ESTIMATING THE FUNDAMENTAL PERIOD OF INFILLED RC FRAME STRUCTURES VIA DEEP LEARNING

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Abstract. The fundamental period is deemed an essential dynamic parameter influencing the seismic design of buildings generally, and the RC structures specifically. In this regard, a number of machine learning models have been suggested for its estimation. However, no deep learning method was employed before, despite its wide success in other fields. The present study aims at generating an alternative model for its computation via the Deep-Neural-Network method, to overcome such limitation. Therefore, a database of 4026 cases, gathered from the literature, was developed in the modeling stage. Furthermore, five relevant inputs were chosen following the literature suggestions. Then, the significant inputs were modeled using DNN; their effectiveness was evaluated using three performance indicators plus the K-fold cross-validation method. The findings demonstrated the supremacy of the (5-9-10-1) model, trained by the Tansig transfer function. This proposed model offered the best estimation, i.e., the closest to the period target values in comparison with other models and equations suggested in the literature. Finally, a reliable and easy-to-use Android app named "Building Period Estimator" was designed and uploaded on Google play store. This latter will greatly assist civil engineers and researchers when approximating the period more efficiently, plus saving both time and money.

Key words: fundamental period, deep neural network, K-fold cross-validation, android application, masonry infilled framed structures.

1. Introduction

There is convincing evidence burgeoning from researches on construction that this process requires a complex set of elements; these elements can be classified into structural and non-structural components. Previously published studies indicated that both components have a direct influence on the dynamical behavior of the structural system (Adham *et al.,* 1990; Cavaleri and Papia, 2003; Freeman, 1977; Kose, 2009; Villaverde, 2006). Although the non-structural components, such as the infill walls, have been disregarded in conventional analysis, the related literature has demonstrated the impact of non-structural elements on the overall construction strength, stiffness, and damping (Adham *et al.,* 1990; Cavaleri and Papia, 2003; Freeman, 1977; Kose, 2009; Villaverde, 2006). Furthermore, building dynamic parameters plays a prominent role in forecasting their seismic comportment, and in choosing the suitable retrofitting method in case of damage (Asteris *et al.,* 2016). Generally, the dynamic parameters (damping ratio ξ, fundamental period T, and modal shape) together with the input ground motion are considered to be the main factors influencing the construction seismic response (Vidal *et al.,* 2014). At this point, it is worth noting that the fundamental period is deemed to be the most important influential factor on the seismic design and evaluation (Charalampakis *et al.,* 2020). It has a principal role in defining the elastic demand, which contributes in assessing the forces that the building will be exposed to during an earthquake, in addition to determining the necessary inelastic performance in static procedures (Joshi *et al.,* 2014). Based on this background, it is needless to say that modeling this parameter as close as possible to reality is a good idea when trying to expect a building seismic performance. Thereupon, in order to predict the fundamental period, numerous characteristics should be taken into consideration, such as the shear walls, the infill walls, the structural regularity, the number of storeys and spans, the height of the buildings, the opening ratio in the vertical components, the loads position, and the size of the elements (Asteris *et al.,* 2016; Charalampakis *et al.,* 2020; Joshi *et al.,* 2014). These characteristics altogether, would give realistic results when measuring its estimation. However, in most cases the period is expressed as a function of the structural system classification and number of storeys or height (Verderame *et al.,* 2010).

For the sake of determining the fundamental period, several methods can be utilized. Undoubtedly the best one is the experimental method, which is based on recording weak earthquakes or simply generating vibrations inside the structures. However, both these techniques take a lot of time and a big budget when applied to many buildings (Vidal *et al.,* 2014). In addition, the theoretical structural dynamic analysis can offer a significant alternative approach. The latter is based on generating an appropriate model of the target structure. Unfortunately, the problem arises when dealing with very complex buildings, more specifically, with prefabricated ones (Kuźniar and Waszczyszyn, 2006).

Over the past few decades, there have been several classical attempts with the Eigenvalue analysis or by a rational method called “Rayleigh’s method to generate accurate estimations (Guler *et al.,* 2008; Kose, 2009). Equally important, ambient noise analysis has frequently proven to be an efficient, quick, and cheap technique, since it does not take much recording time to get stable results (Gallipoli *et al.,* 2009, 2010; Oliveira and Navarro, 2010; Prieto *et al.,* 2010; Vidal *et al.,* 2014). Nowadays, with the latest technological evolution which provided high-speed computers, the dream of new methods came true (Asteris and Nikoo, 2019). Thanks to this development, the period could be calculated via new deterministic approaches, which gave effective results in some previous studies. But the problem arises in aforementioned methods when dealing with very complex buildings, too (Kuźniar and Waszczyszyn, 2006).

Investigators and earthquake codes have specified a number of simple equations in order to estimate the fundamental period depending on the regression analysis of the data acquired from the seismic vibrations of real structures. These equations can effectively estimate the subject under study by providing the storeys number, or the total height. On the other hand, some published studies have indicated that their results varied considerably, particularly when comparing the numerical analysis findings with the ones found in the experiments. Table 1 gives an overview of the empirical formulas proposed in the literature to estimate the subject under study. Interestingly, the advantages of easiness and speed turned the proposed empirical equations to be very beneficial. While traveling this path, some shortcomings have been observed. To begin with, the researchers ignored different structural and non-structural parameters in the period estimation. For example, the infill walls generally increase the structure stiffness, which indirectly affects the period estimation (Asteris *et al.,* 2016). This could lead to oversimplifying the earthquake-complicated mechanism, when several factors have been deemed to enhance the estimability of the empirical equations in predicting the period. In the same respect, the big number of equations used with similar parameters indicated the existence of inherent variability when using them (Benbouras *et al.,* 2019); meaning the presence of external factors, which may have an influence on the equation modeling. Therefore, the use of these equations in other conditions may lead to ineffective results (Benbouras *et al.,* 2017). Also, the traditional regression methods rely basically on simplified assumptions, such as a linear behavior or production heuristics, which makes them less efficient in modeling the complex dynamic behavior of an earthquake (Benbouras *et al.,* 2019).

In this regard, and as a response of the major shortcomings of the traditional regression shortcomings when estimating the basic period of the RC buildings, a remarkable progress in the use of machine learning approaches has been observed over the past two decades (Benbouras and Petrisor, 2021). Unexpectedly, machine learning approaches have revealed an astonishing ability to learn from the existing data (input–output training datasets), and to generate complex equations using multidimensional factors (Benbouras *et al.,* 2021; Benbouras and Lefilef, 2021). Among the significant researches dealing with the period estimation, Chun et al. (2000) have used the multiple regression analysis modeling by examining a database consisting of 50 test data. The selected input factors comprised the number of storeys, the length of building, the width of building, and the height of building. The suggested model effectively estimated the period compared to the traditional methods. Furthermore, Kuźniar and Waszczyszyn (2006) estimated the period by using Artificial Neural Networks with an input layer containing the ratio of vertical unit base pressure to elastic strain, the building dimension in the direction of vibrations, the equivalent bending stiffness, and the equivalent shear stiffness.

Table 1. Correlations proposed by researchers and earthquake codes in the literature.

Authors	Correlations	Equation number	Comments	References
Uniform building formula (UBC)	$T = 0.0466.H_n^{0.9}$	(1)	• H_n is the height of the structure (in meters)	Mohamed *et al.*, 2019
Eurocode 8	$T = C_t.H_N^{3/4}$ $C_t = \frac{0.075}{\sqrt{A_c}}$ $A_c = \Sigma A_i\,(0.2 + \frac{l_{wi}}{H})^2$	(2) (3) (4)	• C_t: The correction factor for the masonry infilled reinforced concrete frames. • A_C: The combined effective area of the Computational Intelligence and Neuroscience. • A_i: The effective cross-sectional area of shear wall I in the direction considered in the first storey of the building, in m². • l_{wi}: The length of the shear wall I in the first storey in the direction parallel to the applied forces, in m.	Mohamed *et al.*, 2019
Algerian seismic regulations "RPA"	$T = 0.05.H_N^{3/4}$	(5)	• H_N: Height measured in meters from the base of the structure to the last level.	Mohamed *et al.*, 2019
The national building code of Canada	$T = 0.1.N$	(6)	• N: Number of storeys.	Asteris *et al.*, 2016
Indian, the Egyptian, Venezuelan, and the French seismic codes	$T = C_t.H_N^{3/4}$ $C_t = \frac{0.09h}{\sqrt{D}}$	(7) (8)	• H: Building's height (in meters). • D: Total base dimension of the masonry infilled RC frame (in meters).	Asteris *et al.*, 2016
Saudi building code	$T = 0.044.H_N^{0.9}$	(9)	H_N: Building's height (in meters).	Alguhane *et al.*, 2016
Goel and Chopra	$T = 0.053H^{0.9}$	(10)	H: Building's height (in meters).	Goel and Chopra, 1997
Hong and Hwang	$T = 0.0294H^{0.804}$	(11)	H: Building's height (in meters).	Hong and Hwang, 2000
Chopra and Goel	$T = 0.067H^{0.9}$	(12)	H: Building's height (in meters).	Chopra and Goel, 2000
Crowley and Pinho	$T = 0.1H$	(13)	H: Building's height (in meters).	Crowley and Pinho, 2004
Crowley and Pinho	$T = 0.055H$	(14)	H: Building's height (in meters).	Crowley and Pinho, 2006

Authors	Correlations	Equation number	Comments	References
Guler *et al.*,	$T = 0.026H^{0.9}$	(15)	H: Building's height (in meters).	Guler *et al.*, 2008
Joshi *et al.*,	$T = 0.0459H^{0.9}$	(16)	H: Building's height (in meters).	Joshi *et al.*, 2014
Amanat and Hoque	$T = \alpha_1 \alpha_2 \alpha_3 C_t . \mathrm{H}_{\mathrm{N}}^{3/4}$	(17)	• α_1: Modification factors for span length, • α_2 : Modification factors for number of spans, • α_3: Modification factors for amount of infill.	Amanat and Hoque, 2006
Kose	T = 0.1367 + 0.301H − 0.1663S − 0.0305I	(18)	• H: The height of a building in meters, • S: The ratio of the percentage of shear walls to total floor area, • I: The area ratio of infill walls to total panels.	Kose, 2009
Shrestha and Karanjit	$T = \frac{0.03H^{0.94}}{D^{0.04}}$	(19)	• H: total building height. • D: base dimension.	Shrestha and Karanjit, 2017

They proved that the Artificial Neural Networks was the optimal model with a high correlation coefficient. Furthermore, Joshi et al. (2014) have proposed an efficient model by means of the genetic programming method, in order to estimate the period by learning from 206 samples. They used the following parameters: the length of the building, the width of the building, the number of columns, the number of beams, the minimum dimension of columns, the maximum dimension of columns, the height of the building, the height of the storey, and the number of floors, as an input layer. The proposed GP model has shown effective results compared to the other methods. In the same respect, Asteris et al. (2016) employed Artificial Neural Networks to estimate the period by taking into consideration the number of storeys, the number of spans, the span length, the strength of infill, and the opening percentage. The suggested ANN model has confirmed its efficacy since it generated a high correlation coefficient. In a parallel view, Asteris and Nikoo (2019) have used Artificial Bee Colony-Based Neural Network for modeling a database consisting of 4026 samples. The BCB-NN model powerfully estimated the period compared to the other methods. Similarly, Charalampakis et al. (2020) predicted the period by using Artificial Neural Networks and the Decision Tree with an input layer containing a number of storeys, opening ratio, span length, masonry wall stiffness, and number of spans. They demonstrated that the ANN model is the optimal one, with a high correlation coefficient. Table 2 illustrates an overview about the proposed models in the literature to estimate the fundamental period.

Table 2. The proposed models in the literature to estimate the fundamental period

Authors	Inputs	Methods	Database	References
Chun *et al.*, 2000	Number of storeys, length of building, width of Building, and height of building.	Multiple Regression Analysis	50	Chun *et al.*, 2000
Kuźniar and Waszczyszyn, 2006	The ratio of vertical unit base pressure to elastic strain, the building dimension in the direction of vibrations, the equivalent bending stiffness, and the equivalent shear stiffness	Artificial Neural Networks	31	Kuźniar and Waszczyszyn, 2006
Joshi *et al.*, 2014	The length of the building, the width of the building, the number of columns, the number of Beams, The minimum dimension of columns along Y. X direction, the maximum dimension of columns along Y. X direction, the height of the building, the height of the storey, the number of floors.	Genetic Programming	206	Joshi *et al.*, 2014
Asteris *et al.*, 2016	The number of storeys, the number of spans, the span length, the strength of infill, the opening percentage.	Artificial Neural Networks	1281	Asteris *et al.*, 2016
Asteris and Nikoo, 2019	The number of storeys, the number of spans, length of spans opening, the percentage of masonry wall stiffness.	Artificial Bee Colony-Based Neural Network	4026	Asteris and Nikoo, 2019
Charalampakis *et al.*, 2020	Number of stories, opening ratio span length, masonry wall stiffness, number of spans	Artificial Neural Networks, and Decision Tree	4026	Charalampakis *et al.*, 2020

Comparative studies stressed the effectiveness of the ANN method, which demonstrated accurate predictions in period estimation compared to the other machine learning methods, the other statistical formulas, and empirical equations. However, certain limitations have been detected. Based on the author's knowledge, the previous researches were mainly limited to the use of the machine learning methods to predict the fundamental period, although recent researches have revealed that deep learning methods could produce more efficient and precise results. This assumption is in line with that of many previous published studies, which stressed that the use of more than one hidden layer can generate the required flexibility for simulating the complex phenomena (Benbouras *et al.*, 2019). In addition, the aforementioned studies have evaluated the predictive ability of their proposed models based on a single split to confirm the data learning validity. Therefore, the capability of their suggested model to overcome the overfitting and underfitting issues cannot be confirmed. Moreover, most available studies suggested their models in the form of long calculated equations, which are difficult to use in future cases. In simple words, investigators and civil engineers will face some difficulties when applying it (Benbouras *et al.,* 2021; Benbouras and Lefilef, 2021). Consequently, for the sake of surmounting these limitations, researchers started to offer their ideal models in the form of an easy-to-use interface developed using some well-known programming languages to generate the model. This idea will not only make the models easy-to-use, but also available to anybody concerned with such issue (Benbouras *et al.,* 2021; Benbouras and Lefilef, 2021). One cannot argue that the conclusions drawn from the aforementioned studies established the research significance, as they form a useful database and enlighten the direction of this research. Therefore, the current study is the first to present a new alternative Deep Neural model in the form of a free Android application, available in Google play store to anyone interested in the period prediction. This app will have many benefits for its users such as enhancing the accuracy of the results, lowering the budget, and saving time.

2. Materials and methods

2.1. Overview of the methodology

Initially, Deep Neural Networks method was used to train 4026 data sample collected from previous studies (Charalampakis *et al.,* 2020). Additionally, a set of multiple input characteristics have been utilized, which are the following: the number of storeys, the number of spans, the span length, the opening ratio, and the masonry wall stiffness. Firstly, the DNN method was used to model the input parameters by means of trial and errors method. Next, the effectiveness of each model was evaluated via various statistical indicators. After that, the optimal model was chosen after a comparison among the experimented ones. Later on, when evaluating the estimation capability of the ideal model, the k-fold cross-validation method, which contained five splits, was used. Lastly, a consistent, simple, and easy-to-use Android app was developed and uploaded on Play Store. This app will be very helpful for civil engineers and scientists when estimating the fundamental period with minimal efforts in future studies.

2.2. Database

The database used here consisted of 4026 datasets collected from previous studies; whose quantitative results are included in the FP4026 Research Database (Asteris, 2016; Charalampakis *et al.,* 2020).The number of storeys, the number of spans, the span length, the opening ratio, and the masonry wall stiffness were opted to be the ideal input factors, following the literature recommendations. Previous published studies dealing with the fundamental period parameters have proven that the above-mentioned input factors are the essential influencing parameters (Asteris *et al.,* 2016; Asteris and Nikoo, 2019; Charalampakis *et al.,* 2020; Kose, 2009). Fig. 1 illustrates the cross-section details of an infilled RC frame. The number of storeys in the structures examined in the current study varied from 1 to 22. The storey height for all constructions was held constant and equal to 3.0 m. Additionally, the number of spans ranged between 2, 4, and 6. For each case, four different span lengths, namely 3.0 m, 4.5 m, 6.0 m, and 7.5 m have been considered. Next, fully or partially infilled walls, with or without openings, were used. It should be noted here that several characteristics have been taken into account for each case. Infill walls were either 0.15 or 0.25m thick, according to the conventional construction of single and double leaf panels. Furthermore, the effect of infill wall openings was similarly considered by using five diverse values as a percentage of the panel area. These were fully infilled walls (0% openings), infill walls with small and large openings (25%, 50%, and 75% openings), and bare frames (100% openings). Besides, five diverse cases for the masonry panel strength were approved to characterize weak, medium, and strong masonry; namely, 1.5MPa, 3.0MPa, 4.5MPa, 8.0MPa, and 10.0MPa. The aforementioned values involve the well-known cases for masonry infill conditions as stated in many studies (Asteris *et al.*, 2016; Asteris and Nikoo, 2019).

All the building cases have been proposed in agreement with both of Eurocodes 2 and Eurocodes 8. In order to make the modeling step accurate, a considerable effort has been made to make the database balanced. This latter was fulfilled by converging both the close mean and the standard deviation in both the training and validation data. Furthermore, the data used in the training and the validation phase have been randomly chosen and were totally separated. The building parameters used for the development of the model are listed in Table 3. Separately, the input training vector was with the dimensions of 1×5, and includes the five aforementioned input parameters. Finally, the fundamental period vectors had the dimension of 1 × 1 and contained the output. Table 4 presents an overview of the variables adopted in this study.

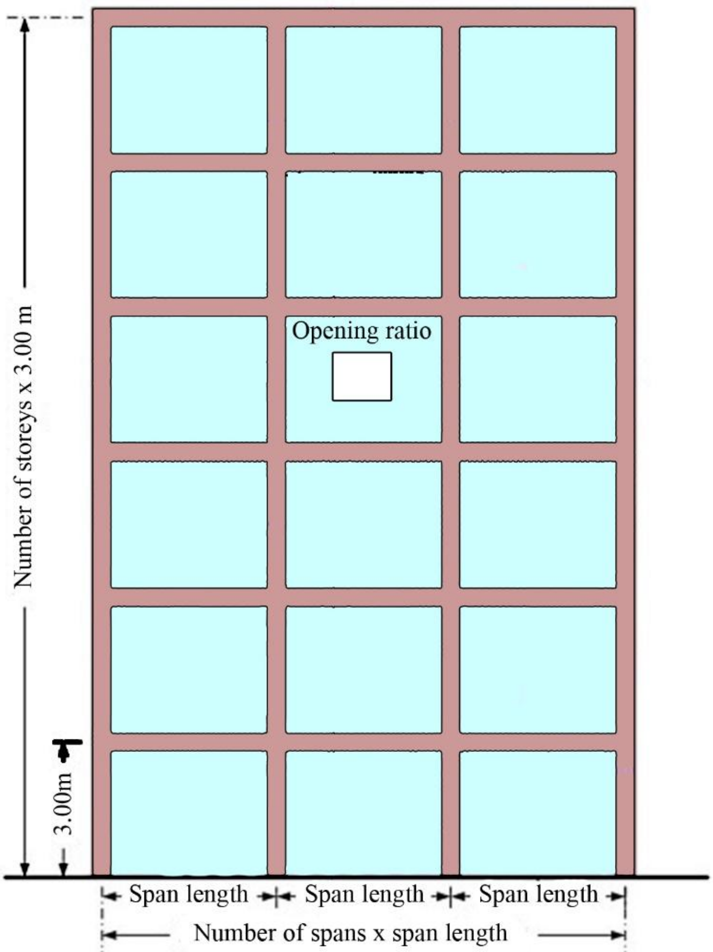

Fig. 1. Cross section details of an infilled RC frame.

Table 3. Building parameters.

Concrete strength	25.00 MPa
Modulus of elasticity of concrete, E_c	31.00 GPa
Steel tensile yield strength	500.00 MPa
Size of beams	250 / 600 mm
Slab thickness	150 mm
Dead loads	*1.50 kN/m2 + 0.90 kN/m²*
Live loads	3.50 kN / m²
Number of floors	1 to 22, by 1
Storey height	3.00 m
Span length	3.00 m, 4.50 m, 6.00 m, 7.50 m
Number of spans	2, 4, 6
Masonry compressive strength, f_m	1.50 MPa, 3.00 MPa, 4.50 MPa, 8.00 MPa, 10.00 MPa
Modulus of elasticity of masonry, E_m	1.50 GPa, 3.00 GPa, 4.50 GPa, 8.00 GPa, 10.00 GPa
Thickness of infill panel, t_w	150 mm, 250 mm
Infill wall opening percentage	0% (fully infilled), 25%, 50%, 75%, 100% (bare frame)

Table 4. Definition of the variables of the database.

Variables	Parameter type	Abbreviations	Subdivision	Minimum	Maximum
Number of storeys	Input	X1	-----	1	22
Number of Spans	Input	X2	X21= 2	2	6
			X22=4		
			X23= 6		
Span length (m)	Input	X3	X31= 3	3	7.5
			X32=4.5		
			X33= 6		
			X34= 7.5		
Opening ratio (%)	Input	X4	X41= 0	0	100
			X42=25		
			X43= 50		
			X44= 75		
			X45= 100		
Masonry wall stiffness (10^5 kN / m)	Input	X5	X51= 1.5	1.5	10
			X52=3		
			X53= 4.5		
			X54= 8		
			X55= 10		
Fundamental period (s)	Output	Y	-----	0.04	3.57

2.3. Deep Neural Network

When talking about Artificial Intelligence methods, one cannot help but bring in what is known as Artificial Neural Networks (ANN), this latter mimics the biological neural systems by simulating the human brain's ability to change and adapt to the environment through a training process from his experiences (Benbouras, 2021; Benbouras *et al.*, 2019; Haddad and Benbouras, 2020). They consisted of neurons called "treatment elements," "nodes," or "units" that are arranged in various layers, as illustrated in the following Fig. 2: an input layer to receive the external data, an output layer which gives the problem solution, and a hidden layer which is an intermediate layer that separates the other two layers. Each unit in a particular layer is related completely or partially to many nodes in the other layers by a dynamic calculation. If there is more than one hidden layer in the network, it is then called "Deep Neural Network". Many published studies have stated that the use of more than one hidden layer could generate the required flexibility for simulating the complex phenomena and, therefore, generating more effective results (Benbouras, 2021; Benbouras *et al.*, 2019; Haddad and Benbouras, 2020).

The basic philosophy of the Artificial Neural Networks comprises an integrated methodology, typically consisting of three stages: training, validation, and testing. The next step is to make a series of adjustments to weights and biases on a frequent procedure, usually via mathematical algorithms, these generally use the back-propagation algorithm to learn from real datasets and provide a mathematical model. Later on, the most appropriate model is selected, which usually consists of a matrix of weights and biases, through which the target value can be effectively predicted by inserting the building parameters with the least possible error. In this study, Deep Neural Networks were chosen because of the precise results they provide. DNN has been modeled in this study by using Matlab software due to its accurate results, confirmed by previous studies (Benbouras, 2021; Benbouras *et al.*, 2019; Haddad and Benbouras, 2020).

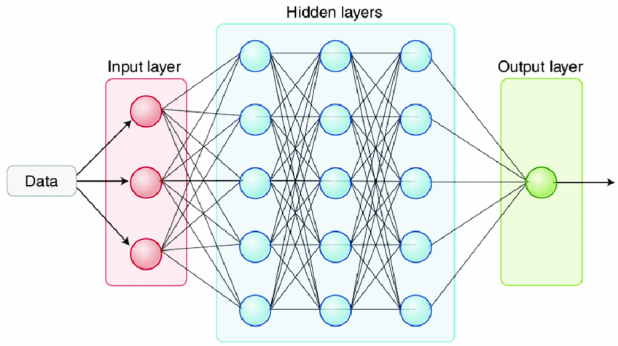

Fig. 2. Model of artificial neural networks.

2.4. The Statistical Performance Indicators

The predictive performance of the proposed models was evaluated using numerous statistical performance indicators and graphical presentation. The statistical performance indicators utilized are as follows: Root Mean Square Error (RMSE), Coefficient of determination (R^2), and Pearson correlation coefficient (R). They are expressed respectively (Benbouras and Petrisor, 2021; Benbouras *et al.*, 2021; Benbouras and Lefilef, 2021):

- Root Mean Square Error (*RMSE*):

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y_{tar,i} - Y_{out,i})^2} \qquad (20)$$

- Coefficient of determination (R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(Y_{tar,i} - Y_{out,i})^2}{\sum_{i=1}^{N}(Y_{tar,i} - \overline{Y_{tar}})^2} \qquad (21)$$

- Pearson correlation coefficient (*R*):

$$R = \frac{\sum_{i=1}^{N}((Y_{tar,i} - \overline{Y_{tar}})(Y_{out,i} - \overline{Y_{out}}))}{\sqrt{\sum_{i=1}^{N}((Y_{tar,i} - \overline{Y_{tar}})^2 (Y_{out,i} - \overline{Y_{out}})^2)}} \qquad (22)$$

where $Y_{tar,i}$, $Y_{out,i}$, $\overline{Y_{tar}}$, and $\overline{Y_{out}}$ distinguish the target, the output, the mean of the target, and the mean of the output period value for N data samples, respectively. It is worthy to note here that the optimal model is the one owning the least RMSE values, and the top R^2, and R value. Next, after selecting the best model using the statistical indicators, its predictive performance was assessed via the K-fold cross-validation method. This method is a progressive method which demonstrates more precision and accuracy when evaluating the capability of the ideal model to overcome over-fitting and under-fitting problems in data learning (Breiman and Spector, 1992; Oommen and Baise, 2010). The method works by separating the dataset into k identical splits. Therefore, for each one, K-1 splits are applied for the training phase and the last one for validation. This process is repeated sequentially until the usage of all data for the validation stage. The fundamental advantage of this method lie in the fact that all the data are used in both the training and the validation steps (Oommen and Baise, 2010). Breiman and Spector (1992) have stated that K = 10 or K = 5 is the optimal selection for evaluating the models (Breiman and Spector, 1992). In the current study, K-fold cross-validation with K = 5 has been adopted for evaluating the predictive performance of the ideal model.

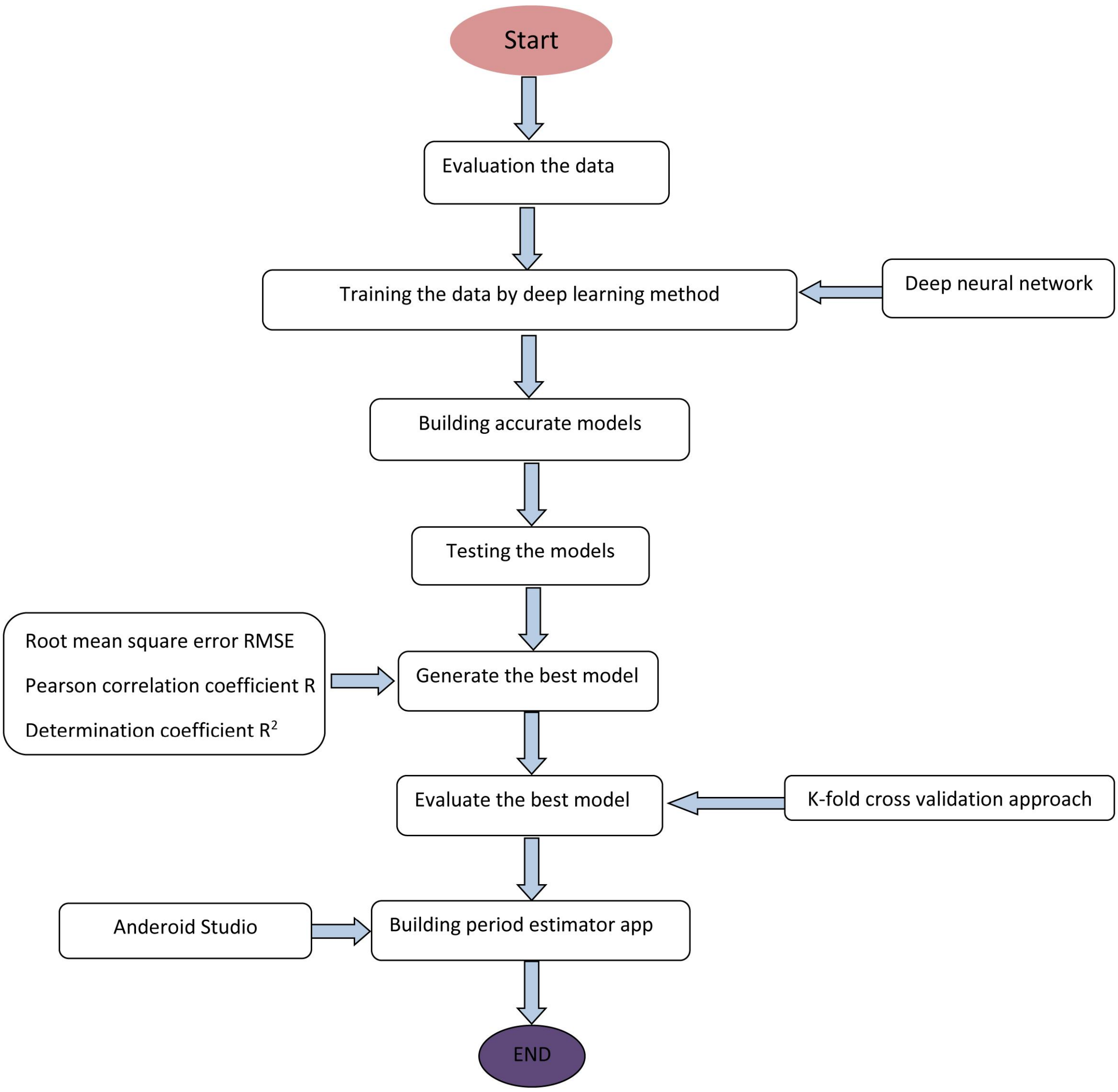

Fig. 3. Flowchart describing the key steps for the methodology of research to estimate the period

2.5. Methodology

In order to determine the optimal model for estimating the fundamental period, the current study followed the following phases:

- A universal dataset involving of 4026 cases was collected from previous published studies.
- Analyzing the data by the DNN method, utilizing MATLAB software. Tan-sigmoid transfer function was chosen due to its effective results when conducting complex regression issues. Two hidden layers were added to the network to attain the required flexibility as suggested by many studied. Trial and error method was used when the nodes' number was changed in each hidden layers in order to choose the best network architecture (1–10 nodes in the first and second hidden layers), resulting into 100 ANN models.
- The best model for approximating the period was extracted after comparing between the suggested DNN models by mean of certain statistical indicators as RMSE, R^2, and R.
- The K-cross-validation approach (with k = 5) was used in order to assess the predictive ability of the optimal model to overcome under-fitting and over-fitting issues.
- The best model was afterwards utilized to generate a graphical, reliable, and easy-to-use Android app, using Android studio software. Later on, the "Building period estimator" app was uploaded to Google play store to make it available to anyone interested or in need for period calculation.

The flowchart presented in Fig. 3 gives an overview about the methodology followed in selecting the best model for predicting the period.

3. Results

3.1. Generation of the database

The dataset utilized in this manuscript included of 4026 samples collected from the existing literature, resulting in a dataset comprising diverse data. This latter is deemed acceptable to carry out an effective study. Moreover, for the sake of doing an efficient modeling phase, a significant effort has been done to make the database balanced in both the training and validation data. Furthermore, the data samples in both these phases were randomly chosen and completely detached. Table 5 displays the descriptive statistics calculated by SPSS software of the adopted parameters including the number of storeys (X1), the number of spans (X2), the span length (X3), the opening ratio (X4), the masonry wall stiffness (X5), and the period (Y). The finding confirmed that both the Skewness and the Kurtosis were close to zero, indicating that all the variables had a normal distribution. Furthermore, the statistical parameters proved that the dataset comprised a wide-range of data.

Afterwards, this database can be utilized to develop new experimental equations or to compare the ones proposed in the literature. Table 6 presents the matrix of correlation between the fundamental period and the input parameters. The results of the interpretation showed that the significance is less than 0.05 in all inputs, meaning that the correlations were statistically significant. Henceforth, according to Smith's classification (1986), the period (Y) has a high correlation with the number of storeys (X1), a moderate correlation with the opening ratio (X4) and the number of spans (X2), together with a weak correlation with the span length (X3) and the masonry wall stiffness (X5). The finding proved that these inputs could have a complex nonlinear relationship with the period (Y). From the author's viewpoint, for the purpose of simulating complex phenomena, the Deep Neural Networks approach can give highly effective results.

3.2. Assessment of the period using DNN

To determine the optimal DNN model, several studies have proposed a set of empirical rules in order to opt for the number of nodes in each hidden layer.

Table 5. Descriptive statistics for the composed models.

	X1	X2	X3	X4	X5	Y
Mean	11.50	4.95	5.0	0.6	11.8	1.1
Median	11.50	6.00	4.50	0.75	11.25	0.91
Mode	1.00	6.00	3.00	1.00	2.25	0.36
Std. deviation	6.35	1.55	1.58	0.40	7.79	0.79
Variance	40.26	2.40	2.49	0.16	60.63	0.62
Skewness	0.00	-1.05	0.16	-0.51	0.38	0.82
Std. error of Skewness	0.04	0.04	0.04	0.04	0.04	0.04
Kurtosis	-1.20	-0.53	-1.19	-1.38	-1.17	-0.06
Std. error of Kurtosis	0.08	0.08	0.08	0.08	0.08	0.08
Range	21.00	4.00	4.50	1.00	22.75	3.53
Minimum	1.00	2.00	3.00	0.00	2.25	0.04
Maximum	22.00	6.00	7.50	1.00	25.00	3.57

Table 6. Matrix of correlation between the fundamental Period and the input parameters.

		X1	X2	X3	X4	X5	Y
X1	Correlation Coefficient	1.000	0.000	0.000	0.000	0.001	0.810
	Signification		1.000	1.000	0.983	0.945	0.000
	Sample Number	4026	4026	4026	4026	4026	4026
X2	Correlation Coefficient	0.000	1.000	-0.111	-0.490	0.086	-0.218
	Signification	1.000		0.000	0.000	0.000	0.000
	Sample Number	4026	4026	4026	4026	4026	4026
X3	Correlation Coefficient	0.000	-0.111	1.000	0.075	-0.007	0.169
	Signification	1.000	0.000		0.000	0.643	0.000
	Sample Number	4026	4026	4026	4026	4026	4026
X4	Correlation Coefficient	0.000	-0.490	0.075	1.000	0.097	0.453
	Signification	0.983	0.000	0.000		0.000	0.000
	Sample Number	4026	4026	4026	4026	4026	4026
X5	Correlation Coefficient	0.001	0.086	-0.007	0.097	1.000	-0.063
	Signification	0.945	0.000	0.643	0.000		0.000
	Sample Number	4026	4026	4026	4026	4026	4026
Y	Correlation Coefficient	0.810	-0.218	0.169	0.453	-0.063	1.000
	Signification	0.000	0.000	0.000	0.000	0.000	
	Sample Number	4026	4026	4026	4026	4026	4026

However, trial and error method remained the most suitable one in terms of effectiveness and accuracy, although it takes a lot of effort and time. Furthermore, DNN was employed in this study because of its flexibility and effectiveness. Since two hidden layers were opted for, with a set of changing nodes (1–10) in the first and second hidden layer, which eventually gave 100 DNN models. Fig. 4 illustrates the variation of the R_{all} with the number of nodes in the first and second hidden layers depending on the obtained 100 DNN models. The findings proved that the one containing 9 nodes in the first hidden layer, and 10 nodes in the second hidden layer (5-9-10-1) was the optimal model. It is noteworthy to mention that this model was trained by Tan-sigmoid activation functions in each hidden layer, and a linear activation function in the output layer. Fig. 5 shows the architecture of the best DNN model; this model was effectively trained in 970 stages. The results proved that the best one was positioned in 964 stage (MSE_{val}=0.00017045, MSE_{train}=0.0001877, and MSE_{all}=0.0001843), as displayed in Fig. 6. Fig. 7 shows the histogram of errors found from modeling the best DNN model. The blue and the green bars are utilized to denote the training and validation data, respectively. The conclusion drawn from Fig. 7 is that the majority of standard errors found between the target and the output values ranged between -0.02834 and 0.002585. Fig. 8 displays the scatter plots of the target and the output period values in the optimal DNN model. The results showed a high correlation coefficient: R_{train}=0.99986, R_{val}=0.99985, and R_{all}=0.99985. Finally, the aforementioned information extracted from the figures undoubtedly revealed the presence of an effective learning of (5-9-10-1) DNN model.

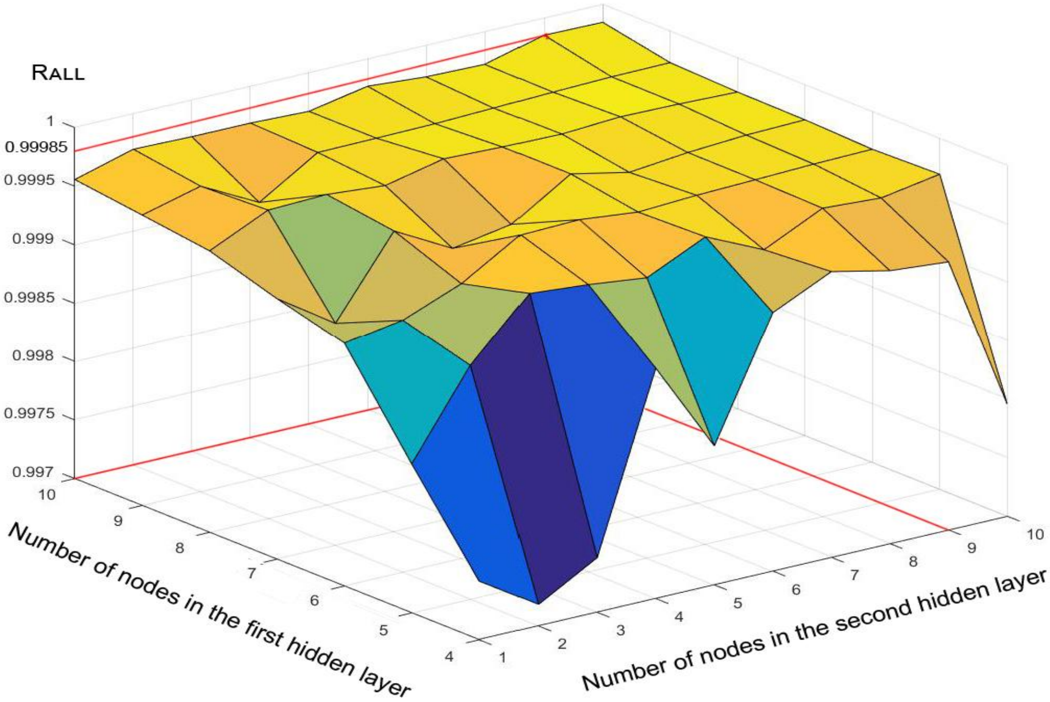

Fig. 4. Changes of the R_{all} with the number of nodes in the first and second hidden layers.

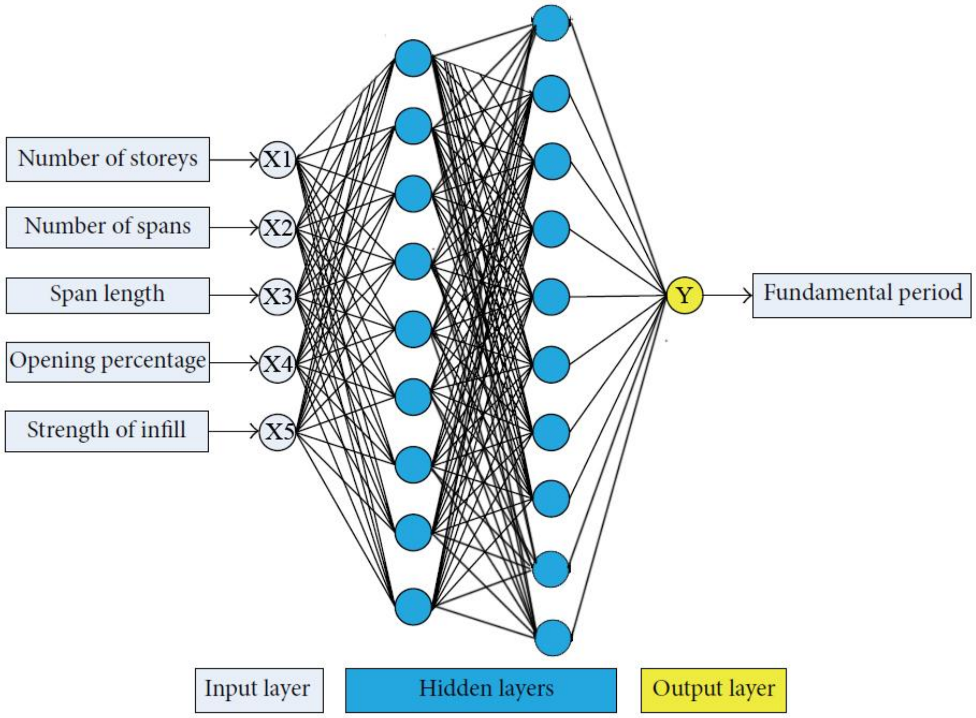

Fig. 5. The architecture of the optimal DNN model (5-9-10-1).

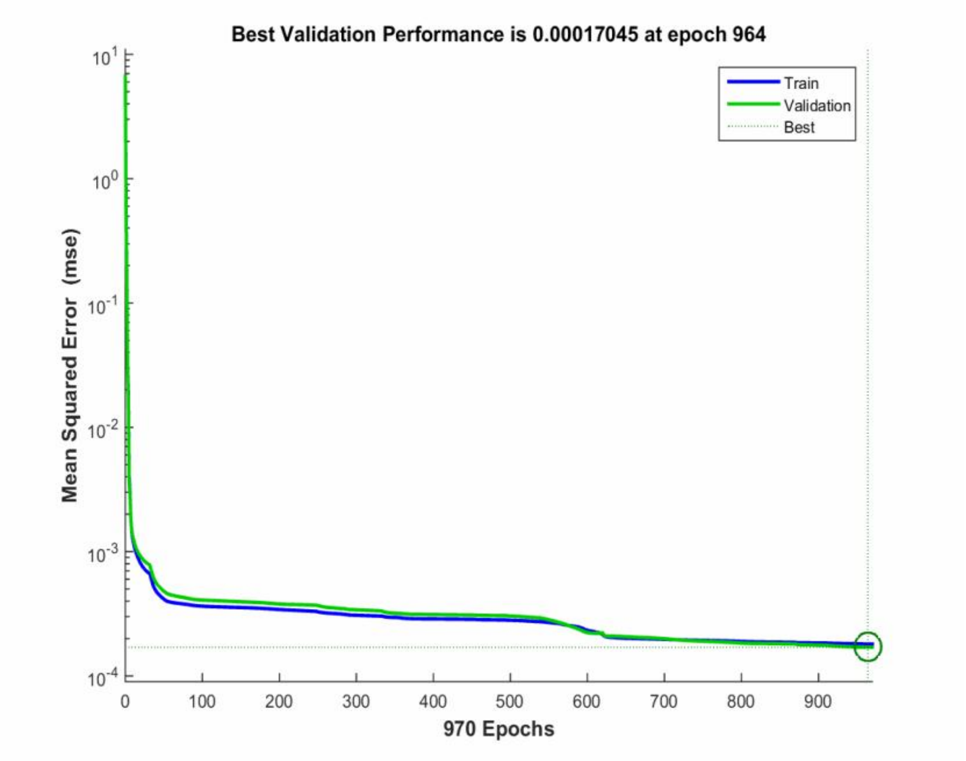

Fig. 6. Best performance epoch of the optimal DNN model (5-9-10-1).

3.3. K-Fold Cross validation

The reasonable ground standing behind opting for the k-fold cross-validation method lies ostensibly in its high predictive ability to approximate the ideal model. On the other hand, the previously mentioned studies concerned with estimating the fundamental period parameter determined the predictive ability of their ideal models based on only one split. Therefore, the capability of their models to surmount the over-fitting and under-fitting difficulties cannot be confirmed. Fig. 9 shows the performance measures of the ideal DNN model using 5-fold cross-validation founded on the training and validation datasets for each split. The fact that R ranged from 0.99933 to 0.99987 in the training data and from 0.99705 to 0.99966 for in validation data in the five splits, indicated the performance of the ideal DNN model for estimating the output and generating new validation data, without causing over-fitting or under-fitting complications.

3.4. Comparison between the our model and other proposed models

Before confirming our conclusion about the proposed model, it is essential to touch upon the way its efficiency has been tested. Initially, a comparative study between both the empirical models proposed in the literature, and the DNN model suggested in the current study was conducted. The comparison was made based on three statistical performance indicators, which are Root Mean Square Error (RMSE), Coefficient of determination (R^2), and Pearson correlation coefficient (R). The findings proved that the proposed DNN model showed the highest performance compared to the other proposed models, with a maximum correlation coefficient (R=0.99985, and R^2= 0.9997 for all data) and the minimum error (RMSE=0.013). Furthermore, this model was closely followed by the hybrid Artificial Bee Colony-Based Neural Network model, which was proposed by Asteris and Nikoo (2019), providing a good precision as it was classified second.

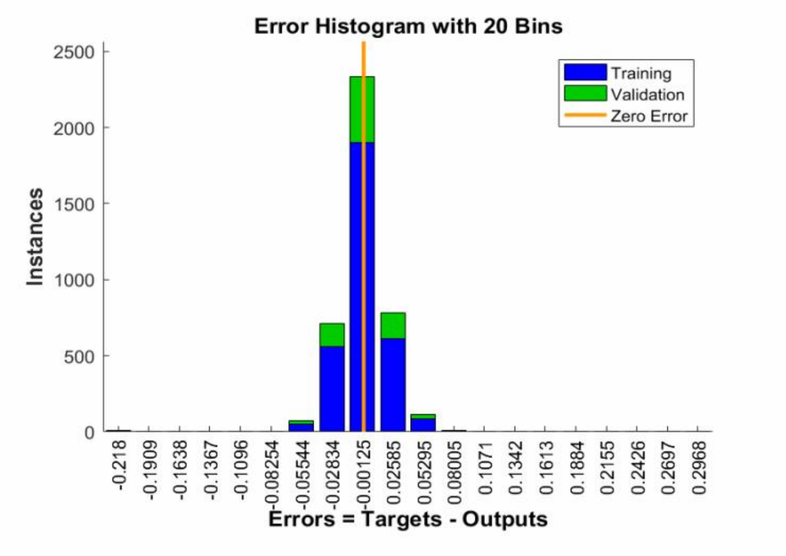

Fig. 7. Error histogram of the optimal DNN model (5-9-10-1).

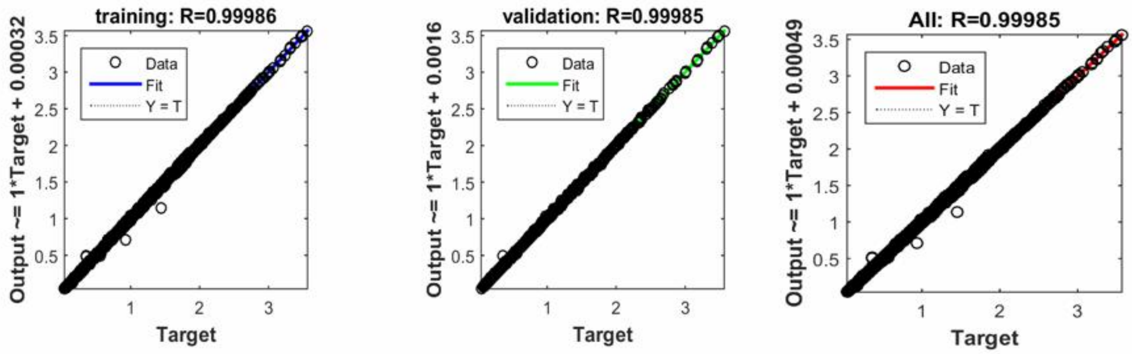

Fig. 8. Scatter plots between the output and the target period in the optimal DNN model (5-9-10-1).

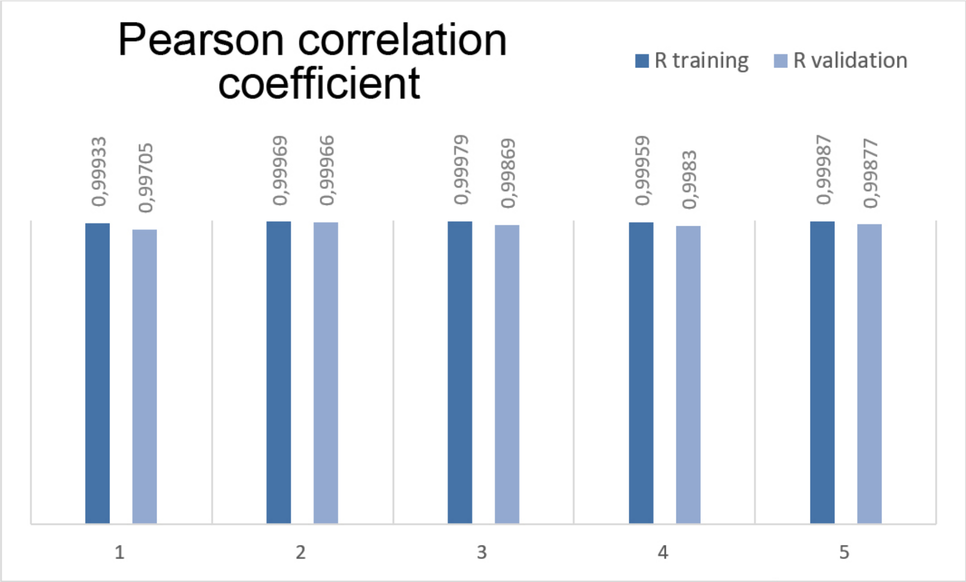

Fig. 9. Performance measures models using K-fold cross validation with K = 5.

Table 6. Comparison between our DNN model and some of the proposed empirical models in the literature.

Authors	Methods	Database	R	R^2	RMSE	References
Kuźniar and Waszczyszyn, 2006	Artificial neural networks	31	Didn't mention	Didn't mention	0.0143	Kuźniar and Waszczyszyn, 2006
Joshi *et al.*, 2014	Genetic programming	206	0.970	0.9409	0.014	Joshi *et al.*, 2014
Asteris *et al.*, 2016	Artificial neural networks	1281	Didn't mention	Didn't mention	0.0135	Asteris *et al.*, 2016
Asteris and Nikoo, 2019	Artificial bee colony-based neural network	4026	0.9995	0.9991	0.0139	Asteris and Nikoo, 2019
Charalampakis *et al.*, 2020	Artificial neural networks	4026	0.9987	0.9975	0.0173	Charalampakis *et al.*, 2020
Current study	Deep neural networks	4026	0.99985	0.9997	0.013	

Finally, it is assumed that the high precision found in the optimal proposed model is due to the DNN modeling, which used more than one hidden layer, offering the required flexibility to model a set of complex phenomena.

3.5. Android application design "Building Period Estimator"

Most of the published researches presented machine learning models results in the form of complex matrices and mathematical formulas, which made it very difficult for future researchers to take advantage from. Apparently, researchers and civil engineers did not benefit enough from this latest contribution. This can be attributed to the fact that machine learning models are generally complex and hard to interpret. From our point of view, the proposed deep learning model should be provided either in the form of a simple programmed interface, or a simple script ready to use by some known programming languages, like Matlab or Python. After taking those points into consideration, the optimal DNN model was presented in the form of a simple, reliable, and easy-to-use

Android application developed by "Android Studio" software using Java language. It was named "Building Period Estimator" as presented in Fig. 10. Afterwards, the app was uploaded to Google play store to make it available to everyone interested in period estimation.

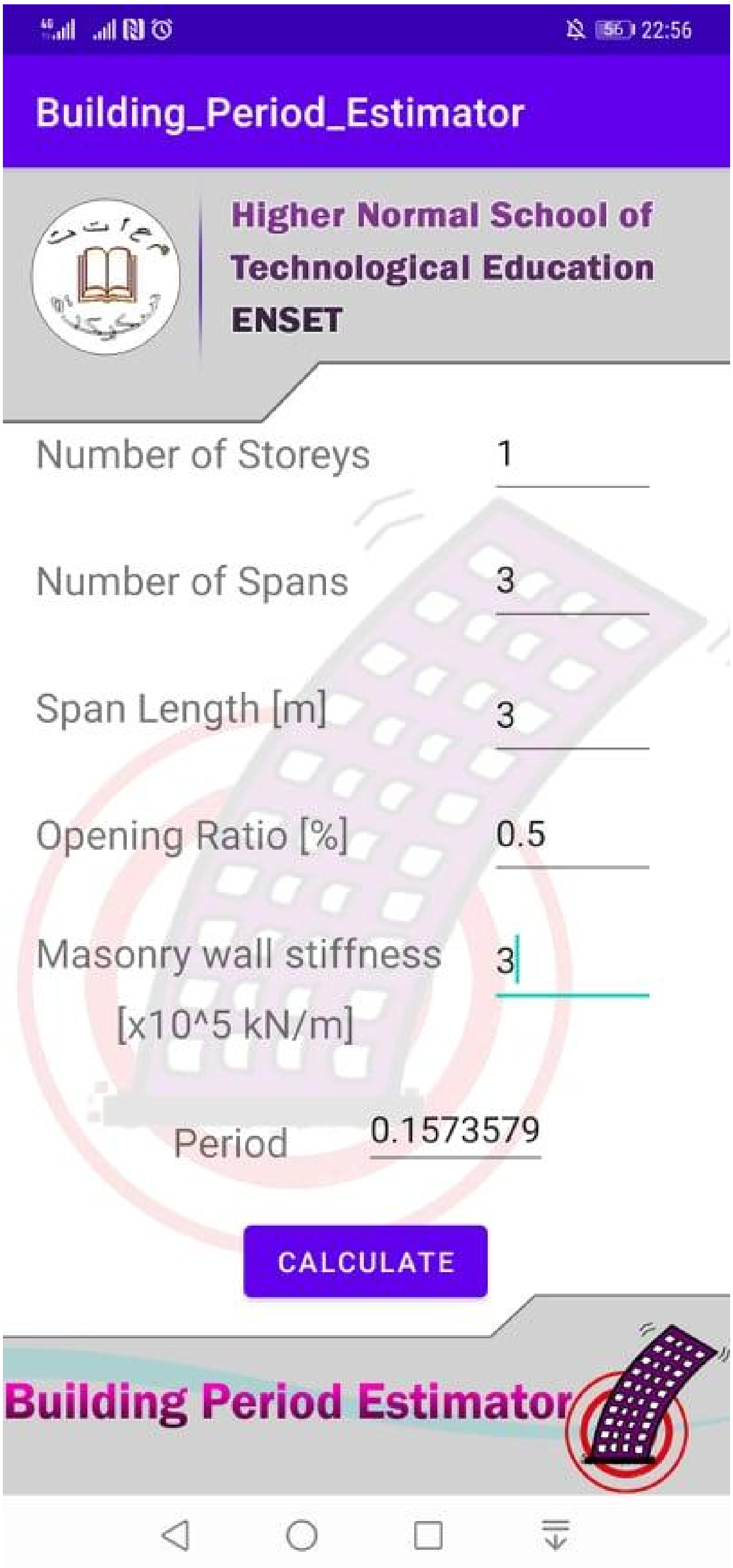

Fig. 10. "Building Period Estimator" application

In order to use the app, the user must insert the input parameters in the boxes accordingly the number of storeys, the number of spans, the span length, the opening ratio, and the masonry wall stiffness. By clicking on "Calculate", the prediction result appears in the output, and the application displays the value of the fundamental period in no time. With that been said, civil engineers and researchers will benefit greatly by using it without facing any difficulty in predicting the value of the fundamental period, which is deemed as one of the most complex parameters to determine.

4. Discussion

This contribution of the current paper tackles a very sensitive process, which is the effectiveness of the fundamental period modeling. It is worth revealing here that the model quality is directly affected by the method used. Accordingly, the study employed a new revolutionary method, which demonstrated effective results in other fields, to predict the fundamental period. The findings clearly indicated that the model containing 9 nodes in the first hidden layer, and 10 nodes in the second hidden layer (5-9-10-1), trained by Tansig transfer function presented the optimal one. After that, this model was subjected to a rigorous comparative study, and the results confirmed that our proposed model provided the least RMSE value, the highest of R^2 value, and R values in comparison with the other models and equations proposed in previous studies and earthquake codes. Besides, the alternative proposed model was evaluated using the advanced K-fold cross-validation technique. The results proved that the best DNN model can generate new data without causing over-fitting or under-fitting problems. Lastly, the suggested model was thereafter used to design a free, graphical, and easy to use Android application, by utilizing "Android Studio" software, in order to simplify its utilization in the future cases. Afterwards, the tool is shared at Google play story. This app is aimed to assist engineers and researchers in civil engineering field, concerned with the period calculation, whatever their level. The proposed app will offer numerous advantages like its precision, ease to use, lowering the budget, and simplifying the process of determining buildings characteristics without doing any expensive experimental tests or time-consuming modelling.

The results obtained from the present study also demonstrated that the effectiveness of the period parameter model was significantly improved by utilizing the DNN. The model estimation with the DNN was enhanced by 10% with the ANN model proposed by Kuźniar and Waszczyszyn (2006); 8.462% with the ANN model proposed by Charalampakis *et al.* (2020); 7.692% with the GP suggested by Joshi *et al.* (2014), respectively; 3.846% with Artificial Bee Colony-Based Neural Network proposed by Asteris and Nikoo (2019). The resulted outcomes were logical because the DNN was efficiently working in both the classification and the prediction issues, which formed multiple connected nodes in several hidden layers, contrary to the traditional ANN methods, to acquire a more precise and stabilized estimation. Based on these outcomes, it can be concluded that the DNN method, which was used in the current study for the first time in order to predict the period, can produce more efficient and precise results compared to other machine learning approaches.

4. Conclusion

The current study contributes to designing a free, precise, and easy-to-use Android application aimed at predicting the fundamental period, this app is called "Building Period Estimator". Initially, a considerable amount of data have been gathered from the existing literature. Then, five significant factors have been chosen depending on the literature suggestions like: the number of storeys, the number of spans, the span length, the opening ratio, and the masonry wall stiffness. To attain our aim, Deep Neural Networks have been employed, for the first time, for doing a practical modeling aiming at predicting the fundamental period. Subsequently, the suggested models were assessed via three performance measures (RMSE, R^2, and R). Later on, the optimal model was subjected to a rigorous comparative study between the different proposed models, and the results confirmed the superiority of the model containing 9 nodes in the first hidden layer, and 10 nodes in the second hidden layer (5-9-10-1), trained by Tansig transfer function. The latter provided the highest accuracy in terms of the RMSE (0.000134 / 0.0001305), R (0.99986 / 0.99985), and R^2 (0.99972 / 0.9997) in both the training / validation stages. For assessing the predictive ability of the proposed DNN model, the K-fold cross-validation approach with K = 5 has been utilized. The results showed that this model has a good coefficient of correlation, ranging from 0.99933 to 0.99987 for training data, and from 0.99705 to 0.99966 for validation data in the five splits, denoting that no over-fitting or under-fitting problem have been faced. The Root Mean Square Error (RMSE), the Coefficient of determination (R^2), and the Pearson correlation coefficient (R) values were, afterwards, utilized for comparing the effectiveness of the best DNN model with the suggested models in the anterior studies. The findings revealed that the proposed DNN model is much more efficient compared to other empirical models and equations. Lastly, the suggested DNN model was used to design a free android app by "Android Studio" software. A free, graphical, and easy to use app called "Building Period Estimator" was, afterwards, shared at Google play. The key benefit of this app is to help civil engineers and researchers concerned with the period estimation, whatever their level, with saving both time and money.

Supplementary materials

The developed application is available online in Google play store at: https://play.google.com/store/apps/details?id=com.Period.building_period_estimator

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