Machine Learning Techniques for Analysing the Seismic Response in Multistorey Steel Structures

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***Abstract*— This paper provides a detailed analysis that uses an Artificial Neural Network (ANN) in forecasting the seismic response in multistorey steel structures. A comprehensive framework has been developed to conduct a parametric study, with the intention of leveraging the outcomes from dynamic analysis, as inputs in the ANN. The framework explores the process of selecting earthquakes by utilizing seismic response spectrums and a nonlinear finite element (FE) model that introduces varied geometric properties, member sizes, and peak ground accelerations to derive eigenfrequencies, horizontal drift and base shear. Results indicate a satisfactory accuracy of the trained Artificial Neural Networks to predict the dynamic response.**

Keywords—machine learning, steel structures, dynamic analysis, non-linear analysis

I. Introduction

Several methodologies have been developed the last years, emphasizing in using Artificial Intelligence tools to evaluate the structural response of different types of buildings and materials. The main concept of this approach, is to introduce a combination of traditional constitutive descriptions, including for instance damage mechanics, contact mechanics, plasticity and others [1], with machine learning tools that make use of relevant accumulated data, obtained either numerically or experimentally.

In this context, several recent studies have been proposed, providing machine learning solutions including among others Artificial Neural Networks (ANNs) to capture the multi-scale response of masonry structures [2], the response of masonry under static or blast loads [3,4], the behaviour of reinforced concrete structures [5] as well as the response of steel structures under seismic actions [6,7,8]. More studies can be found in literature, emphasizing among others in the seismic response of buildings using machine learning applications [9-19].

The proposed study adopts a machine learning (ML) framework for predicting the response of multistorey steel structures. Within finite element analysis (FEA), a parametric design is implemented by developing 1697 computational models, comprising 14 inputs and 9 outputs, with varying input parameters such as geometry, loading, and member sizes of structural steel buildings. The output of each simulation is the horizontal drift, the base shear, and the natural frequency. Input and output parameters are then fed into an ANN model to learn and predict the structural response of random multi-storey steel buildings under seismic actions.

II. Adopted Methodology

A. Seismic actions

The study employs past seismic events obtained from the Pacific Earthquake Engineering Research Centre (PEER) database. Selected seismic events provided the loading of the parametric finite element models, in the form of ground acceleration.

In particular, seismic events exceeding the magnitude of 6 Richter scale were evaluated, focusing on those potentially impacting the vibration response of the investigated structures. The selection process relied on fundamental periods computed from modal analyses using commercial FEM software. Events were chosen based on their potential to induce significant vibration, identified by matching peak response spectrum values to the computed fundamental periods. This ensured that the selected seismic events had the potential to trigger the response of structures with specific geometries and stiffness properties. Subsequently, FE models are constructed to generate damage states for each simulation.

B. Parametric simulations

A conceptual geometric design was developed to simulate real-life multistorey structures, ensuring practicality without compromising accuracy. Bay lengths in structural engineering typically ranges from 4m to 9m for optimal safety and functionality. Hence, two configurations providing dimensions equal to 6m x 4m x 3m and 6.5m x 5m x 3m (L x W x H), were studied to evaluate the impact of bay spacing on seismic responses and accommodate various design preferences. Structural steel buildings with 2 to 10 storeys and 2 to 10 bays in each direction were considered.

Member cross-sectional properties met the standards of the Southern African Steel Construction Handbook (2016). Member sizing under gravity loads followed SANS 10162-1:2005 criteria. To cater to designers' diverse needs, a selection of five cross-sections was made.

C. Developed finite element models

For each of the parametric structural steel buildings, a non-linear finite element model was developed. Structural steel frames were simulated using beam finite elements while concrete slabs with shell elements.

The longitudinal and transverse beams of the steel frames were connected to a 250 mm thick continuous slab to enhance rigidity and structural integrity. It is noted that slabs were positioned on each floor level to improve shear, torsional, and lateral stability, representing response aspects of a conventional multistorey steel building. A beam element formulation was employed for dynamic analysis, utilizing line elements for the steel frame and linear mesh to accurately model the system. Mesh refinement to 500 mm element size was implemented for the frame, while a course element size of 1500 mm was assigned to the slab, to optimize computational efficiency.

To sustain lateral damping stiffness, bracing elements are strategically positioned at the first and last bay in each direction. Structures spanning more than 6 bays feature additional bracing at the central bay. Configurations with less than three bays adopt a single braced bay, except for structures exceeding 6 storeys, necessitating two braced bays. A uniform application of equal leg angles measuring 100 mm x 100 mm x 10 mm ensures consistent lateral resistance throughout the parametric design, obviating the need for shear walls.

Beam-column elements connecting to the weak axis of columns are kept pinned (no moment resistance) to account for the low moment capacity about the column’s y-axis, whilst beams connecting to the strong axis (flange) are fixed, which led to uniaxial strong-axis bending.

Material properties were defined using a nonlinear von Mises plasticity criterion for steel and linear elastic properties for concrete slabs. Nonlinear time history (transient) analysis, incorporating also "large deflections," was undertaken to evaluate the structural behaviour of each steel building over the duration of each seismic event.

The seismic response of the structure was derived using fixed boundary conditions at the base, preventing translation and rotation in all three directions, simulating a fully embedded foundation. In addition, a fixed damping ratio of 0.05 and a damping frequency matching the structure's fundamental frequency from modal analysis were applied to represent inherent energy dissipation.

Directional ground accelerations time-history in x, y and z directions providing the seismic loading were assigned, replicating the ground motion of the earthquake.

Each simulation captured the horizontal drift at top, middle, and bottom levels in both directions, as well as the base shear and eigenfrequencies. These parameters will be used to train the ANN and provide an insight into each structure's overall seismic performance, effectiveness of various geometries, and potential damage under different earthquake events.

D. *Artificial Neural Networks*

The introduction of a data-driven approaches has significantly reduced the gap between theoretical design and actual construction in the industry. By combining experimentally derived or numerically obtained data, these data-driven approaches have proved to yield accurate and effective results. However, it seems that the advancement of research in machine learning techniques for steel structures is not yet fully developed and there are aspects that can further be investigated, adopting models that consider various factors such as different steel connections (fixed and pinned), damage states, geometric configurations, member sizes, and types of loading.

Among the most widely used machine learning approaches in data-driven structural engineering, is the one adopting Artificial Neural Networks (ANNs). The predictive capabilities of ANNs are exploited to minimize computational costs, and provide designers additional tools for a fast and accurate prediction of the seismic response, either in a preliminary or in a more final design stage. This reduces the likelihood of discrepancies and design errors.

Developing an effective ANN model necessitates a comprehensive parametric study with a wide array of input and output parameters, enhancing the accuracy and efficiency of the prediction tool.

In this study, parametric non-linear dynamic simulations were conducted and input-output parameters obtained from these simulations are included in a dataset. The developed dataset is then used to train, validate and test a neural network. Leveraging the capabilities of the Levenberg-Marquardt (LM) and Bayesian regularization algorithms, the training process employed iterative weight adjustments and rapid convergence to achieve accurate output approximation. These algorithms aim in minimizing the error function and identifying optimal weight configurations, leading to the desired output values.

The training data, validation data, and testing data were split in a 70% / 15% / 15% ratio, respectively. This allocation ensures sufficient data for training the model, validating its performance, and evaluating its generalization capabilities on unseen data.

Figure 1 illustrates the process proposed in this study for developing a data-driven solution, aiming to predict the seismic response of multistorey steel structures.

III. Results and Discussions

Modal analysis indicates that shorter buildings with a fixed plan layout exhibit a lower fundamental period, implying increased rigidity. Furthermore, reducing bay spans and increasing the size of member cross-sections decrease the fundamental period and enhance structural stiffness. Tuning the damping frequency with the natural frequency is theoretically expected to significantly reduce the horizonal drift.

First a brief insight is provided on the results of the parametric simulations. The outcomes of the parametric transient structural analysis, utilizing nonlinear time-history simulations, delineate the horizontal drift patterns across a range of geometric configurations and stiffness parameters. Figures 4 and 5, provide the drift magnitudes and a scaled-up deformation shape in the x and z directions for a single simulation taken from the parametric study. The building comprises 10 by 7 bays and 7 storeys with 6 m x 4 m spans and a 305 x 305 x 240 section. It is pertinent to recognise that the maximum drift in both directions is observed at the top of the building, occurring at 10 sec in the x-direction (shown in Figure 2) and at 8.93 sec in z-direction (shown in Figure 3). Thereafter, the maximum drift response from the time-history is taken as input for parametric design.

In Figure 6 the horizontal displacement (drift) due to seismic loading is provided for 7 storey buildings, with increasing number of bays and for different bay dimensions. According to this figure, consistent diagrams for the horizontal drift across each spanning bay are derived. Thus, the graphs exhibit a similar pattern per direction, for the two bay spanning distances. Maintaining all other parameters constant, this pattern suggests a high degree of correlation among the variables. The identified consistency in the data patterns highlights the potential success of utilizing machine learning techniques in this analysis, since it is expected that training of the ANN for such data (depicting some sort of "consistency") will reach a proper accuracy.

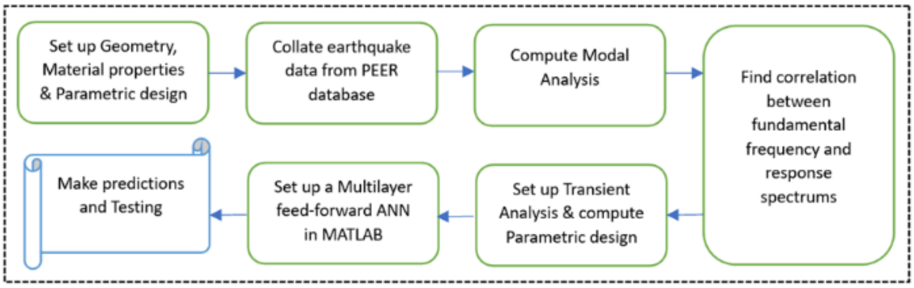

Fig 1. The proposed data-driven scheme

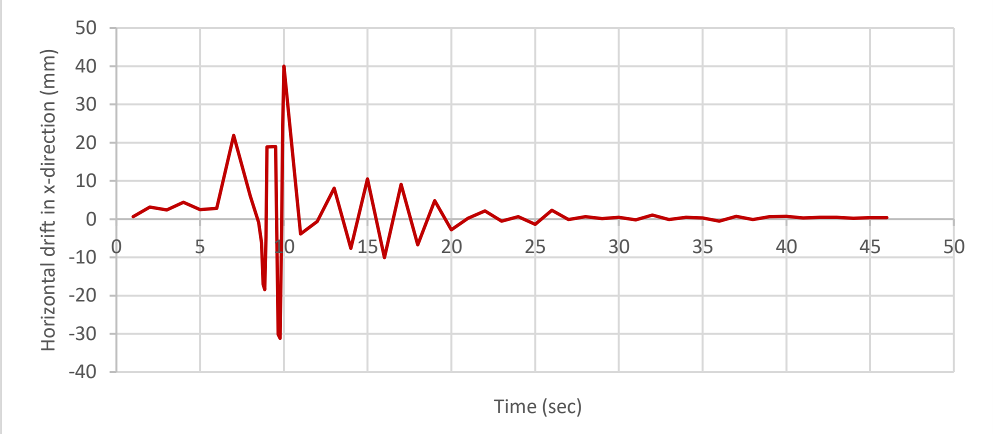

Fig 2. Time-history drift response in the x-direction

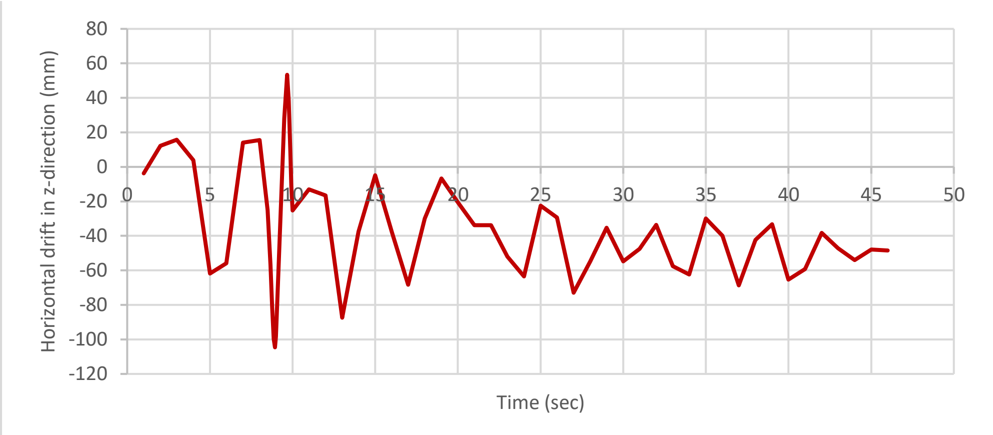

Fig 3. Time-history drift response in the z-direction

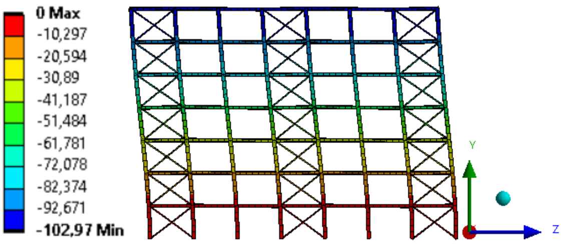

Fig 4. Horizontal drift (mm) and deformation shape in z-direction

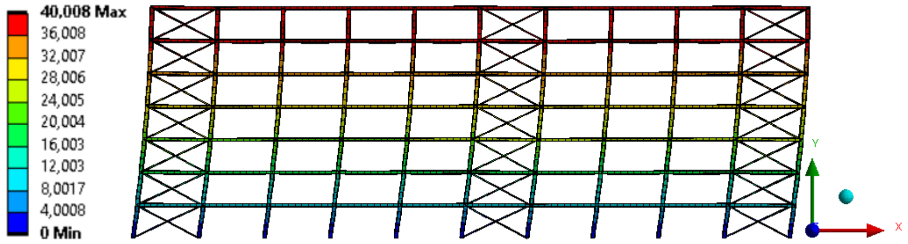

Fig 5. Horizontal drift (mm) and deformation shape in z-direction

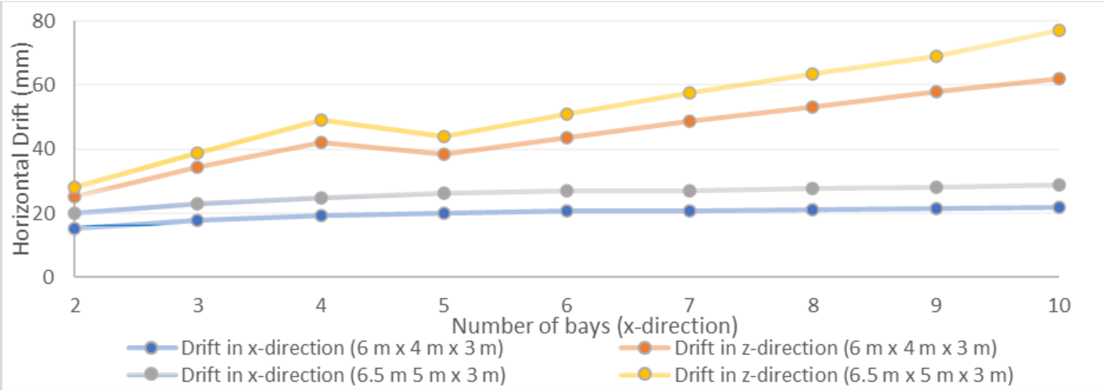

Fig 6. Drift obtained for varying number of bays and span dimensions

The training of the ANN is also discussed in the following lines. To reduce the mean square error (MSE) generated by the ANN, the values of the input and output parameters are normalized in the range -1 to 1. In addition, after preliminary investigations aiming to evaluate the optimal number of neurons per hidden layer, 20 neurons per hidden layer were used to enhance the predictive accuracy. The Levenberg-Marquardt and the Bayesian Regularization algorithms were adopted to implement the training.

The error and the accuracy of the training, validation and testing of the ANN are provided in Table I. In particular, results of the training, validation and testing of the ANN provide correlation factors R for the corresponding regression diagrams, that are close to 1, for the three categories (as shown in Table I) and an MSE converging to zero, representative of a successful neural network training.

Given the complexity of seismic design and the number of simulations that have been conducted during the study, the R-value in each category is judged as satisfactory. The relevant regression diagrams depict real-predicted output values in 45° line, with a relatively small proportion of points diverging.

To further verify the capacity of the trained ANN to predict the dynamic response of steel buildings, comparisons between predicted output and output obtained from finite element analysis simulations were conducted, for input parameters not included in the developed dataset. Thus, the precision of the outcomes was evaluated by comparing the results from the ANN with those generated by the FE software (Ansys) utilizing a new input dataset.

Table II compares the performance of the two ANNs in predicting outputs for a 6 by 3 bay, 5-storey structure designed with a bay spacing of 6.5 m x 5 m and a member size of 533 x 210 x 138 mm. Both methods provide reasonably accurate approximations of the Ansys-generated results for all evaluated features.

The outputs derived from both ANNs were distinctive yet nearly equivalent, indicating a successful training network and confirming the capacity of predicting seismic responses of steel structures indicating suitability for performance-based seismic design. The results in Table II show that the Levenberg-Marquardt method exhibits a marginal improved output prediction than the Bayesian Regularization method, with a lower computational cost. Despite the divergence in their optimization strategies, both techniques yield satisfactory R-values and predictions, maintaining accuracy above 75%. This observation underscores the robustness of the neural network, indicating a well-conditioned model where outputs during training, validation, and testing closely match expected outcomes, indicative of minimal bias or variance.

IV. Conclusions

A first effort is presented in this study, aiming to evaluate the response of structural steel multi-storey buildings under seismic actions, using machine learning. This work aims to contribute to performance-based seismic engineering, by integrating novel computational tools and established methodologies to achieve optimal design outcomes.

Throughout this study, the efficacy of ANNs in capturing the intricate nonlinear behaviour of multistorey steel structures under seismic loading has been extensively examined. The findings underscore that ANNs offer a robust framework for accurately forecasting various seismic responses, including horizontal drifts, base shear, and eigenfrequency, exhibiting notable efficiency and precision when compared to conventional computational approaches. Furthermore, by harnessing the capabilities of ANNs, engineers can efficiently explore a diverse array of design scenarios and optimize structural configurations to enhance seismic performance while reducing time and design costs.

In addition, a coupling is attempted between finite element analysis and artificial neural networks. Integrating advanced, nonlinear dynamic finite element simulations with ANNs, represents a significant step towards performance-based seismic engineering.

By leveraging ANNs, this approach aims to streamline the design process by potentially bypassing traditional steps such as material characterization, modal analysis, and static/dynamic calculations or alternatively, offer a further insight on the structural response before those procedures are fully developed. This effort may lead to cost-effective design and also reduce significantly the underlying computational cost.

Furthermore, the approach may simplify the design process by potentially mitigating the need for extensive seismic expertise, leading to improved design consistency and ultimately safer buildings. In addition, the application of ANNs for predicting seismic responses on multistorey steel structures presents a significant advancement to seismic risk assessment.

However, it is essential to recognise the inherent challenges associated with ANNs, including the need for an extensive dataset, model interpretability and overfitting, and the ability to generalize and predict unseen data. Addressing these challenges requires continuous research endeavours and collaborative efforts among structural engineers and academia.

As the refinement and validation technique of ANN models progress, their widespread application stands to greatly improve the safety and sustainability of the built environment in seismic active regions.

TABLE I. TRAINING, VALIDATION AND TESTING OF THE NEURAL NETWORK

	Levenberg-Marquardt			Bayesian Regularization		
	Observations	MSE	R-value	Observations	MSE	R-value
Training	1194	0.0198	0.9817	1442	0.0206	0.9780
Validation	256	0.0205	0.9816	-	-	-
Testing	256	0.0161	0.9854	255	0.0312	0.9669

TABLE II. TESTING THE TRAIN ANN ON RANDOM INPUT DATA

	Ansys	Levenberg-Marquardt	Bayesian Regularization
Eigenfrequency (Hz)	1.11	1.21	1.36
Roof drift x-direction (mm)	2.27	2.11	2.04
Mid-height drift x-direction (mm)	-1.43	-1.62	-1.43
Bottom drift x-direction (mm)	-0.49	-0.50	-0.47
Roof drift z-direction (mm)	9.97	10.13	10.33
Mid-height drift z-direction (mm)	-7.82	-6.94	-7.04
Bottom drift z-direction (mm)	0,8	1.15	0.78
Base Shear x-direction (kN)	26 904.8	27 731.57	27 379.23
Base Shear z-direction (kN)	12940	13 876.4	9 914.3

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