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Eccomas Proceedia COMPDYN (2023) 1206-1213

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COMPDYN 2023
9th ECCOMAS Thematic Conference on
Computational Methods in Structural Dynamics and Earthquake Engineering
M. Papadrakakis, M. Fragiadakis (eds.)
Athens, Greece, 12-14 June 2023

# DEVELOPING AN ARTIFICIAL NEURAL NETWORK MODEL THAT PREDICTS THE FUNDAMENTAL PERIOD OF STEEL STRUCTURES USING A LARGE DATASET

**Ashley Megan van der Westhuizen[1], Nikolaos Bakas[2] and George Markou[1]**

[1] Department of Civil Engineering, University of Pretoria, South Africa
e-mail: u17179221@tuks.co.za; george.markou@up.ac.za

[2] National Infrastructures for Research and Technology – GRNET
7 Kifisias Avenue, 11523, Athens, Greece
e-mail: nibas@grnet.gr

**Abstract**

*The fundamental period of structures is an important parameter to consider when designing structures in seismic-prone areas. Currently, the formulae available in the international literature and design codes fail to capture the true dynamic behaviour of structures, especially when they are founded on soft soils. It is necessary to develop more accurate models for predicting the fundamental period while taking into account the soil-structure interaction (SSI) effect. For the needs of this research, a dataset of 49,154 models (98,308 numerical results) was created for developing a predictive model for calculating the fundamental period of steel structures. The SSI phenomenon was also considered with structures modelled with a soil domain with varying depths. The model used herein is an Artificial Neural Network (ANN). The ANN model was able to predict the fundamental period with a correlation of 99.99% and a mean absolute percentage error (MAPE) of 0.7%.*

**Keywords:** Seismic Design, Fundamental Period, Machine Learning, Artificial Neural Networks, Big Data


Peer-review under responsibility of the organizing committee of COMPDYN 2023.
doi: 10.7712/120123.10469.20792

# 1 INTRODUCTION

The fundamental period of structures is an important parameter to consider when designing structures in seismic-prone areas. Currently, the formulae available in the international literature and design codes fail to capture the true dynamic behaviour of structures, especially when they are founded on soft soils. They often only consider the height of the structure. Performing a detailed finite element modal analysis is time-consuming and requires a high computational effort when compared to the use of a design code formula. It is thus necessary to develop models that can accurately predict the natural period of structures while accounting for the soil-structure interaction (SSI) effect, hence saving time during the design process.

The use of artificial intelligence (AI) and machine learning (ML) in structural analysis and design problems has been increasing due to the methods' ability to handle complex non-linear structural systems under extreme actions [1-5] or describe a specific characteristic such as fundamental period of a structure [6-8], or even the aesthetic of structures [9]. It is important to note that ML algorithms are not a one-size fits all solution and different methods should be considered to find the most accurate predictive model [2]. This research work focuses on the use of an artificial neural network (ANN) model to predict the fundamental period of steel structures using a large dataset.

A large dataset was developed for the needs of this research work through the use of a high-performance computer (HPC) known as Cyclone. The generated dataset consists of models that are fixed at the base or consider the influence that the SSI effect has on the fundamental period. The models are developed using a finite element (FE) program and a modal analysis is conducted using Reconan FEA (2020) [10], where frequency results are extracted and stored. The largest model that was fully developed and analysed contained 7,895 beam-column FEs and 220,514 8-noded hexahedral FEs. This results in a total of N = 4.33x109 degrees of freedom (DoF), which highlights the need for computational resources to solve this problem. By taking into account that this was one of the 49,154 models developed for the construction of the dataset used herein, it is obvious that the use of a supercomputer is imperative.

# 2 ARTIFICIAL NEURAL NETWORKS

The model is trained with the algorithm presented in [11], which is used to construct the proposed ANN. Specifically, $w_{jk}$, the inner layer's neuron weights, are computed and is equivalent to approximating the problem by:

$$\begin{pmatrix} \sigma(x_{11k}w_{1k} + x_{12k}w_{2k} + \cdots + x_{1nk}w_{nk} + b_k) \\ \sigma(x_{21k}w_{1k} + x_{22k}w_{2k} + \cdots + x_{2nk}w_{nk} + b_k) \\ \vdots \\ \sigma\left(x_{m_k1k}w_{1k} + x_{m_k2k}w_{2k} + \cdots + x_{m_knk}w_{nk} + b_k\right) \end{pmatrix} = \begin{pmatrix} y_{1k}, \\ y_{2k}, \\ \cdots \\ y_{m_kk} \end{pmatrix} \tag{1}$$

and hence,

$$\begin{pmatrix} x_{11k} & x_{12k} & \cdots & x_{1nk} & 1 \\ x_{21k} & x_{22k} & \cdots & x_{2nk} & 1 \\ \vdots & \vdots & \ddots & \vdots & 1 \\ x_{m_k1k} & x_{m_k2k} & \cdots & x_{m_knk} & 1 \end{pmatrix} \begin{pmatrix} w_{1k} \\ w_{2k} \\ \vdots \\ w_{nk} \end{pmatrix} = \begin{pmatrix} \sigma^{-1}(y_{1k}) \\ \sigma^{-1}(y_{2k}) \\ \vdots \\ \sigma^{-1}\left(y_{m_kk}\right) \end{pmatrix} \tag{2}$$

Figure 1 shows the structure of the ANN used to train, test, and validate the corresponding predictive model [7].

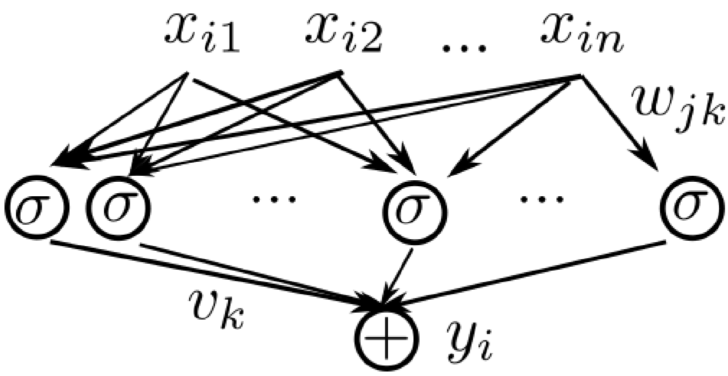


Figure 1: ANN architecture [7].

In general, ANNs architecture foresees the use of interconnected processing neurons, which are inspired by the way that the human brain learns. The overall objective of the training of an ANN is to connect the input variables that are represented by $x_{i1}$, $x_{i2}$,... $x_{in}$ and $v_k$, to the weights of the output layer. A sigmoid function σ was implemented in the hidden layer for all input neurons and the output was a linear combination of nonlinear neurons.

The main components of an ANN that consists of multiple neurons include an input layer, an output layer, and a hidden layer as shown in Figure 2 [12].

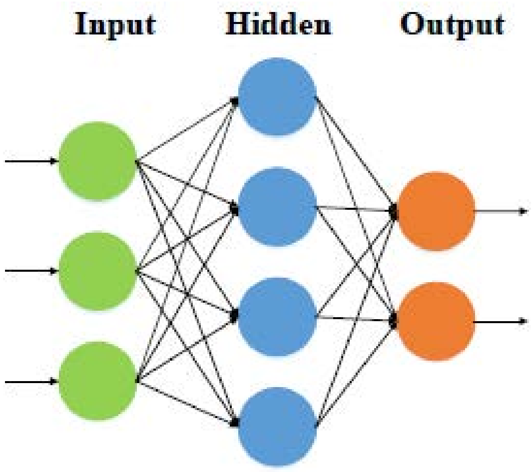


Figure 2: Neural Network components [12].

When constructing the hidden layer, the number of layers and the number of neurons have to be defined, thus their selection is described herein. In general, the number of neurons is equal to:

$$N = \frac{m}{n+1} \tag{3}$$

Where:

$m$ =number of observations
$n$ = number of features

The addition of 1 in the denominator corresponds to the unit column in Equation 3. According to [13] problems requiring 2 hidden layers are rarely encountered and 1 hidden layer can approximate any function that contains a continuous mapping from one finite space to another.

The general rules that should be followed for determining the number of neurons in the hidden layers are that the number of neurons should be:

- Between the size of the input layer and the size of the output layer.
- 2/3 of the size of the input layer.
- Less than twice the size of the input layer.

If too many neurons are assumed this could lead to over-fitting and if too few are used, under-fitting can be encountered. There is also a trade-off between the number of neurons and, the computational time and effort required. If more neurons are used this can become computationally demanding.

A software called Noesys_AutoML has been developed, where ML models are developed using the input dataset. The dataset is used to train and test the algorithm, where it is split into two groups where 85% of the dataset was used to train the data and 15% was used for testing.

## 3 DEVELOPMENT OF DATASET

It is important to note at this stage that the software Reconan FEA [10] was validated through experimental data derived from seismic table laboratory tests [14-16]. The dataset developed for use in developing the ANN model is the largest for any type of problem and consisted of 98,308 numerically obtained fundamental period results. The models were developed through Femap and analysed using Reconan FEA [4]. The initial model was developed that foresaw a plan view with a length of 5 m in the x-direction and 3 m in the y-direction. This model can be seen in Figure 3.

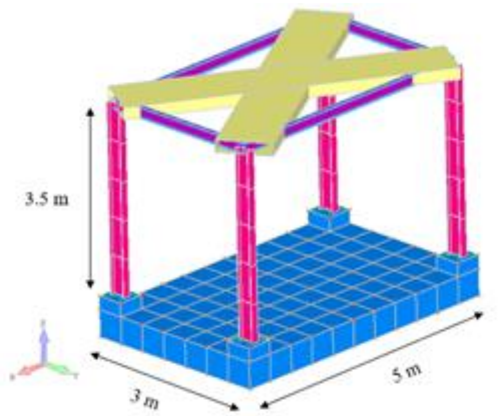


Figure 3: Initial Model [9]

The model was further expanded to include 25 bays in the long x-direction. It is important to note that every second change in the number of bays in the x-direction results in one additional bay in the y-direction. The smallest plan view had a dimension of 5x3 m (1-bay x, 1-bay y), and the largest foresaw a 125x39 m (25-bay x, 13-bay y) plan view. All structures, up to 25 bays, were modified accordingly to include up to 25 storeys. The dataset was then doubled, where the columns were rotated by 90$^{o}$ so that the strong axis of the column is now parallel to the short direction of the building.

So as to account for the SSI effect, a soil domain was discretized with 8-noded hexahedral elements by assuming 8 different soil Young's moduli. The soil domains that were discretized foresaw six soil depths including 1 m, 5 m, 12.5 m 22.5 m, and 37.5 m depths. Models with a soil domain with a depth of 60 m were also developed, but it was found that the fundamental periods on soil with a depth of 60 m were the same as that with a depth of 37.5 m, so it was decided to exclude them from the dataset. The largest model, which is a 25-storey building, that was constructed and successfully analyzed can be seen in Figure 4.

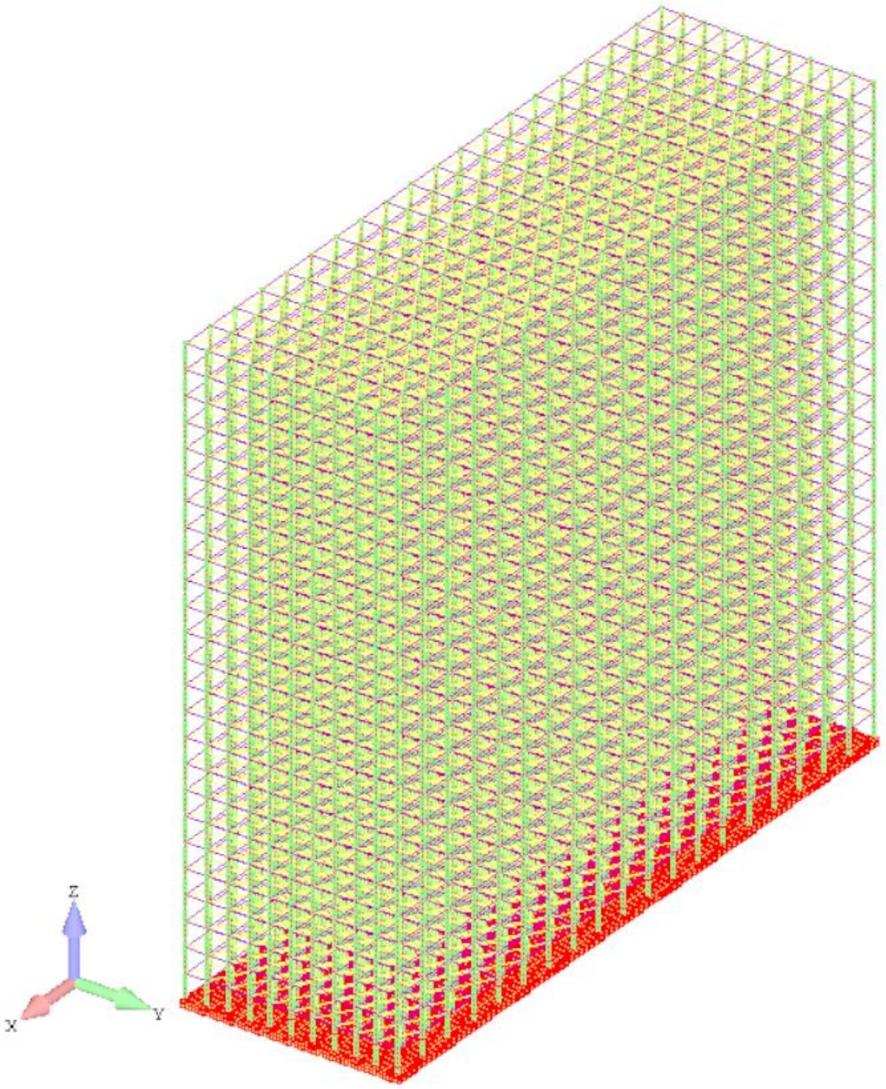


Figure 4: The largest model, without accounting for the soil domain, was constructed, and successfully analysed.

## 4 PREDICTIVE MODEL

The ANN algorithm was implemented in developing a predictive model through the use of Neosys_AutoML which generates the ANN automatically. One hidden layer and 13,846 neurons were used. The procedure in [11] is followed and the optimum ANN is formed by the software where the number of neurons is automatically determined. A comparison between the numerically obtained results and predicted results can be seen in Figure 5.

According to the obtained numerical results, the correlation was found to be equal to 99.9% (test dataset), and the corresponding mean absolute error (MAPE) was equal to 0.7%. It is also observed that the predictive model, when used for the test dataset, has slightly larger value predictions for periods between 0 and 4.5 seconds, while for periods above 7 seconds, the predictions are slightly smaller than the numerically derived results.

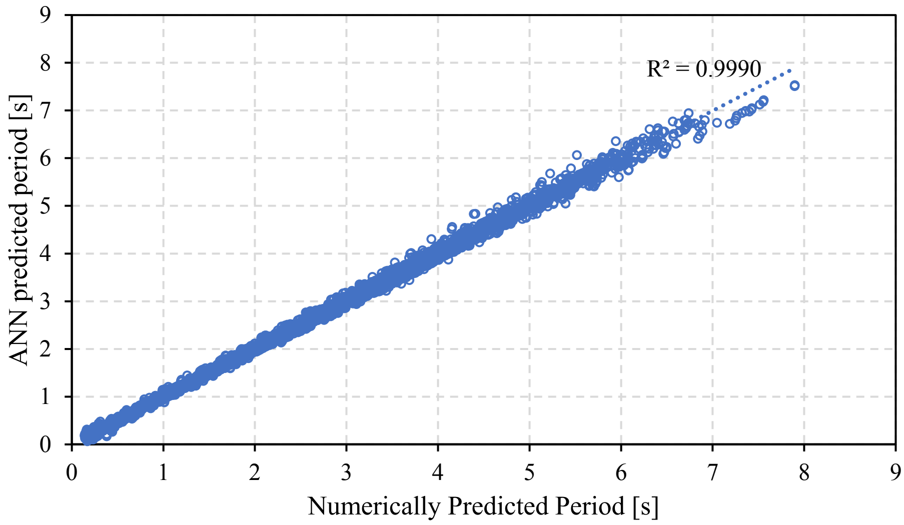


Figure 5: comparison between the numerically obtained fundamental period results and the results from the ANN model.

## 5 CONCLUSIONS

A large dataset that consists of 98,308 numerically obtained fundamental period results was created through the use of an HPC called Cyclone. This is currently the largest dataset of its kind found in the international literature. An ANN model was developed through the software called Neosys_AutoML and the model resulted in a correlation of 99.9% and a MAPE of 0.7% on the test dataset. Some small deviations were found in the prediction of fundamental periods between 0 and 4.5 seconds and above 7 seconds. In general, the ANN approach is not a fit-all solution, where the optimum structure of the network is not known at the beginning of the training. Nevertheless, the network developed for the needs of this research work was found to be near perfect, deriving minimal error.

Future work foresees further development of the Noesys_AutoML software. One algorithm that is currently being developed is the integration of the software with the ability to be able to derive a closed-form expression from the ANN training and testing, and it will soon be available to be used in additional validations when implementing ANNs. Furthermore, this research work foresees the use of the developed dataset in training new models by using different ML algorithms such as XGBoost and Polynomial Regression. This is now being investigated and will be published soon.


## ACKNOWLEDGEMENTS

The financial support from the EuroCC project (GA 951732) and EuroCC 2 project (101101903) of the European Commission is acknowledged. Parts of the runs were performed on the MeluXina (https://docs.lxp.lu/) as well as Cyclone (https://hpcf.cyi.ac.cy/) Supercomputers.

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