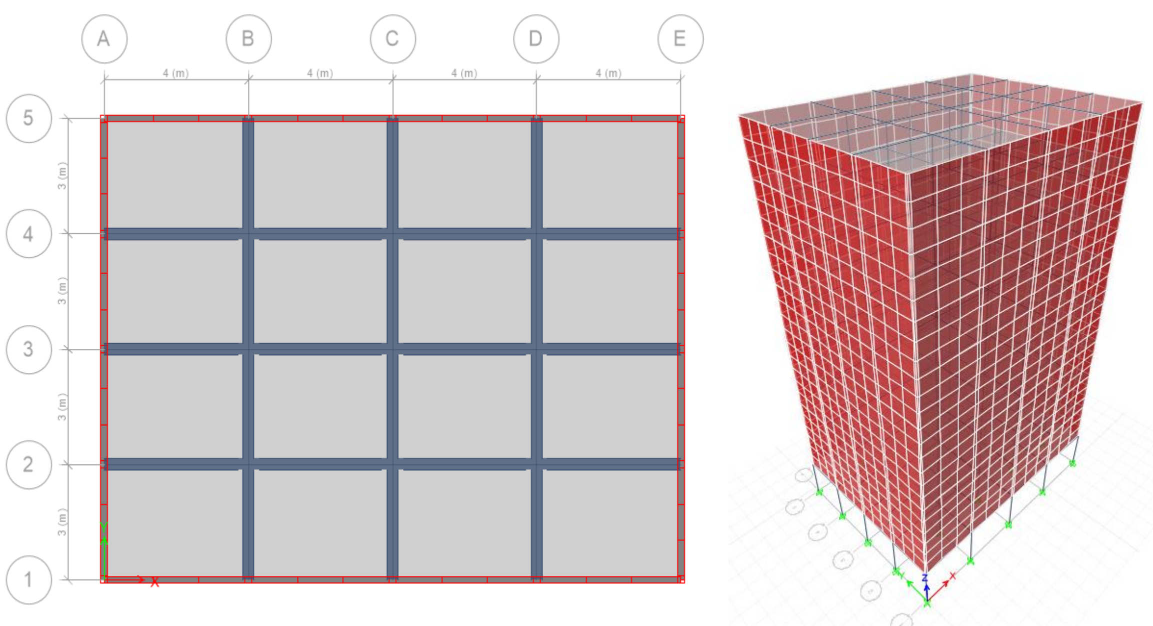

Fig. 1. (a) Plan of one of a considered structure; (b) 3d model of one of a considered structure.

Table 1
Input parameters considered in model.

Model	Parameters	Parameters Values							
Base Model	Height of storey (in m)	3	6	9	12	15	18		
	Bays (Nos.)	2	3	4	5				
	Type of Frame	Shear wall with opening	Shear wall without opening						
	Length of building (in m)	8	12	16	20				
	Breadth of building (in m)	8	12	16	20	6	9	12	15
	Height of building (in m)	9	18	27	36	45	54		
	Type of Section	Without- cracks	With- cracks						
	Size of column (in mm)	300 x 600							
	Size of Beam (in mm)	300 x 450							
	Slab Size (in mm)	4000 x 3000 x 150	4000 x 4000 x 150						
	Shear Wall thickness (in mm)	200	150						
	Grade of Concrete	M40							
Ground floor height changed wrt to base model	Change in building height (in m)	10	19	28	37	46	55		
Concrete grade changed wrt to base model	Grade of Concrete	M30							

Table 2
Training and testing data set summary.

Input parameters	Training Data set					Testing Data set				
	Min	Max	Mean	Median	Std. dev.	Min	Max	Mean	Median	Std. dev.
No of storeys	3	18	10.49	12	5.07	3	18	10.52	9	5.28
No of bays	2	5	3.52	3	1.14	2	5	3.46	4	1.07
Building Height	9	55	31.81	36	15.24	9	55	31.89	28	15.83
Time Period	0.24	1.47	0.74	0.71	0.299	0.25	1.54	0.74	0.75	0.306
Displacement	0.00088	0.07241	0.013	0.011	0.0106	0.0010	0.0477	0.0133	0.0107	0.0105
Story acceleration	0.040	1.32	0.73	0.72	0.104	0.60	0.85	0.73	0.72	0.054

4. Preparation of data set

Rtsudio was used on the 70 percent of the 288 models in order to obtain the split data to be used for training. In the present study, 197 and 91 random samples were selected to obtain split data to be used as training data and testing data respectively. Input parameters were the building height, number of bays, no of storey, time period, storey displacement, and storey acceleration. Table 2 depicts the minimum, maximum, mean, median and standard deviation value obtained for both training and testing data set. Mean absolute percentage error (MAPE), root mean square error (RMSE) and correlation coefficient (CC) was used with test data to compare the efficiency of DNN Keras and resilient BPNN modelling approaches. The hyper-tuning parameters determine the efficiency of DNN Keras and resilient BPNN. Trails runs were carried out to find the optimum value of hyper-tuning parameters by comparing the RMSE and CC. Table 3 provides the optimum value of hyper-tuning parameters used in the present study. The number of nodes in the hidden layer in DNN Keras was obtained using the formula[26] $\boldsymbol{H_n \leq 2N + 1}$, where H_n is the nodes in all hidden layers and N is the input parameters. In the present study, the input parameters are 6 and the nodes in the hidden layer are 13. The performance of DNN Keras and resilient BPNN algorithms was compared and validated using a non-parametric test (Wilcoxon signed-rank test).

Table 3
DNN-Keras [22] and resilient BPNN- hyper-tuning parameters optimum value.

Program Used	Hyper-tuning parameters
DNN-Keras	Layer_dense- 3 (6,5,2 nodes), Layer_dropout-3 with dropout rate=0.1, activation function- "tanh",, optimiser- 'rmsprop', epochs-450, Batch_size-9.
Resilient BPNN	Hidden layer = 1(8 nodes), algorithm = 'rprop+', activation function - "tanh" Threshold- 0.01

Table 4
MAPE, RMSE and CC values with test data.

Modelling Approach	Test Data		
	CC	RMSE	MAPE
DNN Keras	0.9598	0.00120	0.1385
Resilient BPNN	0.8905	0.00193	0.4379

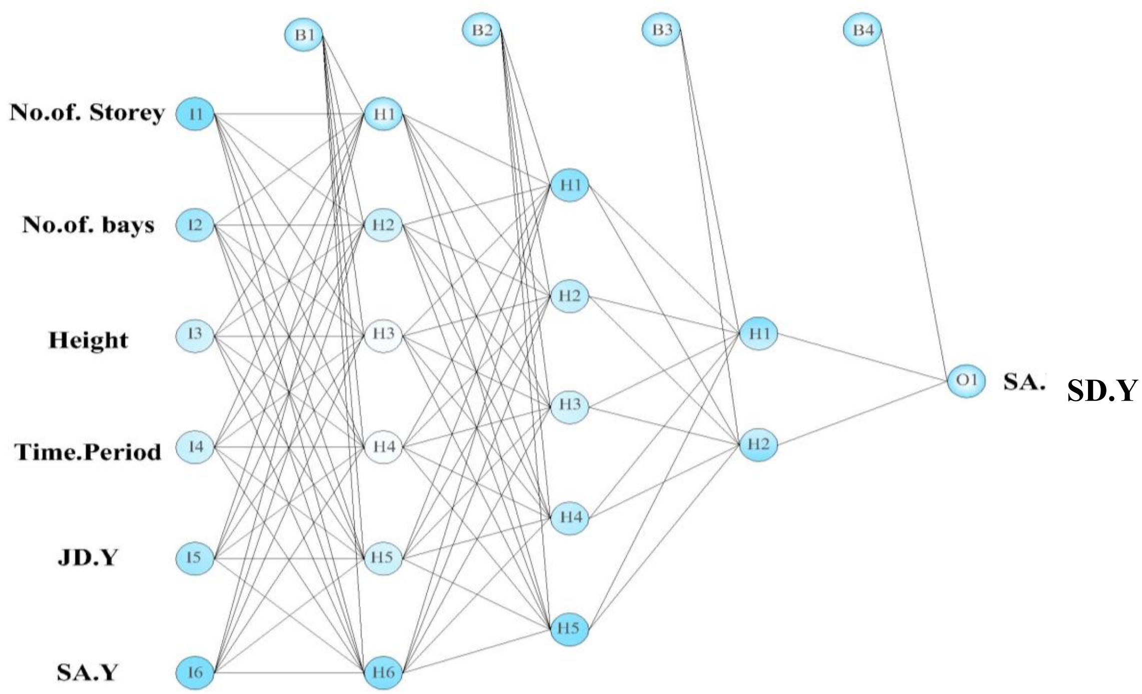

Fig. 2. A 6-6-5-2-1 DNN keras model.

5. Results

Table 4 displays the values of the mean absolute percentage error (MAPE), root mean square error (RMSE) and correlation coefficient (CC) obtained with test data using DNN Keras and resilient BPNN. Table 4 shows that DNN Keras has better accuracy and efficiency than resilient BPNN for CC, RMSE, and MAPE. Trial and error method was used to obtain the optimum value of dropout rate, which in this case was observed to be 0.1 that is a hyper-parameter. Results show that 6-6-5-2-1 is an optimized DNN network (figure 2). In figure 3, the performance of DNN Keras at 450 epochs has been presented in the loss in cross-validation and training dataset. Val_loss is the value of cost function for cross-validation data and loss is the value of cost function for training data, whereas val_mae is the value of mean absolute error for cross-validation data and mae is the value of mean absolute error for training data. To avoid overfitting, while programming early stops function was used if no improvement in the model was found out after 100 epochs. Figure 3 provides the plot between loss, mean absolute error (mae) and the number of epochs. Figure 3 also shows that the model is learning as the loss is decreasing and accuracy is increasing. The mean absolute error (mae) of 0.0009 was achieved with testing data as compare to mae of 0.0012 with training data. Table 4 shows that DNN Keras has significantly higher accuracy and efficiency in predicting storey drifts than resilient BPNN. DNN Keras has a CC of 0.9598, RMSE of 0.00120 and MAPE of 0.1385 in comparison to resilient BPNN which has a CC of 0.8905, RMSE of 0.00193 and MAPE of 0.4379. It is also worthwhile to mention that the efficiency in predicting the storey drift is higher in the case of DNN Keras as compared to resilient BPNN. Improved efficiency of 8 per cent is observed for DNN Keras over resilient BPNN.

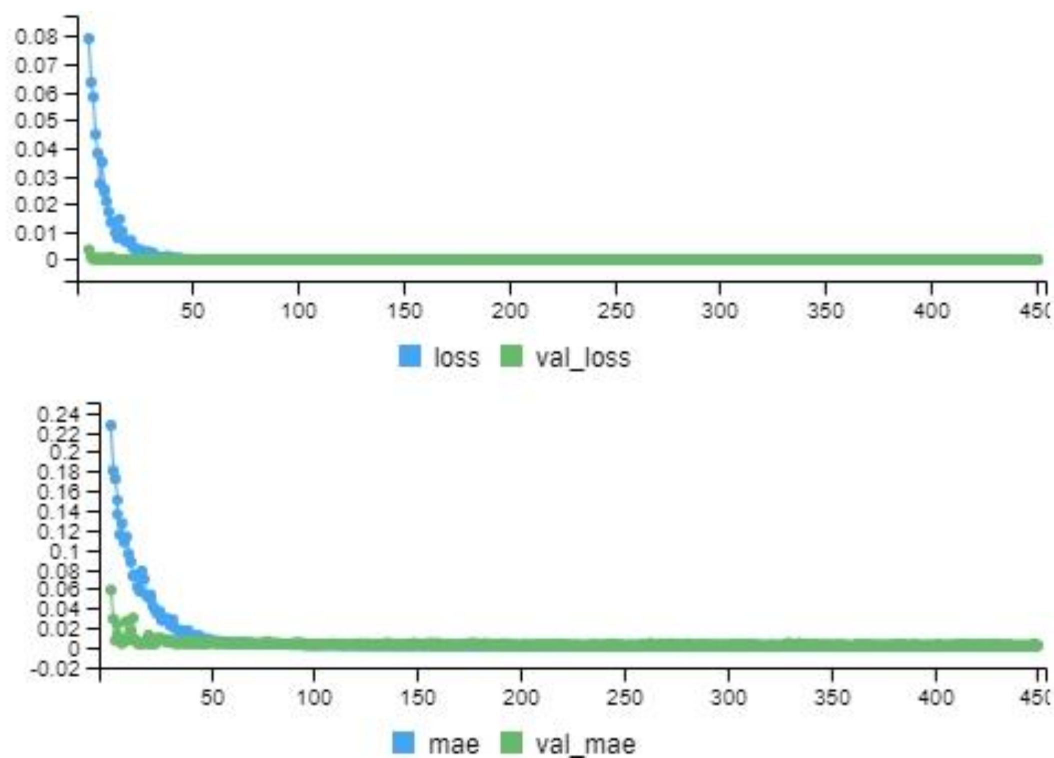

Fig. 3. Best performance of DNN keras at 450 epochs for loss and mean square error.

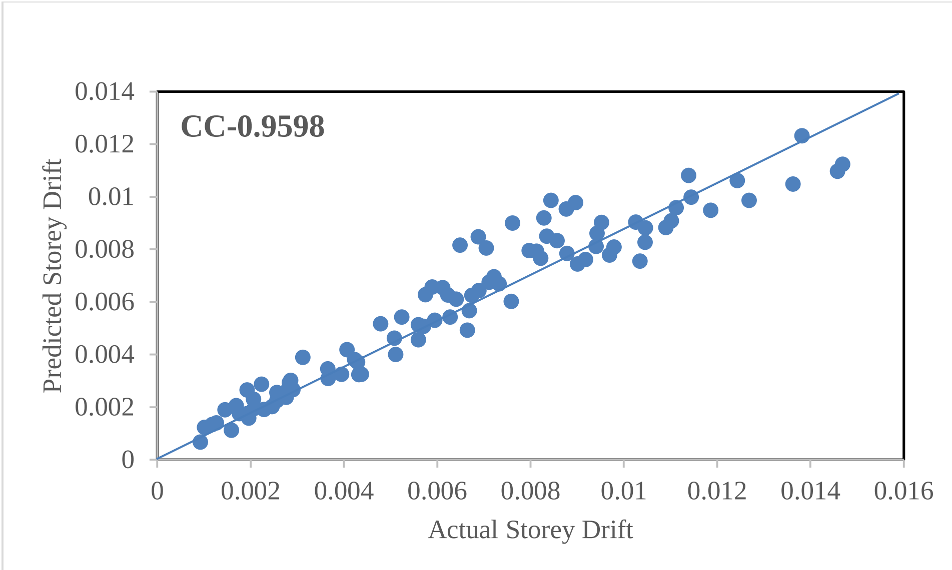

Fig. 4. Actual versus predicted storey drift on testing data for DNN Keras.

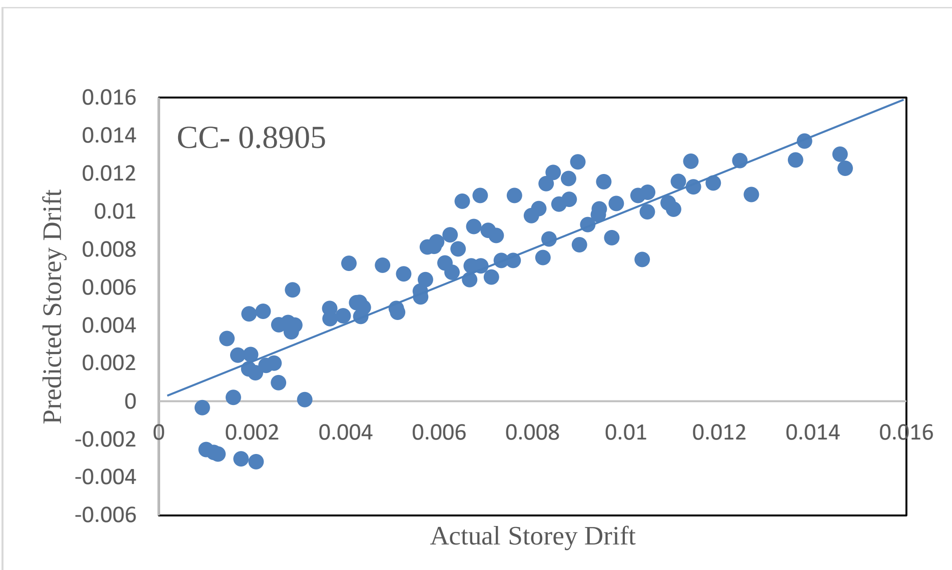

Fig. 5. Actual versus predicted storey drift on testing data for resilient BPNN.

Table 5
Wilcoxon signed-rank test.

Algorithm	z-value	p-value	w-value
DNN Keras vs Resilient BPNN	-5.67 z Critical two-tail- 1.9599	0.0000000071	660

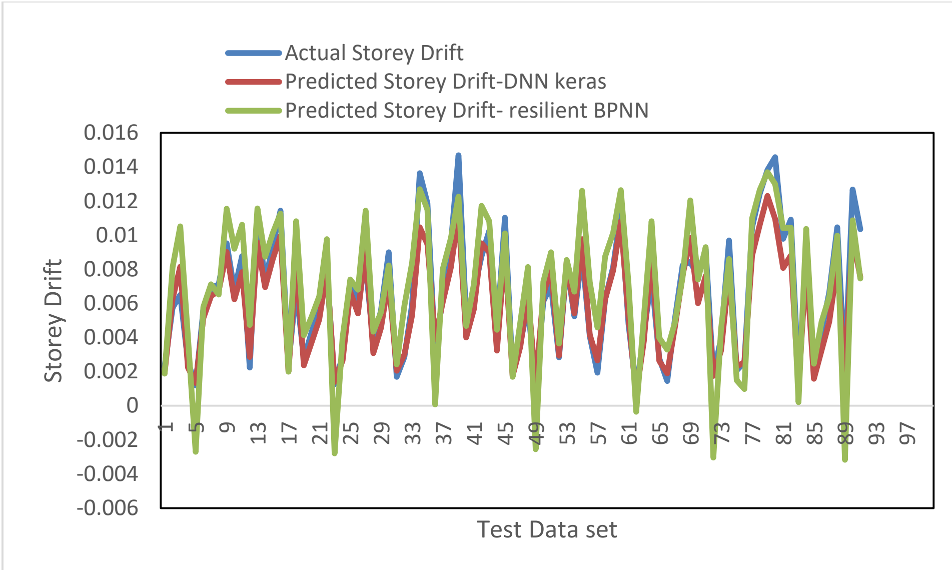

Fig. 6. Variation in predicted values of storey drift using DNN Keras and resilient BPNN to the actual storey drift.

The figure 4 and 5 provide the plots between the actual storey drifts versus predicted storey drifts using test data of DNN Keras and resilient BPNN algorithms. The figure 4 and 5 shows that DNN Keras and resilient BPNN are both good performers for storey drift values in the lower and middle ranges. The storey drift predicted by DNN Keras is in good agreement with the actual storey drift, as shown in the figure. There is five negative value predicted by resilient BPNN program might be considered as a negative of this program. Figure 6 demonstrate the variation of actual and predicted storey drift with the number of test data using DNN Keras and resilient BPNN programs.

To investigate the behaviour of DNN Keras with different batch sizes and epoch counts, the model that produced the best results with test data was used. To avoid overfitting, while programming early stops function was used if no improvement in the model was found out after 100 epochs. Table 6 provides the variation of RMSE with different values of epochs and batch size using test data. The data set performs well with 450 epochs and a batch size of 9, according to the results in table 6. The higher value of epochs will increase the computational cost without increasing the accuracy of the model.

DNN Keras model was validated by Wilcoxon signed-rank test as DNN Keras has better performance as compared to resilient BPNN with a p-value of 0.0000000071 as presented in table 5. The DNN Keras model was used on all data set using the same hyper tuning parameter for calculation of CC, RMSE and MAPE on all data set. Table 7 clearly shows that the test data and all data set have a better fit than the training data set. The analytical models have been validated and practical applicability has been presented by the authors in previously published research [27,28].

Table 6
Variation of RMSE value with varying batch size and number of epochs.

Number of epochs	Batch Size	RMSE
263	1	0.00203
207	2	0.00166
370	3	0.00139
314	4	0.00125
600	5	0.00211
157	6	0.00130
423	7	0.00164
376	8	0.00123
450	**9**	**0.00120**
682	10	0.00311
583	11	0.00131

Table 7
Testing, training and all data.

DNN Keras	CC	RMSE (m)	MAPE
Test data	0.9598	0.00120	0.1385
Training data	0.9349	0.00191	0.1614
All data	0.9391	0.00172	0.1542

6. Verification of the proposed method

This section basically aims in comparison between the analysis results obtained from dynamic analysis, proposed method and IS 1893:2016. This is done to verify the accuracy of the proposed method to predict the storey drift of precast concrete structures. Efficacy and constraint of the proposed method were checked by using a 4 bay-12 storey model. Table 8 shows the comparison of the storey drift obtained for IS 1893:2016, dynamic analysis and the proposed method.

Table 8
Comparison of IS code method, Dynamic Analysis and proposed method for storey drift.

	Dynamic Analysis	Proposed Method	IS 1893:2016
Storey Drift	0.0056 (%)	0.0052 (%)	0.0082 (%)

Results in table 8 clearly show the accuracy of the proposed method in comparison to the IS 1893:2016, proposed method has 53 percent more accuracy than IS1893:2016 in predicting the storey drift but proposed method has a limitation that it can be used only for buildings up to 5 bays, 20 m in length, 20 m in breadth and 60 m in height.

7. Conclusions

In this study, DNN Keras and resilient BPNN was used to obtain the storey drift of concrete structures with precast members. DNN-Keras produced better results as compared to to resilient BPNN for the given data set. DNN Keras has a CC of 0.9598, RMSE of 0.00120 and MAPE of 0.1385 in comparison to resilient BPNN which has a CC of 0.8905, RMSE of 0.00193 and MAPE of 0.4379. The efficiency of DNN Keras in predicting the storey drift of a precast building is explored in this paper. DNN Keras has about 8 per cent improved efficiency in predicting storey drift over resilient BPNN. From the present study, it is also concluded that DNN Keras is a precise and robust modelling technique which may be used in future to solve various problems related to civil engineering. The present study uncovered the use of hidden layer and drop out layer to create the model, but optimization techniques can also be used for the deep neural networks.

Funding

This research received no external funding.

Conflicts of interest

The authors declare no conflict of interest.

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