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APPLICATION OF MACHINE LEARNING ALGORITHMS IN THE INVESTIGATION OF THE DYNAMIC RESPONSE OF MOMENT-RESISTING FRAMES

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Abstract

The contribution discusses some aspects of the design and simulation of a reinforced concrete frame structure's response to a strong ground motion. A machine learning (ML) algorithm is implemented to design some vertical structural elements. To create the database needed to train and validate the ML algorithm, results obtained by response spectrum analysis are employed. After that, the structural response is again investigated using time-history finite-element analysis. Additionally, algorithms reproducing the action of seismic isolators are integrated into the model of the reinforced concrete structure. Results for the structure with and without isolation are compared in terms of displacements and accelerations monitored at a specific location.

Keywords: Finite-element modeling; Machine learning algorithms; Moment resisting frame; Dynamic response; Seismic isolators.

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1 INTRODUCTION

Solutions based on machine-learning (ML) algorithms are increasingly gaining popularity in daily life and various fields of industry, including construction and structural design. A number of recent studies demonstrate the application of ML algorithms as predictors in various cases, such as (i) Damage assessment of prestressed concrete beams [1]; (ii) Strength of steel CHS X-joints [2]; (iii) Shear strength of steel fiber reinforced concrete beams [3]; (iv) Compressive and flexural strength of steel fiber-reinforced concrete [4]; (v) Effective stiffness of precast concrete columns [5]; (vi) Drift capacity of reinforced concrete walls [6, 7]; (vii) Punching shear resistance of concrete slabs [8], (viii) Shear strength of concrete connections [9]; and (ix) Load-bearing capabilities of concrete columns [10]. Generally, the data-driven models reveal interdependencies between the input parameters and the output variables without being biased by specific models.

Within the study presented herein, a synthetic database is compiled based on a preliminary defined layout of the vertical elements in the moment resisting frames. The inputs include the relevant cross-sectional geometrical dimensions and the design values of the shear force, the normal force, the bending moment, and the parameters of the seismic excitation. The required database is populated by running a series of response-spectrum analyses. The ML algorithm is applied at this stage. After that, the structural response is studied using time-history analysis with and without base isolation.

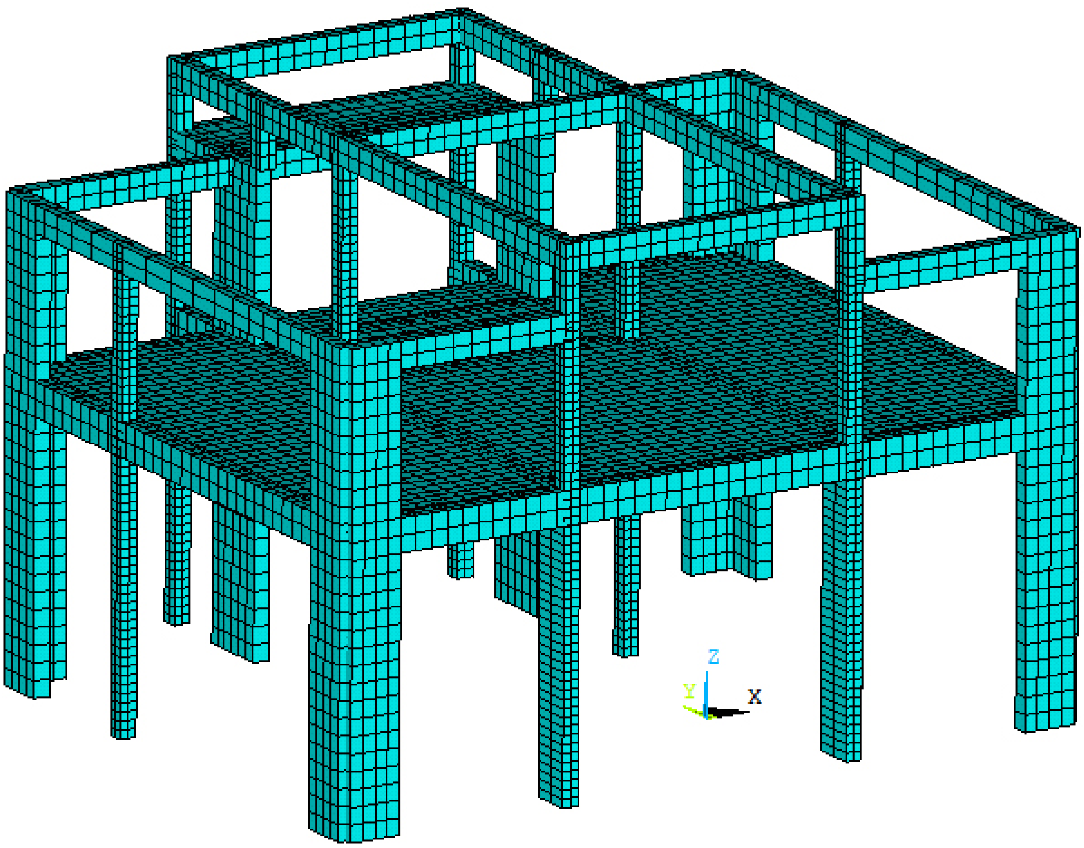


Figure 1. The finite-element model of the studied structure.

2 THE CASE STUDIED

A small residential building with a frame structure in reinforced concrete is considered (Figure 1). The vertical elements resisting the generated seismic forces comprise reinforced concrete columns with a square cross-section of 25x25 cm and shear walls with cross-sections L_ix25cm. The columns' cross-sections are fixed, and the dimensions L_i are varied in different response spectrum analyses.

The finite-element model is kept as simple as possible. It comprises beam and shell finite elements. Specifically, BEAM188 and SHELL181 are employed. BEAM188 is a 3-D finite element of type beam with two nodes; the "six degrees of freedom per node" option is used in the model. SHELL181 is a finite element of type structural shell with four nodes and six degrees of freedom at each node; the degrees of freedom comprise translations in the X, Y, and Z directions and rotations about the X-, Y-, and Z-axes of the nodal coordinate system. Before running the response-spectrum analyses, the nodes at the ground level are fully fixed. Constraints are not displayed in Figure 1. Within the conducted time-history analyses, the seismic input in terms of acceleration time series is applied to nodes at the ground level.

3 THE ML ALGORITHM

3.1 The synthetic database

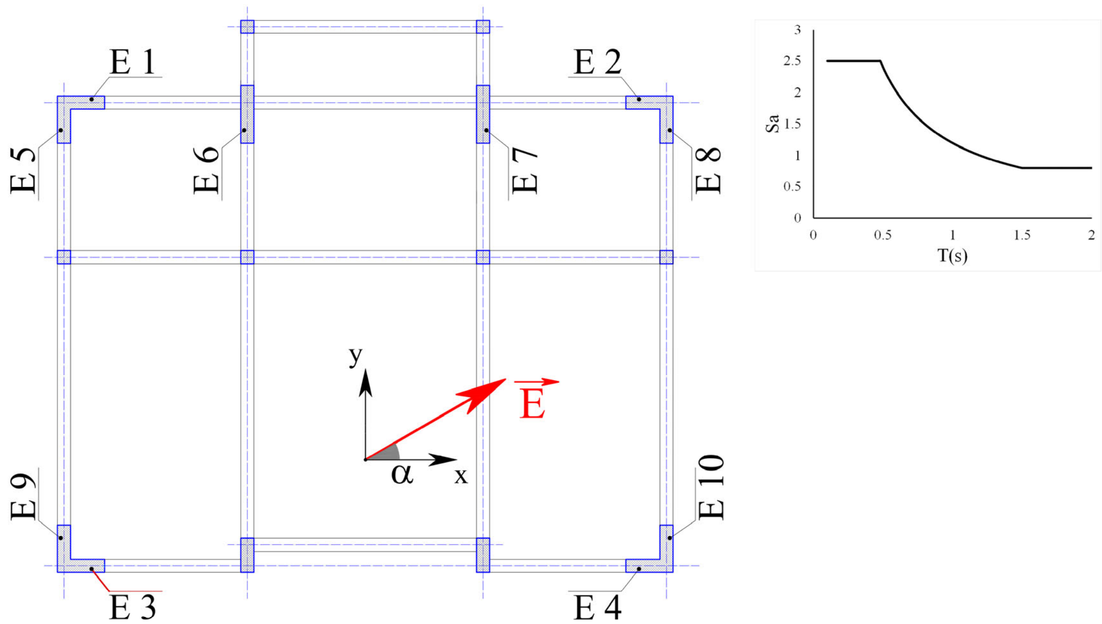


Figure 2. The general layout of the vertical elements, which are subjected to optimization.

The layout of the vertical elements considered within the optimization is shown in Figure 2. Only the geometric characteristics of the labeled elements (i.e., E1 - E10) are subject to investigation. A series of response spectrum analyses is performed by varying the seismic excitation vector (labeled **E** in Figure 2) for a specified seismic hazard and with a relevant spectral curve. The results obtained by the response-spectrum analyses are employed to populate the database used in the ML algorithm (an artificial neural network (ANN)) training and testing.

3.2 The ANN architecture

A convolutional network is built for the purposes of the study. It consists of input and output layers and several hidden layers. Train and test data are normalized before implementation to enhance ANN functioning. The hidden layers conventionally employ the rectified linear unit (ReLU) activation function and batch normalization. Among the hidden layers, some are defined as "flatten" and "dense." The Adam optimizer is used, and an appropriate loss function is chosen, along with suitable metrics. Model size and hyperparameters (e.g., the learning rate) are finally set based on the convolutional network's performance evaluation as a function of their variation.

4 BASE ISOLATION

By assumption, the base isolation is realized by mounting friction-pendulum bearings (Figure 3). The compactness of such seismic isolators makes them an attractive option for retrofit applications [11]. A simplified model of the bearing device is implemented into the finite-element model of the base-isolated structure.

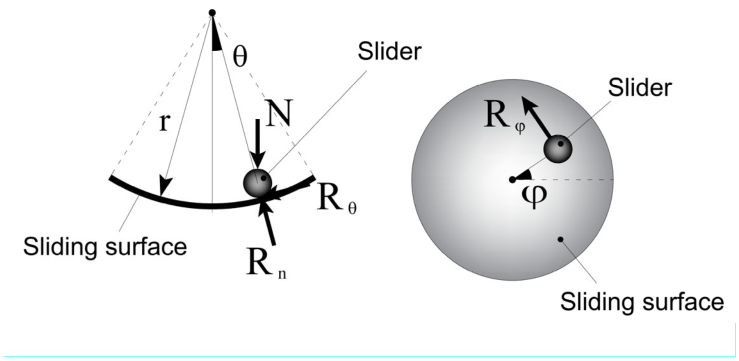


Figure 3. Schematic representation of the friction-pendulum bearing.

The device response is interpreted as the motion of a particle on a spherical surface, as shown in Figure 3. The trajectory of the slider, defined by three degrees of freedom (r, θ, φ in a spherical coordinate system), onto the sliding surface can be obtained using the Lagrangian formalism. In Figure 3, R_n, R_θ, and R_φ are the components of the contact force between the slider and the sliding surface. Assuming that the particle (i.e., the slider) can't lose contact with the spherical surface, two second-order differential equations, in terms of θ and φ, are obtained and solved numerically [12].

Alternatively, a high-fidelity finite-element model of the bearing (Figure 4) can be integrated into the finite-element model of the entire structure, which will maximize the "cost" in terms of computational time and resources needed.

Figure 5 shows the evolution of normalized displacement and acceleration, monitored at a specific location, for the structure with and without seismic isolation. The response of the base-isolated structure is obtained by performing a transient finite-element analysis, using the simplified model of the seismic isolator.

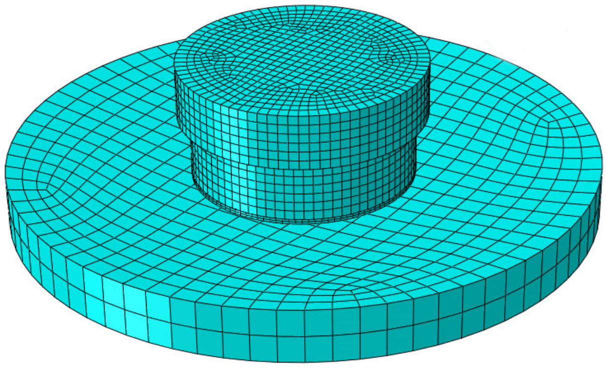
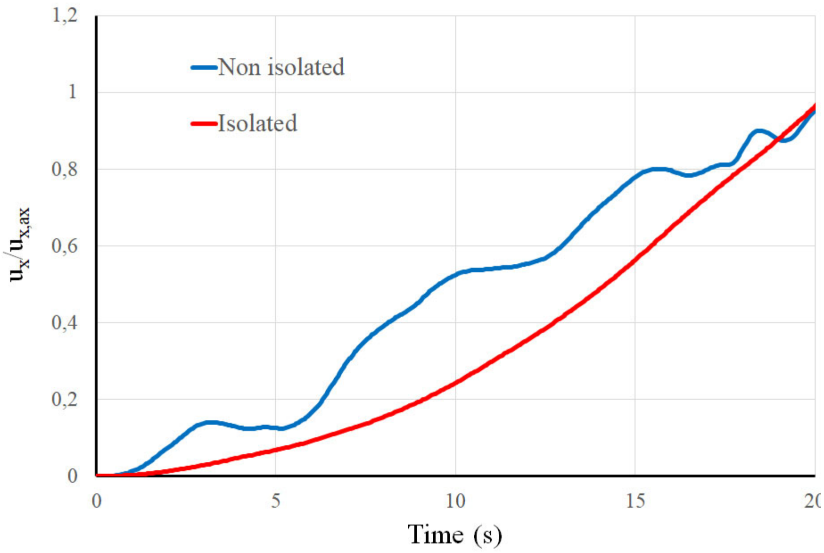
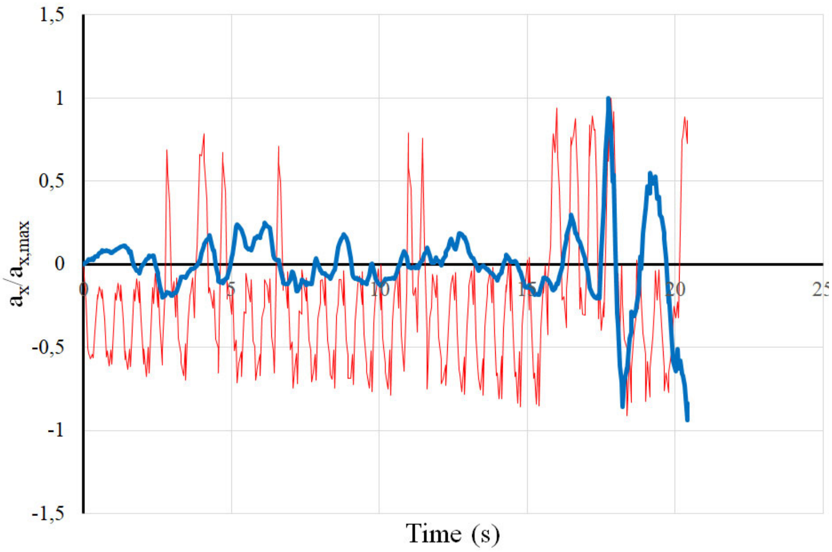


Figure 4. A tentative finite-element model of the bearing.



a)



b)

Figure 5. Response of the isolated structure (red) versus the response of the non-isolated structure (blue) in terms of displacement component (a) and acceleration component (b).

5 CONCLUDING REMARKS

Elements of the design of a reinforced concrete frame structure of a small residential building have been discussed.

A machine learning algorithm (specifically, a convolutional neural network) has been implemented in the design. The required database has been obtained by performing a series of response-spectrum analyses. Additionally, a transient analysis has been carried out.

There exists a standpoint that the results obtained by response spectrum analysis might be misleading since they could lead to the underestimation of the structural demand. However, the presented study aims to suggest optimal dimensions for the vertical structural elements, more precisely, shear walls. Design shear forces, normal forces, and bending moments can be obtained in a subsequent phase by performing a time-history analysis using, for example, recorded accelerograms or equivalent synthetic inputs. An illustrative example has been discussed in the presented study.

The effect of passive seismic isolation, designed to minimize the structural demand during an earthquake, has also been considered. Predictions of the structural response with and without base isolation have been presented.

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