IMPLEMENTATION OF HYBRID ANN-GWO ALGORITHM FOR ESTIMATION OF THE FUNDAMENTAL PERIOD OF RC-FRAME STRUCTURES

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Abstract:

The fundamental period (T_{FP}) of vibration is one of the most important parameters in structural design since it is used to assess the dynamic response of the structures. It is the time taken by a structure or system to vibrate back and forth in its most natural way, without any external forces applied. Simultaneously, T_{FP} depends on the mass distribution and stiffness of the structure, which is largely influenced by infill walls in RC frame structures, and which is why their careful design is necessary. This study aims to develop a fast, accurate, and efficient machine learning (ML) method for the prediction of the fundamental period of masonry-infilled reinforced concrete (RC) frame structures. Hybridization of the stochastic gradient descent (SGD) based artificial neural network (ANN), and meta-heuristic grey wolf optimization (GWO) algorithm is proposed as an effortless computational method. This approach provided even more reliable solutions than robust second-order procedure based on single ML models. A total of 2178 samples of infilled RC frames were collected from available literature, where the number of storeys (*NoSt*), number of spans (*NoSp*), length of spans (*LoSp*), opening percentage (*OP*), and masonry wall stiffness (*MWS*) were considered as input parameters for predicting the output T_{FP} results. The accuracy and exploration efficiency of the proposed ANN-GWO paradigm have demonstrated superiority over existing seismic design codes and other conventional ML methods.

Key words: Earthquake engineering, Machine learning, Artificial neural network, Grey wolf optimization, Infill frames

1. Introduction

Fundamental period of a structure is a starting point of every building design process in civil engineering. Therefore, its determination is of outmost importance. Its value determines the seismic load that will be used in the design of a building, thus it is essential to make a good estimation of its value. In a case of RC frame structures with masonry infill walls, this is a complex task. Infill walls are quite stiff and it influences the fundamental period significantly. In recent years, Artificial Intelligence (AI) techniques have been increasingly used in various engineering fields, including structural engineering [1] and more specifically earthquake engineering [2], [3]. Existing studies are mostly based on shallow machine learning or Deep-Learning (DL) algorithms for solving regression, classification or optimization problems. This study aims to develop a fast, accurate, and efficient ML method for the prediction of the fundamental period of masonry-infilled (RC) frame structures.

2. Material and methods

2.1 Database description

A database consisting of 2178 masonry-infill RC frame structures was collected from the available literature FP4026 Research Database [4]. Table 1 contains information on the distribution of input and output variables, i.e. *NoSt*, *NoSp*, *LoSp*, *OP*, *MWS*, and T_{FP}. This is important because of the possibility to reproduce the results obtained in this study, but also to provide data normalization to the range [-1÷1], which was done by using the MinMaxScaler function in the Python environment.

Variable	Mean	St.Dev.	Min.	Max.
NoSt [-]	11.50	6.35	1.00	22.00
NoSp [-]	5.76	0.87	2.00	6.00
LoSt [m]	4.77	1.45	3.00	7.50
OP [%]	31.76	28.99	0.00	75.00
MWS [10^5 kN/m]	11.38	7.85	2.25	25.00
T_{FP} [s]	0.83	0.59	0.04	3.01

Table 1. Distribution description of input and output variables

Two metrics were used for the performance evaluation of the proposed methods including, mean squared error (*MSE*), and coefficient of determination (R^2) [5].

2.2 Artificial neural network (ANN)

ANNs are a class of machine learning models that are based on the organization and operation of the human brain. They have a number of key benefits, such as the capacity to learn from and adjust to new data, the capacity to process sizable amounts of data concurrently, and the capacity to model intricate, non-linear relationships between inputs and outputs. This study aims to predict the fundamental period of infill RC frames, using the output results from the optimization GWO technique as a starting point for ANN, in order to increase the security against falling into local minima. Validation of the results was performed by comparing the hybrid ANN-GWO model based on the SGD rule, with single first-order SGD model and second-order based adaptive moment estimation (ADAM) model developed from scratch [5]. The stability of the single model was tested using the 10-cross validation (CV) technique. The activation functions adopted for hidden and output layers are hyperbolic tangent and pure linear, respectively. SGD rule implemented in this work can be mathematically expressed as:

$$w_{i+1}=w_i-\mu\cdot g_i+\eta\cdot\Delta w_{t-1} \tag{1}$$

where μ=0.1 [0÷1], and η=0.9 [0÷1] are learning rate and momentum as hyperparameters with values adopted according to the recommendations derived from other studies [5], g_i is the gradient calculated after each sample i, and Δw_{t-1} is weight increment from previous iteration. Based on previous studies of the same task [6]–[8] where ANNs either with one or multiple hidden layers were adopted, the authors of this work investigated several architectures with a single layer and different numbers of neurons. The adopted splitting strategy considers 80% of the samples for training and the other 20% for the test phase. The most optimal ANN-GWO architecture (5-8-1) contains eight neurons in the hidden layer.

2.3 Grey wolf optimization (GWO)

The social structure and foraging habits of grey wolves in the wild served as inspiration for the development of the GWO meta-heuristic optimization algorithm. GWO was first proposed by [9] in 2014. As gray wolves usually live in the pack, it is important to note their social hierarchy, which consists of 4 groups: alpha (α), beta (β), delta (δ), and omega (ω). The alpha wolf as the best manager in the pack is the most dominant member, while the beta, delta, and omega wolves have a lower rank, respectively. The optimization process involves updating the positions of the wolves in the search space based on their initially random location. Grey wolves traditionally have a strict hunting procedure which can be mathematically described as follows:

$$X(t+1)=(X_1+X_2+X_3)/3 \tag{1}$$

$$X_1=X_\alpha(t)\text{-}A_1\cdot D_\alpha,\ \ X_2=X_\beta(t)\text{-}A_2\cdot D_\beta,\ \ X_3=X_\delta(t)\text{-}A_3\cdot D_\delta \tag{2}$$

$$A_i=2\cdot a\cdot r_1\text{-}a,\ \ C_i=2\cdot r_2 \tag{3}$$

$$a=2\cdot(1\text{-}iteration/maxiteration) \tag{4}$$

$$D_{\alpha,\beta,\delta}=\left|C_i\cdot X_{\alpha,\beta,\delta}(t)\text{-}X(t)\right| \tag{5}$$

where t refers to the current iteration, X is the vector of the grey wolf position, X_1, X_2, and X_3 are predicted position vectors of the alpha, beta, and delta wolves, X_α, X_β, X_δ are relative position vectors of alpha, beta, and delta wolves, A_i and C_i are coefficient vectors, r_1 and r_2 are random vectors in range [0,1], a is a component that linearly decreased from 2 to 0, and $D_{\alpha,\beta,\delta}$ are vectors that depend on the position of the prey. One of the advantages of GWO is that it has a relatively simple algorithm, without the need to calculate function derivatives, which makes it easy to implement and understand. The fundamental principle behind using GWO for training ANNs is to find the weights and biases in a more optimal manner, by reduction of the *MSE* as a fitness function between the predicted and the actual outputs. The main benefit is its superior ability to explore the high-dimensional parameter space compared to some other optimization algorithms. The authors proposed the initial random generating of 30 wolves as search agents. In the training phase, GWO iterates 10 times, followed by only 320 ANN iterations (see Table 2), which is optimal compared to mostly at least 1000 epochs necessary for the convergence of a single conventional model from scratch. The improvement of the positions of search agents is performed by applying the procedure described in the previous section. All search agents were separately considered as vectors with 57 parameters of the neural network that were initially randomly generated in the range [-5÷5].

3. Results and discussion

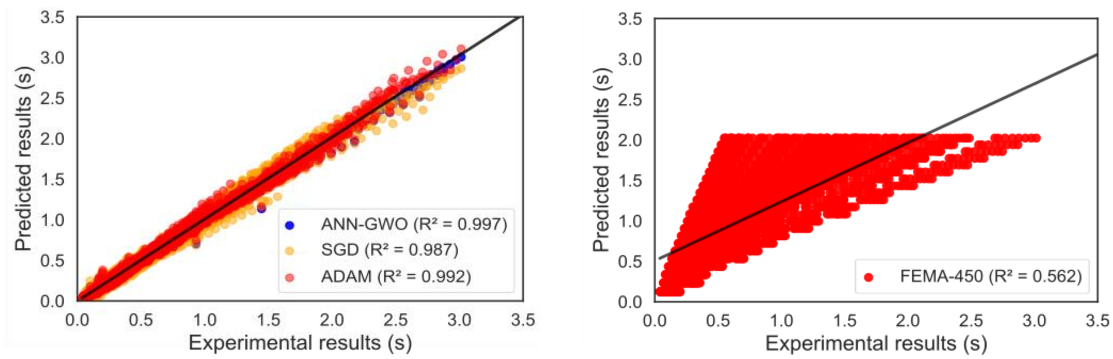
The results presented in Figure 1, show that on the entire domain the hybrid ANN-GWO algorithm is superior over the pure SGD and ADAM models from scratch, as well as the FEMA-450 [10] design code that proposes the following equation for calculating the fundamental period:

$$T_{FP}=0.0466\cdot H_n^{0.9} \tag{6}$$

where H_n is the height of the structure in meters. Table 2 summarizes the performances of the mentioned approaches, whose results are illustrated in Figure 1. It can be concluded that the hybrid algorithm has the slightly better processing power and faster convergence (320 versus 1000 epochs) even than the second-order ADAM algorithm. A similar conclusion is reached in the case of comparison with SGD from scratch, while the robustness of the hybrid procedure is particularly pronounced in comparison to the results of the FEMA-450 design code.

Measure	R^2				MSE ($\cdot 10^{-3}$s^2)			
Method	ANN-GWO	SGD	ADAM	FEMA-450	ANN-GWO	SGD	ADAM	FEMA-450
Iteration	320	1000	1000	-	320	1000	1000	-
Architecture	5-8-1			-	5-8-1			-
Train	0.997	0.987	0.992	-	1.178	4.735	2.771	-
Test	0.997	0.988	0.991	-	1.189	4.894	3.194	-
All	0.997	0.987	0.992	0.562	1.179	4.767	2.856	247.690

Table 2. Performance indicators of the proposed hybrid and single ML models



(a) ANN-GWO, SGD and ADAM models (b) FEMA-450 design code

Fig 1. Performance comparison of the proposed hybrid ANN-GWO model with SGD/ADAM methods, and provisions of FEMA-450 design code on all data

4. Conclusions

This paper suggests the implementation of a meta-heuristic GWO algorithm to enhance the processing power of the ANN-SGD, used for the prediction of the fundamental period of RC frame structures. Proof that the hybrid algorithm outperforms traditional procedures is made by comparing it with the first-order ANN-SGD and the second-order ANN-ADAM algorithm made from scratch, as well as seismic design codes. ANN-GWO provided a faster convergence, and a higher coefficient of determination values, making it more accurate even than the second-order algorithm. In addition, GWO enables more successful avoidance of falling into a local minimum, which is often a problem of single ANN models. Generally, all three approaches are suitable to make predictions of the fundamental period, with some differences in speed. As part of future research, it is necessary to examine the potential application of the GWO algorithm and its hybrid variations on a wider range of problems, in order to uncover new possibilities and validate its effectiveness.

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