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SEISMIC PERFORMANCES OF STRUCTURE USING ARTIFICIAL NEURAL NETWORKS – A REVIEW

Muhammad Faizzuan Ikmal Mohd Fazully[a], Siti Khadijah Che Osmi[a*], Nursyafikah Hafizi[a], Maidiana Othman[a], Fakroul Ridzuan Hashim[b]

[a] Department of Civil Engineering, Faculty of Engineering, National Defence University of Malaysia, Sg. Besi Camp, 57000 Kuala Lumpur, Malaysia
[b] Department of Electrical & Electronics Engineering, Faculty of Engineering, National Defence University of Malaysia, Sg. Besi Camp, 57000 Kuala Lumpur, Malaysia

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ABSTRACT

Earthquakes are among the most catastrophic natural disasters, resulting in considerable structure destruction, fatalities, and extensive impact on socioeconomic. The design of earthquake-resistant structures has emerged as a crucial priority for addressing the risk associated with seismic events. Recent advancements in artificial intelligent, particularly neural networks (ANNs), have highlighted the capability of artificial intelligence, in improving seismic performance evaluation of structures. This paper reviews current research on the application of ANNs in predicting the seismic performance of structures. It examines how ANNs are utilized to develop probabilistic seismic demand models (PSDM) for aboveground and underground structures, highlighting their advantages over traditional methods in terms of accuracy and efficiency. The review demonstrates the capacity of artificial neural networks to simulate intricate seismic responses, facilitating novel and dependable strategies for reducing earthquake hazards and enhancing structure resilience. This study seeks to elucidate the present status of ANN applications and their capacity to enhance seismic performance assessments.

1.0 Introduction

Malaysia is frequently regarded as a country with low to moderate seismicity due to its location in the relatively stable Southeast Asia region (Figures 1 and 2). As a result, earthquake-resistant design has not been prioritized in structural engineering practices [1]. However, the unpredictable nature of natural disasters, including earthquakes, highlights the need for a reassessment of such assumptions. Earthquake, characterized by ground shaking or failure caused by sudden release of energy in the Earth's crust [2], often result in significant structural damage and pose serious risk to human lives and socioeconomic stability. Tectonic plate movements, friction, and resulting seismic events necessitate building designs capable of withstanding such impacts [3]. Structures subjected to near-fault ground vibrations, for example, may require reinforcement to maintain performance and ensure safety [4].

In response to these challenges, researchers have explored seismic performance evaluation methods, employing both analytical and experimental approaches. These methodologies simulate and analyse structural responses, providing valuable insights for incorporating seismic considerations into design processes [5]. Factors such as structural configuration, dynamic properties, and the characteristics of seismic ground motion play critical roles in determining a structure's seismic performance [4]. Recent advancements in artificial intelligence, particularly artificial neural networks (ANNs), have significantly enhanced seismic performance assessment in structures. ANNs, inspired by the human brain's neural architecture, excel in modelling complex, nonlinear relationships, making them invaluable in earthquake engineering [6]. Unlike traditional linear regression models, which rely on simplified assumptions about

*Corresponding Author | Che Osmi, S. K. | sitikhadijah@upnm.edu.my

the relationship between intensity measures and damage measures (e.g., tunnel lining bending moment capacity) [7], ANNs can model complex, nonlinear behaviours, offering more accurate predictions of structural responses during earthquakes. For example, Malik et al. [8] introduced a physics-informed recurrent neural network to evaluate the seismic response of nonlinear systems, demonstrating improved accuracy over conventional finite element analyses. Similarly, Zhang et al. [9] proposed a physics-informed neural network (PINN) framework that effectively predicts seismic responses of structures and has been validated through numerical simulations and experimental data.

Additionally, ANNs have been applied to various structural forms, including rocking structures. Shen and Malaga-Chuquitaype [10] developed a physics-informed convolutional neural network to predict the seismic response of rocking structures, achieving high accuracy in response history estimations. These innovations emphasize the potential of ANN-based models to overcome limitations in traditional approaches, such as their inability to fully account for the nonlinear dynamic response of structures [11]. Comprehensive reviews, such as the one by Xie [12], further highlight the growing interest in deep learning applications within earthquake engineering, draw attention to the ability of ANNs to address challenges like uncertainty in earthquake occurrences and complex structural behaviours.

Along this line, this study aims to review the current research on application of ANNs in seismic performance evaluation, focusing on their ability to model complex structural behaviours and enhance the reliability of seismic design practices, by identifying the gaps in traditional methodologies and highlighting the potential of ANN-based approaches, this work contributes to advancing innovative tools for mitigating seismic risk and improving resilience in the built environment.

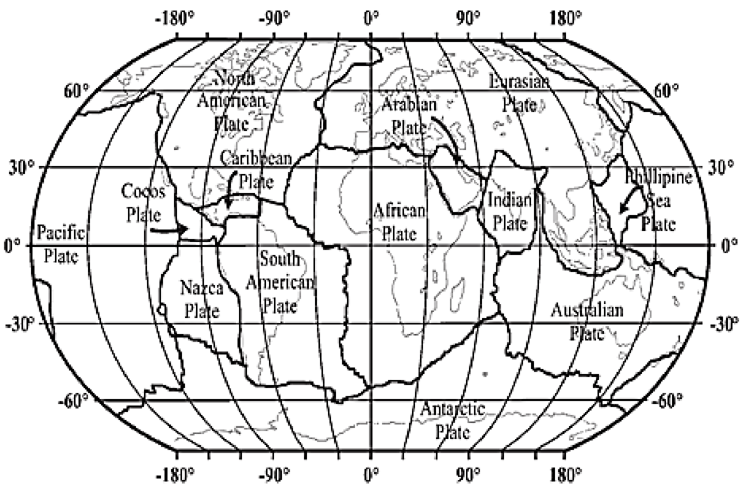

Figure 1. World tectonic plates [13]

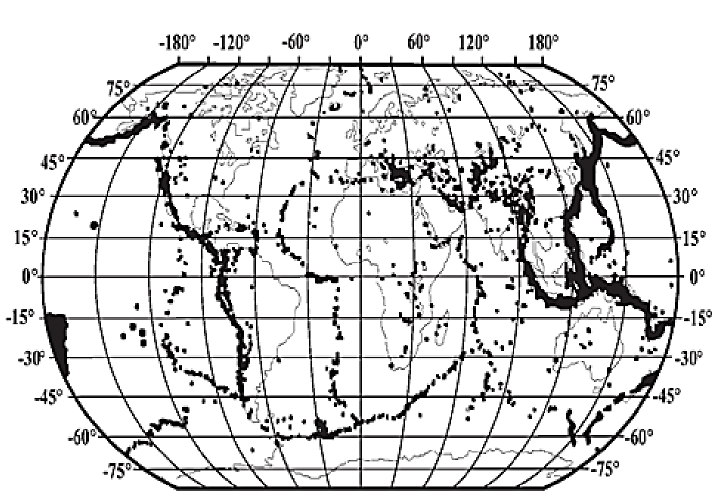

Figure 2. Location of earthquake epicentre on world [14]

*Corresponding Author | Che Osmi, S. K. | sitikhadijah@upnm.edu.my

2.0 ARTIFICIAL NEURAL NETWORKS (ANN)

2.1 Definition

Theories and models regarding how the brain functions sensory input are the basis for inspiration for artificial neural networks and it create ANN by modelling the neural networks model [15]. Neural networks known as artificial neural networks or Simulated Neural Networks (SNN) have been gaining popularity in the civil engineering field in the past decades [16] such as in geotechnical, structural, and water resources engineering on the strength of the flexible system that can modify its structure according to both internal and external information in any circumstance [4]. The processing units of an artificial neural network are called neurons which consist of input and output as hidden layers such as in Figure 3 where the algorithm imitates the structure and behaviour of the biological neuron to have the same function as a brain which accommodates the function to determine the activation of its neuron [6].

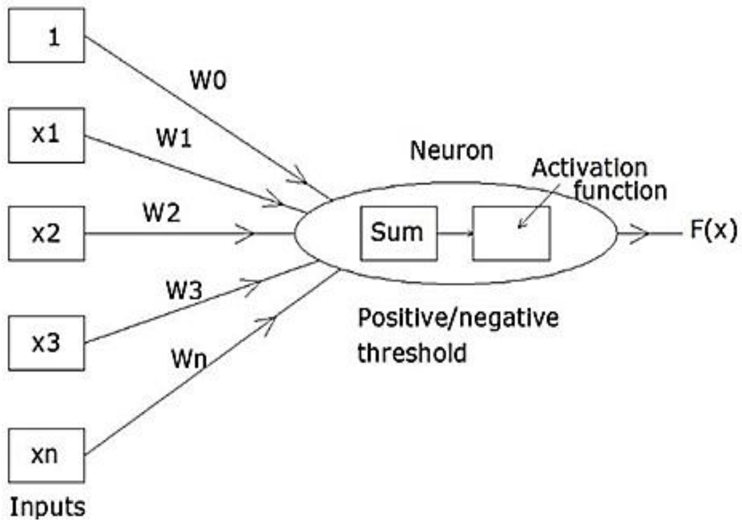

Figure 1. Artificial neuron model [6]

2.2 Application of ANN

In successfully entering the engineering field as a model of brain function, it acts as an impressive regression tool and has the capability can capture complex and various interactions of situations better than the traditional way [4]. The application of ANN has been utilized in various research which can be divided into four categories of prediction, classification, data association, and data filtering which gives an impressive output. Prediction. This is the sturdy network for engineering estimations where it is frequently operated the backpropagation network model using the input values to obtain the prediction through the output data. Classification. Commonly used in the recognition of patterns using the input values. Data association. To identify the classification of data, simulation is being used along with detecting the incorrect data. Data filtering. Used to analyse the data input and produce a smooth output value for the simulation [6].

2.3 Training process

Artificial neural networks are made up of many nodes and their connection [17] which is stated as an imitation of the human brain. Liu Z. et al. [17] also state the connection in ANN is used to provide the transmission values known as weight which is a memory of the artificial intelligence to obtain the prediction or estimation for the seismic performance of a structure from the input data through the learning process. ANN is divided into two groups which are supervised and unsupervised learning methods [6]. The most used method in the training of ANN is back propagation neural network (PBNN) which is a supervised learning method and feed-forward neural networks (FFNN). It is commonly utilized for the classification and prediction of training data. The architecture of ANN is the perception consisting of two inputs and one output for a single neuron that are classified into two classes for data classification. In a flexible system, ANNs can adapt their structure in response to internal and external information that spreads throughout the network [4].

*Corresponding Author | Che Osmi, S. K. | sitikhadijah@upnm.edu.my

As mentioned above, BPNN is most used especially for more complex applications or data besides multilayer perceptions (MLP) that contain input, output, and hidden layers as in Figure 4. The author in [6] also mentioned the outputs of hidden layers in the BP algorithm are propagated to the output layer, where the output is computed. For the specified input, this output is compared to the desired output. Epochs refer to this progressive motion from input to output and from output to input. A collection of known input data is initially sent to a neural network, and it is then instructed to produce a known output. The network is trained in this approach. The network continues through numerous iterations of this kind until the error (difference between the expected and actual output) is within a predetermined tolerance. The network is now recognized as trained. The weights between all the neurons in all the layers are set throughout the training phase. The weights obtained in this method from a neural model are used to determine how the network will react to unknown data.

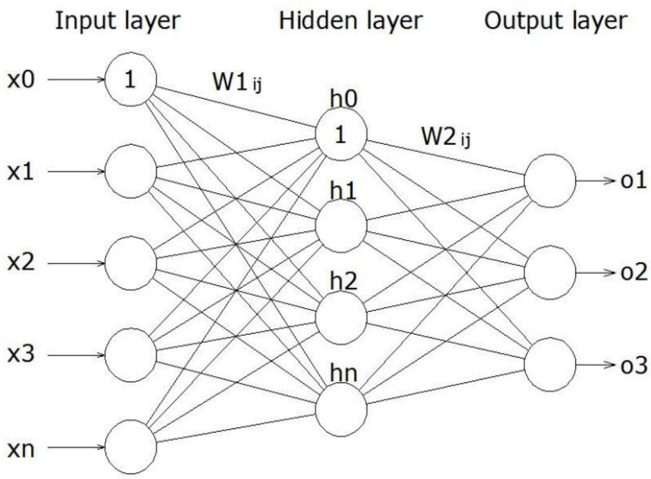

Figure 4. Architecture of artificial neural networks [6]

2.4 Advantages and limitation

The interest in using ANN is because of its capability to provide a prediction or estimation to any engineering problem and it also has lots of advantages by becoming a reliable method compared to the traditional way. ANN is an adaptive learning network where it can adapt and able to learn and solve a task based on the given data through experience or training. It can also be organized by itself based on the information given and it can carry out the computation of data simultaneously in real time. Besides, ANN is a fault tolerance with messy and incomplete data to give an output [15]. The human brain is slower than ANN in processing data such as data classification, pattern recognition, and unclear data. However, ANN cannot be employed when the data input and output as well as the task that must be done is precisely known [6].

3.0 SEISMIC PERFORMANCE

Academics in the engineering community have consequently focused a great deal of attention and research interest on the characteristics of near-fault ground motion and the associated seismic reactions of constructions [18]. To study the optimum performance of a structure when subjected to seismic loading, lots of methodologies have been proposed by researchers [19] based on several earthquake events that happened worldwide such as the Longxi tunnel during the Wenchuan earthquake (2008), the Daikai subway station in 1995 during Kobe earthquakes, 1999 Chi-Chi earthquakes which involve tunnel, 1989 Loma Prieta and 994 Northridge in California, Kocaeli in Turkey in 1999 and the effect of 2004 Indian Ocean Tsunami [18], [20]–[23]. However, the earthquake disaster is primarily brought on by the damaging effect of existing reinforced concrete framed buildings rather than ground movement [24]. The comparison of design features between the above and underground structure is the kinematic loading force acting on the structure that influenced the seismic behaviour [25]. Since the seismic impact on structure, soil-structure interaction is taken into consideration during the seismic design process for a structure which is more efficient and cost-effective and produces a safer structure compared to the fixed base design process [26].

Machine learning (ML) successfully offers fresh perspectives on how to evaluate a structure's vulnerability and seismic performance such as using artificial neural networks to describe the relationship

*Corresponding Author | Che Osmi, S. K. | sitikhadijah@upnm.edu.my

between the damage intensity measure (IM) and demand measure (DM) of ground motion [27]. This is due to the relation between the identified ground motion and the designated maximum allowable damage state of the structure to assess its seismic response and performance [24]. However, the response of the above and underground structures is different such as in Figure 5 as the surrounding soil inertia is higher than the underground structure itself thus it is controlling the response of the embedded structure while the above structure remains at the same position after the inertia forces is applied to it [28].

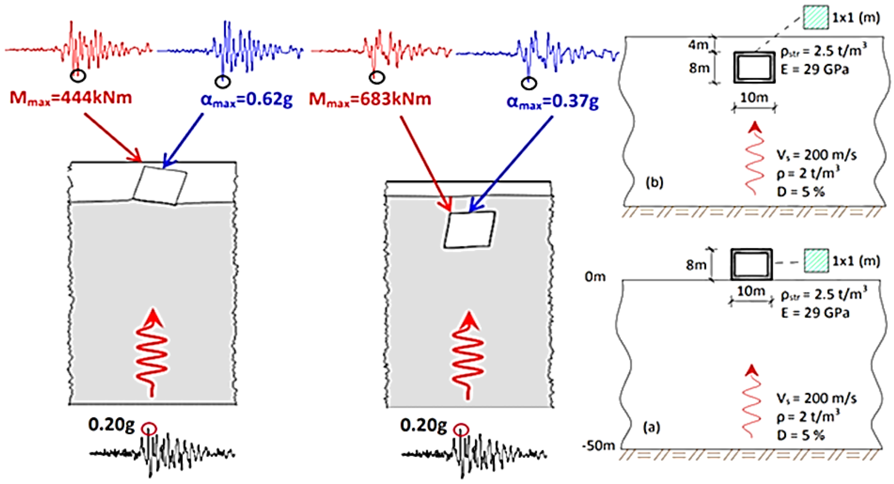

Figure 5. Seismic response of a structure above and underground [28]

Offering an alternative solution in describing the structural vulnerability, Huang P. and Chen Z. [27] developed the fragility curves for two-story and three-span subway stations through a combination of ANN-based trend model and Probabilistic Neural-Network (PNN)- based error model to form a complete Probabilistic Seismic Demand Model. The approached PSDM in this study offers the estimation error of the Demand Measures (DM) predicted by using a statistic-based trend model compared to previous ANN-based PSDM which used the physical-mechanism-based numerical model. The results through the combination of trend and error model indicated that the assumption of column drift ratio is accurately predicted, as well as the error model in evaluating the heteroscedasticity of the error between the predicted seismic responses and the actual values. In obtaining a reliable result of seismic vulnerability, the efficient intensity measure should be taken to give an output that relatively has low dispersion in the seismic response of the examined structure [11].

4.0 CONCLUSION

This study emphasises the utilisation of artificial neural networks (ANNs) as an effective instrument for assessing the seismic performance of structures subjected to earthquake loads. The review indicates that artificial neural networks, because to their capacity to model complex and nonlinear interactions, surpass conventional methods in both accuracy and efficiency, especially in forecasting seismic vulnerability. Leveraging artificial neural networks, researchers have created sophisticated models such as the probabilistic seismic demand model (PSDM), which offer dependable forecasts of structural performance for both aboveground and subterranean structures. The results highlight the capability of artificial neural networks to tackle issues in earthquake engineering by promoting the creation of resilient designs and alleviating the socioeconomic effects of seismic occurrences. Artificial Neural Network (ANN) methodologies can optimise the seismic analysis procedure, decreasing computing duration while preserving high accuracy, which is essential for extensive engineering endeavours. This strategy enhances cost-effective and sustainable construction operations by facilitating improved risk assessment and resource allocation.

Future research should concentrate on the integration of artificial neural networks with real-time monitoring systems to improve early-warning capabilities and dynamic reaction analysis during seismic events. Moreover, extending ANN applications to encompass a wider array of structural typologies and materials could enhance their reliability and versatility. This work enhances the application of artificial intelligence in seismic analysis, facilitating novel solutions in earthquake engineering and promoting safer, more robust built environments.

*Corresponding Author | Che Osmi, S. K. | sitikhadijah@upnm.edu.my

5.0 CONFLICT OF INTEREST

The authors declare no conflicts of interest.

6.0 AUTHORS CONTRIBUTION

Hafizi, N. (Simulation work; Writing- contributed to manuscript drafting)
Che Osmi, S. K. (Writing - critical revision of the article for important intellectual content)
Mohd Fazully, M. F. I. (Conceptualization; Literature review; Writing - original draft)
Othman, M. (Writing- contributed to manuscript drafting)
Hashim, F. R. (Simulation work)

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*Corresponding Author | Che Osmi, S. K. | sitikhadijah@upnm.edu.my