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BENBOKHARI Abdellatif

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**PERFORMANCE AND VULNERABILITY BASED SEISMIC
DESIGN USING ARTIFICIAL INTELLIGENCE: CASE OF FRAMED
STRUCTURES**

Defended on 23/02/2025, before the jury composed of:

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Invité

I would like to dedicate this thesis to my family, especially my parents for their continuous and unlimited support. Your prayers and kind words have been my source of motivation. There are no words that can explain how deeply grateful I am.

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ملخص

يعد التصميم الزلزالي خطوة أساسية لضمان استقرار المنشآت وقدرتها على مقاومة القوى الزلزالية. بالنسبة للمباني الحيوية والاستراتيجية، مثل المستشفيات، فإن أدائها أثناء الزلازل أمر بالغ الأهمية. وهنا يأتي دور التصميم الزلزالي القائم على الأداء (PBSD)، المعروف بتعقيده واعتماده غالباً على التحليل الزمني غير الخطي (NLTHA)، الذي يتطلب وقتاً طويلاً. قد تستغرق عملية إيجاد التصميم الزلزالية المثلى ساعات أو حتى أياماً.

في هذه الأطروحة، يتم اقتراح نهج جديد يستبدل استخدام البرامج الإنشائية والأساليب العددية مثل NLTHA لتحديد أداء المنشآت أثناء الزلازل. يعتمد النهج المقترح على الذكاء الاصطناعي (AI) ويتكون من خطوتين رئيسيتين. تركز الخطوة الأولى على تحديد أفضل نموذج تعلم آلي ((LM)) قادر على التنبؤ بالاستجابات الزلزالية، بما في ذلك نسبة الانحراف القصوى بين الطوابق (MIDR)، وقوى القص القاعدية القصوى ((MBS))، ونسبة انجراف السقف القصوى (RDR). يتم استخدام خوارزميات تقليل الأبعاد لتحسين دقة التنبؤ من خلال تقليل عدد المدخلات وإعادة توجيه المحاور الأصلية إلى محاور جديدة.

تشمل الخطوة الثانية استخدام تحسين الأهداف المتعددة ((MOO)) لإيجاد أفضل تصميم يحقق التحقق المزدوج من الأداء تحت مستويين من شدة الزلازل، مع الأخذ في الاعتبار درجة الضرر وتكلفة الإنشاء الأولية.

للتحقق من صحة هذا النهج، تم اختيار ثلاثة إطارات مقاومة للعزوم الخاصة ((SMFs)). تم تصميم هذه الإطارات باستخدام كل من التصميم القائم على القوة ((FBD)) والنهج المقترح القائم على الذكاء الاصطناعي. تم إجراء تحليل مقارنة لسلوك التصميم لتقييم فوائد النهج المقترح مقارنةً بالتصميم التقليدي. أظهرت النتائج أن النهج المقترح قلل بشكل فعال التكلفة الأولية، وحسن نسبة درجات الضرر، وخفض احتمالية تجاوز مستويات الضرر. بالإضافة إلى ذلك، ضمن النهج المقترح عدم تجاوز الانحراف بين الطوابق ((ISD)) للحد المسموح به تحت مستويات الزلازل الشديدة، على عكس تصميم (FBD).

بشكل عام، نجح النهج المقترح في تحقيق توازن بين التكلفة والأداء في التصميم الإنشائي مع تقليل وقت المعالجة. توفر هذه الطريقة السريعة والدقيقة تصاميم أكثر كفاءة دون الحاجة إلى موارد كبيرة.

الكلمات المفتاحية: التصميم الزلزالي القائم على الأداء، والذكاء الاصطناعي، والتحسين متعدد الأهداف، والتنبؤ بالاستجابة الزلزالية، وتحليل التاريخ الزمني غير الخطي، وتحليل الدفع.

Abstract

Seismic design is a crucial step in ensuring structural stability and the capacity to withstand seismic forces. For critical and strategic buildings, such as hospitals, performance during an earthquake is vital. This is where performance-based seismic design (PBSD) comes into play. PBSD is known for its complexity and often relies on Nonlinear Time History Analysis (NLTHA), which can be time-consuming. The process of finding optimal seismic designs can take hours or even days.

In this thesis, a new approach is proposed that replaces the use of structural software and numerical methods like NLTHA for determining structural performance during an earthquake. The proposed AI-based approach is divided into two main steps.

The first step focuses on identifying the best Machine Learning (ML) model capable of predicting seismic responses, including Maximum Inter-story Drift Ratio (MIDR), Maximum Base Shear (MBS), and Maximum Roof Drift Ratio (MRDR). Dimensionality reduction algorithms are employed to enhance ML predictions by reducing input features and re-orienting the original axes to new ones. The second step involves using Multi-Objective Optimization (MOO) to find the best design that satisfies a dual performance check under two seismic intensity levels, taking into account damage grade and initial construction cost. To validate this approach, three special moment frames (SMFs) were selected. Both Force-Based Design (FBD) and the AI-based approach were used to design these SMFs. A comparative analysis of the design behavior was performed to evaluate the benefits of the proposed approach relative to FBD. The results indicated that the proposed approach effectively reduced the initial cost, improved the damage grade ratio, and lowered the probability of exceeding damage levels. Additionally, the proposed method ensured that the inter-story drift (ISD) did not exceed the fixed performance threshold for extensive earthquake levels, unlike the FBD design.

Overall, the proposed approach successfully balanced cost and performance in structural design while reducing processing time. This fast and accurate method allows for quicker and more efficient designs without the need for extensive resources.

Keywords: Performance-based seismic design, Artificial Intelligence, multi-objective optimization, seismic response prediction, Nonlinear time history analysis, pushover analysis.

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Nomenclature

DPM	Damage Probability Matrix
VIM	Vulnerability Index Method
I_v	vulnerability index
HAZUS	Hazard US
NIBS	National Institute of Building Science
FEMA	Federal emergency management agency
PSHA	Probabilistic Seismic Hazard Analysis
IDA	Incremental Dynamic Analysis
ISA	Incremental Static Analysis
MIDR	Maximum inter-story drift ratio
EDP	Engineering demand parameters
CDF	Cumulative density functions
GDr	Global damage ratio
D_r	Damage ratio
AI	Artificial intelligence
ML	Machine learning
KNN	K-nearest neighbor
ASM	Attribute selection measure
ANN	Artificial neural network
NSE	Normalized squared error
CEE	Cross entropy error
NSGA-II	Non-dominated Sorting Genetic Algorithm II
PSO	Particle Swarm Optimization
GA	Genetic Algorithms
MOOPSO	Multi-Objective Particle Swarm Optimization
MOO	Multi-objective optimization
AGM	Artificial ground motions
MBS	Maximum base shear
MRDR	Maximum roof drift ratio
MIDR	Maximum inter-story drift ratio
R²	Correlation coefficient
PBias	Percent bias
RSR	RMSE-Standard Deviation Ratio
RMSE	Root mean squared error
NLTHA	Nonlinear time history analysis
δ_y	Yield displacement
δ_u	Ultimate displacement
V_y	Yield shear
V_u	Ultimate base shear
μ_u	Ultimate ductility
μ_d	Displacement demand
V_d	Shear demand

Chapter 1

Introduction

Seismic design is a critical aspect of civil engineering that ensures structures can withstand the destructive forces of earthquakes. Its importance goes beyond the structural integrity of buildings; it significantly impacts socio-economic stability and damage control, particularly for strategic buildings such as hospitals, schools, and government facilities. From a socio-economic perspective, effective seismic design minimizes both direct and indirect costs associated with earthquake damage. Direct costs include the immediate expenses for repairing or reconstructing damaged structures. Indirect costs encompass economic disruptions, such as business interruptions, loss of productivity, and the long-term economic burden on communities and governments. By reducing these financial impacts, seismic design contributes to the overall economic resilience of a region.

In terms of damage control, properly designed structures can prevent catastrophic failures, thereby reducing casualties and injuries during an earthquake. This is particularly crucial for strategic buildings that serve as critical infrastructure during emergencies. Ensuring that hospitals remain operational, schools can serve as shelters, and government buildings can coordinate relief efforts is essential for effective disaster response and recovery.

Moreover, the psychological impact of resilient structures should not be underestimated. Communities that trust in the safety of their buildings are better equipped to respond to and recover from seismic events. This trust can foster a quicker return to normalcy and support long-term social stability. Choosing the appropriate seismic design philosophy depends on various factors, including the type of structure, expected seismic intensity, desired performance objectives, and available resources.

Performance-based design (PBD) is ideal for high-value and critical infrastructure, ensuring specific performance outcomes. Force-Based Design (FBD) is straightforward and aligns well with basic code compliance for conventional buildings. Capacity-based design (CBD) is crucial for ensuring controlled and ductile failure modes and enhancing safety. Displacement-based design (DBD) provides a realistic assessment of structural behavior, leading to resilient designs in high seismic regions. Each philosophy has its strengths and limitations, and the selection depends on balancing these factors to achieve optimal

seismic performance.

1.1 Research Problem or Question

PBD is known for its complexity and time consuming due to the use of NLTHA. Finding the best design may take several hours or days to achieve depending on several factors (structural complexity, number of selected ground motions, ground motion record duration).

Recently, the integration of machine learning (ML) techniques in seismic design has gained traction, promising more efficient and equally reliable alternatives. The central question of this research is: "Can machine learning techniques, specifically Artificial Neural Networks (ANN) and optimization algorithms, effectively replace traditional NLTHA methods in the performance-based seismic design of special moment RC frames?" This question addresses the need for more efficient, scalable, and accessible seismic design methods in structural engineering.

1.2 Objectives

In this study, our main goal is to create a machine learning-based framework for performance-based seismic design. We aim to show that this framework is effective and useful compared to traditional methods. Our specific objectives are as follows:

1. Develop an alternative method for Nonlinear Time-History Analysis (NLTHA) using machine learning. We will achieve this by creating a machine learning model using an artificial neural network (ANN) to analyze the relationships between input and output data. To ensure accurate predictions, we will need a large dataset.
2. Use hybrid machine learning models including the use of dimensionality reduction techniques (Auto-encoder and principal component analysis).
3. an investigation on the effect of the hybrid methods on the performance of the training of the model.
4. implementing a multi-objective optimization (MOO) algorithm to find the best models for predicting seismic responses. This process involves determining fitness functions to optimize and using the MOO algorithm to identify the best designs meeting the code design requirements. The structural parameters are selected randomly in the MOO process and then validated using ACI 318-19 and ASCE codes. Finally, a

selection protocol will be used to identify the best design from the multiple solutions provided by the MOO algorithm, as none of the solutions is considered unique.

1.3 Organization of the dissertation

The thesis consists of seven chapters:

1. **Chapter 1:** An introduction to the thesis, presenting the research problem, objectives, key questions, and overall structure.
2. **Chapter 2:** A literature review about the machine learning use in seismic response prediction and the use of MOO in the seismic design.
3. **Chapter 3:** General overview of seismology and signal processing of ground motions, including techniques such as selection, matching, scaling, and ground motion parameters.
4. **Chapter 4:** Summary of seismic design analysis procedures used in civil engineering. It also covers the performance analysis of structures, comparing NLTHA with procedures adopted by FEMA-356 and FEMA-440 for seismic demand estimation.
5. **Chapter 5:** Presentation of seismic vulnerability assessment methodologies used to evaluate structural fragility, including an explanation of relevant terminologies.
6. **Chapter 6:** Summary of artificial intelligence techniques and machine learning algorithms, along with a discussion of various optimization algorithms.
7. **Chapter 7:** Introduction of a new hybrid machine learning algorithm to enhance seismic response prediction using unsupervised and supervised machine learning algorithms.
8. **Chapter 8:** Presentation of the proposed AI-based methodology to identify the best design for special moment frame RC structures. The methodology is based on the procedure proposed in Chapter 7 and multi-objective optimization.

Chapter 2

Literature review

2.1 Introduction

This thesis aims to propose a seismic design methodology that utilizes a precise deep learning model within a multi-objective optimization algorithm to determine the most optimal design. This design will aim to strike a balance between performance, damage resistance, and cost. The focused application will be on special moment frames within reinforced concrete structures. This part will cover a literature review of recent works about two fields:

- Seismic response prediction using ML.
- Seismic design optimization using MOO and ML-MOO.

2.2 Seismic response prediction using ML

Machine learning for seismic response prediction is an innovative field of research. Thanks to processor advancements, computers can now effortlessly handle complex computation tasks.

Salimi et al. [6] used ML methods to develop seismic fragility curves for reinforced concrete moment-resisting frames. They found that ML methods demonstrated comparable results to traditional approaches while significantly reducing computational costs and enhancing efficiency in seismic risk assessments. Kazemi et al. [7] developed an ML-based framework for the seismic evaluation of framed structures, incorporating soil-structure interaction (SSI) parameters. The framework was validated against conventional methods, demonstrating that the ANN provided superior accuracy in predicting engineering demand parameters (EDPs) compared to traditional approaches. The results indicated that the ANN reduced overestimation errors significantly, enhancing the reliability of seismic assessments and offering a robust tool for structural engineers in seismic design.

Noureldin et al. [8] employed ML algorithms to predict the seismic response and performance of reinforced concrete (RC) buildings. The methodology includes training ML models using datasets generated from Incremental Dynamic Analysis (IDA) performed on 165 RC moment-resisting frames (MRFs) with varying configurations. The study utilizes various ML techniques such as Boosting algorithms and Support Vector Machines (SVMs), achieving high prediction accuracies for maximum inter-story drift ratio (MIDR) and seismic limit-state capacities. The proposed models are validated on case study buildings, demonstrating accuracies above 87% for all scenarios. Additionally, a Graphical User Interface (GUI) is developed for practical application of the models. Oliver and Piotr [9] presented a method for predicting seismic-induced damage in 2D reinforced concrete (RC) frames using Artificial Neural Networks (ANNs). The approach involved describing both the structure and ground motion using various properties. Dynamic structural responses were simulated using nonlinear finite element method (FEM) analysis. Damage indices were calculated to quantify the extent of the damage. The input parameters for the ANN included 13 structural properties and 6 ground motion properties, such as the number of stories, bay width, beam and column dimensions, reinforcement ratios, concrete strength, damping ratio, Peak Ground Acceleration (PGA), Peak Ground Velocity (PGV), Peak Ground Displacement (PGD), Spectrum Intensity (SI), dominant frequency, and effective duration. The ANN was then trained to map these inputs to the calculated damage indices. Lagaros and Papadrakakis [10] developed an ANN for seismic time-history prediction of 3D buildings. The findings demonstrate that the ANN-based prediction scheme can effectively predict the non-linear seismic response of 3D reinforced concrete buildings. The predicted results show good agreement with the results obtained from Finite Element Analysis (FEA), highlighting the potential of ANN models to serve as a reliable alternative for seismic response prediction. The use of both adaptive and non-adaptive schemes showed promising results, with the adaptive scheme providing slightly better performance due to its ability to update the model parameters dynamically during the prediction process.

machine learning also showed a good performance in other type of structures, like bridges [11–14], steel structures [15–19], masonry buildings [20–22]. It was also used for crack identification and damage assessment [23–26].

The literature review demonstrated that the ML represents a high-performance alternative for complex deterministic and analytical approaches such as NLTHA, which is known for its complexity and time-consuming. In some other research papers, supervised machine learning such as ANN was coupled with some dimensionality reduction algorithms like Principal components analysis (PCA) to reduce the input features. Few research has studied the impact of dimensionality reduction on the performance of ML models in terms of training time, and predictability. Marijana et al. [27] utilized principal component analysis (PCA) and artificial neural network (ANN) methodology to model

the entrepreneurial intentions of students efficiently. They compared different modeling strategies to assess the impact of classifying students' intentions and highlighted the importance of reducing input dimensions while maintaining accuracy. The model with variables extracted from principal component factors was found to be the most efficient in recognizing students with entrepreneurial intentions, while also reducing the time needed for data collection and model training. The study highlighted the benefits of combining PCA and ANNs in modeling entrepreneurial intentions and suggested further research in this area. Mohamed-Saleh et al. [28] investigated the use of the PCA technique to eliminate correlation in raw Electrical Capacitance Tomography (ECT) data to enhance the learning capability and generalization of a Multi-Layer Perceptron (MLP) system for estimating oil fraction from gas-oil flows. Two PCA data processors were implemented in MATLAB - a PCA pre-processor to eliminate correlation in training samples and a PCA post-processor to transform validation and test datasets. The PCA technique involved finding linear transformations of original components to create uncorrelated components. The results showed that using PCA to eliminate correlation in raw ECT data improved the MLP oil fraction estimation capability and reduced network training time due to dimensionality reduction. The study suggested that the PCA data processing method is useful for enhancing MLP performance in complex problems with many input data. Liu et al. [29] aimed to evaluate the performance of the HPCANN method compared to other neural-network-based approaches for detecting anomalies and misuse in intrusion detection systems. Results indicated that the HPCANN method outperformed other methods, achieving high detection rates (DR) and low false positive rates (FPR) for different intrusions such as DOS, R2L, and Probe. Specifically, the HPCANN model demonstrated exceptional performance in misuse detection, achieving 100% DR with an FPR lower than 1% for specific intrusions, and in anomaly detection, it achieved a DR of 97.1% with an FPR of 2.8%. These findings highlight the effectiveness and superiority of the HPCANN method in detecting various types of intrusions accurately and efficiently. In the civil engineering field, Wan et al. [30] compared four ML models for predicting the compressive strength of concrete. The methods include linear regression, support vector regression, extreme gradient boosting, and ANNs. The results indicate that linear regression has the poorest performance, while the support vector regression, extreme gradient boosting, and artificial neural network models show promising performance. Additionally, the study highlights the impact of dimensionality reduction on the models, particularly the positive effect on execution time for certain models. He also noted that this investigation was not thoroughly studied in this area. In this thesis, one chapter will focus on a detailed comparative study of the impact of dimensionality reduction on the performance of machine learning models and the dataset size. The best model from this study will be used in the proposed methodology for seismic design considerations.

2.3 multi-objective optimization for seismic design

Optimization is a vital topic in the engineering field. Its application is crucial for minimizing costs, dimensions, and design, as well as for enhancing performance. It can address multiple aspects simultaneously.

Sabbaghzade et al. [31] developed a Multi-Objective IGMM-based algorithm (MO-IGMM) for engineering optimization to achieve a set of non-dominated designs that represent the best trade-offs between conflicting objectives in structural design. They considered lifetime cost and injury cost as fitness functions where the endurance time method (ET) was used to estimate the seismic response of the building. They managed at the end to reduce the lifetime cost, injuries, and rental. Moller et al. [32] proposed a structural optimization procedure for PBD using NN. The study concludes that integrating neural networks into performance-based seismic design offers a powerful tool for optimizing structural designs. The approach meets reliability targets and minimizes costs, considering both initial construction and future repair needs. The flexibility, efficiency, and adaptability of neural networks make them ideal for handling the uncertainties and complexities of earthquake engineering. However, the generated dataset was limited to 5*900 samples, which may affect the model's generalizability. The structures were not checked for each iteration in the optimization process and the seismic parameters were not included in predicting the seismic responses which makes it related to the structural geometry only. Lopez et al. [33] presented an optimization framework for identifying effective above-code design improvements to meet building-specific recovery goals. By developing surrogate models, it enables rapid estimation of recovery performance and supports complex optimization. Using a case study of an office building, the study reveals that achieving a 21-day recovery target requires enhancing nonstructural components, as increasing structural strength can be counterproductive. For less ambitious targets, larger importance factors can negate the need for nonstructural improvements. These findings highlight that recovery-based design effectiveness is highly dependent on user-defined criteria. Hong et al. [34] successfully optimized 18 design variables for reinforced concrete RC frames using the ANN-based Hong-Lagrange algorithm, achieving cost reductions of up to 44.983% and weight reductions of 33.111%. High training accuracies were reported, with a mean square error of 1.2727E-04 and a regression value of 0.9991. The optimized designs were validated against conventional methods, demonstrating enhanced accuracy and reliability. However, the seismic load was a response spectrum analysis, not a nonlinear time-history analysis, and the nonlinear performance and behavior were not discussed in this work which makes it applicable to linear range only. Gholizadeh et al. [35] focused on the multi-objective performance-based seismic optimization of steel moment frames using an efficient algorithm. It aims to develop a framework for finding a Pareto front for the multi-objective optimization problem of steel moment frames, considering the global

damage index and initial cost as conflicting objective functions. The seismic performance and collapse capacity of the optimal designs are evaluated using damage indices and incremental dynamic analysis, assessing seismic damage costs and adjusted collapse margin ratios. By considering these aspects, the research aims to enhance the seismic resilience and safety of steel moment frames under earthquake loading conditions. Joyner et al. [36] employed a MOO methodology to enhance building resilience against seismic hazards, analyzing four building types (4, 7, 10, and 15 stories). It utilizes conditional and life span performance evaluations, applying the NSGA-II genetic algorithm for optimization. Findings reveal that a 2% increase in initial costs can reduce loss of function by 30%-45%. The ASCE 7 design criteria effectively optimize performance, particularly for 4, 7, and 15-story buildings. The pruned design alternatives support stakeholder decision-making by balancing resilience and cost, demonstrating the value of integrating resilience into seismic design. Other interesting works include the use of optimization algorithms with and without ML, for shear walls [37,38], and steel frames [39–41].

2.4 Conclusion

This chapter covers a general literature review about recent and relative researchs about the use of Machine learning in earthquake engineering for seismic response and fragility assessment of structures and the use of optimization algorithm in seismic design.

Chapter 3

Seismology and signal processing

3.1 Introduction

The seismic response of structures critically depends on the seismic records. Initially, the accelerograms were recorded using photographic film and needed to be digitized to assess their characteristics accurately. After the invention of the digital accelerograph, recorded data became more accessible with improved quality and resolution. This chapter will explain the ground motion (GM) characteristics and how GMs should be processed before they are used in structural analysis.

3.2 Seismology and ground motion characteristics

Magnitude and Intensity are the most common terms in earthquake engineering. Firstly, the magnitude is the released energy at a fault zone related to the Richter scale [42, 43]. It depends on the fracture's length and transversal dimension that happens in the fault. It depends on the fracture's length and transversal dimension that happens in the fault. An earthquake of magnitude eight can involve a fault slip that reaches 400 km and releases energy exceeding that of the largest tested nuclear bomb [42, 44].

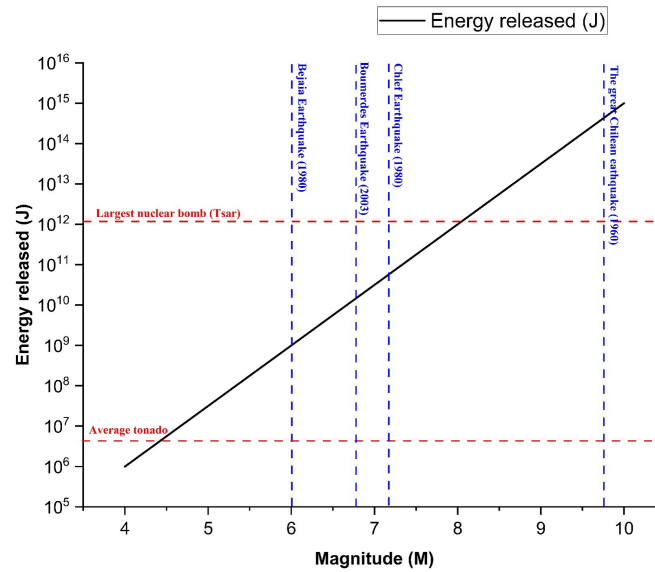


Figure 3.1: Magnitude and released energy relationship

Figure 3.1 shows that the energy released is proportional to the magnitude of the power of 1.5. Low-magnitude earthquakes occur frequently and have the highest annual probability of occurring. Intensity depends on earthquake magnitude, distance to the fault, rupture mechanism, and soil types/ground conditions at and between the site and fault. Mercalli scale was used in the past to assess the earthquake intensity and its effect descriptively [45]. Various attempts have been made to correlate measurable record characteristics such as peak ground acceleration (PGA), peak ground velocity (PGV), and peak ground displacement (PGD) to the structural damages that occur after an earthquake, but none of them have been successful. It is impossible to find two identical accelerograms even if they have the same magnitude, source, duration, or PGA (same for PGV and PGD).

Figure 3.2 shows two ground motions (The Friuli (Italy) earthquake of May 06, 1976. Recording station: TOLMEZZO (000) and The Kocaeli (Turkey) earthquake of August 17, 1999. Recording station: YARIMCA (KOERI330). The figure illustrates that even the GMs have almost the same PGA, but they have different velocity and displacement ground motions due to the frequency and amplitude content of each of them.

3.3 Time history development

Studying the dynamic response of structures using ground motions is a crucial step in assessing their behavior under earthquake conditions. Choosing the most appropriate ground motions is vital for an accurate analysis. Dynamic analysis uses two types of ground motions: real records and artificially generated ground motions. Real GMs are recorded ground shakings during an earthquake event at specific stations. These records

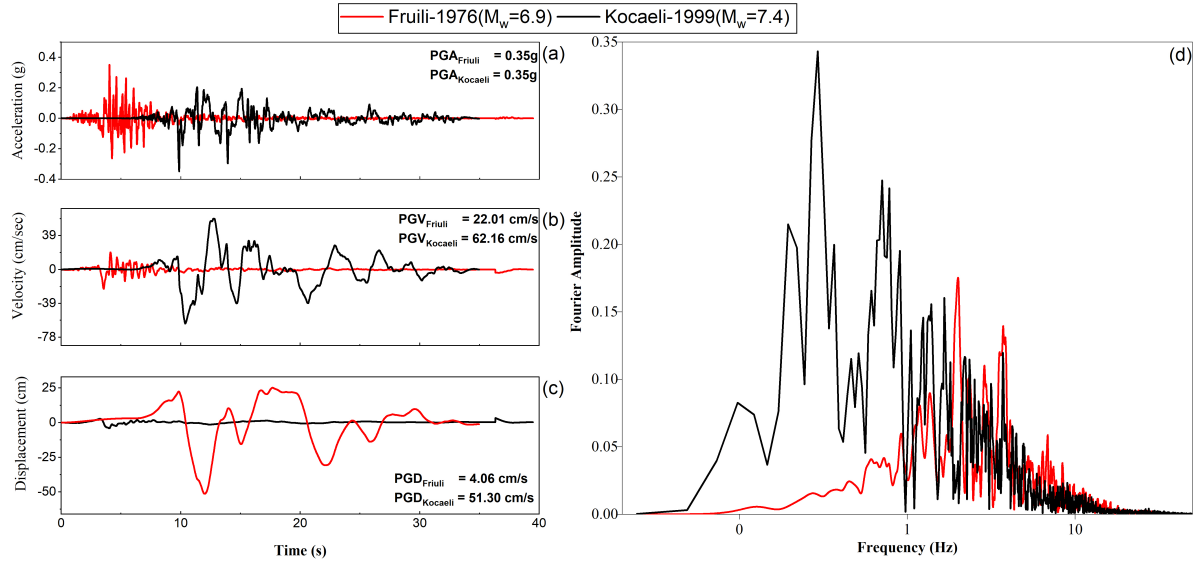


Figure 3.2: Comparative study between two GM characteristics: a) acceleration, b) velocity, c) displacement, and d) frequency content

vary depending on the stations' location, distance, and soil condition. Real GMs are convenient for dynamic analysis (linear, nonlinear, incremental) as they represent ground shakings that may occur in the future, with similar characteristics such as intensity, frequency content, and velocity. Studying the dynamic response of structures using ground motions is a crucial step in assessing their behavior under earthquake conditions. Choosing the most appropriate ground motions is vital for an accurate analysis. Dynamic analysis uses two types of ground motions: accurate records and artificially generated ground motions. Real GMs are recorded ground shakings during an earthquake event at specific stations. These records vary depending on the stations' location, distance, and soil condition. In addition, the actual earthquake time history retains natural variance regarding spectral acceleration, and its variability is real. However, these existing ground motions are sometimes unavailable or insufficient to perform a time history analysis in some places with different soil conditions. On the other hand, artificial ground motions (AGMs) solve the problem of availability and variability. They are easy to generate and control, allowing analysts to customize their characteristics [46, 47]. As shown in Figure 3.3, the response spectra of the produced artificial ground motion (AGM) are compared to an actual ground motion (GM) - EL-Centro. The AGM was generated so that its spectral acceleration matches the real GM with a mean error of 9.59%. Similarly, the velocity and displacement of AGM were also compared to the actual GM's.

3.4 Ground motion Parameters

Each ground motion has its unique characteristics in terms of acceleration, displacement, velocity, and frequency content. Due to fault sources, magnitude, location, and soil

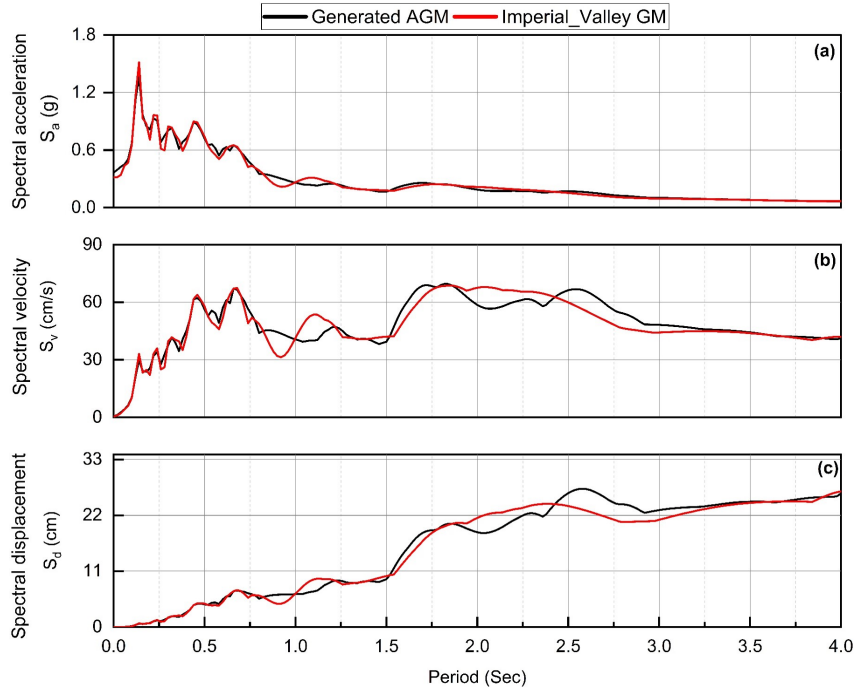


Figure 3.3: The response spectra of the generated artificial ground motion ($M_w = 7.0$) and matched into Imperial-Valley GM (EL-Centro): a) acceleration, b) velocity, and c) displacement

conditions, finding identical earthquake records in history is impossible. These differences make each record specific to the ground motion it represents and can be characterized by many features that can serve as identifying information. Many researchers and parameters have been introduced to study the recorded signal feature.

3.4.1 Peak Ground Acceleration (PGA)

PGA measures the maximum absolute acceleration that occurs during an earthquake. It is commonly used as a seismic feature to characterize the intensity of a ground motion and the seismic demand on structures. The PGA is expressed in units of gravitational acceleration (g), with 1 g representing the acceleration due to gravity at the Earth's surface. The higher the PGA value, the stronger the ground motion and the greater the potential for damage to structures and infrastructure. Therefore, accurate estimation of the PGA is crucial for seismic hazard assessment and earthquake engineering.

3.4.2 Peak Ground Velocity (PGV)

PGV is a widely used parameter in earthquake engineering to quantify the intensity of ground shaking. PGV refers to the maximum velocity of the ground during an earthquake. It is measured in units of centimeters per second (cm/s). PGV is an important parameter

because it is closely related to the damage caused by an earthquake. The higher the PGV, the more likely it is that buildings and other structures will experience damage. Engineers use PGV measurements to design and construct buildings that can withstand the ground shaking caused by earthquakes. They also use PGV data to assess the potential damage to existing buildings and infrastructure after an earthquake has occurred.

3.4.3 Peak Ground Displacement (PGD)

PGD is another important parameter used in earthquake engineering to quantify the intensity of ground shaking. PGD refers to the maximum displacement of the ground during an earthquake. It is measured in units of centimeters (cm) or meters (m). PGD is an important parameter because it is closely related to the potential for ground failure and landslides. The higher the PGD, the more likely it is that slopes and other land features will experience deformation or failure.

3.4.4 Cumulative Energy (E_{cum})

The cumulative energy of a ground motion is an important characteristic that describes the total energy released during an earthquake. It is calculated by integrating the acceleration time history over time. The cumulative energy is directly related to the damage potential of an earthquake, and it is a key parameter in the design of earthquake-resistant structures. High cumulative energy ground motions are associated with long-duration earthquakes, which can cause significant damage to structures. On the other hand, short-duration earthquakes with low cumulative energy may not cause as much damage, but they can still be dangerous if the structures are not designed to withstand them. Therefore, it is important to consider the cumulative energy of a ground motion when designing earthquake-resistant structures. It can be calculated using Equation (3.1)

$$E_{cum} = \int_0^{T_d} (acceleration)^2 dt \quad (3.1)$$

3.4.5 Arias intensity (I_a)

Arias intensity is a useful parameter that quantifies the total amount of energy transmitted to a site or structure during an earthquake. It is widely utilized in engineering and seismology to determine the potential of an earthquake to induce damage, especially for structures that are sensitive to ground motion. Engineers employ this information to create and assess the earthquake resistance of buildings, bridges, and other infrastructure. It can be calculated using Equation (3.2)

$$E_{cum} = \frac{\pi}{2g} \int_0^{T_d} (acceleration)^2 dt \quad (3.2)$$

3.4.6 Cumulative Absolute Velocity (CAV)

it is calculated by integrating the absolute value of the acceleration vector as shown in Equation (3.3). It represents the area under the acceleration time series. The CAV includes also the effect of the ground motion duration which makes it an advantageous parameter that correlates with structural damage.

$$CAV = \int_0^{T_d} |acceleration| dt \quad (3.3)$$

3.4.7 Spectral responses

They represent the elastic spectral acceleration (S_a), velocity (S_v) and displacement (S_d) at the fundamental vibration period (T_1) and $\xi=5\%$ damping ratio. These parameters represent the maximum response in terms of acceleration, velocity and displacement of the first mode that represents the predominant vibration mode. They characterize the seismic demand of the structure when it is subjected to a ground motion. They can be calculated analytically using Equations (3.4), (3.5), and (3.6) or numerically as shown in Figure 3.4.

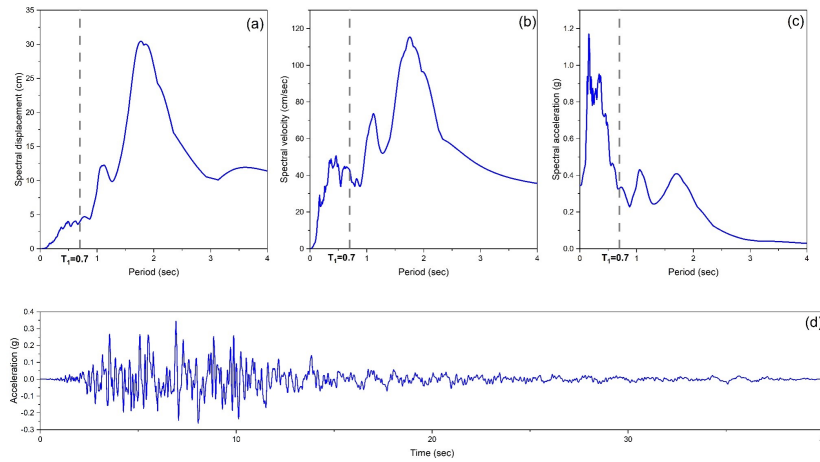


Figure 3.4: Response spectra of The Kobe (Japan) earthquake of January 16, 1995 “Source: PEER Strong Motion Database”: a) spectral displacement, b) spectral velocity, c) spectral acceleration, and d) acceleration time series.

$$S_d(T_1, \xi = 5\%) = \frac{1}{m} \max \left(\left| \int_0^t p(\tau) \exp(-\xi_n(t - \tau)) \sin[D(t - \tau)] d\tau \right| \right) \quad (3.4)$$

$$S_v(T_1, \xi = 5\%) = \frac{2\pi}{T_1} S_d(T_1) \quad (3.5)$$

$$S_a(T_1, \xi = 5\%) = \left(\frac{2\pi}{T_1} \right)^2 S_d(T_1) \quad (3.6)$$

3.4.8 Housner intensity (HI)

Housner intensity is a measure of earthquake ground motion intensity, which takes into account both the amplitude and frequency content of the motion. It is defined as the square root of the area under the pseudo-acceleration response spectrum, normalized by the peak ground acceleration. The Housner intensity is useful for comparing the effects of different ground motions on structures with similar natural periods. It is commonly used in earthquake engineering to assess the seismic performance of structures and to design earthquake-resistant buildings. The Housner intensity is named after the American engineer George Housner, who developed this measure in the 1950s. It can be calculated using Equation (3.7).

$$HI = \int_{0.1}^{2.5} PS_V(T, \xi = 5\%) dT \quad (3.7)$$

3.4.9 Acceleration, Velocity and displacement Spectrum Intensity (ASI, VSI, DSI)

The parameters measure the strength of the ground motions by calculating the area under the response spectrum of acceleration, velocity, and displacement. They are used for structures with high-frequency fundamental vibration modes, ranging from 10 Hz to 2 Hz. These parameters were first introduced by Von Thun et al. in 1988 [48] to evaluate the response of earth and rock-fill dams. Their equations are illustrated in Equation (12), Equation (13) and Equation (14).

$$ASI = \int_{0.1}^{0.5} S_a(T, \xi = 5\%) dT \quad (3.8)$$

$$VSI = \int_{0.1}^{0.5} S_V(T, \xi = 5\%) dT \quad (3.9)$$

$$DSI = \int_{0.1}^{0.5} S_d(T, \xi = 5\%) dT \quad (3.10)$$

3.4.10 Predominant period (PP)

it is the period that corresponds to the maximum spectral acceleration for a 5% damping ratio, as shown in Figure 3.5.

3.4.11 Duration

- **Uniform duration** (U_d): It represents the total duration during which the acceleration exceeds a fixed threshold of 5% of the PGA. (see Figure 3.6-a)

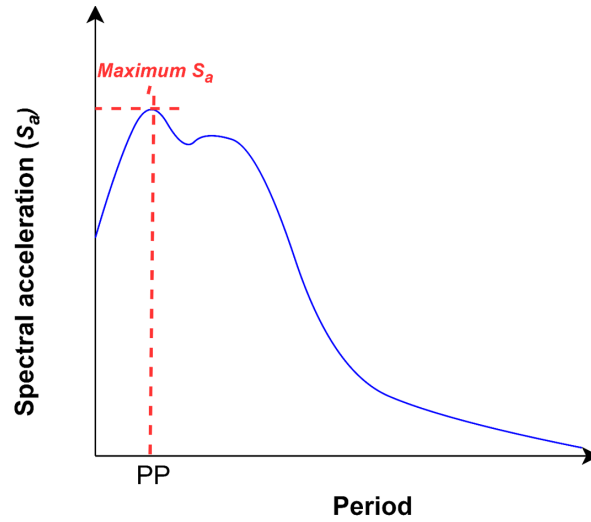


Figure 3.5: The predominant period (PP) representation in a spectral acceleration plot.

- **Bracket duration** (B_d): The elapsed time between the first and last “5% PGA” acceleration excursions. (see Figure 3.6-b)
- **Significant duration** (SD): The default interval for accumulating a proportion of total Arias Intensity is between the 5% and 95% thresholds. (see 3.6-c)

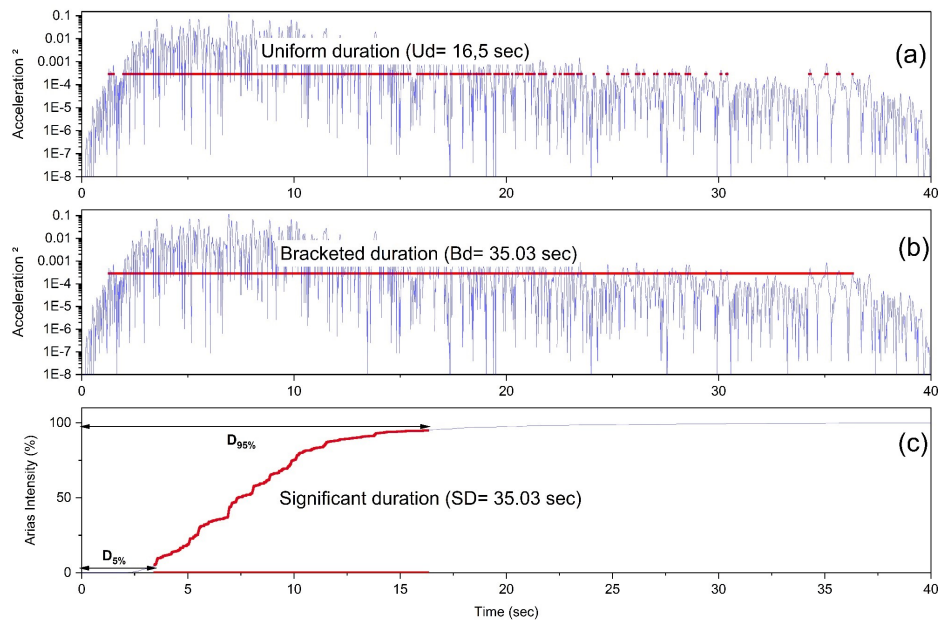


Figure 3.6: Duration characteristics of Kobe earthquake: a) Uniform duration, b) Bracketed duration, and c) Significant duration.

3.4.12 frequency content

- **Dominant frequency:** It corresponds to the frequency with the highest amount of energy i.e., The frequency of the highest Fourier amplitude (see Figure II.15-a).
- **Bandwidth:** The bandwidth of a Fourier amplitude spectrum represents the frequency range over which the amplitude of the Fourier transform exceeds a certain threshold. This threshold is usually set at half the maximum value of the power spectrum, which corresponds to an amplitude of 0.707 (-3db) times the maximum Fourier amplitude. However, the irregular shape of individual Fourier amplitude spectra can make it challenging to calculate bandwidth accurately. It is easier to determine bandwidth for smoothed spectra.
- **Central frequency:** The mean frequency between the upper (f_1) and the lower frequencies (f_2) of the smoothed frequency content.

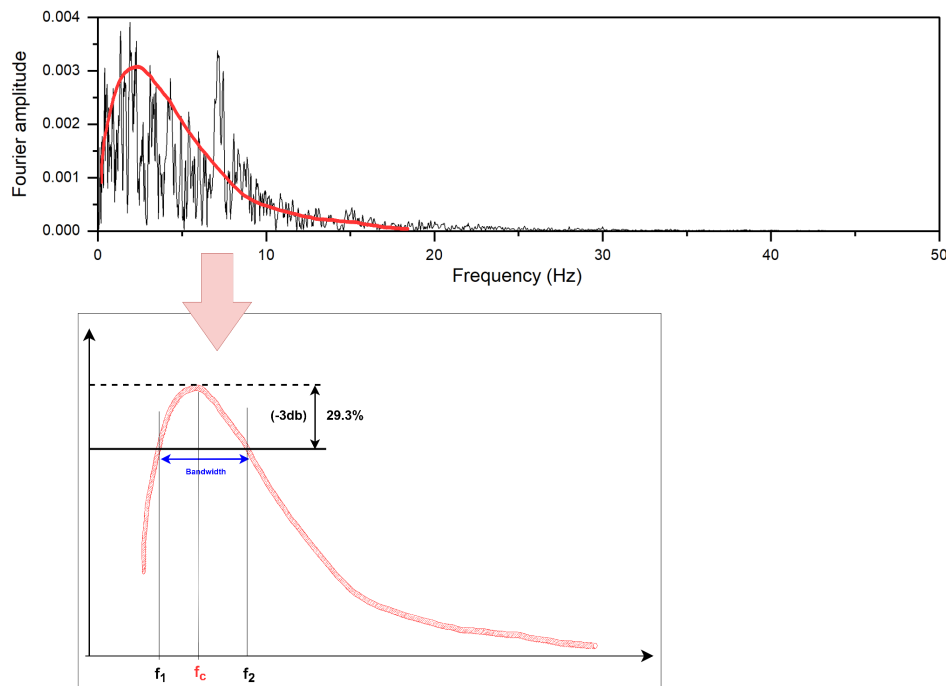


Figure 3.7: The frequency content characteristics (Fast Fourier Transformation (FFT), Bandwidth, Central frequency).

3.5 Scaling and matching ground motions

The ground motions generated or recorded may sometimes contain irrelevant characteristics that do not match the site conditions or the seismic hazard. This can lead to overestimation of the earthquake intensity and its frequency content. Therefore, analysts

must modify the accelerograms to match the required ground shaking while retaining the original parameters.

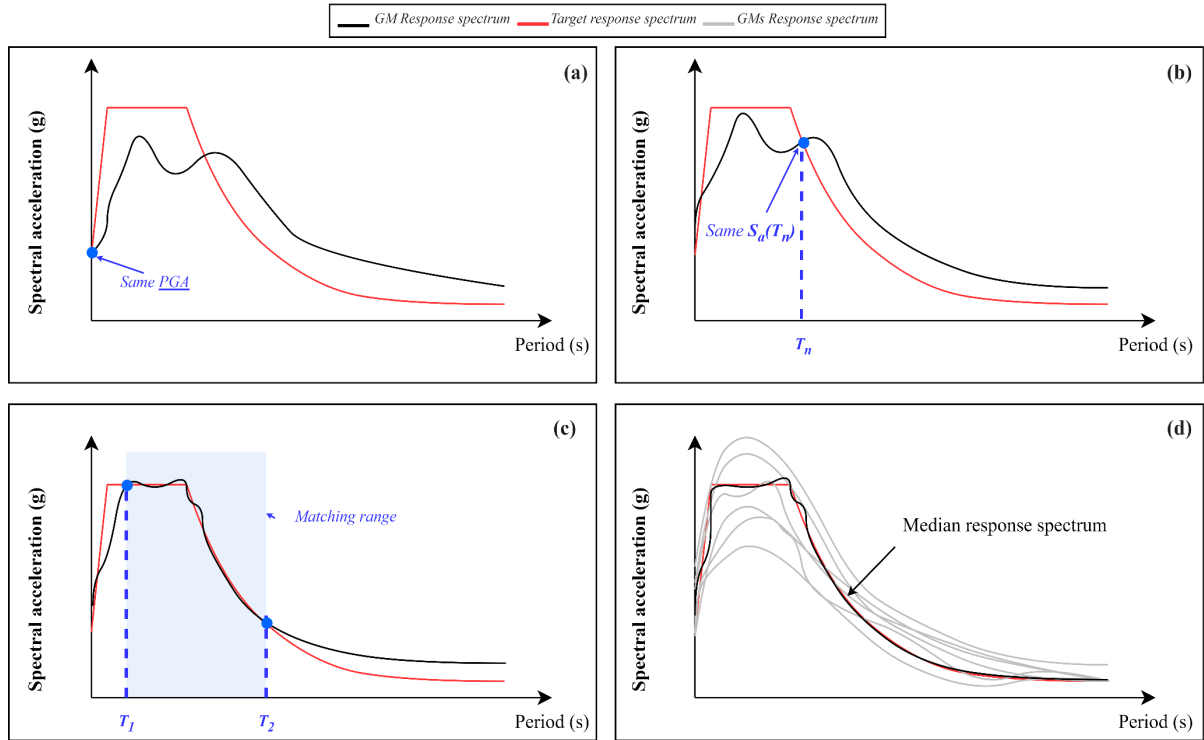


Figure 3.8: Matching and scaling methods: a) PGA matching, b) $S_a(T_1)$ matching, c) period range matching and d) median response spectrum matching

For example, incremental dynamic analysis (IDA) is a nonlinear dynamic analysis based on using a series of ground motions scaled to many intensity measures (IM) such as PGA, $S_a(T_1)$, $S_v(T_1)$, and $S_d(T_1)$. Scaling methods can change the acceleration record to match the target response spectrum, as shown in Figure 3.8. To improve the accuracy of fragility assessments and achieve more precise results, it is recommended to use the GM (Ground Motion) method. However, using many GMs for complex structures and long-duration GMs can be time-consuming. To overcome this, ATC-58 [49] suggests using at least 11 pairs of GMs (i.e., two orthogonal motion components) to obtain reliable results with reduced dispersion, as shown in Figure 3.9.

3.6 Seismic hazard (Probabilistic and deterministic) analysis

Two common approaches to developing design ground motions in earthquake engineering are deterministic and probabilistic. Despite being in use for over 30 years, there is still a widespread misunderstanding of these two approaches among engineering and earth science professionals.

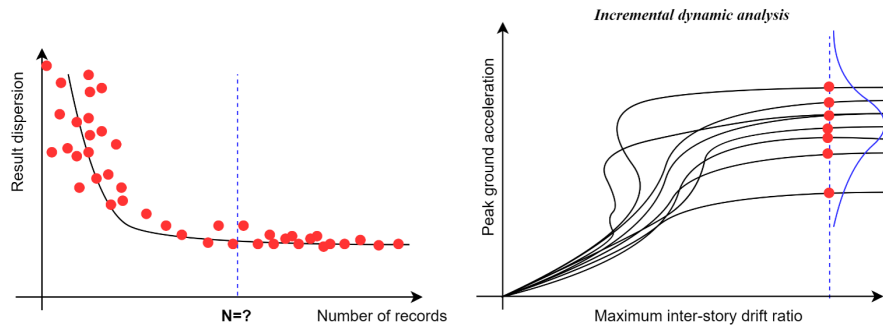


Figure 3.9: Number of GMs required to have a stable result dispersion for a collapse limit state

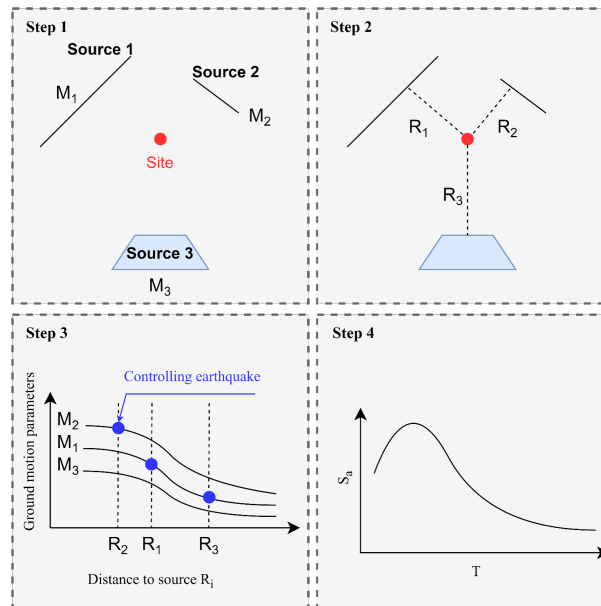


Figure 3.10: Deterministic seismic hazard approach (DSHA)

Determining seismic hazards involves four fundamental steps, as shown in Figure 3.10. First, seismic sources in the region, such as active faults or other known seismic sources, must be identified. These sources are usually responsible for generating earthquakes or other seismic events. Second, the seismic sources should be characterized by determining the distance, magnitude, and previous earthquakes recorded in each seismic zone. Third, a controlling earthquake corresponding to the highest ground motion parameters, such as PGA, PGV, S_a , etc., will be selected. Finally, a seismic hazard scenario will be established for different return periods, such as 100 or 500 years. The DSHA was initially developed for nuclear power industry applications and is still used for mega-structures such as nuclear power plants, large bridges, and large dams. However, it tends to overestimate the seismic event without considering the probability of occurrence and the annual rate, which can result in less economic designs.

The probabilistic approach quantifies the hazard level at a specific site, considering all earthquakes of varying magnitudes and distances and the frequency of seismic activity.

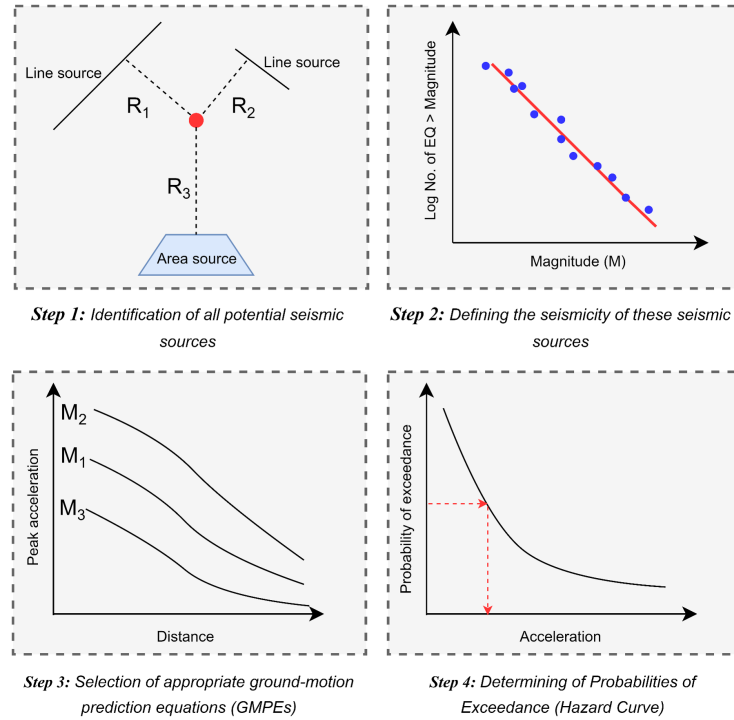


Figure 3.11: Probabilistic Seismic Hazard Approach (PSHA).

This approach is helpful because earthquakes occur randomly, and their intensity is unpredictable. It factors in the seismic potential of the seismic source and the earthquake itself. The probabilistic seismic hazard map was developed by C.A. Cornell in 1968 and later by the United States Geological Survey (USGS) in 1976, followed by the Uniform Building Code (US) in 1988. The approach is based on four essential steps illustrated in Figure 3.11.

3.7 Response spectra

3.7.1 Response spectrum of an accelerogram record

In general, the response spectrum represents the dynamic response of SDOF systems with different periods of vibration, as shown in Figure 3.12. The process is based on solving the differential equation of motion of an SDOF system (see Equation (3.11)) using numerical methods such as Newmark or Central Difference Method [50–52].

$$m\ddot{x} + c\dot{x} + kx = -m.a_g(t) \quad (3.11)$$

Where:

- m is the mass of the SDOF.
- c is the damping factor.

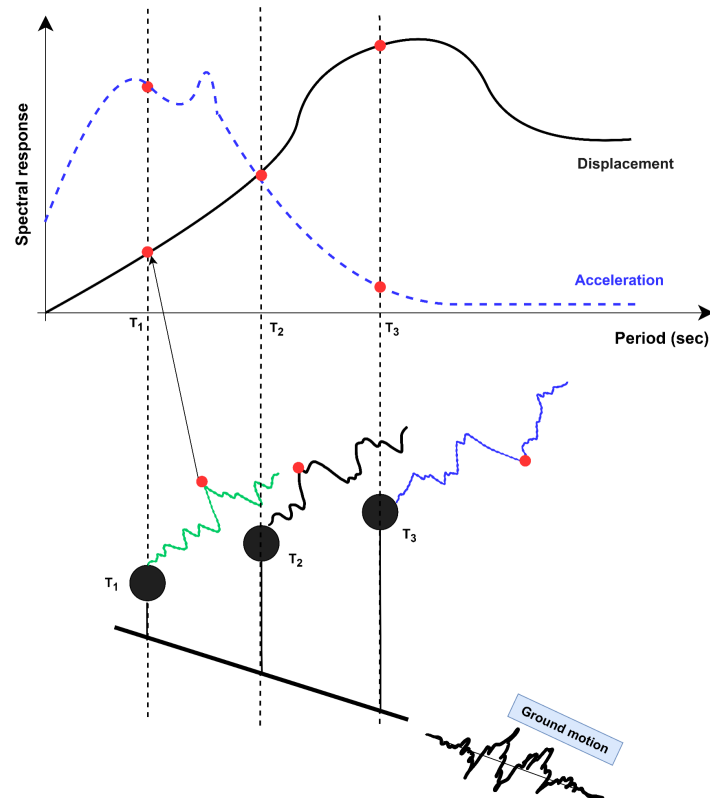


Figure 3.12: Response spectra representation using an accelerogram.

- k is the stiffness of the SDOF.
- $a_g(t)$ is the time history acceleration of the ground motion.

After solving Equation (3.11), we will obtain a vector representing the history of displacement, velocity, and acceleration. Each vector's maximum absolute value corresponds to T_i 's spectral response for each vibration period. These results are then represented as a response spectrum that depicts the ground motion's response.

Response spectra are typically calculated with a 5% damping ratio representing elastic behavior. However, it's also possible to plot inelastic response spectra using various levels of ductility and effective damping ratios, as shown in Figure 3.13. The period can represent either the elastic period of the SDOF or the effective period of the SDOF for inelastic behavior. Based on Figure 3.13-a, we can see that the Chichi response spectrum shows a peak ground acceleration (PGA) of 0.18g and a peak response acceleration of 0.67g at $T=0.11$ sec, indicating a strong earthquake. However, the displacement response spectrum at the same period does not exceed 0.2 cm, considered a low peak displacement for an equivalent SDOF system with a damping level of 5%. Therefore, if the studied structure can withstand this peak spectral displacement, it should not suffer any damage during the seismic event despite the high peak response acceleration. These types of ground motions can only affect the brittle and stiff structures. Based on Figure 3.13-b, spectral acceleration for a period $T > 1.4$ sec is impossible to extract due to low acceleration levels

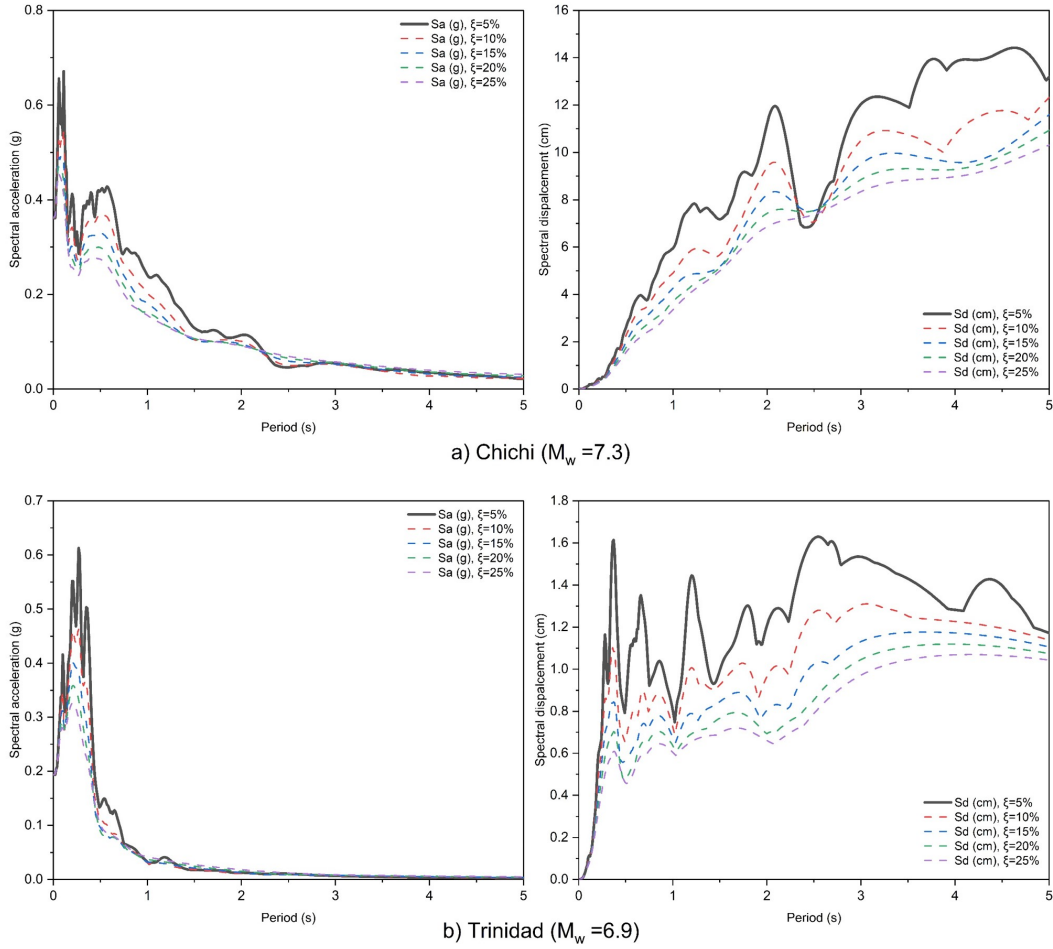


Figure 3.13: Acceleration and displacement response spectra of a) Chichi (1999) and b) Trinidad (1983).

(<0.02g). On the other hand, the spectral displacement represents more information for the same period range.

3.7.2 Design response spectra

3.7.2.1 Acceleration response spectra (Elastic)

Accurately assessing the risk of earthquakes in a given area is of utmost importance for ensuring the safety of structures built in that location. The Peak Ground Acceleration (PGA) has traditionally been used in seismic codes for this purpose. However, newer codes such as the International Building Code (IBC) [53] and the Italian Seismic Code [54] have replaced PGA with the spectral acceleration at two or three vibration periods for a given return period and soil condition. This revised approach provides more precise information about the seismic hazard and mapping.

To access this information, a software-based database can be used with the longitude and latitude coordinates of the site. However, it is essential to note that while this

technique is currently available for acceleration response spectra, it is not yet available for displacement response spectra in many codes.

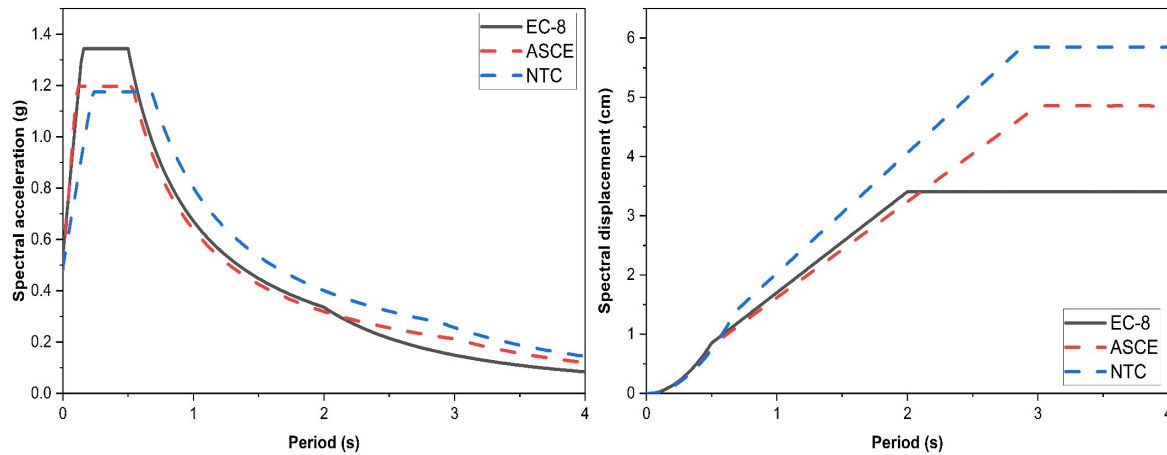


Figure 3.14: Seismic response spectra of the EC-8, ASCE and NTC.

Figure 3.14 displays the smoothed shape of the elastic response spectra design. This design represents the average spectral acceleration of multiple response spectra obtained from various accelerograms. It uses probabilistic models to estimate the contribution of earthquakes with less intense ground motions and those with fewer ground motions of high intensity. As a result, the obtained spectrum has a uniform probability of occurrence based on the considered return period.

Figure 3.14 also represents the elastic displacement spectra of three response spectra using EC-8, ASCE, and NTC codes. It can be observed that three segments characterize the displacement spectra. The nonlinear segment corresponds to the constant acceleration Plato, the linear segment where the velocity is constant, and finally, the constant displacement range where all the period $T > T_c$ will have the same displacement demand where T_c is the corner period.

3.7.2.2 Design return period

The term "Return Period" refers to the likelihood of experiencing a seismic event of a certain intensity in a given period, typically 50, 100, or 1000 years. It depends on the significance of the building and the seismic risk of the location. The higher the probability of occurrence and return period, the more likely a seismic event of greater intensity will occur. According to ASCE, it defines three seismic levels/ damage limit states as shown in Figure 3.15 and explained below:

1. **Earthquake Hazard Level (I):** It has a 50% probability of exceeding 50 years, corresponding to 72 years. No structural damage is expected, and the structure should remain operational under this seismic level.

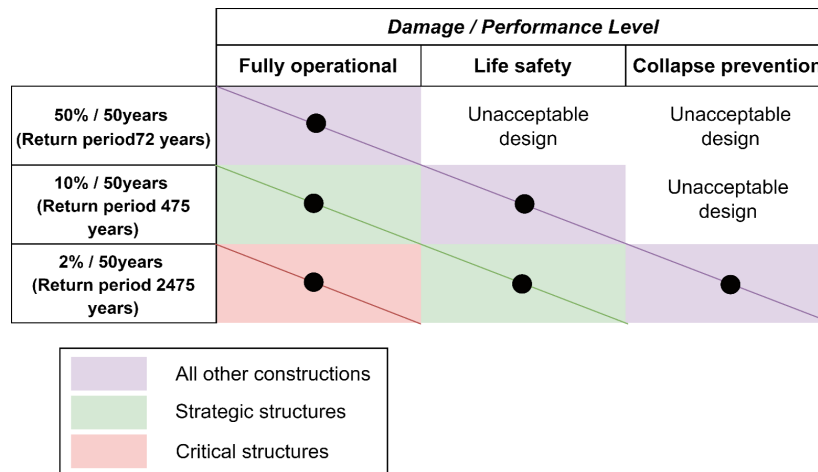


Figure 3.15: Return period for each seismic level and damage/Performance level.

2. **Earthquake Hazard Level (II):** Repairable structural damage is permitted, and the structure may be suspended during the repairing period. There will be no severe damage. The structure has a 10% probability of exceeding 50 years, corresponding to 475 years.
3. **Earthquake Hazard Level (III):** It has a 2% probability of exceeding 50 years, corresponding to 2475 years. Severe damage is expected on the structural and nonstructural elements, but no collapse should occur. The repair cost far exceeds the initial cost of the building.

3.8 Ground motions used in the thesis

The Machine Learning (ML) algorithms require substantial data to ensure the model is highly predictable. Ground motions represent the seismic event that causes lateral deformation of structures. Several parameters have been selected to characterize ground motions, as described in section 1.7. Adding more parameters could potentially enhance the performance of the ML algorithm and reduce the required dataset size to achieve acceptable performance. However, selecting parameters correlated to the Engineering Demand Parameters (EDPs) or outputs is important. Choosing irrelevant GM parameters may decrease the model's predictability and increase the training time. This section examines specific ground motions and generates Artificial Ground Motions (AGMs) to statistically represent the GMs utilized in ML models.

- **Artificial Ground Motions used for training the ML model:** The Artificial ground motions were generated using “SeismoArtif” software. 80 AGMs were matched to a target response spectrum according to ASCE 41/17, which has the parameters summarized in Table 3.1

Table 3.1: Response spectrum parameters according to ASCE 41-17

Probability	10% in 50 years	
Ss	0.21	MCER ground motion (period=0.2s)
Fa	0.8	Site amplification factor at 0.2s
Sxs	0.968	Site modified spectral response (0.2s)
S1	0.428	MCER ground motion (period=1.0s)
Fv	0.8	Site amplification factor at 1.0s
Sx1	0.342	Site-modified spectral response (1.0s)

- **Real Ground Motions (RGMs):** Using real ground motion is essential for performance evaluation, vulnerability, and fragility assessment as it reflects the actual seismic hazard. Therefore, in this work, ten known real ground motions will be utilized to evaluate the designs in Chapter VII. The earthquakes' record stations, year, Magnitude, frequency content, and country are summarized in Table 3.2. The response spectra and the characteristics of unmatched and matched RGMs are illustrated in Figure 3.18, Figure 3.19 and Figure 3.20.

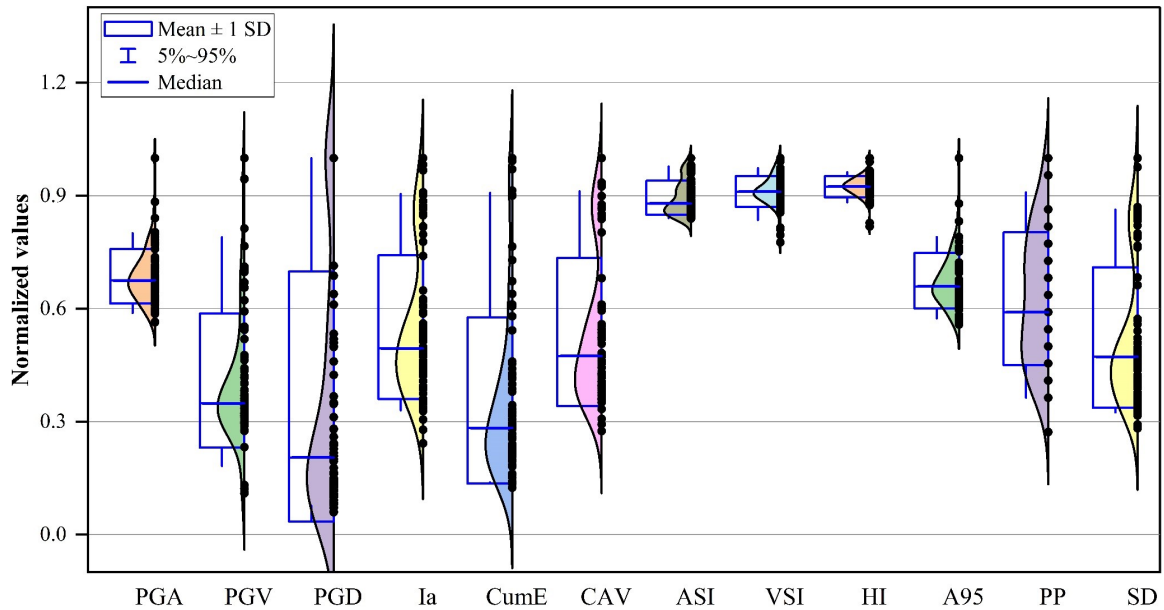


Figure 3.16: (80) generated artificial ground motions characteristics (seen GMs).

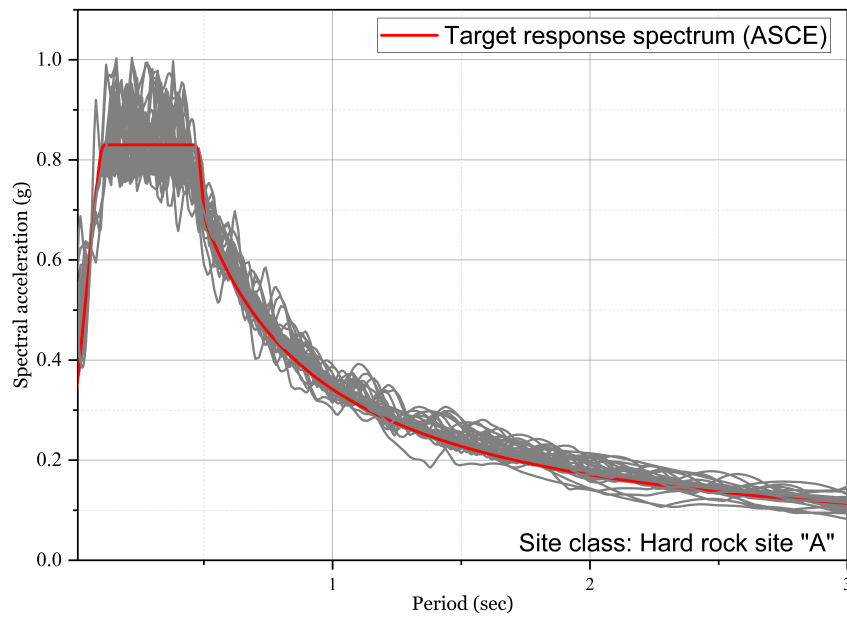


Figure 3.17: generated artificial ground motion characteristics matched to ASCE response spectrum.

The mean response spectrum of the generated ground motions and ASCE target spectrum is represented in Figure 3.16 and the seismic characteristics of the 80 AGMs are depicted in Figure 3.17.

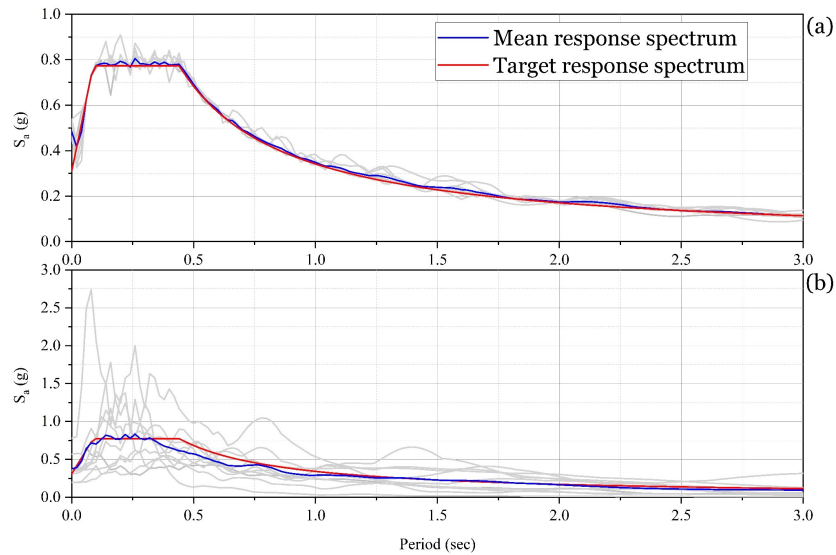


Figure 3.18: Response spectra of (10) real ground motions and the mean curve: a) Matched GMs and b) Original GMs. .

Table 3.2: earthquake stations with their occurrence year, magnitude, frequency content, and respective countries

Earthquake	Year	Station	Magnitude	Frequency content (Hz)	Country
Chi-Chi	1999	TCU045	7.6	0.02-50.0	Taiwan
Friuli	1976	TOLMEZZO	6.4	0.1-30.0	Italy
Hollister	1961	USGS	5.6	0.11-11.0	USA
Imperial- Valley	1979	USGS	6.4	0.1-40.0	USA
Kobe	1995	KAKOGAWA	6.9	0.1-50.0	Japan
Kocaeli	1999	YARIMCA	7.6	0.07-50.0	Turkey
Landers	1992	SCE STAT.24	7.3	0.08-60.0	USA
Loma-Pieta	1989	CDMG-47381	6.9	0.1-40.0	USA
Northridg	1994	CDMG-24278	6.9	0.12-23.0	USA
Trinidad	1983	CDMG-1498	3.2	0.15-30.0	USA

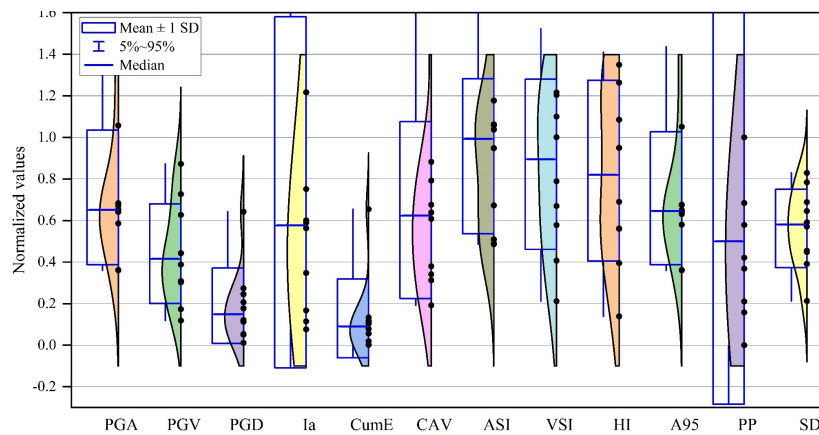


Figure 3.19: (10) Real Ground motion characteristics (Unseen and unmatched GMs).

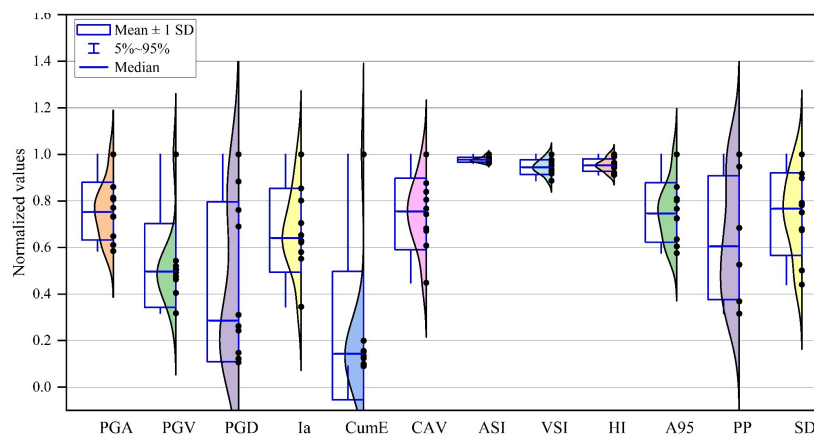


Figure 3.20: (10) Real Ground motion characteristics (Unseen and matched GMs).

3.9 Conclusion

In this chapter, we discussed the earthquake phenomenon and some of its characteristics such as ground motion records. We provided an overview of ground motions and the parameters that will be used in machine learning in the upcoming chapters. Two types of ground motions were considered: artificial and real records. Artificial ground motions are created using the target response spectrum, while real ground motions are adjusted to match the same target spectrum. A comparative study of ground motion parameters was conducted.

Chapter 4

Seismic response analysis

4.1 Introduction

Understanding how structures respond to seismic events is crucial in designing buildings that can withstand them and evaluating the behavior of existing structures. There are two ways to study structural responses - static and dynamic analysis. A building's resilience can be affected by various stresses such as dead loads, live loads, wind loads, explosions, and earthquakes. This chapter provides a general overview of seismic analysis and explores static and dynamic approaches for elastic and inelastic systems. It also focuses on the dynamic analysis of an SDOF system to better understand the terminologies necessary for understanding the following chapters. Lastly, the chapter summarizes the approaches proposed by FEMA and ATC to estimate the target displacement. A comparative study investigates the estimation performance using four approaches compared to the NLTHA results.

4.2 Seismic Analysis of Buildings

The seismic analysis of structures is a process that assesses the structural response to earthquakes or ground motions. Its main goal is to identify the performance of the building and ensure the stability and safety of its occupants during and after an earthquake. The study is based on understanding and estimating the seismic forces generated by earthquakes using mathematical models and simulations considering the building materials and geometry. The results can be used to evaluate the state of an existing building and its capacity, make new sustainable structures, and improve the current design codes.

Figure 4.1 illustrates the four types of seismic analysis used to design structures, estimate the seismic demand, and assess the seismic vulnerability of existing buildings.

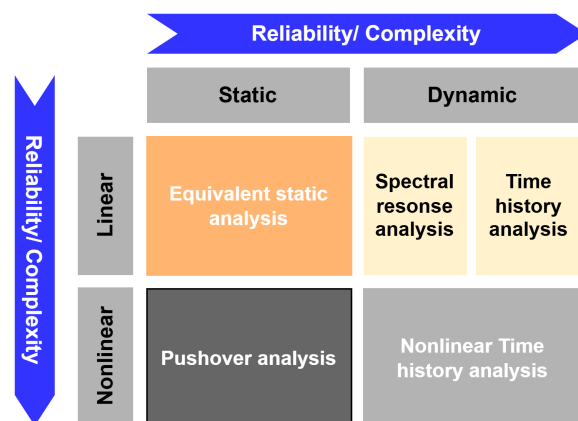


Figure 4.1: Types of the seismic analysis of structures

4.2.1 Equivalent static Method (ESM)

The ESM assumes that the ground motion can be simplified into a static load applied on the different levels of the structure. Many codes and standards adopt it due to its simplicity and rapid performance compared to dynamic analysis. However, the method's accuracy is considered reasonable if the following conditions are fulfilled:

- The approach is restricted to a fixed number of storeys.
- The structure should present a plan and elevation regularity.
- low-, and mid- height structures where the higher modes do not contribute significantly in the seismic response.
- The distance between the center of stiffness and the center of gravity should not exceed 15% (according to EC8) of the width of the building, as shown in Figure 4.2.
- The building represents sufficient ductility.
- The building can dissipate the vibration energy provoked by the earthquake.

Using the ESM does not exceed the engineering field and design, and the underestimation of the seismic demand is replaced using safety coefficients. The static analysis can be simplified by considering that the fundamental mode dominates the total response. In addition, this mode's deformation is arbitrarily assimilated to a straight line in the case of portal frame structures and parabolic shape in case structures with wall shear, as shown in Figure 4.3

4.2.2 Spectral response analysis (Linear-dynamic analysis)

The modal spectral analysis is based on estimating the maximum effect of an earthquake on a structure by representing the seismic load in the form of response spectra, if the

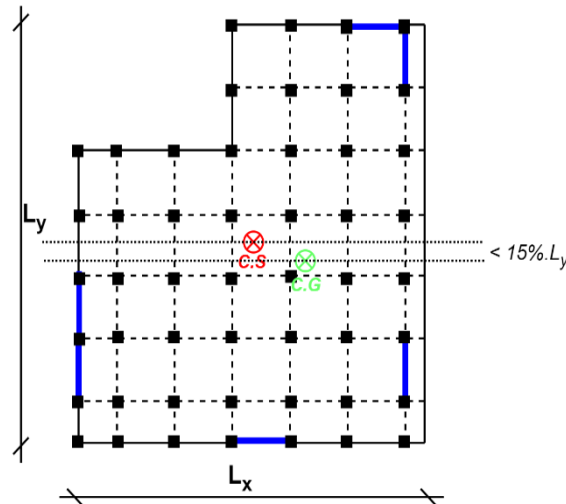


Figure 4.2: The allowable ratio between the center of stiffness and center of gravity with the building's dimension

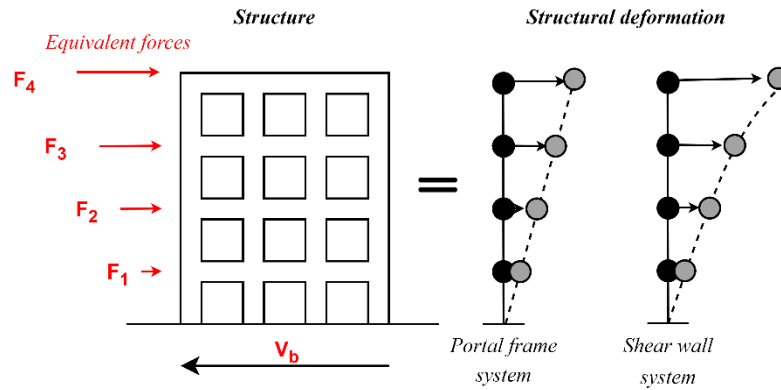


Figure 4.3: The fundamental vibration mode shape for portal frames and shear wall systems

structural behavior remains elastic. This hypothesis allows us to calculate the vibration modes of the studied structure. This dynamic method can be applied to any structure (regular /irregular buildings, bridges, etc.) except systems with a geometrical or mechanical nonlinearity. The procedure is based on four steps, as illustrated in Figure 4.4.

4.2.3 Nonlinear static analysis (Pushover analysis)

The nonlinear behavior of structure represents a challenging field for engineers and researchers to simulate a real-world scenario and be close to an exact study. This powerful technique goes beyond linear analysis by considering the geometric, material, and contact nonlinearity, as explained in Figure III.5. The “static” word refers to the absence of motion and time where the load is applied slowly, and no dynamic effect is captured. This method is called “Pushover analysis” because it uses horizontal loads progressively until

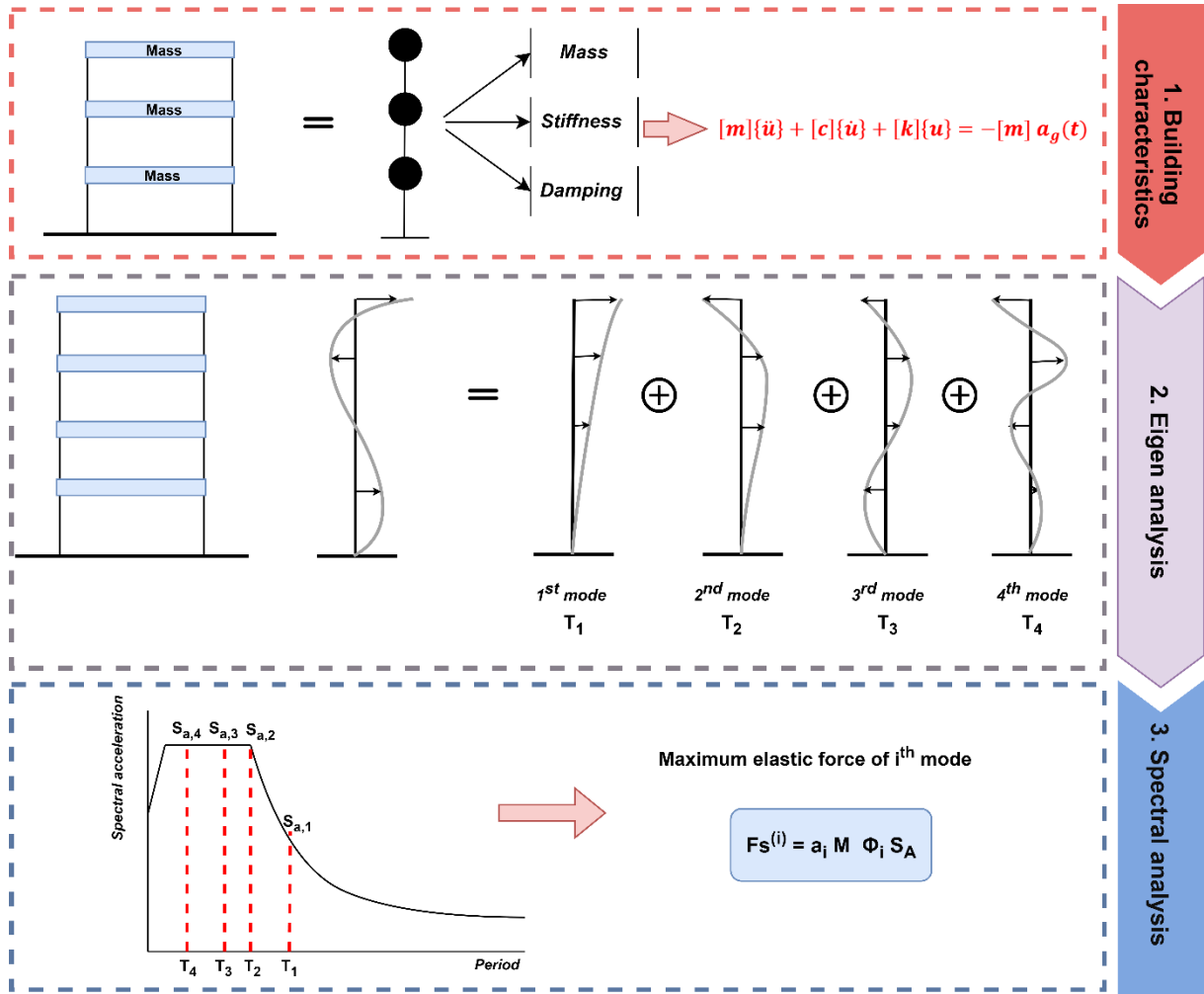


Figure 4.4: steps of the spectral response analysis

the structure reaches its capacity limits.

Two types of pushover analysis can be used to perform the research: force control and displacement control. For the first type, a whole load combination should be applied to the structure in different forms (triangular, uniform, illustrative), and the roof displacement will be captured. This operation has limitations when the target displacement is associated with a minor, null, or negative lateral post-yield stiffness due to the P-delta effect or material behavior model. The displacement-controlled analysis is based on applying a roof displacement and finding the corresponding base shear. This technique allows us to avoid the mentioned problem of the force-controlled research and to capture the stiffness and strength degradation after reaching the ultimate strength, as shown in Figure 4.6. The pushover curve summarizes the static behavior of the structures beyond the elastic limit and estimates their ultimate lateral capacity in terms of displacement and base shear. It represents several advantages compared to the other analysis:

- Simple and quick to perform.
- Very reliable results for low- and mid-rise buildings where the first mode of vibration

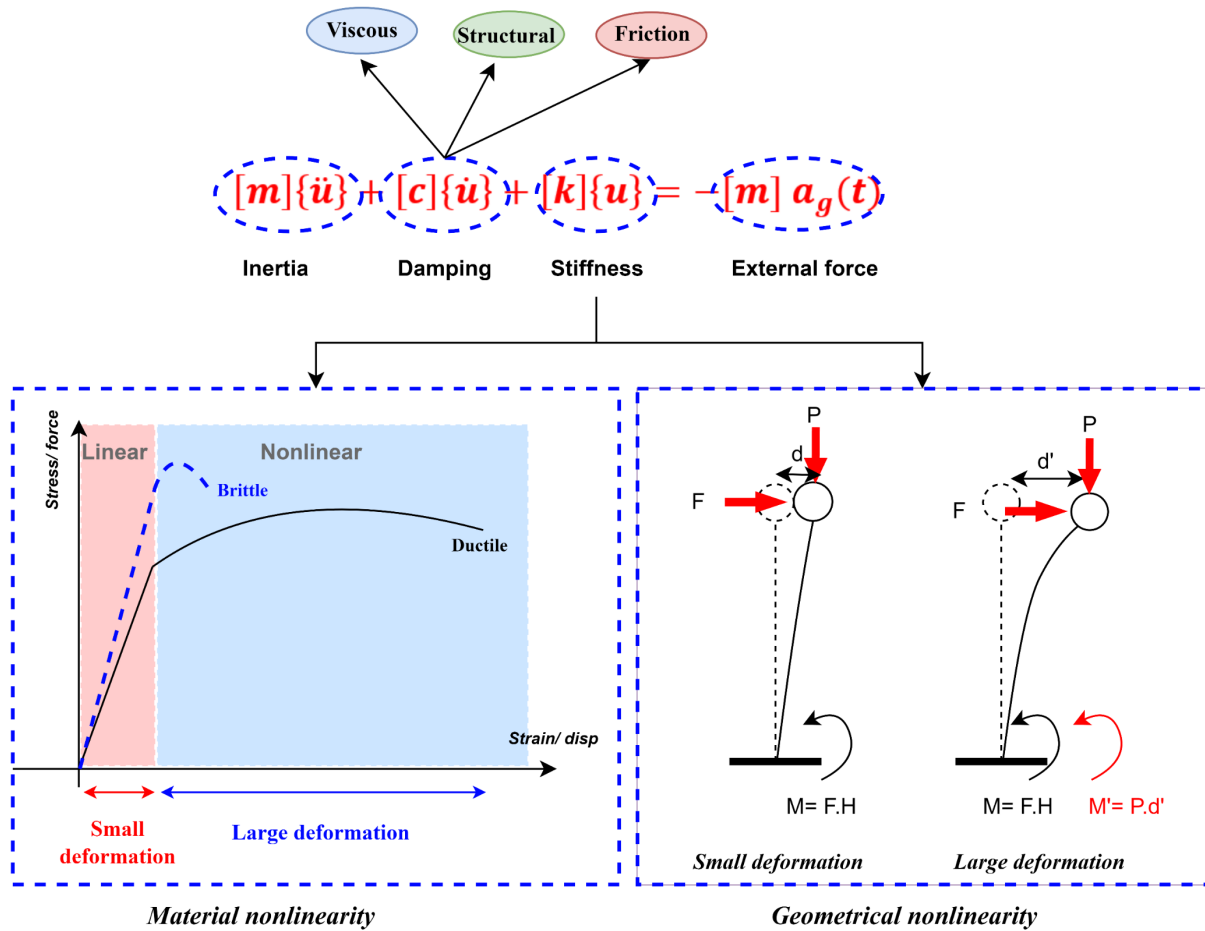


Figure 4.5: The material and geometrical nonlinearity in structural analysis

is the predominant.

- It does not require a high computational time and hardware equipment.
- It can capture the effects of changing the stiffness and the strength.

However, the nonlinear static analysis represents some disadvantages; we mention some of them:

- It does not account for dynamic effect and hysteresis loops.
- Inaccurate results for tall buildings where the higher mode effect appears.

4.2.4 Nonlinear time history analysis (NL-THA)

Many researchers and structural engineers use nonlinear analysis (static and dynamic) to assess the seismic vulnerability of structures and their performance for retrofit and strengthening processes. The response spectrum analysis is limited to being used in linear cases only because it depends on the superposition of the modal response, which is not the case for nonlinear behavior. A time history analysis or response history analysis

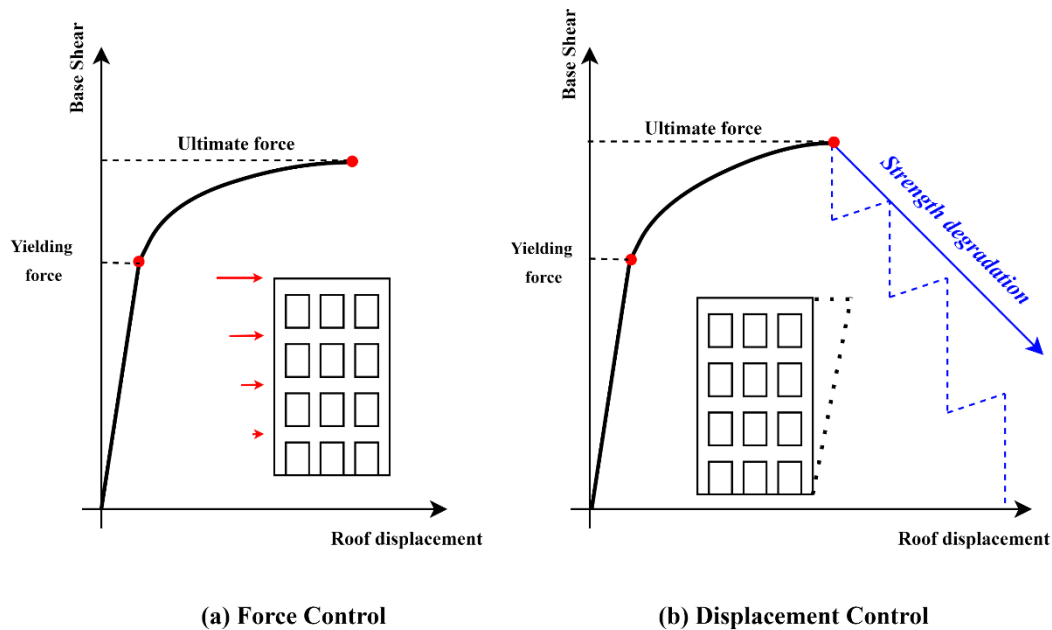


Figure 4.6: Pushover analysis: a) force-controlled analysis, b) displacement-controlled analysis

is a nonlinear dynamic analysis based on a step-by-step integration method to find the exact solution/ behavior of the emotional response in terms of displacement, velocity, acceleration, etc.

The linear dynamic analysis is less complicated than the nonlinear analysis due to some reasons mentioned below:

- The linear analysis uses only the elastic range of the material behavior, and only the young modulus, section, and inertia are needed to perform it. However, the nonlinear analysis uses much more complicated details such as the nonlinear deformation of the materials, the P-delta effect, and the type of the hysteresis model (elastic perfectly plastic, Takeda, isotropic, kinematic), which makes the process take much time to be performed.
- Nonlinear analysis requires a deep understanding of the field and is to be performed by experts only. On the contrary, linear analysis can be used by engineers with some limited knowledge of dynamic analysis.
- Nonlinear analysis can take much more computing time than linear analysis, and it depends on the complexity of the building, the number of elements/ components, and the selected behavior material model.
- Nonlinear analysis has the potential to predict the global damage that may occur during an earthquake event.

Figure 4.7 summarizes the steps to perform nonlinear time history analysis in OpenSees. The process starts with defining the nodes' locations and the connectivity of the elements (beam, column, wall, etc.). Secondly, after determining the materials' behavior (steel-concrete) and specifying the cross-section of each element, a ground motion should be selected, matched, or scaled before performing NL-THA. The selection of convenient ground motions is essential in risk assessment and should be made by experts. Finally, the outputs of this process can be expressed in terms of time history vectors (acceleration, velocity, displacement, and forces/ stresses). The NL-THA can also be used to perform incremental dynamic analysis (IDA), which is based on finding the maximum engineering demand parameter (EDP), varying the intensity measure (IM), and constructing the IDA curves. The IDA can be used to assess the fragility of a structure and ground motion uncertainties by selecting the appropriate GMs.

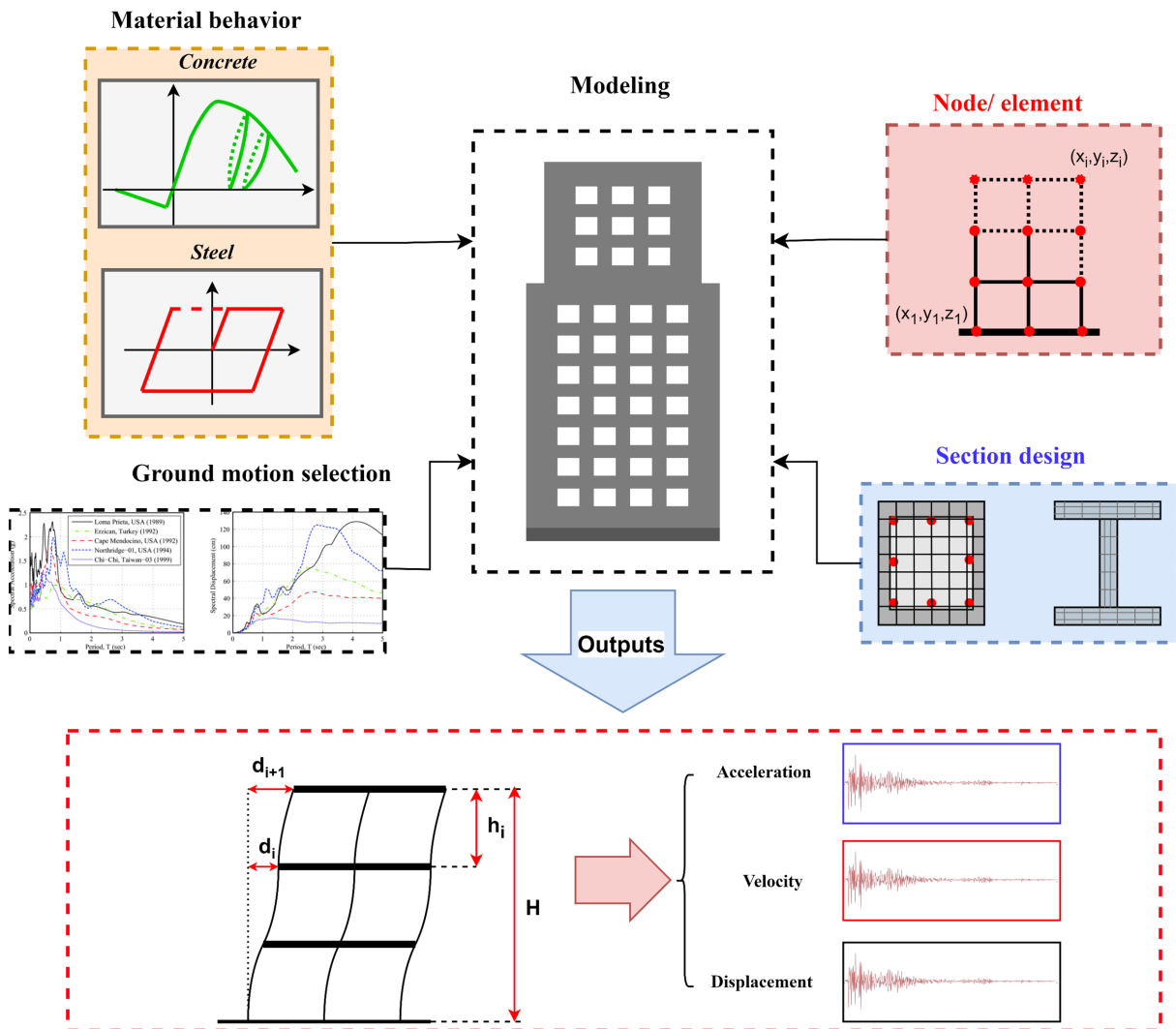


Figure 4.7: The essential steps to perform NL-THA on OpenSees

4.3 The inelastic seismic response of a single degree of freedom (SDOF)

The elastic seismic response refers to a system's behavior when the material's strain-stress relationship exhibits elastic behavior or when the seismic excitation is not strong enough to cause the material to yield. In other cases, the seismic forces exceed the yielding limit (f_y), causing the material to behave plastically. To simplify the analysis, the force-displacement or stress-strain relationship can be idealized by determining the equivalent area that equals the area of the actual curve without exceeding the maximum displacement (d_u), as shown in Figure 4.8.

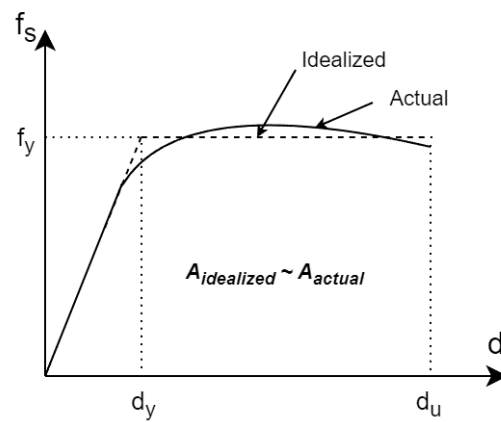


Figure 4.8: Elastic perfectly plastic idealization of an actual force-displacement relation.

In the scenario depicted in Figure III.9, an SDOF system with an elastic perfectly plastic (EPP) force-displacement relation is exposed to cyclic loading, unloading, and reloading forces. It can be observed that the yielding point remains constant regardless of the direction of displacement. When the maximum positive displacement is reached, unloading occurs along a path parallel to the initial stiffness slope. The same is true for reloading from the minimum displacement. Consequently, the resisting force is influenced by the deformation history associated with the loading or unloading phase.

4.3.1 Corresponding linear system

The goal is to determine the maximum deformation in an elastoplastic system during an earthquake and compare it to the maximum deformation caused by the same earthquake in a corresponding linear system. The elastic system had the same stiffness as the elastoplastic system when initially loaded. Both systems have the same mass and damping, and the natural vibration period of the corresponding linear system is the same as the period of the elastoplastic system when it undergoes small oscillations ($d < d_y$). However, the

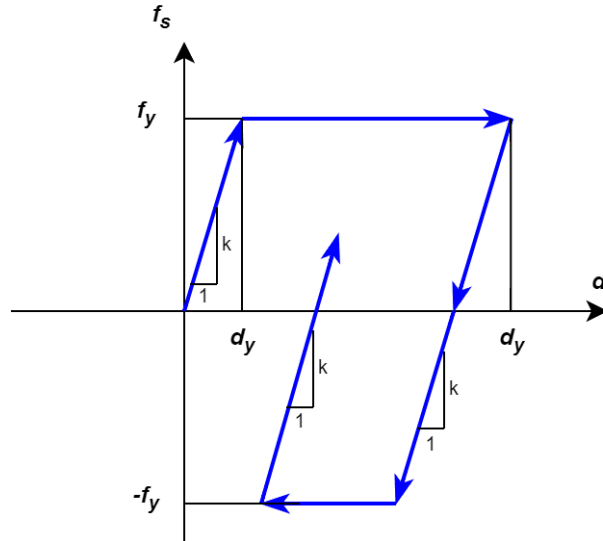


Figure 4.9: Elastic perfectly plastic cyclic loading, unloading, and reloading.

natural vibration period of inelastic systems is not defined at larger amplitudes of motion. See Figure 4.10 for a visual representation.

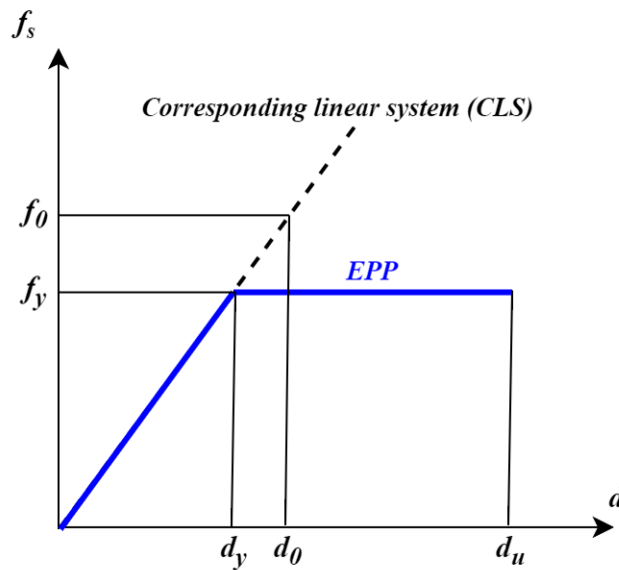


Figure 4.10: The elastic perfectly plastic system and the corresponding linear system.

The ratio between the d_y and d_0 or between the f_y and f_0 represents the normalized yielding strength $\overline{f_{yield}}$ as shown in Equation (4.1).

$$\overline{f_{yield}} = \frac{f_y}{f_0} = \frac{d_y}{d_0} \quad (4.1)$$

The normalized yielding strength is less than 1, representing a state where the behavior is in the elastic range, and no yielding occurs. On the other hand, if the normalized yielding strength is less than or equal to 1, the resisting force exceeds the yielding limit,

and the system cannot stay elastic but plastic.

Alternatively, the relation between f_0 and f_y can also represent the yield strength reduction factor (R) as shown in Equation (4.2).

$$R = \frac{f_0}{f_y} = \frac{d_0}{d_y} \quad (4.2)$$

As discussed previously with the normalized yielding strength factor, the R greater than 1 indicates that the system's response cannot be elastic, and the applied forces will provoke a plastic deformation (exceeding the yielding limit).

On the other hand, the relationship between the maximum displacement (d_u) and the yielding displacement limit (d_y) is represented by the ductility factor (ν). When the response is inelastic, the ductility factor exceeds 1, and the more ductile the system is, the more it dissipates dynamic energy.

4.3.2 Equation of motion of inelastic SDOF

The linear relationship between force and displacement of an SDOF system can be represented as mentioned in the previous section. The equation of motion of the SDOF system can be written as follows in Equation (4.4):

$$m\ddot{u} + c\dot{u} + ku = -m\ddot{u}_g(t) \quad (4.3)$$

However, the linear relationship between force displacement (or stress-strain) is no longer linear in inelastic behavior. The force (f_s) now is in the function of displacement (u) as shown in Equation (3.3)

$$m\ddot{u} + c\dot{u} + f_s = -m\ddot{u}_g(t) \quad (4.4)$$

Where f_s represents the resisting force, and the solution $u(t)$ can be solved using numerical procedures such as Newmark (average or linear acceleration) [55].

Figure 4.11 illustrates two types of seismic response of two SDOFs subjected to “El-Centro” ground motion (PGA= 0.316 g). Both systems have vibration periods ($T_n = 2.81$ sec) and different yielding limits as illustrated in Figure III.1-b ($f_y = 100$ N and $f_y = 400$ N). Figure 4.11-a depicts the displacement time history of the SDOFs, where the difference in the behaviors can be illustrated. For $t < 5$ sec, both SDOFs have the same behavior, and this is because the seismic forces are less than 100N, which is the lowest yielding limit of these SDOFs.

As shown in Figure 4.11, the yielding limit affects the displacement response of a struc-

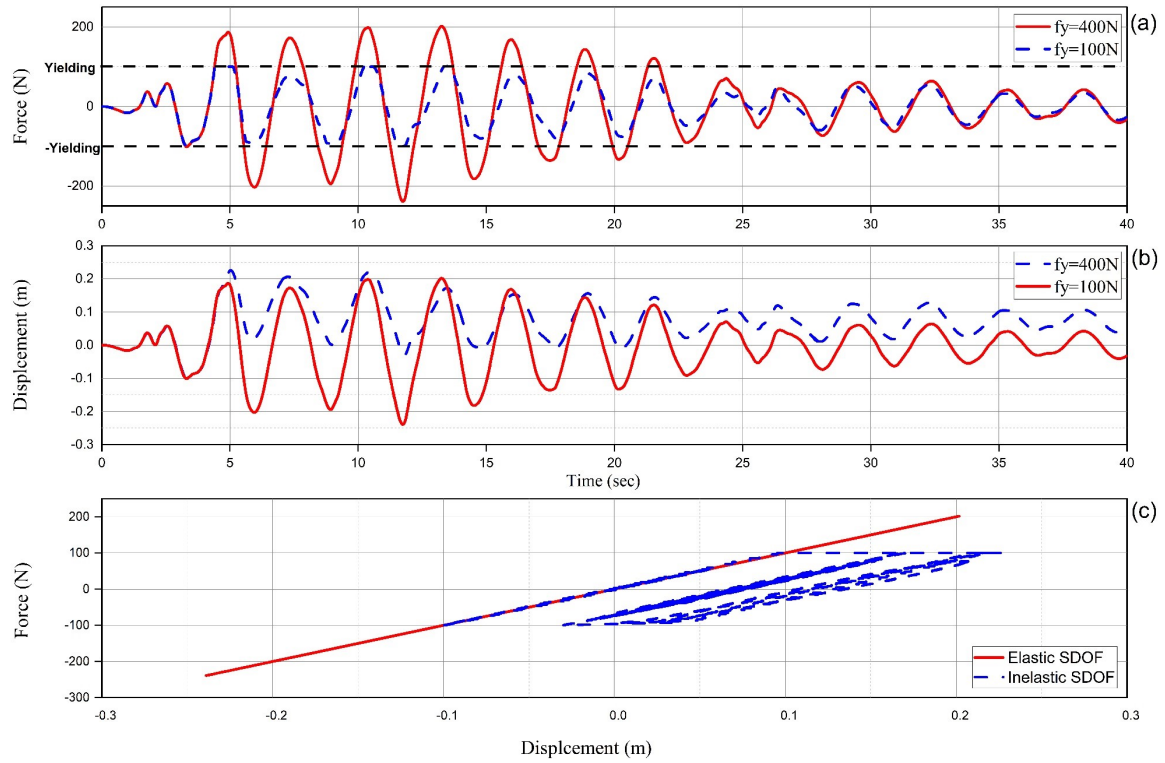


Figure 4.11: The elastic perfectly plastic system and the corresponding linear system.

ture by causing a residual deformation that remains permanent in the SDOF behavior. The time history of the SDOFs demonstrates that the absolute structural displacement differs from the maximum dynamic response of other systems with different yielding limits, even if they have the same period and elastic stiffness.

4.4 Target displacement and performance point estimation

Evaluating seismic safety in existing structures and designing new ones requires engineers to use inelastic analysis techniques. The primary goal of inelastic seismic analysis is to predict how a structure will react during an earthquake. The emergence of performance-based engineering (PBE) as a technique for seismic evaluation and design has made this prediction increasingly crucial. PBE characterizes performance in terms of expected damage to structural and nonstructural components and contents, which informs decisions about safety and risk. Traditional design and analysis procedures that use linear elastic techniques can only predict performance implicitly, as structural damage implies inelastic behavior. In contrast, inelastic seismic analysis procedures aim to estimate the intensity of inelastic deformations.

The inelastic response usually has the same linear process in that the analysis uses a finite element model of a building subjected to a ground motion. The results of this analysis

can be an engineering demand parameter (EDP) that includes global response (roof displacement, story displacement, or story drift) or even forces and stresses.

Various inelastic procedures are used to obtain the inelastic seismic response using different representations for the seismic action or the structural model.

4.4.1 Nonlinear static procedures (Capacity spectrum method of ATC-40 [1])

4.4.1.1 Hysteretic models

The FEMA-356 [56] and FEMA-440 [57] use four different hysteretic models as shown in figure III.4:

- **Elastic nonlinear model (EN)**: This model as shown in Figure 4.12-a has one path of loading and unloading, making the behavior with no hysteretic energy to dissipate during the excitation. Its behavior is like the rocking structures’.
- **Elastic perfectly plastic (EPP)**: the EPP has been used widely by many researchers in different investigations and it is used as a reference for the effect of other hysteretic behavior models as shown in Figure 4.12-b.
- **Stiffness degradation (SD)**: Clough proposed the SD [58] in 1966 and modified by Mahin and Lin in 1983 [59] to simulate the flexural controlled RC structures where the lateral stiffness decreases and related to the current displacement to simulate the stiffness capacity loss of damaged systems as shown in Figure 4.12-c.
- **Stiffness and strength degradation (SSD)**: this model reproduces the behavior of structures with lateral stiffness and strength degradation as maximum displacement increases for each cycle as shown in Figure 4.12-d.

The Capacity spectrum method (CSM) is based on equivalent linearization which means the maximum displacement of an SDOF system can be obtained from other elastic SDOF systems with higher periods and damping ratios than the initial nonlinear SDOF system. The higher values of the periods and the damping ratios are called equivalent periods and equivalent damping ratios.

4.4.1.2 The methodology of the CSM procedure

The CSM procedure aims to find the target displacement or the performance point on a linear or nonlinear system. The procedure is based on several steps to obtain the seismic response of the equivalent SDOF system:

- Conversion of the capacity curve.

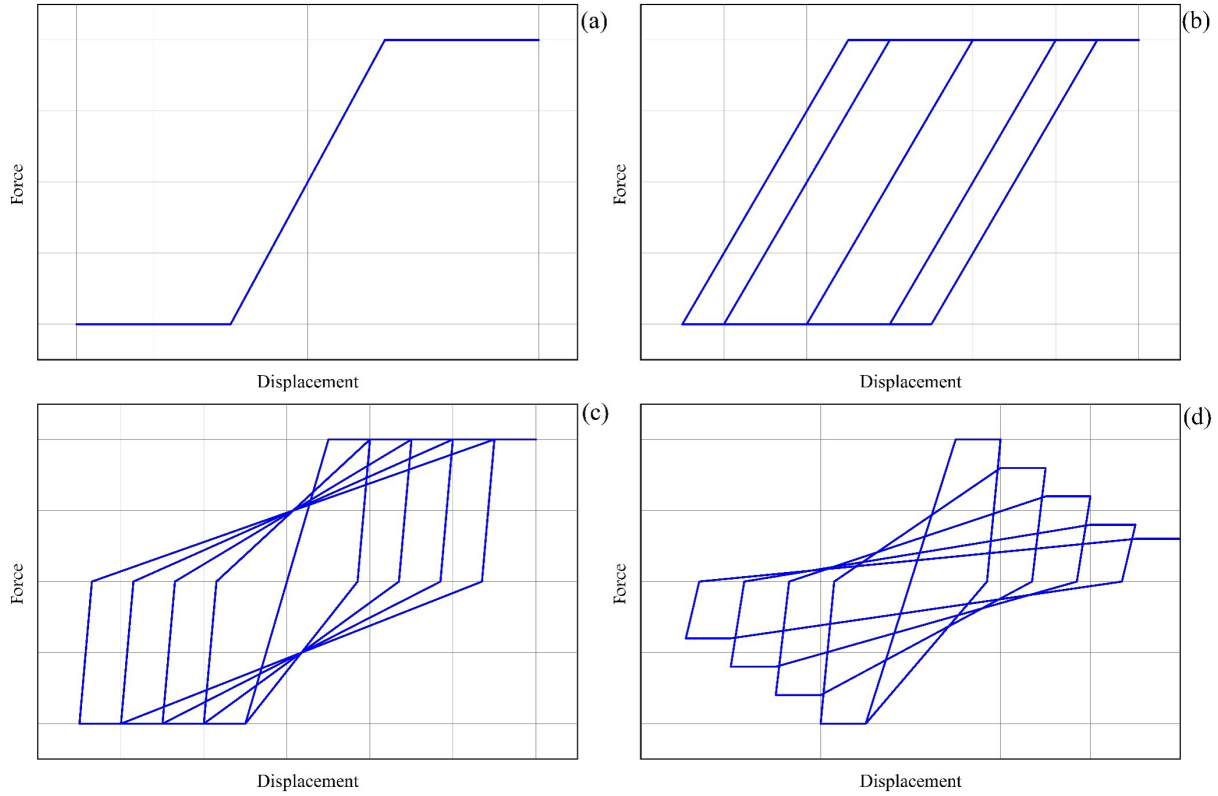


Figure 4.12: Hysteretic models used in FEMA-356 and FEMA-440 to evaluate the adopted procedure: a) Elastic Nonlinear model (EN), b) Elastic perfectly plastic (EPP), c) Stiffness degradation (SD) and d) Strength and stiffness degradation (SSD).

- Conversion of the demand curve.
- Finding the intersection point between capacity and demand spectra curves.

4.4.1.2.1 Conversion of the capacity curve into ADRS spectrum

Both mentioned steps aim to plot both curves (capacity and demand) in the same curve. The capacity curve is usually plotted where the roof displacement in the x-axis and base shear in the y-axis and for the demand curve, it relates the spectral acceleration with the period of vibration frequency. The curves should now be plotted in an acceleration displacement response spectrum (ADRS).

The capacity curve conversion into an ADRS plot can be performed using the following Equations (4.5), (4.6), (4.7), and (4.8):

$$Participation\ Factor\ (Pf) = \frac{\sum_{i=1}^n (m_i \cdot \phi_{i,1})}{\sum_{i=1}^n (m_i \cdot \phi_{i,1})^2} \quad (4.5)$$

$$Modal\ Mass\ Coefficient\ (Cm) = \frac{\sum_{i=1}^n (m_i \cdot \phi_{i,1} / g)}{[\sum_{i=1}^n (m_i / g) \cdot [\sum_{i=1}^n (m_i \cdot \phi_{i,1})^2 / g]} \quad (4.6)$$

$$Spectral\ Acceleration\ (S_a) = \frac{V_{base}}{M \cdot g \cdot C_m} \quad (4.7)$$

$$\text{Spectral Displacement } (S_d) = \frac{\delta_{roof}}{P_f \cdot \phi_{roof,1}} \quad (4.8)$$

Where: m_i is the mass of the i th level, $\phi_{i,1}$ is the eigen value of the first mode, $M.g$ is the total mass including dead and live loads that are likely to participate in vibration, δ_{roof} is the roof displacement and V_{base} is the base shear.

4.4.1.2.2 Conversion of the demand curve into ADRS spectrum

For the demand conversion to ADRS, the only change may happen is changing the period axis into spectral acceleration using Equation (4.10):

$$\text{Spectral Displacement } (S_d) = \frac{T_i^2}{4\pi^2} S_a g \quad (4.9)$$

The design response spectrum is composed of two regions, constant-spectral acceleration region and it is delimited with period (T_0) and a constant-spectral velocity delimited with a period region (T_1) as shown in Figure 4.13.

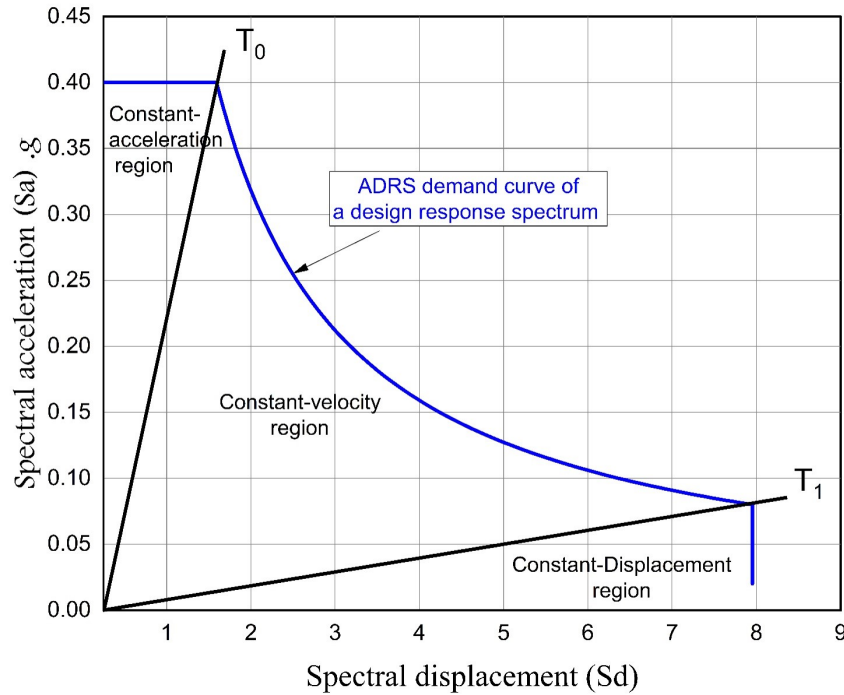


Figure 4.13: Demand response spectrum conversion into ADRS representation.

4.4.1.2.3 Finding the intersection point between capacity and demand spectra curves

The target displacement or performance point is the seismic response where the demand and capacity are equal, accounting for nonlinearity effects on period and damping ratio of

the SDOF system. The CSM according to ATC-40 proposes three procedures to estimate the performance point. Two of them are analytical procedures that need iterative steps to converge to an acceptable solution and the third is a graphical procedure.

The procedures are based on the same concept which is to use the ADRS representation of the capacity and demand. The capacity curve then should be converted into a bilinear curve to calculate the effective period and damping ratio for each displacement step in the capacity curve, as illustrated in Figure 4.14.

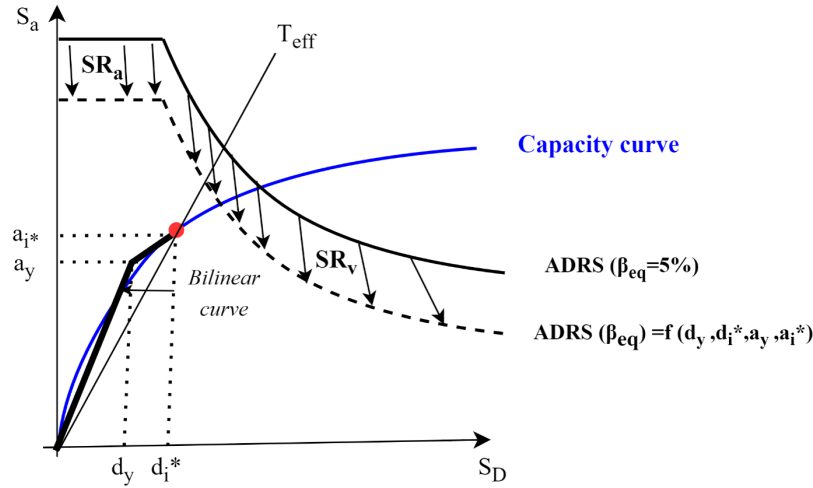


Figure 4.14: Bilinear representation and performance point first iteration.

The equivalent period can be determined by considering the ductility ratio (μ), post-yield stiffness ratio, and the initial period. Similarly, the equivalent damping ratio can be calculated based on the ductility ratio (μ), post-yield stiffness ratio, and the initial damping ratio. According to ATC-40, the equivalent period and damping ratio can be obtained by using the secant stiffness as mentioned in Equations (4.10), and (4.12) and shown in Figure 4.15.

$$T_{eq} = T_0 \sqrt{\frac{\nu}{1 + \alpha\nu - \alpha}} \quad (4.10)$$

$$\beta_{eq} = 0.05 + \kappa \frac{2(\nu - 1)(1 - \alpha)}{\pi\nu(1 + \alpha\nu - \alpha)} \quad (4.11)$$

Where κ represents the corrector factor to consider the hysteretic behavior on reinforced concrete buildings and it is defined for each hysteretic model. T_0 is the vibration period on the initial nonlinear SDOF system. α is the post-yield plastic over elastic stiffness. κ is related to the area of cyclic loops of the hysteretic curves. The highest values of the κ correspond to the EPP hysteretic behavior due to the wide area covered by the loops. Similarly, the smallest effective damping values correspond to the SSD hysteretic behavior due to the low area covered by the hysteretic loops.

The κ values are summarized in Table 4.1 where the κ is in function of hysteretic

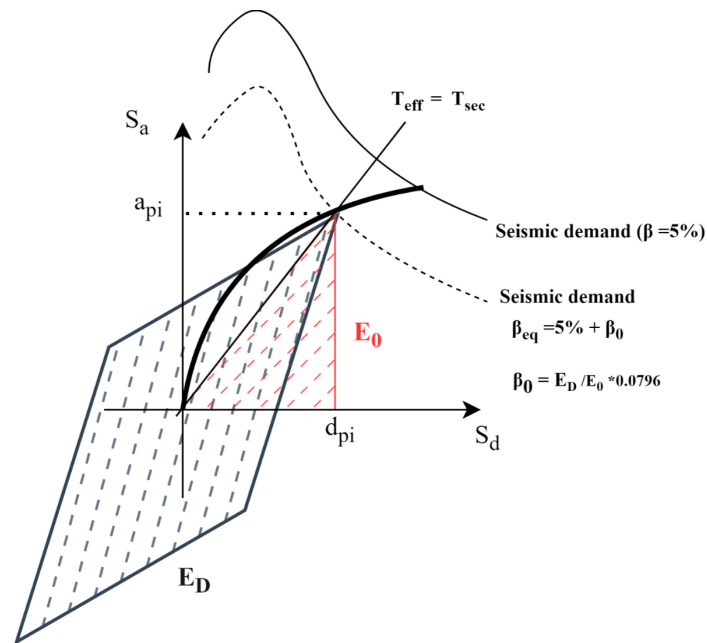


Figure 4.15: Capacity spectrum method according to ATC-40.

Table 4.1: κ values according to ATC-40

Hysteretic behavior	β_0	κ
EPP	≤ 0.1625	1.0
	> 0.1625	1.13-0.51 $(\pi/2)$ β_0
SD	≤ 0.25	0.67
	> 0.25	0.845-0.446 $(\pi/2)$ β_0
SSD	Any value	0.33

behavior system (EPP, SD, SSD).

ATC-40 recommends using reduction factors to decrease demand seismic spectrum for design spectra in constant acceleration and constant velocity regions by effective damping ratio using equations (4.12) and (4.13), as depicted graphically in Figure 4.16.

$$SV_A = \frac{3.21 - 0.68 \ln(100\beta_{eff})}{2.21} \quad (4.12)$$

$$SV_A = \frac{2.31 - 0.41 \ln(100\beta_{eff})}{1.65} \quad (4.13)$$

The ATC-40 imposes a minimum allowable limit for the reduction factors depending on the hysteretic behavior type as shown in Table 4.2.

Table 4.2: The values of reduction factors for each hysteretic behavior model

Hysteretic behavior	SRA	SRV
EPP	0.33	0.5
SD	0.44	0.56
SSD	0.56	0.67

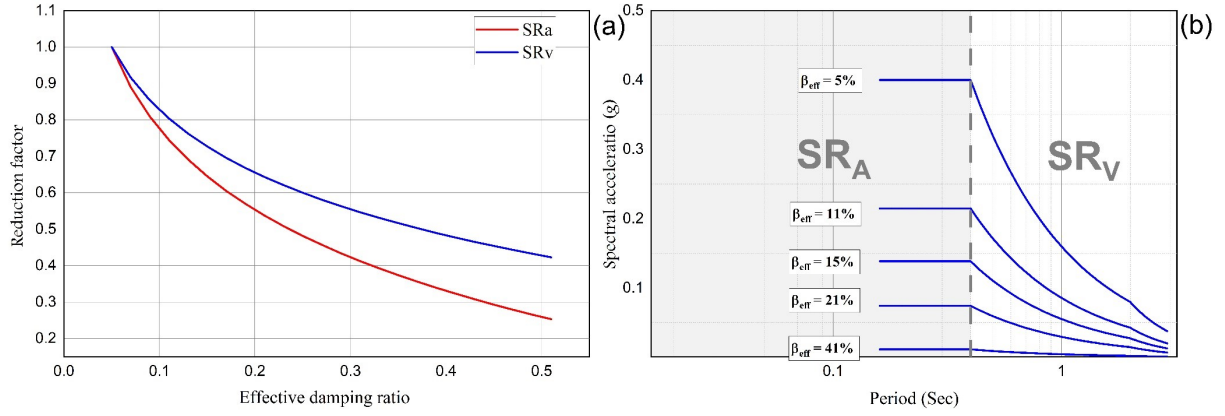


Figure 4.16: The reduction factors SRA and SRV: a) the empirical relation between the reduction factors and the effective damping ratio, b) Design spectra reduction using SRA and SRV in constant-acceleration and velocity regions.

The procedures are summarized in Figure 4.17, Figure 4.18 and Figure 4.19 according to ATC-40. Procedure A is an analytical method, and it is considered the clearest and direct method. However, Procedure B is the most convenient to perform on EXCEL or any programming language. Procedure C is a graphical method, and it can be performed manually (hand analysis).

4.4.2 Displacement coefficient method

In contrary of the iterative CSM, the DCM provides a non-iterative numerical method for estimating the displacement demand and target displacement without the need to convert the capacity curve into ADRS representation.

The method is limited to regular structures where no torsional or higher mode effect occurs. If so, some recommendations should be followed to better estimate the target displacement. The procedure is based on three main steps:

1-The capacity curve should be converted to a bilinear curve as shown in Figure 4.20:

- Find the elastic effective stiffness K_e by constructing a line between the origin and the $0.6V_y$ where the V_y is the intersection between the K_e and the plastic effective stiffness K_p .
- The area between the pushover curve and the bilinear representation should be equal.

2- Find the effective fundamental vibration period that corresponds to K_e using Equation (4.13):

$$T_e = T_i \sqrt{\frac{K_i}{K_e}} \quad (4.14)$$

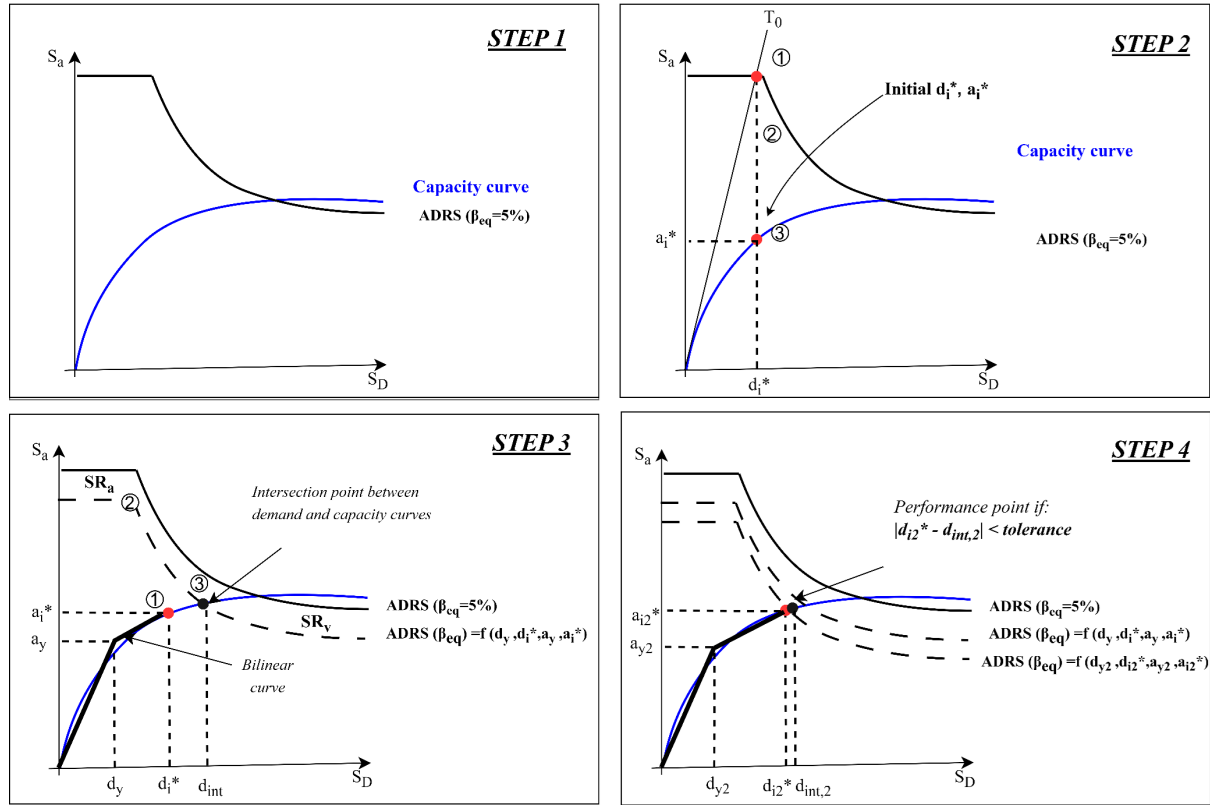


Figure III.16: Capacity spectrum method-Procedure A according to ATC-40

Figure 4.17: Capacity spectrum method-Procedure A according to ATC-40.

Where:

- K_i is the initial stiffness that represents the first slope of the capacity curve.
- K_e is the effective elastic stiffness or the first slope of the bilinear representation.
- T_i is the initial vibration period or the fundamental period.

3- Use Equation (4.15) to estimate the target displacement:

$$\delta_t = C_0 C_1 C_2 C_3 S_a \frac{T_e^2}{4\pi^2} \quad (4.15)$$

Table 4.3: Modification factor's values in function of number of stories.

Number of stories	Modification factor C0
1	1
2	1.2
3	1.3
5	1.4
+10	1.5

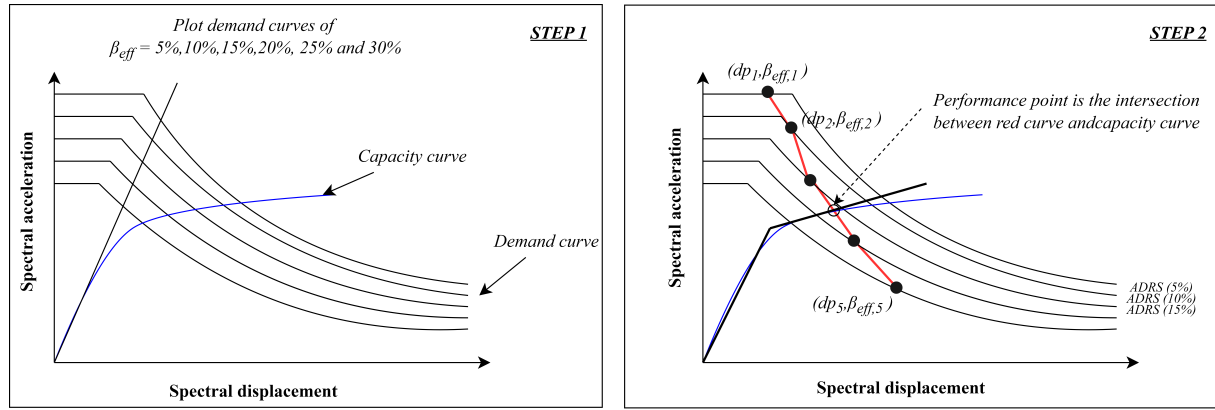


Figure 4.18: Capacity spectrum method-Procedure B according to ATC-40.

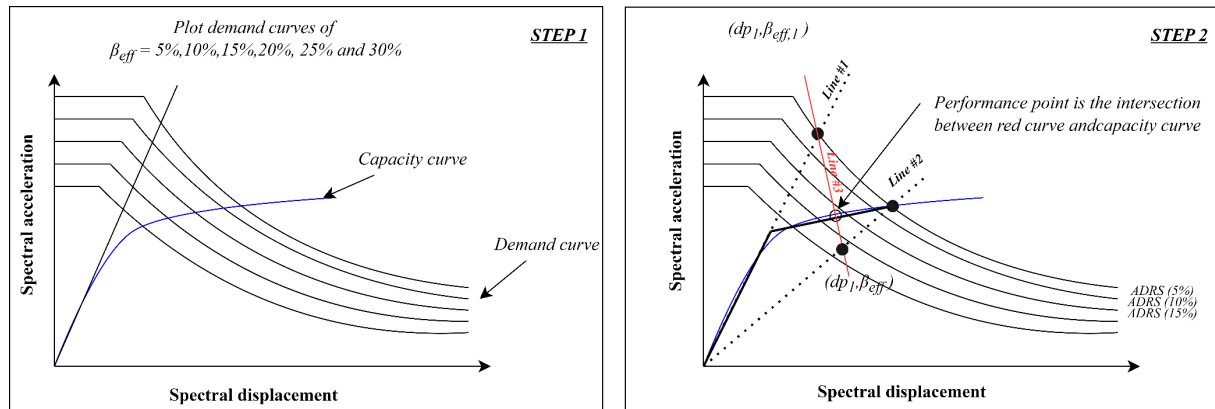


Figure 4.19: Capacity spectrum method-Procedure C according to ATC-40.

Where: C_0 : represents a modification factor that relates to the spectral displacement of the roof, and it can be calculated using:

- The first modal participation factor of the roof story.
- The participation factor using the shape vector.
- The values illustrated in Table 4.3.

C_1 = represents a modification factor that relates the expected inelastic response to the elastic response using the following formula:

$$C_1 = \begin{cases} 1.0 & \text{for } T_{eff} > T_0 \\ \left[1.0 + \frac{R-1}{T_e}\right] \frac{1}{R} & \text{for } T_{eff} \leq T_0 \end{cases}$$

Where, R is a strength reduction factor that can be calculated using Equation (4.16):

$$R = \frac{S_{aw}}{V_{yg}} \cdot \frac{1}{C_0} \quad (4.16)$$

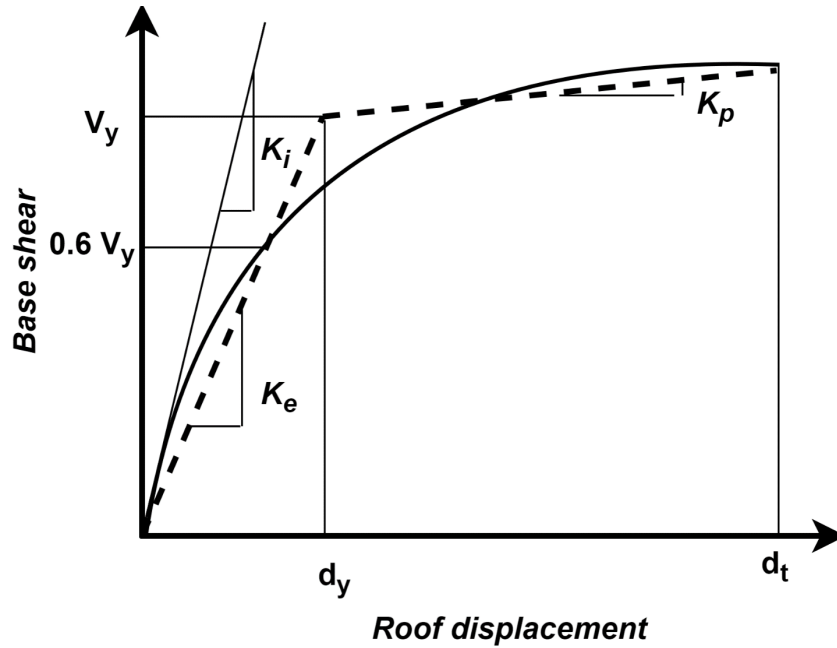


Figure 4.20: Bilinear representation of the capacity curve.

Table 4.4: C_2 modification factor for each performance level

	Frame type 1	Frame type 2	Frame type 1	Frame type 2
	$T = 0.1 \text{ sec}$		$T > T_0$	
IO	1	1	1	1
LS	1.3	1	1.1	1
CP	1.5	1	1.2	1

C_2 = is a modification factor to include the hysteresis loop shape effect on the target inelastic displacement. Its values are summarized in Table 4.4 where a linear interpolation can be used to obtain intermediate values.

C_3 = is a modification factor that includes the influence of second-order effects. For structures with a positive post-yield ratio, C_3 equals 1.0 and for a negative ratio C_3 can be calculated using Equation (4.17):

$$C_3 = 1 + \frac{|\alpha|(R-1)^{3/2}}{T_e} \quad (4.17)$$

Where α is the post-yield stiffness ratio.

- **Torsional effect:** To accurately capture the torsional effect in a building, a 3D model should be used. In this case, the lateral load should be applied in the center of mass of each story, and the recorded roof displacement would represent the center of mass response. However, if a 2D model is used instead, it must be ensured that the maximum displacement of any point at any floor does not exceed 120% of the center of mass displacement.

Table 4.5: Effective period and damping as a function of ductility.

Ductility	Effective period (T_{eff})	Effective damping (β_{eff})
$1.0 < \mu < 4.0$	$[0.2(\mu - 1)^2 - 0.038(\mu - 1)^3 + 1] T_0$	$= 4.9(\mu - 1)^2 - 1.1(\mu - 1)^3 + \beta_0$
$4.0 \leq \mu \leq 6.5$	$= [0.28 + 0.13(\mu - 1)] T_0$	$= 14 + 0.32(\mu - 1) + \beta_0$
$\mu > 6.5$	$= \left[0.89 \sqrt{\frac{\mu-1}{1+0.05(\mu-2)}} - 1 + 1 \right] T_0$	$= 19 \left[\frac{0.64(\mu-1)-1}{0.64} \right] \left(\frac{T_{eff}}{T_0} \right)^2 + \beta_0$

- **Higher mode effect:** Tall buildings experience prolonged periods of vibration, which means that the fundamental mode does not accurately represent the main response of the structure. Therefore, relying solely on one mode to calculate the response will not yield an accurate result, as other modes also contribute to the total response. To address this issue, a multi-modal pushover curve must be plotted. This involves applying a lateral force vertically to the structures for each vibration mode, resulting in a capacity curve that plots roof displacement and base shear. Each mode's participation factor and effective mass should be used to convert this into an ADRS. The CSM should then be used to calculate the performance point. Finally, each structural component can be assessed for each mode.

4.4.3 Improved procedures for performance point estimation using equivalent linearization (FEMA-440)

Based on the ATC-40 and FEMA-356, The equivalent linearization is a procedure that uses the pushover curve and demand curve and convert them into a ADRS plot. Using the effective damping and effective period, the performance point can be calculated either graphically or numerically illustrated and explained in the previous section.

FEMA-440 procedure proposed a different empirical formula for the effective period and effective damping. In addition, a modification factor has been introduced to the demand curve to reduce the demand curves and estimate the performance point.

4.4.3.1 Effective damping

Effective damping and effective period values are expressed in terms of percentage of the initial damping values, initial period, and ductility as illustrated in Table 4.5.

4.4.3.2 Modified ADRS using secant period

The CSM in ATC-40 is a conventional approach used to determine the maximum displacement. This approach uses the secant period where the target displacement is the

intersection between capacity curve and demand curve. It provides to advantages points. Firstly, it can be used graphically, and engineers can obtained and compare the intersection visually. Secondly, it is effective for modifying the ADRS demand curve (MADRS) and find the intersection between it and capacity curve.

The ADRS demand curve's ordinate should be multiplied by a modification factor (M) (see Equation (4.17)) to reduce the demand curve to make the MADRS correspond to effective damping ratio as shown in Figure 4.21.

$$M = \frac{a_{max}}{a_{eff}} = \left(\frac{T_{eff}}{T_{sec}} \right)^2 = \left(\frac{T_{eff}}{T_0} \right)^2 \cdot \left(\frac{T_0}{T_{sec}} \right)^2 = \left(\frac{T_{eff}}{T_0} \right)^2 \cdot \frac{1 + \alpha(\mu - 1)}{\mu} \quad (4.18)$$

Where:

- a_{max} : The spectral acceleration corresponds to maximum displacement of the capacity curve.
- a_{eff} : represents the spectral acceleration that corresponds to the effective period.
- T_{sec} : is the period that corresponds to the maximum spectral displacement/acceleration.
- α : is post yield stiffness ratio.

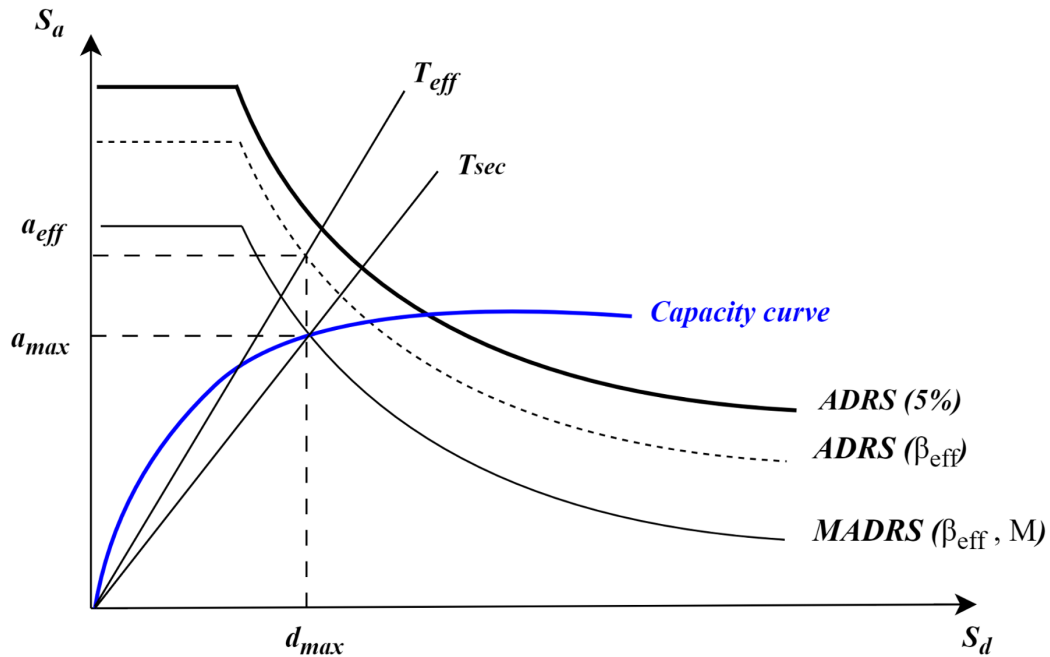


Figure 4.21: The secant period and the modified ADRS (MADRS) curve.

4.4.3.3 Proposed procedures

Effective damping and effective period are functions of ductility. The estimation of target displacement using equivalent linearization needs iterative process or graphical method.

Three procedures are proposed to obtain the performance point according to FEMA-440, and this procedures are based on the same initial steps are shown in Figure 4.22. It begins with converting the demand curve and capacity curve into ADRS format. The initial displacement is the intersection of the initial period line and ADRS demand curve. Next, a bilinear curve shall be plotted defining the yielding and maximum acceleration/displacement. Ductility and post yield stiffness ratio will be used to design the effective period and effective damping.

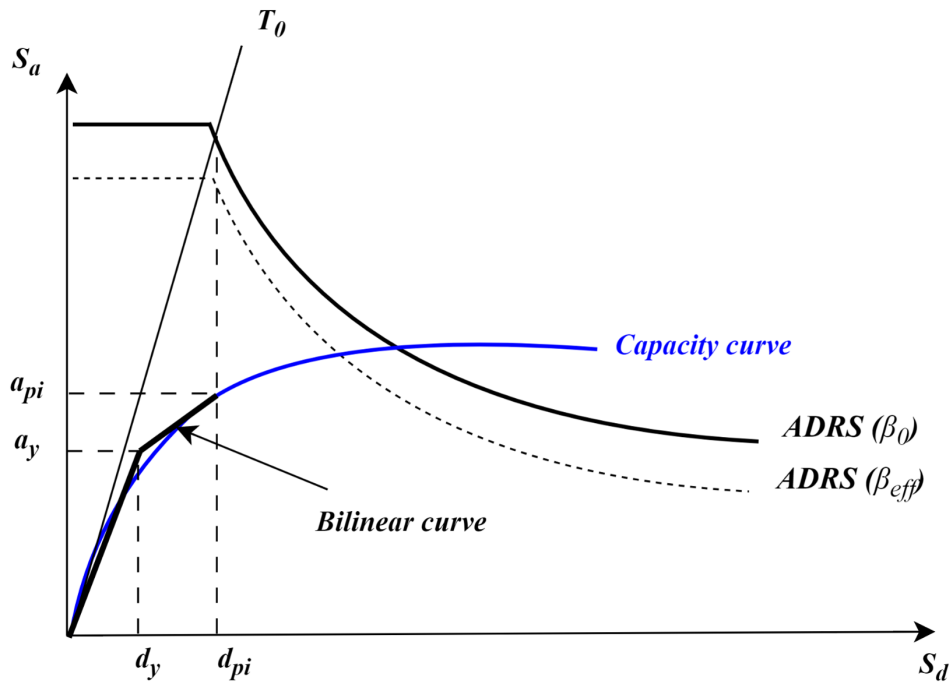


Figure 4.22: The initial steps to perform FEMA-440 proposed methods to estimate the performance point.

Procedure A: After the initial steps are performed, a T_{eff} shall be calculated using the calculated ductility demand of the bilinear curve. The intersection between the effective line and the ADRS demand curve (of the effective damping) is the susceptible performance point if $|d_{pi} - d_p| < \text{tolerance}$ as shown in Figure 4.23.

Procedure B: it involves using a modification coefficient on the ADRS to reduce the demand due to the increase of the effective damping as well as the period. The MADRS's intersection with the capacity curve shall be the performance point (d_p) if $|d_{pi} - d_p| < \text{tolerance}$ as shown in Figure 4.24, where d_{pi} is the maximum displacement of the bilinear representation .

Procedure C: It is based on plotting the secant periods for different ductility demand $\mu = \{1, 2, 3, \dots\}$ and calculating the corresponding effective damping. Various MADRS

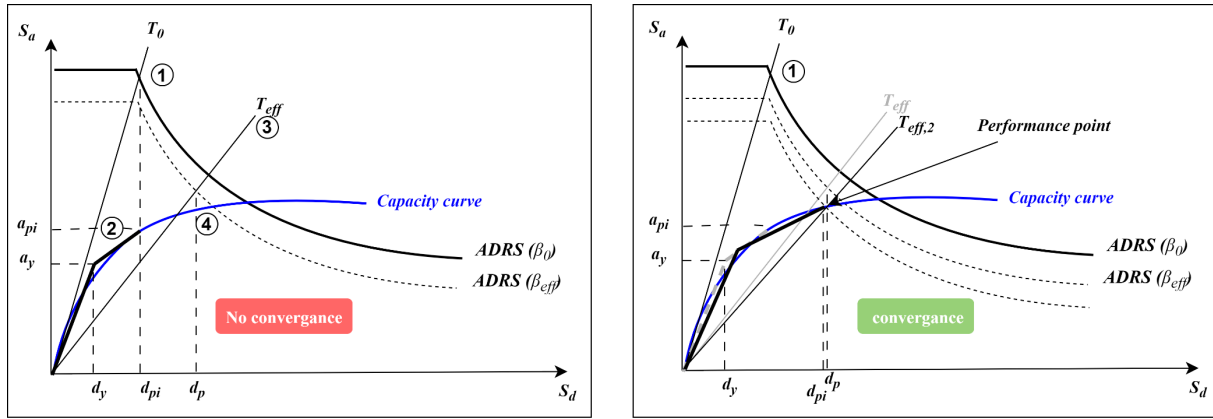


Figure 4.23: Procedure A according to FEMA-440 for performance point estimation.

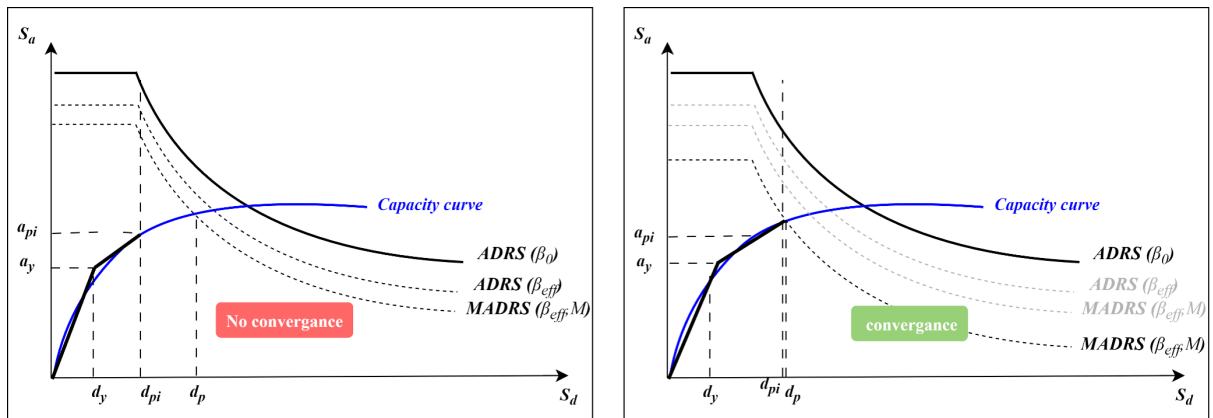


Figure 4.24: Procedure B according to FEMA-440 for performance point estimation.

curves shall be plotted using the calculated effective damping. The intersection of each secant period and the corresponding MADRS will form a Locus point that represents the possible performance point. The performance point is the intersection between the locus line and the capacity curve as illustrated in Figure 4.25.

4.4.4 Modified coefficient method according to FEMA-440

In FEMA-356, a CDM has been introduced and presented previously. Several improvements are made in FEMA-440 concerning the used coefficients. C_1 is abandoned in the newly proposed approach. In addition, FEMA-440 recommends C_2 which considers hysterical behavior. C_3 is eliminated and only strength limits are recommended.

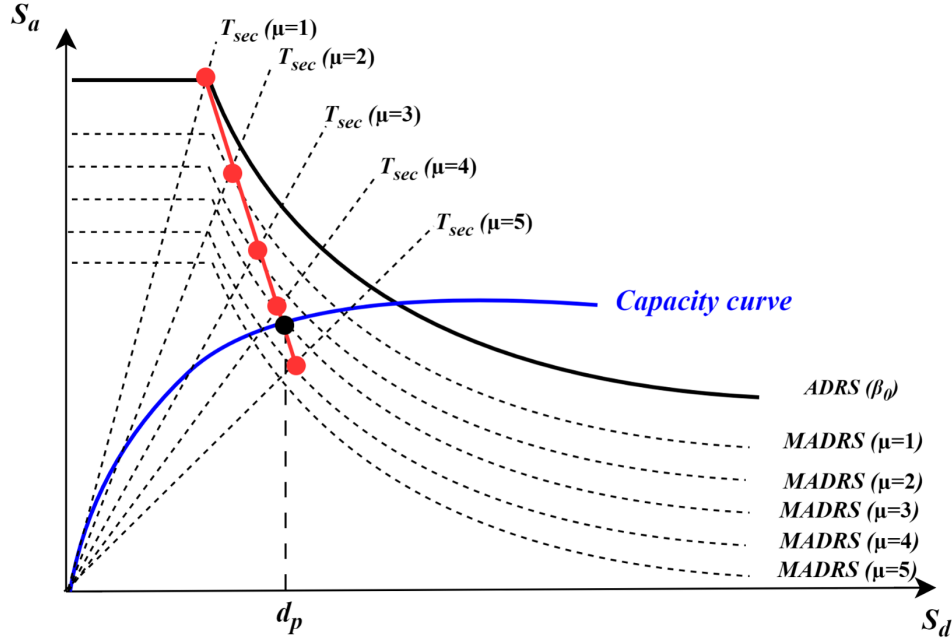


Figure 4.25: Procedure C according to FEMA-440 for performance point estimation.

4.4.4.1 Modified expression

For C_1 coefficient, FEMA-440 proposes the following Equation (4.19):

$$C_1 = 1 + \frac{R - 1}{\alpha T_e^2} \quad (4.19)$$

Where: R represents the strength ratio and T_e is the effective period. α equals 130, 90, and 60 for site types B, C, and D. In the case of periods that exceed 1 sec, C_1 equals 1.0. C_2 is also modified where Equation 4.20 illustrates the new empirical formula that includes the hysteretic behavior effect on the maximum displacement estimation.

$$C_2 = 1 + \frac{1}{800} \frac{R - 1}{T}^2 \quad (4.20)$$

4.5 A comparative analysis of the procedures

This part of the chapter will focus on the performance of the adopted procedures to estimate the performance point/target displacement compared to NLTHA. The evaluation will be conducted using three periods of vibration $T = [0.2s, 0.5sec, 1.0sec]$ and three SDOF systems with different behavior reduction coefficients $R = [2, 4, 8]$.

19 GMs have been selected to perform the evaluation and their unmatched characteristics are summarized statistically in Figure 4.26 The GMs are matched to three periods (0.2, 0.5, 1.0 sec), and the GM spectral response is illustrated in Figure 4.27. Figure 4.27 -a, -b, and -c represent the matched GMs to a target response spectrum. Figure 4.27-d

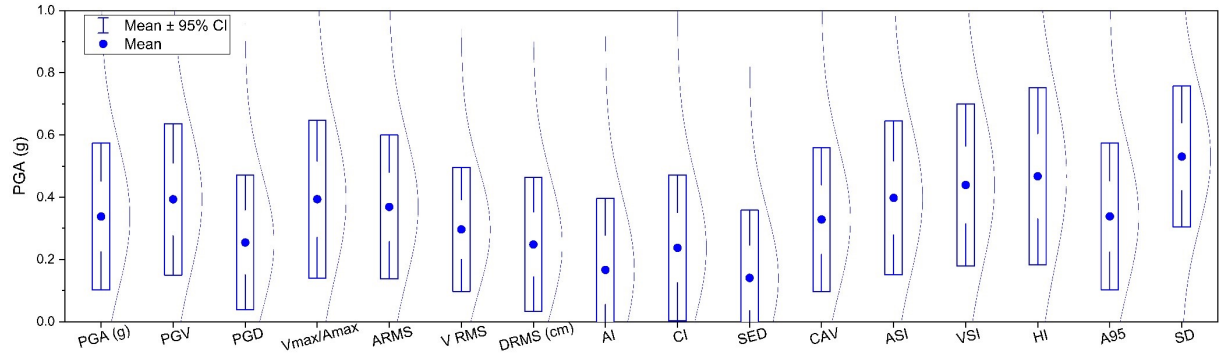


Figure 4.26: The GM characteristics selected for the evaluation normalized to 1 .

illustrates the original unmatched response spectra. It can be observed that the matched GMs have the same acceleration response in the selected periods. This matching will make the analysis more meaningful in terms of response statistically.

4.5.1 Nonlinear time history analysis

Figure 4.28 displays the response of a Single Degree of Freedom (SDOF) system to ground motion. The results of the Nonlinear Time History Analysis (NLTHA) will be used as a reference to evaluate the adopted methods and their estimation. The maximum absolute relative displacement of the NLTHA output will be considered the target displacement. Three reduction factors are used, where the yielding limit of the SDOF is the spectral acceleration response times mass divided by the strength reduction factor (R).

4.5.2 Results

The study focuses on the seismic response estimation using the adopted procedures in and ATC-40, FEMA-356, and FEMA-440 named, CSM, DCM, EL, and MCM.

The study will be conducted also by measuring the mean relative ratio error and the standard deviation of these errors between the exact and estimated displacements for all GMs, as shown in Equations (4.21), (4.22), (4.23).

$$E_R = \frac{\delta_{estimated}}{\delta_{NLTHA}} \quad (4.21)$$

$$\overline{E_R} = \frac{1}{n} \sum_{i=1}^n E_{R,i} \quad (4.22)$$

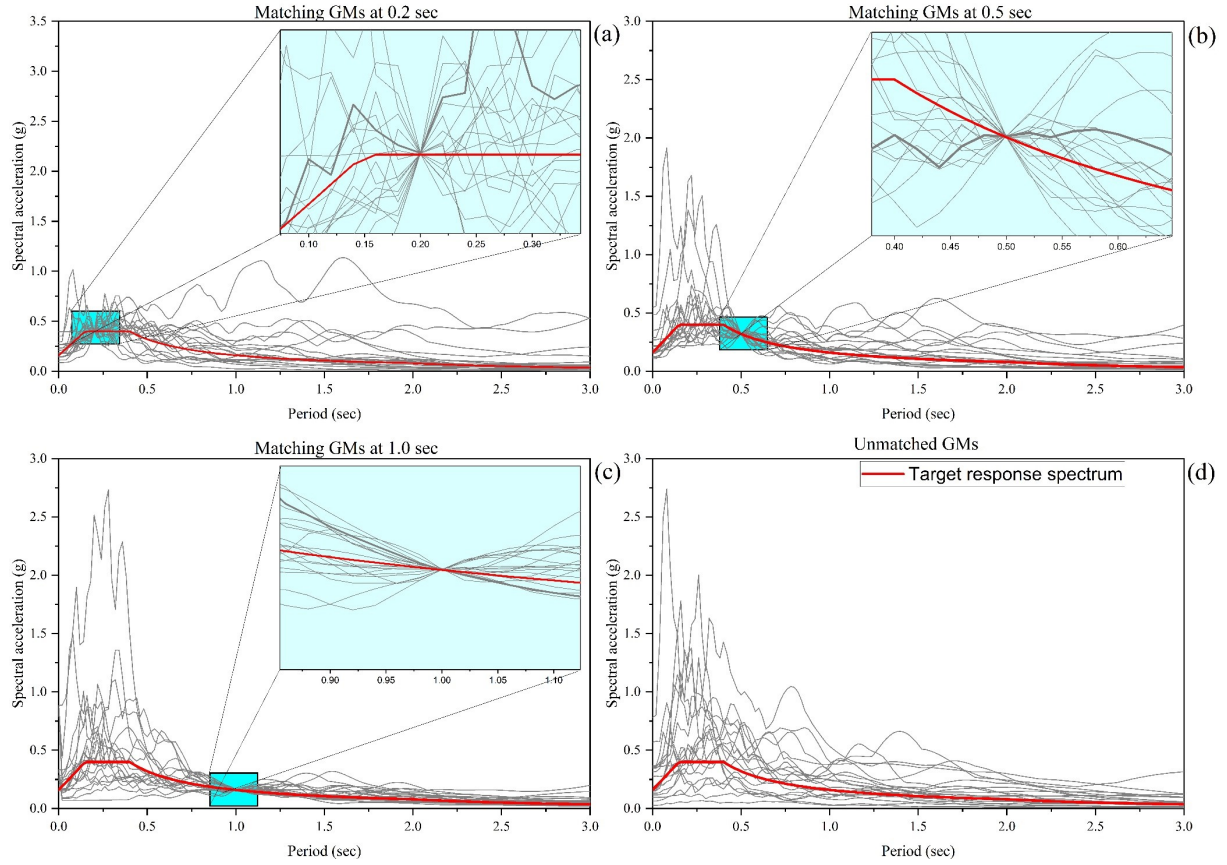


Figure 4.27: The target response spectrum and GMs response spectra are compared for four scenarios: a) GMs matched at $T=0.2$ sec, b) GMs matched at $T=0.5$ sec, c) GMs matched at $T=1.0$ sec, and d) unmatched GMs

$$\sigma_E = \sqrt{\frac{1}{n-1} \sum_{i=1}^n [E_{R,i} - \overline{E_{R,i}}]^2} \quad (4.23)$$

where:

- $\delta_{estimated}$: is the estimated response using CSM, DCM, EL or MCM.
- δ_{NLTHA} : is the exact solution of the dynamic response using NLTHA.
- n : is the number of ground motions.
- $\overline{E_R}$: is the mean relative error of using all GMs.
- σ_E : is the standard deviation of the relative error of all the GMs.

In the study of single-degree-of-freedom (SDOF) systems, the mean error is used across all periods and strength reduction values. If the value is less than one, it means that the approach has underestimated the results. On the other hand, if the value is greater than one, it means that the approach has overestimated the results. To determine the dispersion and unbiased estimation of each approach, the standard deviation is used by

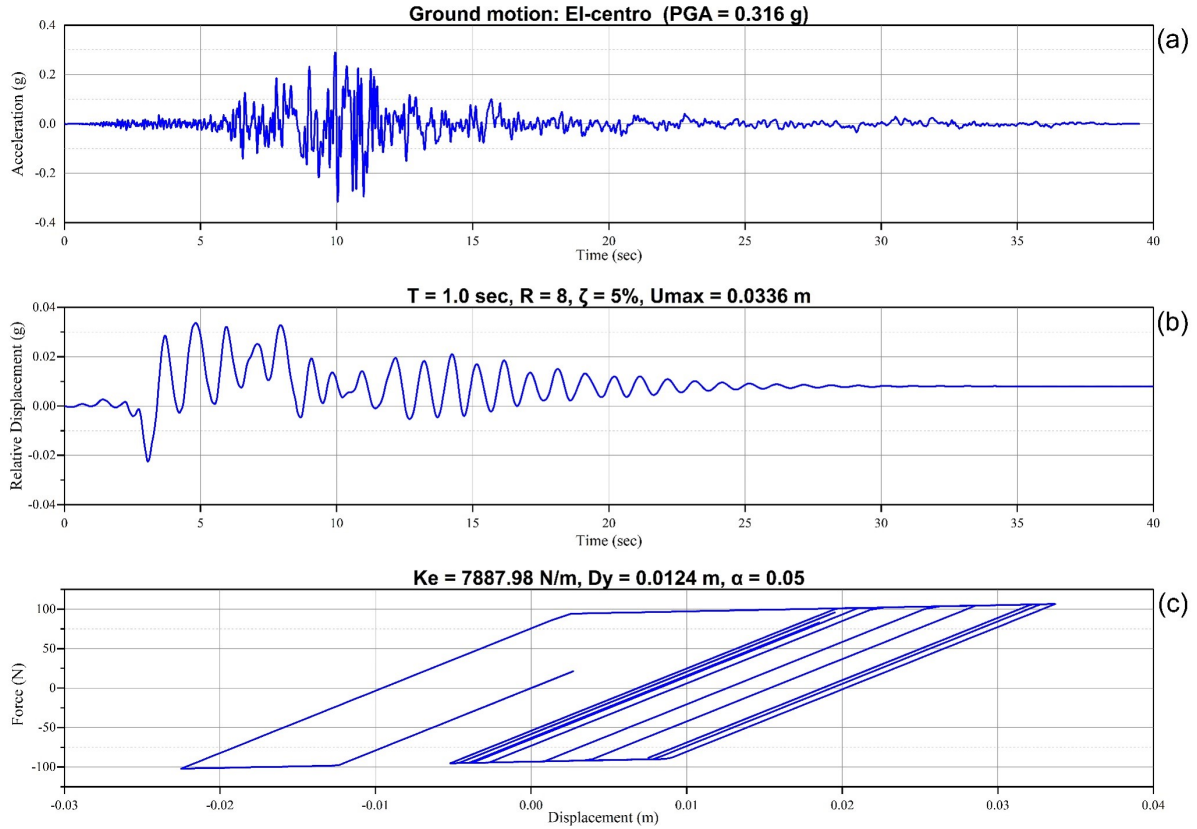


Figure 4.28: Nonlinear-time history analysis of an SDOF ($m=200$ KG and $K_e = 7887.98$ N/m and $T = 1.0$ sec subjected to GM): a) El-centro matched GM at $T = 1.0$ sec, b) Relative displacement response history, c) Force-displacement relationship of the SDOF.

analyzing all the ground motions.

Figure 4.29 shows the mean response of each approach of $R = 2, 4$, and 8 at $T=0.2, 0.5, 1.0$ sec. The plot also depicts the standard deviation of the NLTHA response for each strength reduction factor. After analyzing the graphs, it can be concluded that the methods used to estimate the response tend to underestimate it for short periods of vibration ($T=0.2$ sec). The estimated results fall outside the 16% probability of the normal distribution of the responses obtained from Nonlinear Time History Analysis (NLTHA). Conversely, the ATC-40 approach underestimates the responses for longer periods of vibration, and its estimation lies outside the confidence interval of the mean plus and minus standard deviation.

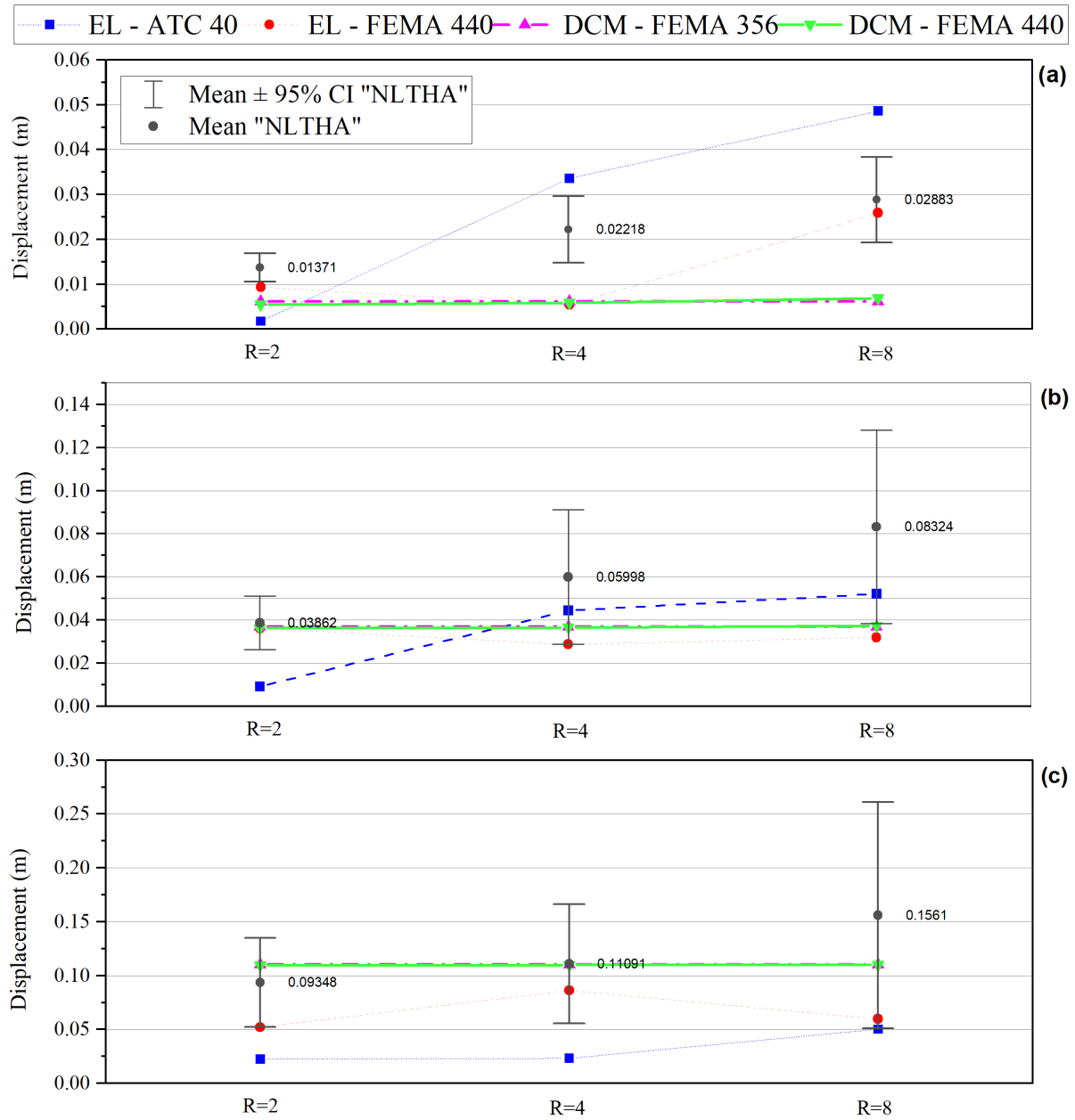


Figure 4.29: Comparative study between the NLTHA and adopted approaches mean dynamic response of three strength reduction factors: a) $T = 0.2$ sec, b) $T = 0.5$ sec, and c) $T = 1.0$ sec .

Analytically, according to Figure 4.30, the calculated errors represent the ratio between the proposed approaches and the NLTHA responses. The following point can be captured from the Figure 4.30:

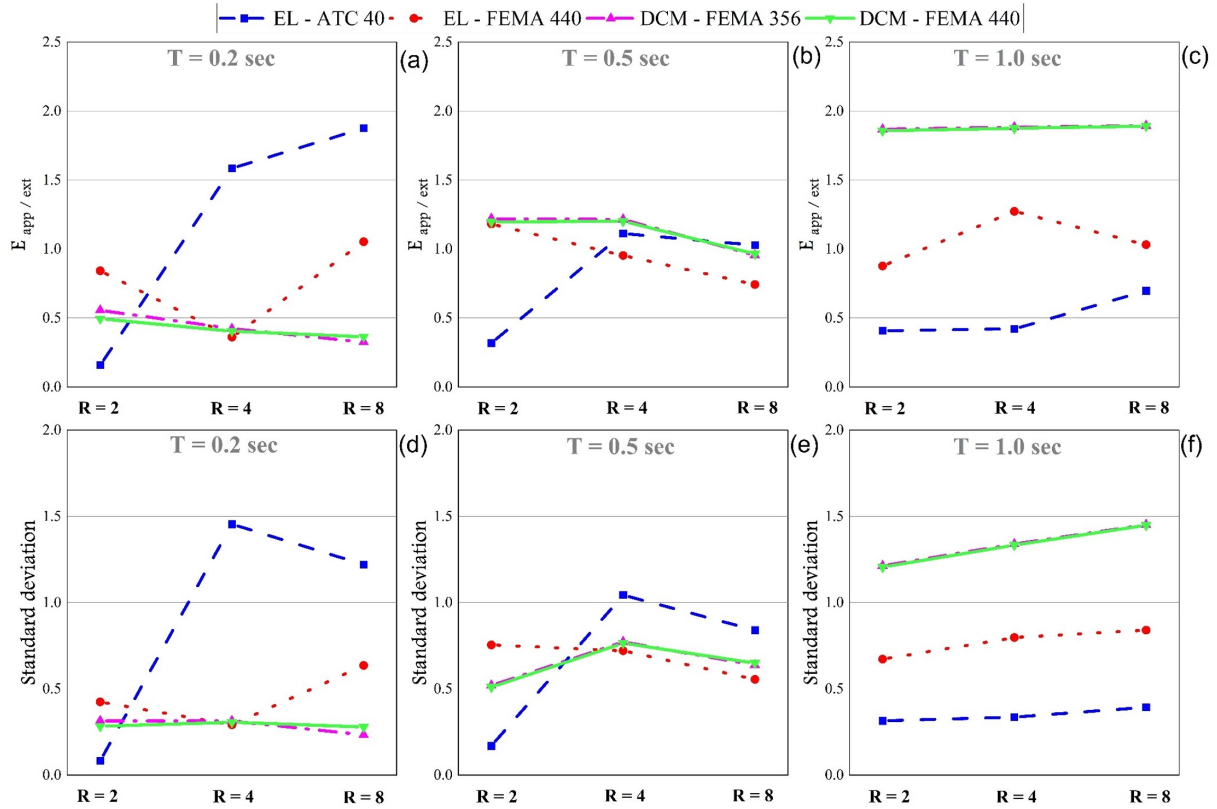


Figure 4.30: Errors and standard deviation between NLTHA and adopted approaches mean dynamic response of three strength reduction factors: a) E ($T = 0.2$ sec), b) E ($T = 0.5$ sec), c) E ($T = 1.0$ sec), d) STD ($T = 0.2$ sec), e) STD ($T = 0.5$ sec), and f) STD ($T = 1.0$ sec).

1- **CSM-ATC-40**: It underestimates the seismic response for structures with $R=2$ for all the periods with the lowest standard deviation compared to the other approaches. It ensures that the distribution of the results is close to the mean value.

2- **EL-FEMA-440**: The improved equivalent linearization procedure has demonstrated an enhancement in its predictability when compared to the previous version used in ATC-40 and FEMA-356. The estimated values are significantly better than those obtained from the CSM, especially for low values of R . The evaluation of errors confirms that the mean errors of the approach tend to underestimate the response for short vibration periods and overestimate the response for period $T=1$. The standard deviation increases when the period increases. It shows that the estimated responses are concentrated near the mean value for the short vibration period, however the standard deviation gets higher for $T=0.5$ and 1.0 sec.

3- **DCM- FEMA 356 and DCM-440**: The following are two non-iterative methods that can be used to estimate the target response without the need to transform the pushover curve into ADRS plot. Our investigation leads us to conclude that both approaches give almost the same mean response for all systems and standard deviation. However, they may underestimate the target displacement for a short period and overes-

timate the response for longer periods. Nevertheless, they are considered acceptable for T values of 0.2 and 0.5 seconds, as their standard deviation is the lowest for the same period values. On the contrary, the responses are less meaningful for long-period vibrations, with a high dispersion.

4.6 Conclusion

Understanding structural responses to seismic events is essential for designing resilient buildings and assessing existing structures' behavior. This chapter provides an overview of seismic analysis, exploring both static and dynamic approaches for elastic and inelastic systems, with a focus on the dynamic analysis of single-degree-of-freedom (SDOF) systems. It also reviews methodologies proposed by FEMA and ATC to estimate target displacement, comparing these approaches to Nonlinear Time History Analysis (NLTHA) results. Analysis reveals that methods tend to underestimate responses for short periods ($T=0.2$ sec) and overestimate them for longer periods ($T=1$ sec). Specifically, the ATC-40 approach shows significant underestimation for long periods. Comparative evaluation indicates that the EL-FEMA-440 approach improves predictability over its predecessors, while DCM-FEMA 356 and DCM-440 approaches yield consistent mean responses but may underestimate for short periods and overestimate for longer periods. These findings underscore the need for careful consideration of period-specific performance in seismic design.

Chapter 5

Seismic vulnerability and fragility assessment of structures

5.1 Introduction

Earthquakes occur when the Earth's crust suddenly releases stored energy, often caused by tectonic plates shifting and resulting in strain in rock formations. This energy is then transmitted to the Earth's surface through seismic waves, which can cause the ground to shake violently. Though some earthquakes may only cause minor tremors, larger ones can start with small vibrations, intensify into powerful shocks, and eventually subside with aftershocks.

As urbanization accelerates, cities are expanding with taller and more complex structures. This increases the risk of damage and collapses in urban areas compared to rural ones in the event of an earthquake. Therefore, predicting and disseminating potential earthquake damage can be crucial in prompting responsible authorities to prioritize preventive measures, disaster preparedness, response strategies, and mitigation efforts.

This chapter summarizes the required literature review concerning seismic vulnerability and fragility assessment using the fragility curves. Various techniques and approaches will be presented to give the readers the minimum background to better understand the following chapters. It includes the definition of the vulnerability and fragility assessment of buildings and the existing methods and approaches that researchers have used.

5.2 SEISMIC VULNERABILITY AND FRAGILITY ASSESSMENT OF STRUCTURES

In the last few decades, researchers have extensively studied and developed methodologies to quantify the damage caused by earthquakes to structures. This has led to the development of various indices of seismic risk and vulnerability assessment that help quantify

the damage caused to structural elements or the overall structural system. Figure 5.1 summarizes the main three categories of seismic vulnerability assessment methodologies.

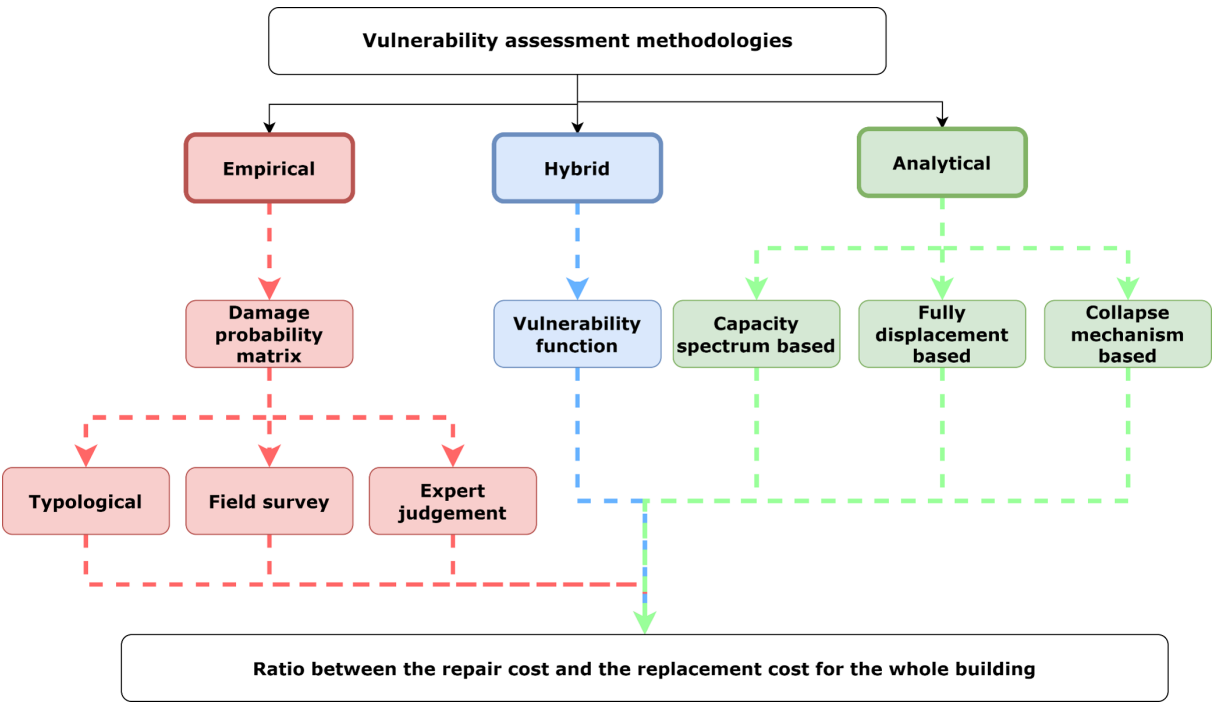


Figure 5.1: Flowchart of the seismic vulnerability assessment methodologies.

Table 5.1: Seismic vulnerability assessment methods and their applicability

Expenditure	Reliability / computational efforts			
Scale application	Building stock		Individual building	
Method	Field survey	Expert opinion	Simple analytical models	Score assignments

Table 5.1 presents a classification of seismic vulnerability assessment methods based on their application scale, complexity, and accuracy. Large-scale assessments require fast methods to cover many buildings and make quick decisions based on field surveys and expert judgments. However, these methods have low accuracy results and may vary from expert to expert. On the other hand, individual building assessments can be done using analytical approaches, especially when enough data is available, such as architectural layouts, material characteristics, reinforcement, and other data that may affect the structural behavior. These approaches tend to be more accurate and provide more certainty; however, they are more complex and require a good understanding of the analysis.

5.2.1 Empirical methods

During the 1970s, methods were developed to evaluate the seismic vulnerability of buildings on a large geographical scale using empirical approaches. These approaches were

Table 5.2: The damage probability matrix proposed by Whiteman et al.

DS	Structural Damage	Non-structural damage	Damage Ratio (%)	Intensity of Earthquake				
				V	VI	VIII	IX	X
0	None	None	0-0.05	-	-	-	-	-
1	None	Minor	0.05-0.3	16.4	0.5	-	-	-
2	None	Localized	0.3-1.25	40	22.5	-	-	-
3	Not noticeable	Widespread	1.25-3.5	20	30	2.7	-	-
4	Minor	Substantial	3.5-4.5	13.2	47.1	92.3	58.8	14.7
5	Substantial	Extensive	7.5-20	-	0.2	5	41.2	83
6	Major	Nearly total	20-65	-	-	-	-	2.3
7	Building condemned		100	-	-	-	-	-
8	Collapse		100	-	-	-	-	-

based on micro-seismical intensities and were used to create hazard maps. At the time, no physical quantities correlate with intensities such as PGA. Therefore, the methods were calibrated with a large amount of scatter. Despite this, the empirical methods remained the only feasible approaches that could be initially employed in seismic risk analyses on a large scale.

Two primary empirical methods are used for seismic vulnerability assessments of buildings based on the damage observed after earthquakes. These methods can be referred to as "damage-motion relationships." The first method is damage probability matrices (DPM), which express the conditional likelihood of attaining a damage level j due to a ground motion of intensity. The second method is vulnerability functions, which are continuous functions that express the probability of exceeding a given damage state, given a function of the earthquake intensity.

5.2.2 Damage Probability Matrices

DPM is a tool used in seismic vulnerability assessment to predict the probability of buildings or structures being in a particular damaged state given a specific level of earthquake intensity. The DPM provides a systematic way to quantify the likelihood of different levels of damage based on historical data, empirical observations, or analytical models. It typically presents the probabilities of various damage states (e.g., no damage, minor damage, extensive damage, collapse) for different levels of ground shaking intensity. The DPM is valuable in seismic risk analysis as it helps estimate potential losses, prioritize mitigation efforts, and develop emergency response plans. By utilizing DPMs, stakeholders can better understand the vulnerability of buildings and infrastructure to earthquakes, leading to more informed decision-making processes in disaster preparedness and risk reduction strategies. Whiteman [60] introduces the concept of DPMs for probabilistic prediction of earthquake damage to buildings, providing insights into the development and application of DPMs based on data from the 1971 San Fernando earthquake. Table 5.3 illustrates the DPM proposed by Whiteman et al.

5.2.3 Vulnerability index method

The Vulnerability Index Method (VIM) is a widely used approach in seismic vulnerability assessment that aims to quantify the vulnerability of buildings or structures to earthquake-induced damage. This method involves assigning a vulnerability index to each building based on various parameters influencing its susceptibility to seismic forces. The Vulnerability Index Method typically consists of the following key steps:

- **Parameter Selection:** The process entails selecting and defining specific parameters that indicate a building's susceptibility to earthquakes. These parameters may include structural attributes such as building material, age, and height; site conditions such as soil type or proximity to fault lines; and non-structural aspects such as architectural features and occupancy type.
- **Weighting and Scoring:** To determine a building's vulnerability, each parameter is given a weight based on its relative importance. These weights are typically determined using expert judgment, statistical analysis, or historical data. The parameters are then evaluated based on their condition or characteristics, with higher scores indicating greater vulnerability.
- **Vulnerability Index Calculation:** The vulnerability index for a building is calculated as the weighted sum of the scores assigned to each parameter. This index quantitatively measures the building's overall vulnerability to seismic events. The index can be expressed as a single value or categorized into vulnerability classes (e.g., low, moderate, high).
- **Validation and Calibration:** The calculated vulnerability indices are often validated and calibrated using observed earthquake damage data. This helps ensure that the method accurately reflects the actual vulnerability of buildings in seismic events. Calibration may involve adjusting the weights assigned to parameters or refining the scoring criteria based on empirical data.
- **Risk Assessment:** Once the vulnerability indices are determined for a set of buildings, they can be used in seismic risk assessment to prioritize mitigation efforts, develop emergency response plans, and estimate potential losses in future earthquakes. Buildings with higher vulnerability indices are considered at greater risk of damage and may require targeted interventions.
- **Advantages and Limitations:** The Vulnerability Index Method provides a systematic and quantitative approach to assess the seismic vulnerability of buildings. It allows for comparing vulnerability levels across different structures and facilitates decision-making in risk-reduction strategies. However, the method relies on

Table 5.3: VIM parameters and their weights

Parameters		Class				Weight
		A	B	C	D	
1	Position of the building and foundations	0	1,35	6,73	12,12	0,75
2	Floor plan configuration or geometry	0	1,35	6,73	12,12	0,5
3	Elevation configuration	0	1,35	6,73	12,12	1,0
4	Distance between walls	0	1,35	6,73	12,12	0,25
5	Non-structural elements	0	0	6,73	12,12	0,25
6	Type and organization of the resistant system	0	1,35	6,73	12,12	1,5
7	The quality of the resistant system	0	1,35	6,73	12,12	0,25
8	Horizontal structures	0	1,35	6,73	12,12	1,0
9	Roofing	0	1,35	6,73	12,12	1,0
10	Conservation status	0	1,35	6,73	12,12	1,0
11	Environmental alterations	0	1,35	6,73	12,12	0,25
12	Construction system alterations	0	1,35	6,73	12,12	0,25
13	Vulnerability to fire	0	1,35	6,73	12,12	0,25

subjective parameter selection and weighting judgments, which can introduce uncertainties. Additionally, the accuracy of the vulnerability indices is highly dependent on the quality of data and assumptions used in the assessment.

The VIM is an indirect method because it relates the seismic damage and the seismic action through the vulnerability index (I_v) calculation. The I_v can be calculated using Equation (5.1).

$$I_v = \sum_{i=1}^{11} K_i W_i \quad (5.1)$$

Where K_i represents the qualitative coefficient that identifies the field survey of the structural characteristics, including eleven parameters such as foundation type, plan, elevation irregularities, the quality of materials, etc., W_i represents the weight and the relative importance of the parameters as illustrated in Table 5.3.

The obtained IV ranged from 0 (least vulnerable) to one hundred (most vulnerable). The vulnerability functions are calibrated using past earthquake data to relate the global damage factor for a seismic intensity measure (e.g., PGA or macroseismic intensity). The damages are assumed to be negligible if the PGA is less than the threshold and the damage factor increases linearly in the function of PGA until the collapse (damage factor = 1) for each IV, as shown in Figure 5.2.

- **RISK-UE Project:** The RISK-UE project [61] is a significant research project first financed by seven European towns (Catania, Bitola, Barcelona, Sofia, Bucharest, Nice, and Thessaloniki). Its principal project was to develop a vulnerability assessment methodology for European buildings. They proposed an empirical where the VIM was used and an analytical approach.
- **The Catania Project:** discussed in the works of Faccioli et al. [62] and GNDT [63]

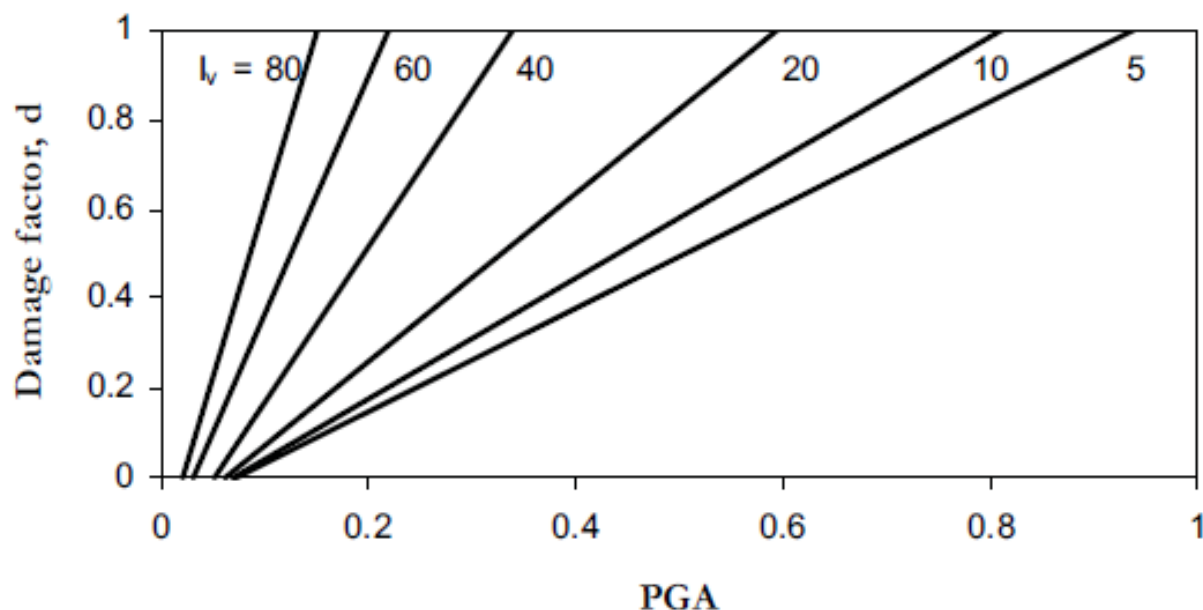


Figure 5.2: The linear relationships between each vulnerability index's damage factor and the PGA.

utilized a modified vulnerability index method to evaluate the risk of masonry and reinforced concrete buildings. The project adjusted the original vulnerability index procedure. A rapid screening method was employed to define the vulnerability scores for buildings, following the guidelines outlined in ATC-21 [64]. The vulnerability score was calculated based on the weighted sum of eleven parameters, with some parameters based on historical or recent construction practices specific to the region. Each building's vulnerability score had an upper and a lower bound determined based on a range of values associated with the various parameters. The vulnerability functions for old masonry buildings were calibrated using observed damage data from significant earthquakes such as the 1976 Friuli and the 1984 Abruzzo earthquakes. Guagenti and Petrini's [65] proposed a relationship was used to correlate damage and PGA—the Catania Project aimed to provide valuable insights into seismic vulnerability, particularly for buildings in high-risk areas.

5.2.4 Analytical/mechanical methods

Hybrid models combine observed post-earthquake damage statistics and simulated analytical damage statistics created using a mathematical model of the building typology under consideration. They are instrumental when insufficient damage data is available at certain intensity levels for the geographic area under consideration. Hybrid models also allow for calibration of the analytical model, reducing computational efforts required to produce analytical vulnerability curves of DPMs.

Kappos et al. [66] developed damage probability matrices using a hybrid procedure. They used data from past earthquakes to construct parts of the DPMs for each intensity level, following the "Vulnerability Index Procedure." They formed the remaining parts of the DPMs using the results of nonlinear dynamic analysis of models that simulated the behavior of each building class. They ran 120 analyses of typical Greek buildings designed for the 1959 code and combined the statistical damage results with observed damage from the 1978 earthquake in Thessaloniki.

In 1996, Barbat et al. [67] conducted a hybrid vulnerability assessment of urban areas in Spain using the "Vulnerability Index Methodology" from Italy. Two ground motion records with a maximum intensity of VII on the MSK scale were studied, and the damage caused was analyzed. The researchers obtained the vulnerability function for MSK intensity level VII by correlating the damage to masonry structures with the vulnerability and damage indices used in the Italian methodology. They used computer simulation with 2000 hypothetical buildings and calibrated weighting factors to estimate the vulnerability functions at other intensity levels.

The main challenge with using hybrid methods is related to the calibration of analytical results. This is because the two vulnerability curves include different sources of uncertainty, making them not directly comparable. The empirical data is subject to unquantifiable variability, while analytical curves have defined sources of uncertainty generated during the curve generation process.

The method used to calibrate the analytical vulnerability curves using empirical data should depend on the aim. If the goal is to include the additional uncertainty in the empirical data that is not accounted for in the analytical data, then a different approach should be taken. On the other hand, if the goal is to improve the analytical model used to define the building stock's capacity, it is preferable to calibrate the vulnerability curves considering the median (50 percentile) values. An adaptation of the analytical model could be made such that the two median values coincide. This way, the observational data can calibrate the analytical model. However, analytically derived vulnerability curves with their known and specified sources of uncertainty are used in the loss model.

This approach is valid only when uncertainty related to the capacity of the building stock is required and not when ground motion is not involved. For instance, such curves are needed when a probabilistic seismic hazard assessment defines the ground motion. This ensures that the latter variability is not double-counted.

5.2.4.1 Capacity Spectrum-Based Methods

HAZUS (Hazard US) is a pivotal outcome of a project conducted for the National Institute of Building Science (NIBS) under a cooperative agreement with the Federal Emergency Management Agency (FEMA). This significant project aimed to develop a methodology

that could be applied nationally to estimate the potential losses from earthquakes on a regional basis Whitman et al. [68] FEMA [57].

The methodology is a comprehensive framework encompassing several main modules. These include the estimation of Potential Earth Science Hazards (PESH), which consist of ground motion, ground failure (liquefaction, landslides, and surface fault rupture), and tsunami/seiche. The inventory is meticulously divided into various categories: buildings, facilities, transportation systems, utility systems, and hazardous material facilities. Each category is subdivided into pre-defined building classes with similar damage/loss characteristics.

Direct physical damage is calculated for each building class to determine the probability of none, slight, moderate, extensive, and complete structural and non-structural damage due to each type of PESH. Induced physical damage from inundation, fire, hazardous materials, and debris is also estimated. Direct economic/social losses due to casualties, persons rendered homeless, and financial losses directly correlated to the damage are estimated. Indirect economic losses due to downtime, which can cause a chain reaction through the regional economy, are also calculated.

The vulnerability assessment component of the procedure is a crucial part of the direct physical damage module. It is based on the Capacity Spectrum Method of ATC-40 [1]. In this method, the performance point of a building type under a particular ground-shaking scenario (or PESH) is determined from the intersection of an acceleration-displacement spectrum, representing the ground motion. A capacity spectrum (pushover curve) represents the horizontal displacement of the structure under increasing lateral load [69], as shown in Figure 5.3. The demand spectrum is reduced for both damping and duration effects. The spectrum reduction is applied to account for the hysteretic damping that occurs during the inelastic behavior of the structure, where the damping is based on the area enclosed by the hysteretic loop at peak response displacement and acceleration. A reduction factor is applied to the hysteretic damping as a function of shaking duration to simulate the hysteresis loop's degradation (e.g., pinching) during cyclic response.

The capacity spectrum for each building class in the US was created by using model buildings designed for various levels of design practices. The performance point obtained from an average building is used as a displacement input into the limit state vulnerability curves. This helps determine the probability of a building being in a specific damaged band. Transitional phrases can be used to connect these ideas. The vulnerability curves are a probabilistic representation of a lognormal distribution where the standard deviation combines the damage state threshold uncertainty, the capacity properties of the building, and the ground motion demand uncertainty.

Once the curves are constructed for all the damage states (sight, moderate, extensive, and

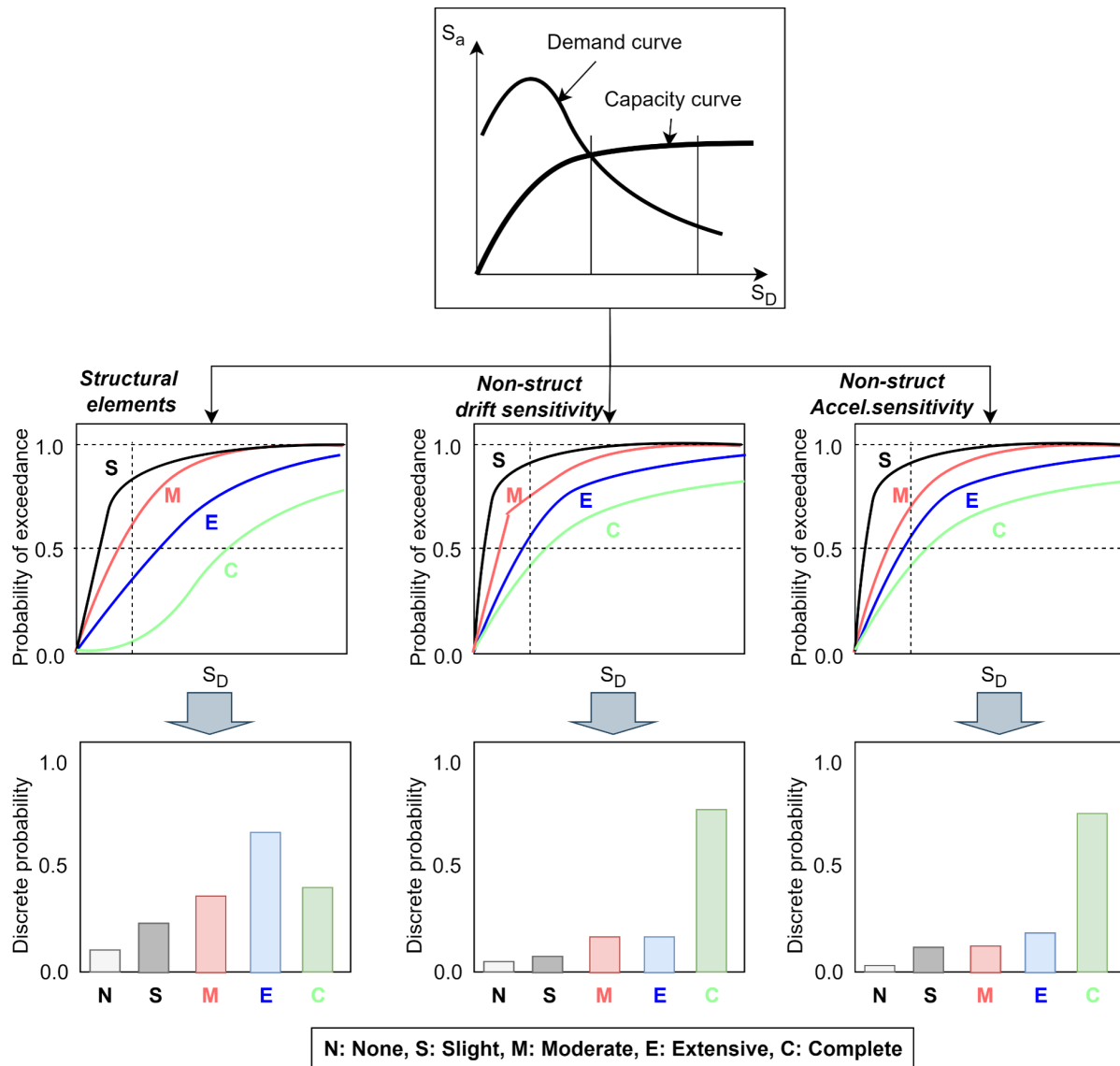


Figure 5.3: The damage state estimation using HAZUS methodology

complete damage state), the repair cost can be estimated by summing the probabilities multiplied by the weight of each damage state, as shown in Table 5.4.

Although computationally efficient, using Probabilistic Seismic Hazard Analysis (PSHA) in regional loss models is theoretically less robust than representing the seismic hazard by generating a large number of earthquake scenarios that are compatible in terms of magnitude, location, and frequency of occurrence with the regional seismicity. (e.g., Crowley and Bommer; Bazzurro and Luco [70]).

Table 5.4: Repair cost weights adopted by HAZUS

Damage state	No damage	Slight	Moderate	Extensive	Complete
Repair cost Weight (%)	0	2	10	50	100

The HAZUS method has a building height range limit for creating vulnerability and capacity curves. For other types of structures, calibration is necessary example (Turkey carried out by Bommer et al. [71], the seismic risk assessment of Oslo documented by Molina and Lindholm [72], the loss estimation of Taiwan (using a modified version of HAZUS called Haz-Taiwan) as discussed in Yeh et al. [73], and the RISK UE project for the risk assessment of 7 European towns. Moreover, the method requires accurate information about the building, such as reinforcement details, which can be challenging.

5.2.4.2 Fully Displacement-Based Methods

In 1999, Calvi's [74] research paper proposed a new method for assessing structural vulnerability called the fully displacement-based vulnerability assessment framework. This approach used displacements as the primary damage indicator and a spectral representation of earthquake demand. The methodology was based on the Direct Displacement-Based Design method principles, which model MDOF structures as an SDOF system. The framework considers different displacement profiles based on the failure mechanism or displacement profile at a given limit state, using the geometric and material properties of structures within a building class. The displacement capacities of column-sway (soft-story) and beam-sway (distributed damage) failure mechanisms are considered for reinforced concrete frames. On the other hand, different in-plane failure modes have been identified for masonry structures. This approach is beneficial for loss estimation studies because it is computationally efficient and allows extensive and repetitive parametric studies to be conducted cost-effectively while allowing customization of any building stock characteristics.

To begin the method, a random population of buildings is generated to represent the urban building stock. Monte Carlo simulation creates buildings with unique material and geometrical properties such as story height, beam length, section dimensions, and steel yield strain. The variability of each property is predetermined using mean values, standard deviations, and probabilistic distributions.

After generating the population, the yield period will be estimated empirically as a function of the height of the building. For the RC buildings, Equation (5.2) is proposed by Crowley and Pinho [75] for filled RC European buildings.

$$T_y = 0.055H \quad (5.2)$$

The displacement capacity of the building is estimated for each building in the population at different damage state limits. For the RC frame buildings, two response mechanisms are assumed: the first represents the non-seismically designed structures (column sway), as shown in Figure 5.4-b, and a seismically designed structure (beam sway), as

shown in Figure 5.4-a. Masonry buildings' response mechanisms are assumed to be a column sway response at the first story

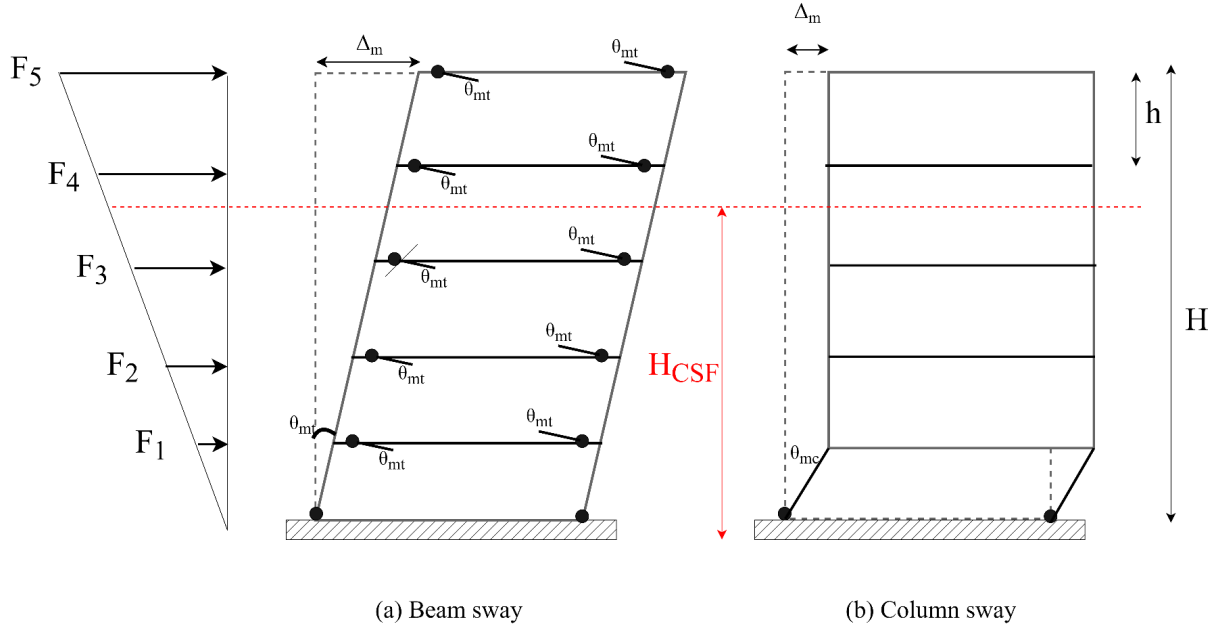


Figure 5.4: The response mechanisms for RC frame buildings: a) beam sway, b) column sway

The displacement capacity can be calculated at the center of the seismic force of both mechanisms using Equation (5.3) and Equation (5.4).

For beam way:

$$\Delta_{LS} = \theta_{by}\kappa_1 H + (\theta_{bLS} - \theta_{by})\kappa_1 H \quad (5.3)$$

For column sway:

$$\Delta_{LS} = \theta_{by}\kappa_1 H + \kappa_2(\theta_{bLS} - \theta_{by})\kappa_1 h \quad (5.4)$$

Where:

- θ_{cy}, θ_{by} : represent the yielding capacity of columns and beams, respectively.
- κ_1, κ_2 : the effective height coefficient.
- H : the building's total height.
- $\theta_{cLS}, \theta_{bLS}$: the rotation capacity at a given limit state of columns and beams.
- h : is the 1st story's height.

The estimated displacement capacities are equal to the top displacement of the equivalent SDOF system, as shown in Figure 5.5.

An equivalent linearization approach is used in DBELA. Therefore, assuming an elastic-perfectly plastic behavior for post-yield limit states, buildings can be modeled

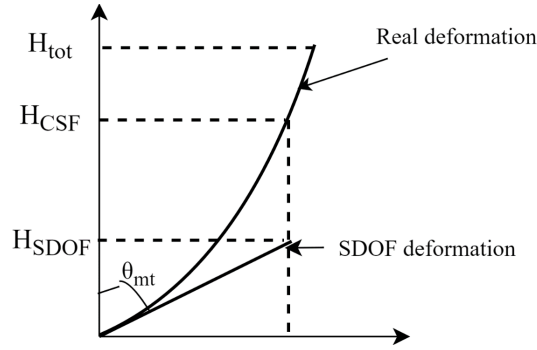


Figure 5.5: The response mechanisms for RC frame buildings: a) beam sway, b) column sway

using the secant period of vibration, calculated using the following formula (Equation (5.5)):

$$T_{LS} = T_y \sqrt{\mu_{LS}} \quad (5.5)$$

Where μ_{LS} is the ductility of the SDOF at a given limit state.

Utilizing a database containing the structural characteristics of a specific building stock makes it possible to create random groups of buildings for each building category. For example, a sample of reinforced concrete column-sway frames with a specific number of stories can be generated. Next, the vibration period and displacement capacity at three different damage limit states can be calculated for each randomly generated building .

To assess a building's vulnerability, it is necessary to compare its structural capacity with the ground motion anticipated from a potential earthquake scenario. It relies on ground-motion prediction equations to specify the demand in terms of overdamped displacement response spectra to achieve this. To this end, the damping correction equation outlined in the 1994 edition of EC8 [76] (EC8, 2008) is utilized, as recommended by Priestley et al. [77].

$$\eta = \sqrt{\frac{7}{2 + \xi_{eq}}} \quad (5.6)$$

where: η : is the correction factor representing the viscous damping ratio of the equivalent nonlinear response and ξ_{eq} is the equivalent damping ratio (%).

The displacement demand for a given building can be compared with its displacement capacity by using a displacement response spectrum. This comparison helps estimate the probability of exceeding a given limit state. To calculate the probability, the sum of all buildings whose displacement capacity is lower than the displacement demand shall be divided by the total number of buildings in the random population. The sample size is gradually reduced from one limit state to the next by removing the buildings that do not exceed the limit state.

5.2.4.3 Incremental dynamic analysis

Incremental Dynamic Analysis (IDA) is a dynamic method equivalent to pushover analysis. It is recommended in ATC-63 [78] and ATC-58 [49]. IDA can be used in any building type to determine the capacity of different medians. However, to perform IDA, the analyst must define a complete hysteretic behavior of the materials and repeat the analysis for numerous GMs. The time required for computation can be significant, depending on the complexity and material type of the building. The analyst should ensure that the model type is consistent with the analysis type, retaining sufficient model complexity. To achieve this, it is necessary to define hysteretic curves for structural and non-structural elements, use median values for structural characteristics-related parameters, simulate all modes of component damage and failure, or account for them a posteriori. It is also important to define permanent gravity actions.

IDA is a method developed by Vamvatsikos and Cornell in 2002 [79]. It is a comprehensive technique for extracting the conditional distribution of structural response, such as peak inter-story drifts or peak floor accelerations, given the IM (Intensity Measure) for any number of IM levels, ranging from elasticity to global collapse. This is achieved by subjecting a structural model to non-linear time history analysis using a range of ground motion accelerograms that are scaled to increasingly higher levels of the IM until collapse is reached as shown in Figure 5.6.

When applying the procedure, it is important to increment the amplitude of each chosen ground motion and perform a non-linear response history analysis until either global dynamic or numerical instability occurs in the analysis. This indicates that either collapse, story drift exceeding non-simulated collapse limits, or a large increase in story drift associated with small increments in spectral acceleration is affecting the structure. Please refer to Figure 5.6 for a better understanding. The output of IDA is a set of discrete points obtained by scaling each of the selected ground motions, showing the IM versus the demand parameter of interest such as the $S_a(T_1)$ and the MIDR.

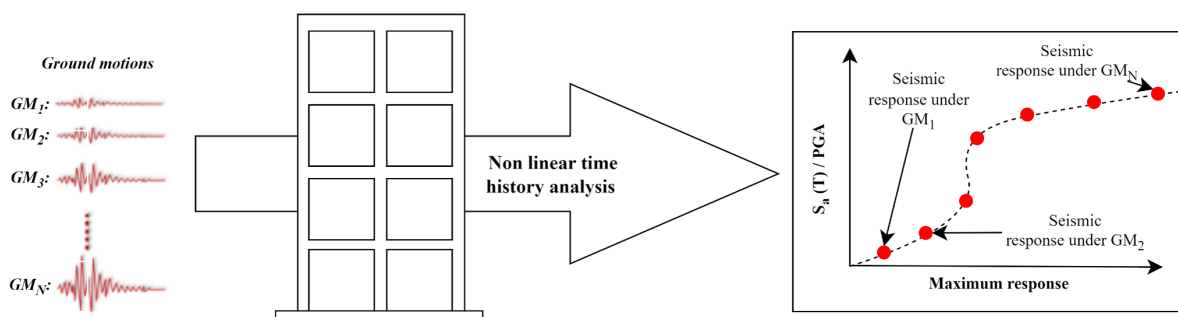


Figure 5.6: Incremental dynamic analysis procedure

To evaluate a structure's seismic response, the process must be repeated for the chosen set of ground motions. The median IDA curve represents 50% of all the maximum responses observed at each level of IM, which is illustrated in Figure 5.7. presents the median values and range of each damage threshold. When identifying Slight, Moderate, and Extensive damage thresholds, the analyst can estimate them based on a progression of local damage through several elements (considering the combination of the structural and non-structural performance levels). The associated MIDR values in the IDA plot can be assigned to extract the corresponding median capacity in terms of spectral acceleration. As mentioned earlier, the median collapse capacity can be determined at the level of IM, which results in either numerical instability or a non-simulated collapse mode. Note that if 2D models are used, the median collapse capacity should be taken as the smaller value obtained for either direction.

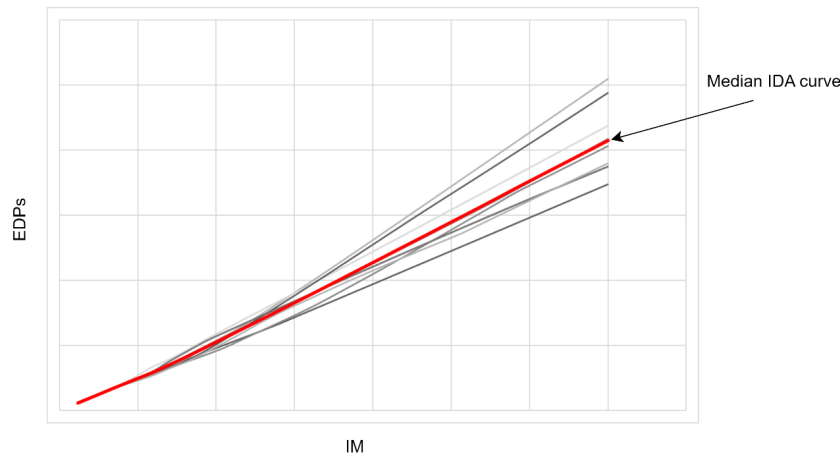


Figure 5.7: The median IDA curve

The lognormal standard deviation for the selected records can be used to estimate the record-to-record dispersion directly. For instance, the following formula (Equation (5.7)) can calculate the record-to-record dispersion associated with each damage threshold [80]:

$$\beta = \sqrt{\ln\left(1 + \frac{STDEV}{MEAN}\right)} \quad (5.7)$$

The analysis utilizes STDEV and MEAN values to help study various uncertainties such as geometrical or materials and ground motion variabilities. These values represent the standard deviation and mean of the IDA point for a given IM threshold.

5.2.4.4 Nonlinear static analysis

The Incremental Static Analysis (ISA) is an alternative procedure to IDA for performing vulnerability and fragility assessments. Compared to IDA, the ISA is faster and less complex, making it a better solution to obtain acceptable results.

The procedure involves selecting and matching GMs to a target response spectrum. The GMs are then scaled from the least intense to the most intense, capturing different elastic and inelastic responses. After scaling, demand and capacity curves are plotted in ADRS representation to calculate the performance point.

A performance point shall be calculated for each seismic intensity, and the results are illustrated in Figure 5.8.

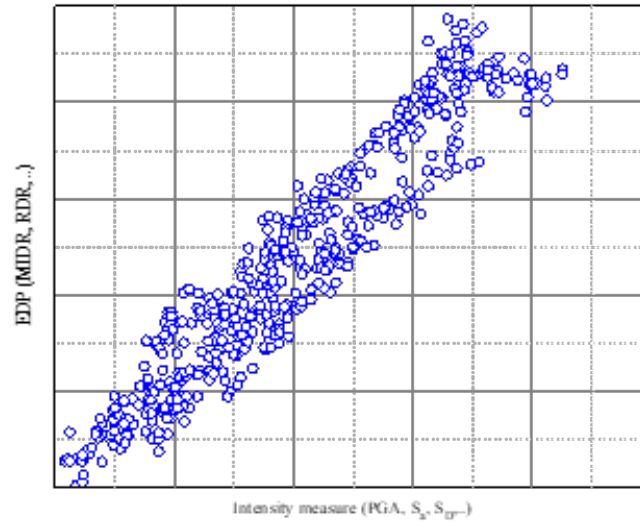


Figure 5.8: Performance point cloud using ISA

5.2.4.5 Seismic fragility assessment

fragility curves are a popular tool used in vulnerability assessment to represent the probability of exceeding a damage state limit for a given earthquake. They show the relationship between the seismic intensity and the likelihood of a structure being damaged ($P[ds > DS|IM]$). These curves are an analytical representation of the damage probability matrix, which provides valuable information about the damageability of a structure in an earthquake. Similarly, vulnerability curves show the relationship between the EDP and the probability of reaching or exceeding a damage state limit.

5.2.4.6 Damage state limits

The behavior of a structure dictates its performance, which is measured by various codes and standards that indicate different limits of damage and functionality, affecting the resilience of the building.

It is recommended that analysts who possess a high degree of experience and knowledge of structural behavior should evaluate different damage states. To do this, they should refer to the definitions implemented in ATC-58-2 [1] and Eurocode-8 [76]. 5.5. summarizes some of the most used performance limit states for the MIDR.

Table 5.5: Performance level limits of inter-story drift ratio (MIDR)

Authors	Performance level(MIDR) (%)				
	O	IO	DC	LS	CP
Rosowsky and Ellingwood [81]	0.5	1.0	-	5.0	5.0
Lee and Rosowsky [82]	-	1.0	-	2.0	3.0
Uma et al. [83]	0.5	0.14	3.0	3.5	5.3
Ibrahim and El-Shami [84]	0.5	1.0	1.5	2.0	2.5
García and Manriquez [85]	-	0.7	-	2.5	5.0
Silva et al. [86]	0.05	0.3	1.15	2.8	4.36
Aishwarya and Mohan [87]	-	1.0	-	2.0	4.0
Negulescu et al. [88]	0.031	0.4	0.66	1.19	2.07
Pragalath et al. [89]	-	1.0	-	2.0	4.0

5.3 Fragility curves

Various studies have been conducted concerning the construction of fragility curve references. They represent probabilities of reaching or exceeding a given damage or performance limit state in the form of cumulative density functions (CDF).

Many equations have been proposed to generate fragility curves, as summarized in Table 5.6. However, the general equation for constructing fragility curves is expressed in Equation (5.8):

$$CDF = P[ds = DS | IM = im] \quad (5.8)$$

Where:

- DS is the damage or performance limit state.
- IM is the ground motions measure (e.g., PGA, PGV, etc.).

The fragility curve functions in some cases are used to fit experimental or calculated probability data.

5.3.1 Logistic regression

Statistically, logistic regression is a model that uses the logit function to fit a binary dependent variable (0 or 1, true or false). The logistic regression converts the log-odds to probability outputs using a sigmoid function as shown in Figure 5.9.

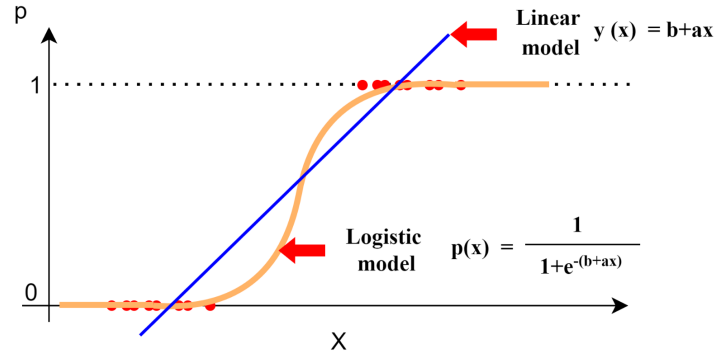


Figure 5.9: the linear and logistic regression

5.3.1.1 Odds and log-odds

the odds (log-odds) are the ratio between true and false events. For example, if we have 5 buildings with the same height and type and they are subjected to an earthquake event and four of them are damaged, then the odds of damaged structures are 4 to 1 as explained in Equation (5.9).

$$Odds_{damage} = \frac{Damaged}{undamaged} \longleftrightarrow \log(Odds_{damage}) = \log\left(\frac{Damaged}{Undamaged}\right) \quad (5.9)$$

The odds can be calculated from the probability as shown in Equation (5.10):

$$Odds = \frac{p}{1-p} \quad (5.10)$$

Where p is the probability of occurrence (of damaged buildings for the previous example).

Table 5.6: Fragility curves equations

Researcher	Equation	Parameters
Singhal and Kiremidjian [90]	$P_{[\text{MMI}]}[d \text{MMI}] = \int P_{[d S_a]}[d S_a] f_{S_a \text{MMI}}[S_a \text{MMI}] ds$	<ul style="list-style-type: none"> • $P_{[\text{MMI}]}[d \text{MMI}]$ is the conditional probability of a limit state MMI. • $P_{[d S_a]}[d S_a]$ probability of exceedance of spectral acceleration. • $f_{S_a \text{MMI}}[S_a \text{MMI}]$ Probability condition function of S_a at MMI.
Yamaguchi and Yamazaki [91]	$P(x) = \Phi\left(\frac{\ln x - \lambda}{\sigma}\right)$	<ul style="list-style-type: none"> • $\Phi(.)$ is the standardized normal distribution function. • λ is the mean of the logarithmic samples $\ln(x)$. • σ is the standard deviation of the logarithmic samples $\ln(x)$.

Table 5.6: Fragility curves equations (continued)

Researcher	Equation	Parameters
Kircil and Polat [92]	$FR(x) = \Phi\left(\frac{\ln x - \lambda}{\sigma}\right)$	<ul style="list-style-type: none"> • $\Phi(.)$ is the standardized normal distribution function. • λ is the mean of the ground motions logarithmic samples $\ln(x)$. • σ is the standard deviation of the logarithmic samples $\ln(x)$.
Ibrahim and El-Shami [84]	$P[D PGA] = \Phi\left(\frac{\ln(PGA) - \lambda}{\sigma}\right)$	<ul style="list-style-type: none"> • $\Phi(.)$ is the standardized normal distribution function. • λ is the mean of the $\ln(PGA)$. • σ is the standard deviation of the $\ln(PGA)$.
Jeon et al. [93]	$P[D > C IM] = \Phi\left(\frac{\ln(S_a/S_C)}{\sqrt{\beta_D^2 + \beta_C^2 + \beta_{EM}^2}}\right)$	<ul style="list-style-type: none"> • D is the aftershock seismic demand. • C is the structural capacity. • S_a is the mean of demand.

Figure 5.10 summarizes the logistic procedure to develop a fragility curve.

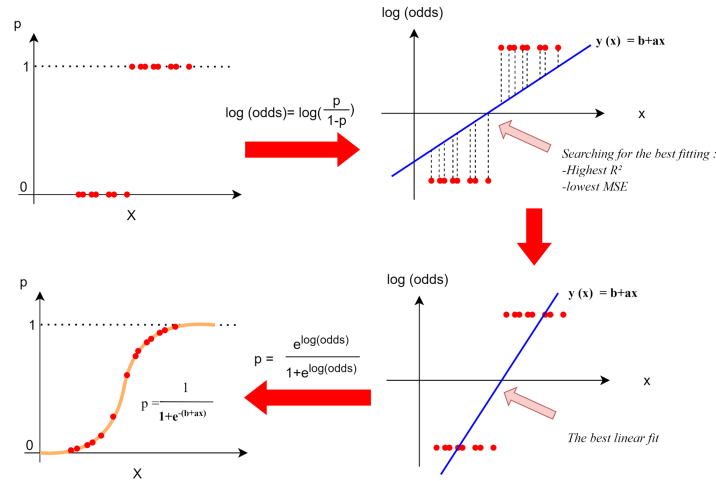


Figure 5.10: Logistic regression procedure applied on ISA: a) Cloud points obtained from ISA or IDA, b) IO Fragility curve, c) LS fragility curve, and d) CP fragility curve.

This process can be used when several responses are recorded in the case of the IDA or ISA and the damage/performance state limits are defined. Next, a binary classification shall separate the exceeding and not exceeding points as shown in Figure 5.11.

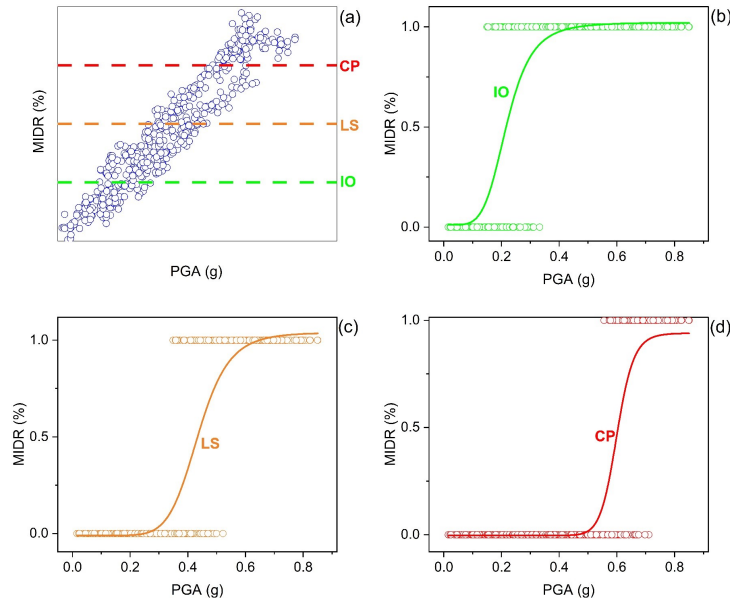


Figure 5.11: Logistic regression procedure applied on ISA: a) Cloud points obtained from ISA or IDA, b) IO Fragility curve, c) LS fragility curve and d) CP fragility curve.

5.3.2 loss function: Damage ratio

The damage ratio of structures is an important factor in assessing the performance and safety of buildings and other facilities. It is often categorized into different levels based on observed damage and structural behavior. These categories can include slight damage

(SD), Moderate Damage (MD), extensive Collapse (EC), and Complete Collapse (CC), which provide a framework for understanding the extent of damage and the potential hazards to life safety. Various studies have proposed performance level limits based on inter-story drift ratio (MIDR) and fragility curves to quantitatively evaluate the damage ratio of structures, allowing for a more comprehensive understanding of the impact of different ground motions and structural types on building damage. Additionally, fragility curves equations developed by researchers offer a systematic way to express the probability of reaching or exceeding a given damage or performance limit state, which is crucial for risk assessment and mitigation strategies.

The global damage ratio GD_r indicates the cost of damage to a building about its initial cost. It can be calculated using fragility curves for various damage states and the damage ratio for each state. Equation (5.11) represents the GD_r formula:

$$\begin{aligned} GD_r &= \sum P_E(D_s = d) D_r \\ &= [P_{nodamage} - P_{slight}] D_{r1} + [P_{slight} - P_{moderate}] D_{r2} \\ &\quad + [P_{moderate} - P_{extensive}] D_{r3} + [P_{extensive} - P_{complete}] D_{r4} \end{aligned} \quad (5.11)$$

Where $P_E(D_s = d)$ is the probability of exceedance of a damaged state (d). D_r is the damage ratio that corresponds to a damage state (d).

5.4 Conclusion

In this section, an in-depth exploration of the seismic vulnerability and fragility assessment of structures is conducted. The section delves into various procedures, methods, and projects dedicated to evaluating seismic vulnerability and fragility. Additionally, it comprehensively explains terminologies such as fragility curves and elucidates the process of obtaining them using Incremental Dynamic Analysis (IDA) and Incremental Static Analysis (ISA).

Chapter 6

Artificial Intelligence algorithms

6.1 Introduction

In recent years, there has been a rapid advancement in the field of artificial intelligence (AI) and machine learning (ML), which has been transforming various industries. AI and ML are two revolutionary technologies that have the potential to change the way we live and work. AI refers to the ability of machines to perform cognitive functions normally associated with human beings, such as learning, reasoning, perception, and decision-making. While, ML is a subset of AI that involves the development of algorithms and statistical models that enable machines to learn from data and improve their performance over time without being programmed explicitly.

The applications of AI and ML are vast and diverse, ranging from healthcare to finance, transportation to entertainment, and manufacturing education. In this chapter, we will delve deeper into the world of AI and ML, exploring the concepts, techniques, and applications of these two technologies. We will start by defining AI and ML and discussing their brief history and evolution. We will then describe the different categories of AI and ML, such as supervised, unsupervised, and reinforcement learning, and their respective applications. We will also discuss the challenges and limitations of AI and ML, such as bias, ethics, and explainability, and how to address them. In this chapter, we will discuss artificial intelligence and machine learning concepts and algorithms in detail to enhance understanding in the upcoming chapter.

6.2 What is Artificial intelligence?

Artificial intelligence (IA) is a term that describes the most used technology in this decade. Intelligence refers to learning from past experiences and adapting to new situations, and “Artificial” represents the use of inhuman tools such as computers. IA now is used in several fields including civil engineering such as structural design and manage-

ment, decision-making software, earthquake engineering, and damage predictions. AI has various applications, including automation and data analysis. Automation involves using AI-powered systems to perform repetitive tasks, which increases efficiency and minimizes the possibility of human error. On the other hand, data analysis involves using AI to analyze large amounts of data to identify patterns. This tool is particularly useful for analysts who can make data-driven decisions and predict future trends with greater accuracy.

AI can be categorized into three main categories:

- ***Machine learning***: it is based on the use of sample data to train a model to recognize patterns. It allows the computer to execute tasks without being programmed. The model's performance depends on the algorithms and data quality. [94]
- ***Natural language processing***: it is a field that is sometimes mistaken for simple speech recognition. While it does involve understanding spoken language, it encompasses much more than just converting audio into text and vice versa. The main objective of natural language processing is to enable computers to comprehend and analyze documents. [95]
- ***Robotics***: Robots have been around for hundreds of years, but those that can assist without human intervention are relatively new. One of the earliest autonomous robots was installed in 1961 to lift hot metal pieces from a machine. Since then, robots have become increasingly common and are now used in a variety of applications, including space exploration and household cleaning tasks such as vacuuming carpets. [95]

6.3 Overview of Machine learning

In the previous section, we defined ML as a complex algorithm that uses data to create a model capable of predicting outcomes for new scenarios. The primary objective of ML is to enable computers to learn from previous experiences automatically, without any human intervention.

ML has become increasingly popular in civil engineering, particularly in earthquake engineering, due to its accuracy and predictability in performance.

6.3.1 Types of machine learning

6.3.1.1 Supervised Learning [2]

Supervised learning is an algorithm that creates a model capable of learning from a dataset containing input and output features [96]. The algorithm finds the best model to predict

outputs with minimum cost or error. It can be used for both regression and classification. The main types of supervised learning are:

6.3.1.2 Linear Regression

The simple linear regression algorithm is widely used in statistics. It helps to find the linear relationship between one or more independent variables (inputs/features) and dependent variables (outputs).

This method aims to determine the fitting line or hyperplane that best represents the relationship between the inputs and outputs.

Line equation: in the case of simple one feature (1D) as shown in Figure 6.1, the regression is a line with the Equation (6.1) :

$$y(x) = ax + b \quad (6.1)$$

where:

- **y**: is the dependent variable (output).
- **x**: is the independent variable (input).
- **a**: is the slope of the line or the regression coefficient.
- **b**: is the intercept of the line.

In the case of multiple linear regression (nD), as shown in Figure 6.1, the equation becomes:

- **y**: is the dependent variable (output).
- $x_1, x_2, \dots, x_n$: are the independent variables.
- $a_0, a_1, a_2, \dots, a_n$: are the regression coefficients.

The linear regression is simple to perform and easy to interpret. In addition, it is fast and works well for small datasets. However, it is not suitable for nonlinear problems and is sensitive to the outliers in the dataset.

6.3.1.3 Logistic Regression

LR is a model used for binary classification tasks to predict the probability of an input belonging to a class. It is useful for determining the likelihood of specific outputs.

The LR uses a sigmoid function to fit the probabilities (from 0 to 1) and it is given by Equation (6.1):

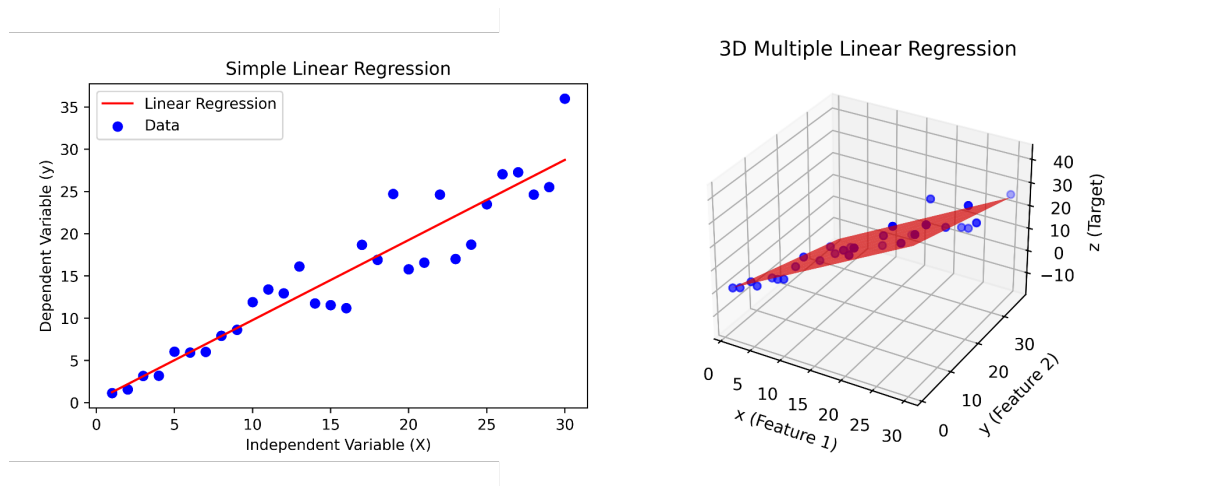


Figure 6.1: Linear regression example (simple and multiple regression).

$$P(z) = \frac{1}{1 + e^{-z}} \quad (6.2)$$

Where:

- **P(x)** : is the probability of the input belonging to a class (0/1 or false/true).
- **Z**: is the linear combination of the independent variables and coefficients ($z = a_0 + a_1x_1 + a_2x_2 + \dots + a_nx_n$).

The limit threshold of reaching a class is generally where the probability exceeds $P = 0.5$.

6.3.1.4 K-nearest neighbor (KNN) algorithm

The K-nearest neighbor (KNN) algorithm is a simple and effective classification and regression algorithm. It is based on the concept of finding the k-nearest data points to a query point and using their labels to make predictions.

The KNN algorithm stores all the data and groups them based on their feature similarities. When new data appears, the KNN algorithm classifies it by comparing the similarity of each class. The KNN algorithm is known as a lazy learner algorithm because it does not learn from a training dataset, it only stores and classifies data. For instance, if the KNN algorithm is used to identify whether a picture is a dog or a cat, it will search for similar features in the picture. The algorithm will then determine whether it is a dog or a cat based on the similarity percentages.

The KNN requires several steps to be performed:

- **Step1: Choosing the K value:**

The parameter 'k' is the number of the nearest neighbors to consider. The lowest

K value corresponds to the highest noises and it requires less computation time and the model may represent an underfitting. On the contrary, a larger K will make the decision boundaries smoother and lead to less precise predictions and it may lead to overfitting as shown in Figure 6.2.

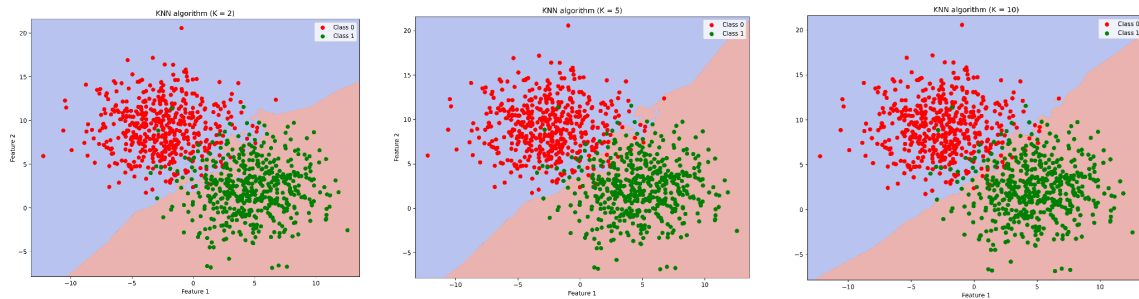


Figure 6.2: KNN example .

- **Step2: Choosing distance metric**

Euclidean (Equation (6.3)), Manhattan (Equation (6.4)), and Minkowski are the most common distance metric methods used to determine the similarity between two data points.

$$d(x, y) = \sqrt{\sum (x_i - y_i)^2} \quad (6.3)$$

$$d(x, y) = |\sum (x_i - y_i)| \quad (6.4)$$

where: $d(x, y)$ is the mean distance between all the particles and the new data. x_i, y_i are the cartesian coordinates of the data point.

- **Step 3: Prepare the dataset**

To prepare the dataset for analysis, we need to perform some initial steps. Firstly, we need to split the dataset into independent and dependent variables. Secondly, we have to clean the dataset by removing any missing or illogical data that may affect the accuracy of our analysis. Lastly, we need to standardize the dataset to ensure that all input features are normalized or standardized for better analysis results.

- **Step 4: Make predictions**

It starts with calculating the distance from the query points to all the points during the training using the distance metric. Then, the distances are sorted and the K-nearest neighbors are defined. Next, for classification tasks, the frequent label among the K-nearest is chosen as the predicted label, and for the regression tasks,

the average of the target values among the K-nearest is selected as the predicted value.

- **Step 5: Model evaluation**

This step consists of assessing the model performance and its accuracy using the appropriate metrics such as the mean squared error, accuracy, recall, or precision for regression tasks. And the confusion matrix for the classification tasks. The hyperparameter 'k' should be adjusted and optimized based on the evaluation results. This step is critical for the performance of the model.

6.3.1.5 Decision Trees [3]

The decision tree is a supervised algorithm that uses a dataset to train a model to predict outputs and it can be used in regression and classification. Based on the features and the data value, the decision tree processes in terms of groups. The algorithm is composed of root (starting point), branches (decision points), and leaves (final points), as shown in Figure 6.3.

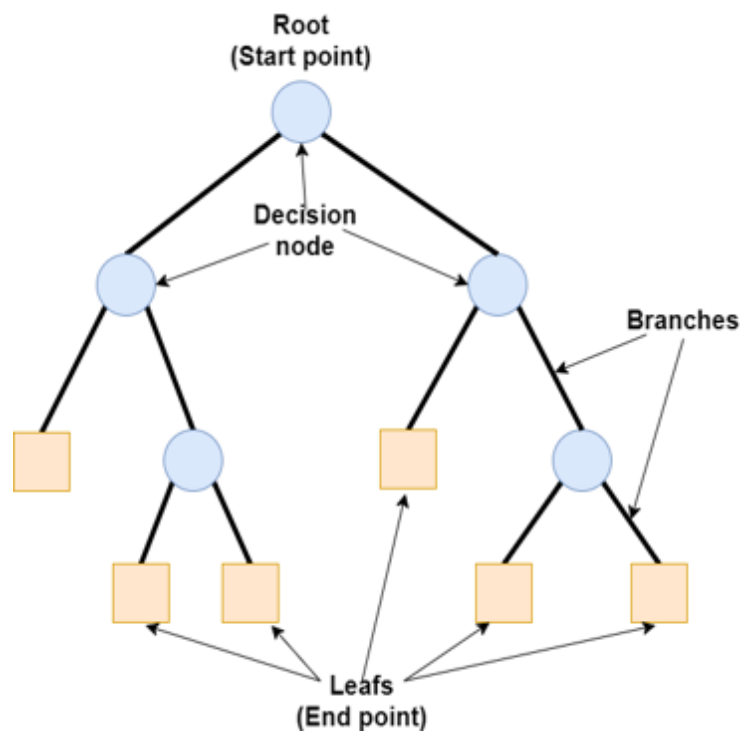


Figure 6.3: KDecision tree design .

How to perform a Decision Tree?

For predicting the classes of a given data point, the decision tree algorithm begins with the root node. It compares the root node and real values and jumps to the following node. The

algorithm will move to another node called a sub-node and it moves further. The process shall be repeated until the last leaf node of the tree is reached. Figure 6.4 summarizes the decision tree algorithms' steps.

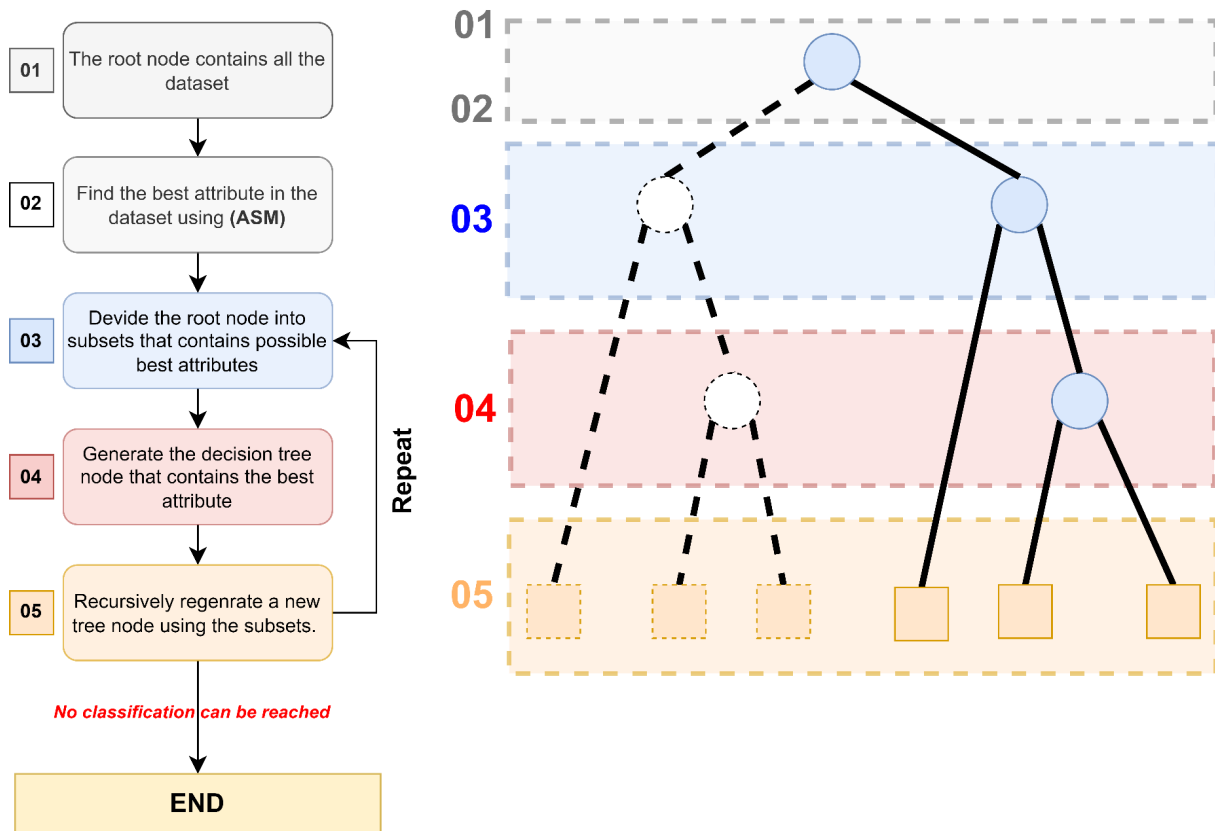


Figure 6.4: Decision tree steps.

While performing a decision tree algorithm, the main problem is how to select the best attribute for the root node and sub-nodes. To solve this issue a technique called Attribute selection measure (ASM) is used. Two popular ASMs are frequently used:

- **Information gain:** It measures the changes of entropy after the segmentation of a dataset based on the attribute where the amount of information is obtained from a feature in a class. Based on the information gained, the nodes will be split and the decision tree will be built. The decision tree algorithm always attempts to maximize the information gain, the node with the highest information gain will be split first using Equation (6.5).

$$I_G = Entropy_{Samples} - (Average\ weights) Entropy_{feature} \quad (6.5)$$

- **Gini index:** it measures the purity or impurity in a given attribute while creating a decision tree. The high value of the Gini index is preferable to a low value in the

attribute, as shown in Equation 6.6. The lowest Gini index indicates the highest information gain and the node with the highest Gini information.

$$G_i = 1 - \sum_{k=1}^n P_{i,k}^2 \quad (6.6)$$

- **Pruning process:** Optimal decision trees are obtained by removing unnecessary nodes from a tree. Overfitting may occur if the tree is too large and a small tree may also underfit the training. The pruning is the best option for reducing the tree's size without affecting the accuracy.

6.3.1.6 Support vector machine (SVM) [4]

It is used for regression and classification problems. Its goal is to find the best hyperplane decision boundaries that divide the $n - D$ space into classes so it can easily classify a new data point.

SVM selects the extreme points of the dataset called support vectors that will help to define the hyperplane. Figure 6.5 illustrates two categories that are separated using the hyperplane. These two regions are the classes as the dataset and the SVM separates them using the decision boundary.

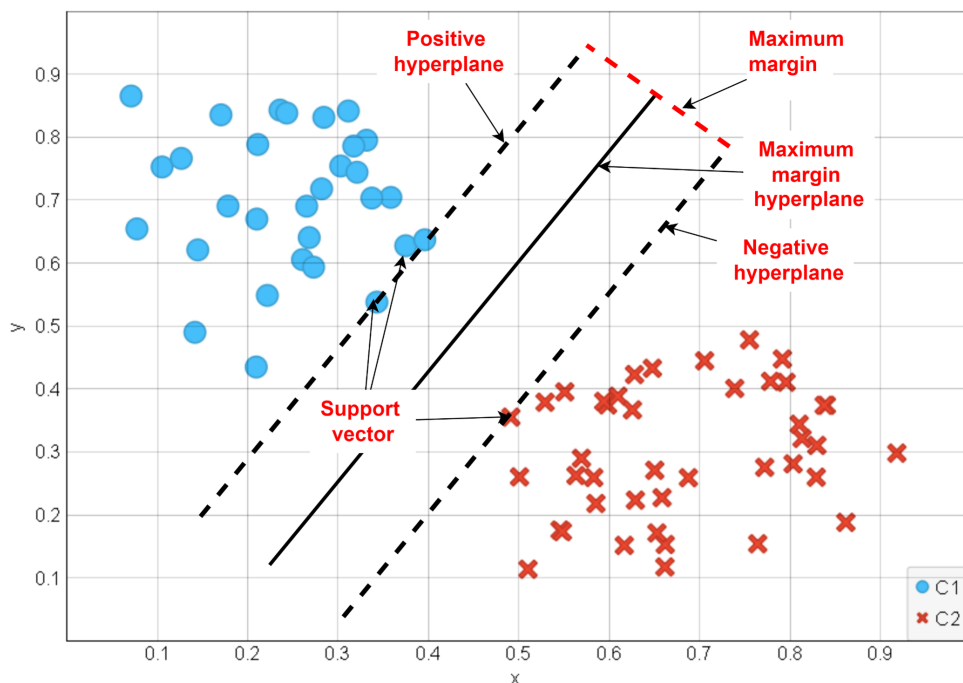


Figure 6.5: Support vector machine terminologies.

Based on the dataset, SVM can have two types, linear and non-linear problems. The Linear SVM is used when the data can be classified into two classes using a linear line

(Straight). However, if the data can not be classified and separated using a linear line then the Non-linear SVM will be used.

The hyperplane always corresponds to the maximum margin and distance between the points. The number of hyperplanes and their shape depends on the dimension of the problem. If the problem has 2 features as in Figure 6.5 then the hyperplane is a single straight line. However, if there are 3 features, the hyperplane is a 2D plane.

6.3.1.7 Artificial neural networks [5]

The ANN algorithm is based on the same biological operation inside our brains. Neurons in our brains transmit electrical signals to each other through axons. The human brain is capable of containing more than 100 billion neurons, making it the most complex natural neural network. Monkeys, which have a high IQ compared to other animals, have almost 1/100 the number of neurons that humans have. In contrast, the mosquito brain contains less than 200,000 neurons. Therefore, the number of neurons and their complexity represent the intelligence and ability to perform various tasks.

The ANN is composed of a large number of neurons and layers as shown in Figure 6.6.

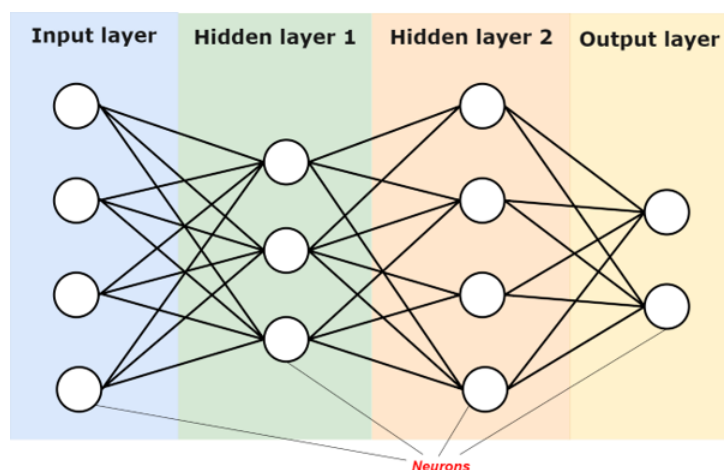


Figure 6.6: ANN architecture.

The input layer of an Artificial Neural Network (ANN) represents the independent variables of the dataset. The number of neurons in this layer is fixed and unchangeable. The output layer is the last in the ANN model, and it contains the output values obtained from the calculation of the network. The number of hidden layers in an ANN varies depending on the complexity of the problem. For linear regression tasks, the ANN may have no hidden layers, and for deep networks, it may have many hidden layers (e.g., 96 hidden layers in the case of Chat GPT-3.5). The number of neurons in the hidden layers also changes from one problem to another. Determining the best number of hidden layers and neurons is crucial for the performance of the ANN model. The user must find the best combination to achieve the highest accuracy and avoid underfitting and overfitting.

How it works

The ANN model contains many neurons and layers. Each neuron of a layer is connected with another one or many neurons of the next layer (it is a bit different for other types of neural network algorithms like recurrence neural networks). The connection between them is the weight ($W_{i,j}$) and it represents the strength of the connection. The bias neuron (B_i) is a fixed value that is used to calculate the input using the following equation and it is unique for each layer.

$$Z(x) = W_{i,j}X_i + B_i \quad (6.7)$$

Once an input value reaches a neuron, it is multiplied by a weight and added to a bias. An activation function is then applied to calculate the output. This local output is then passed to the next neuron in the layer, and it can be considered as the global output of the network. For a detailed summary of this procedure, please refer to Figure 6.7.

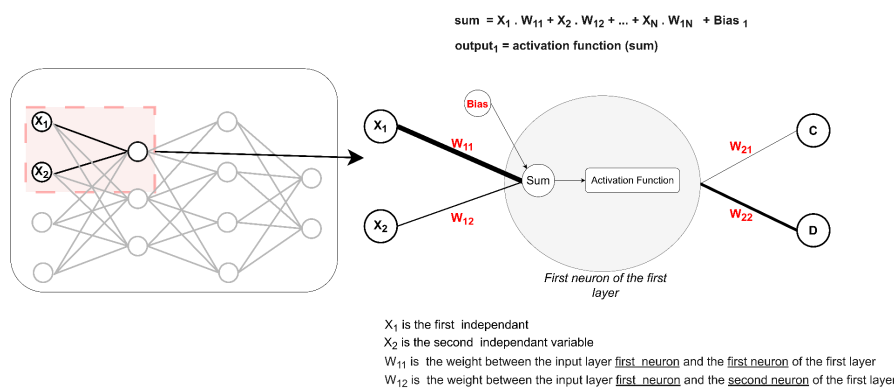


Figure 6.7: ANN terminologies.

As illustrated in 6.7, the width of the connection is proportional to the importance of the weight; the larger the weight, the more influential it is.

The activation function, also known as the transfer function, is a mathematical function used within a node in a neural network to calculate the output. It takes into account the input values, weights, and bias to determine the output. The activation function is used in both linear and nonlinear tasks and helps to introduce nonlinearity into the model. It also enables the activation or deactivation of neurons in the network.

Figure 6.8 illustrates some activation functions and their equations, which are the most commonly used ones. The selection of the activation function depends on the type of output values and what they represent. For instance, if the outputs are probability predictions, then the sigmoid function would be the most suitable choice since its outputs are between zero and one, exactly as probabilities should be. On the other hand, if the problem is classification, then the Tanh function would be the more logical choice to predict the classes.

To train the ANN model two algorithms are mainly used to perform the training process known as Feedforward and backpropagation neural networks. For feedforward NN, The

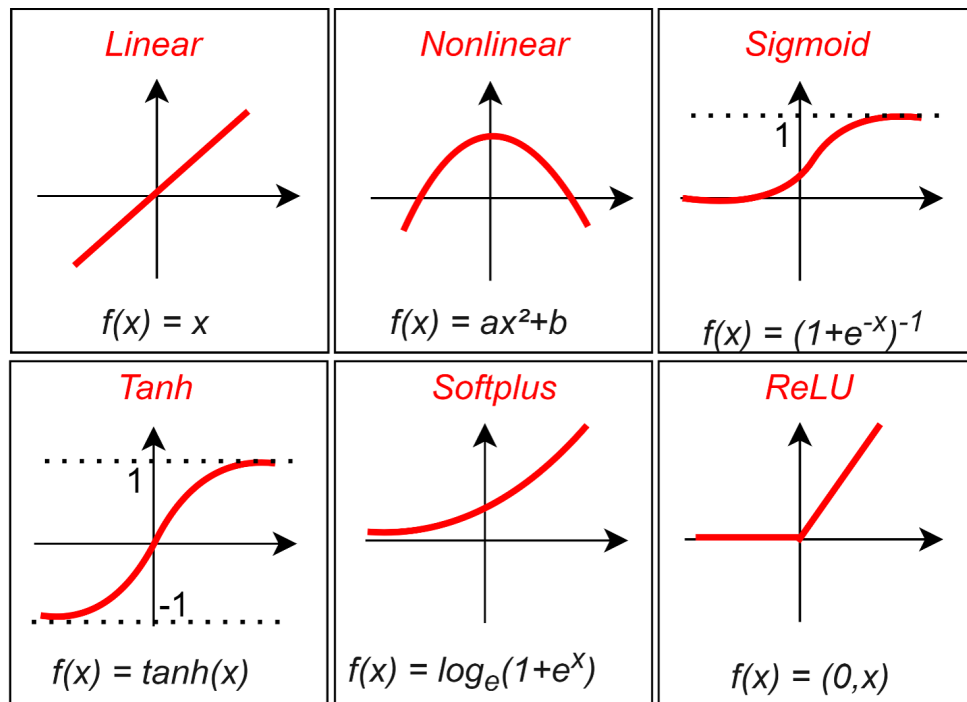


Figure 6.8: The most used Activation functions in the ANN.

training samples will be inserted into the first layer of the NN [97]. The neuron of the first hidden layer transfers the input vector $x_1, x_2, \dots, x_n$ to an output value (h) (see Equation (6.8)):

$$h_i^1 = \Phi(b_1 + \sum_{i=1}^n w_i x_i) \quad (6.8)$$

Where Φ is the activation function, b is the bias, w_i is the weight of the neuron as explained in Figure 6.7. This operation should be repeated for all the neurons of the first hidden layer using the first row of the input values. After that, the new h_{ij} vector $h_{11}, h_{21}, \dots, h_{m1}$ which represents the obtained values in the neurons of the first hidden layer calculates the new h_{i2} vector of the second hidden layer using the same process. The process should be repeated as many as the number of hidden layers until the output layer is reached.

On the other hand, the Backpropagation algorithm aims to minimize the average error (cost function) between the predicted outputs using the weights and biases of the network and the real values of the dataset [5].

The cost function can be written as Equation (6.9):

$$J = \frac{1}{n} \sum \|y_i - \hat{y}_i\|^2 = \frac{1}{n} \sum_{i=1}^n \sum_{j=1}^m (y_{i,j} - \hat{y}_{i,j})^2 \quad (6.9)$$

Where y_i is the output vector of the dataset $y_1, y_2, \dots, y_n$ and $\hat{y}_{i,j}$ is the predicted value. The cost function will be used to update the weights and biases to minimize as

possible the cost function to the outputs to get closer to the desired values. This function can be calculated for a small number of samples instead of all the samples calling this process the mini-batch gradient descent. Also, the stochastic gradient descent can be used where the weights and biases will be updated after calculating each sample in the training dataset.

To perform this update, the cost function should be tested to find its sensitivity to the changes in the weights and biases. To do so, the partial derivative of J to them should be calculated using the chain rule.

Let's assume that w_1 and b_1 are the weight and bias of the first neuron, and w_2 and b_2 are the weight and bias of the output neuron. Z_2 is the calculated output using Equation V.5 and y is the real output and the activation function is a linear function. The partial derivative of the J to w_2 will be obtained using Equations (6.10), (6.9), (6.12), and (6.13):

$$\frac{\partial J}{\partial W_2} = \frac{\partial z_2}{\partial W_2} \frac{\partial y}{\partial z_2} \frac{\partial J}{\partial y} \quad (6.10)$$

$$\frac{\partial J}{\partial y} = \frac{\partial (y - \hat{y})^2}{\partial y} = 2(y - \hat{y}) \quad (6.11)$$

$$\frac{\partial y}{\partial z_2} = 1 \quad (6.12)$$

$$\frac{\partial z_2}{\partial w_2} = \frac{\partial (w_2 h + b_2)}{\partial w_2} = h \quad (6.13)$$

So Equation (6.10) can be written as follows (Equation (6.14)):

$$\frac{\partial J}{\partial w_2} = 2h(y - \hat{y}) \quad (6.14)$$

So the w_2 update shall be obtained by subtracting the current value and the $\frac{\partial J}{\partial w_2}$ times the learning rate as written in Equation (6.16).

$$w_2 = w_2 - \eta \frac{\partial J}{\partial w_2} \quad (6.15)$$

the same process should be applied to calculate the updated bias. To apply the update using all the datasets, the derivative will be equal to the average of the individual derivatives.

It should be noted that the backpropagation is not the training algorithm but a strategy to calculate the NN gradient. However, the parameter updating should be done using the training algorithm such as Adaptive moment estimation, stochastic gradient descent, and gradient descent.

6.3.1.8 Optimization algorithms used in the training process

During the training phase, the model tries to minimize the loss function J which measures its performance on a given dataset. The optimization problem can be either one-dimensional or multidimensional, but the same steps should be followed. These steps include the feedforward and backpropagation procedures. The loss function is calculated by estimating the error between the estimated output and the target output. This error is measured using one of the error terms listed in Table 6.1.

Table 6.1: The error terms and their expressions used in the ANN.

Error term	Expression
Mean squared error (MSE)	$= \frac{\sum (outputs - target)^2}{samples\ number}$
Normalized squared error (NSE)	$= \frac{\sum (outputs - target)^2}{Normalization\ coefficient}$
Cross entropy error (CEE)	$= - \sum ((target.log(output) + (1 - target).log(output)))$

Optimization algorithms are a key step in the NN process, and they require varying levels of computation and storage to perform effectively. The algorithms play a significant role in determining the accuracy and speed of the NN's performance and results. Many optimization algorithms are available for use with ANN, but there is no one-size-fits-all solution. Analysts must choose the right algorithm based on their specific needs. Table V.2 describes the most used optimization algorithm.

Table 6.2: The most used optimization algorithm in the ANN.

Algorithm	Description
Gradient descent (GD) [98]	In each epoch, the parameters will be updated in the negative direction of the loss function (J) where the learning rate should be also adjusted.
Conjugate gradient (CG) [99]	It represents faster convergence than the GD where the update will be performed in the conjugate directions.
Quasi-Newton Method (QNM) [100]	Calculating the learning direction using the inverse Hessian matrix of the loss function is faster than Newton's method because it doesn't require the second derivative.
Levenberg-Marquardt algorithm (LM) [101]	It is applicable only for MSE and SSE error terms of the loss function. It is preferable because it uses the Jacobian matrix instead of the Hessian matrix.

Stochastic Gradient Descent (SGD) [102]	It uses a different concept, the parameters will be updated at each epoch so many times using the Batches of data.
Adaptative Linear Momentum (ADAM) [103]	It converges faster and it is suitable to calculate the training direction.

6.3.2 Unsupervised Learning

As supervised learning requires the output labels to train the model, unsupervised learning finds by itself the hidden patterns of the dataset and predicts without any supervision. It tries to find the structure of the data in terms of clustering or associations. Unsupervised learning is more similar to the human brain function and it is more suitable for unlabeled datasets due to its ability to learn by itself [104].

Several algorithms are considered unsupervised learning algorithms: (Principle component analysis, K-means, KNN, and T-SNE).

6.3.2.1 Principle component analysis

Principal Component Analysis (PCA) is a statistical technique that can help identify the linear relationship between input features in a dataset. In simpler terms, it can be used to transform the original dataset into a new dataset with lower dimensions, without losing any important information. The new set of features created by PCA is known as principal components. PCA is an unsupervised learning type that can reduce the number of features in a dataset by capturing the most important ones. It is a dimensionality reduction technique that can simplify complex datasets [105].

Figure 6.9 demonstrates how PCA can be used to reduce the number of features. The example shows that PC_1 contains more information than PC_2 . PC_2 contains much less information (*lessthan2%*) and hence is less important to the dataset. The analyst can choose to ignore the use of PC_2 to reduce the number of input features.

Principal Component Analysis (PCA) is a statistical method that involves five key steps as illustrated in Figure 6.10. These steps can be summarized as follows:

- ***Subtracting the mean from the original dataset:*** To center a dataset, the mean value of each feature should be calculated. The original axis should then be moved to a new location where its new location is the mean of features. This can be achieved by subtracting the mean of each feature from the original dataset. The new dataset will have a zero mean of all the features.

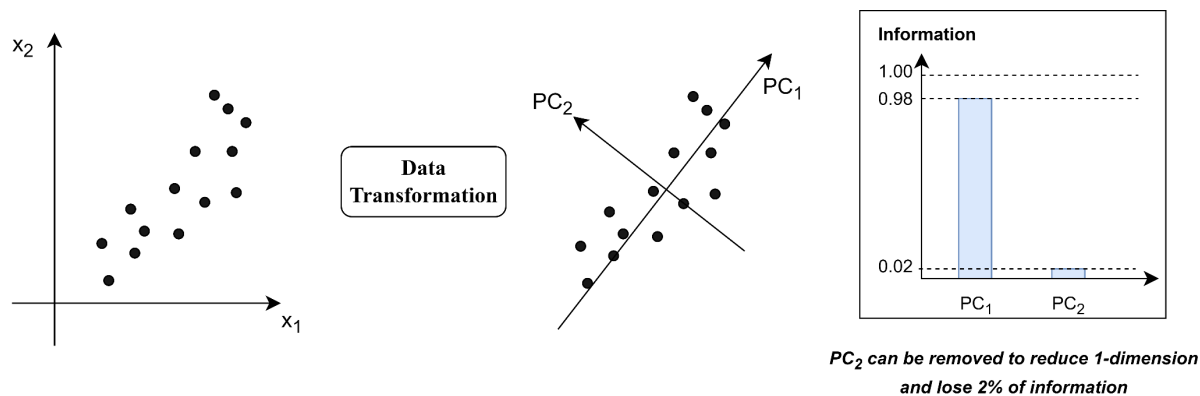


Figure 6.9: PCA for dimensionality reduction.

- **Covariance matrix:** The covariance matrix shows how much the variables vary from their average value. The sign of the covariance tells us about the relationship between two variables. If the covariance is positive, the variables are directly proportional to each other. On the other hand, if the covariance is negative, the variables are inversely proportional to each other.

It is important to note that variance measures the spread of data around the mean while covariance measures the direction of the relationship between two variables.

The covariance can be calculated using Equation (6.16):

$$COV(x, y) = \frac{\sum (x_i - \hat{x})(y_i - \hat{y})}{N} \quad (6.16)$$

where: $\hat{x}$ and $\hat{y}$ are the mean values of x and y features, N is the dataset size.

- **Eigenvectors and eigenvalues:** Eigenvalues and eigenvectors are important concepts in linear algebra and data analysis. Eigenvectors are vectors whose direction remains unchanged even after a linear transformation, while their length is multiplied by a factor called the eigenvalue. The number of eigenvectors is equal to the dimension of the dataset, and they can be calculated using the covariance matrix. Eigenvectors represent the direction where the dataset has the highest variance, while eigenvalues represent the variance of the dataset in that direction. By plotting the dataset using the new eigenvectors, we can get a clearer picture of the data distribution. For example, instead of using X_1 and X_2 as axes, we can use eigenvector 1 and eigenvector 2. This is illustrated in Figure 6.10.
- **Principal component selection:** After calculating the eigenvectors, the analyst should select the ones that correspond to the highest cumulative variance. It's important to note that relative variance represents the variance in a direction that corresponds to a principal component. Cumulative variance represents the sum variance for each component. The first PC always has the highest variance, while

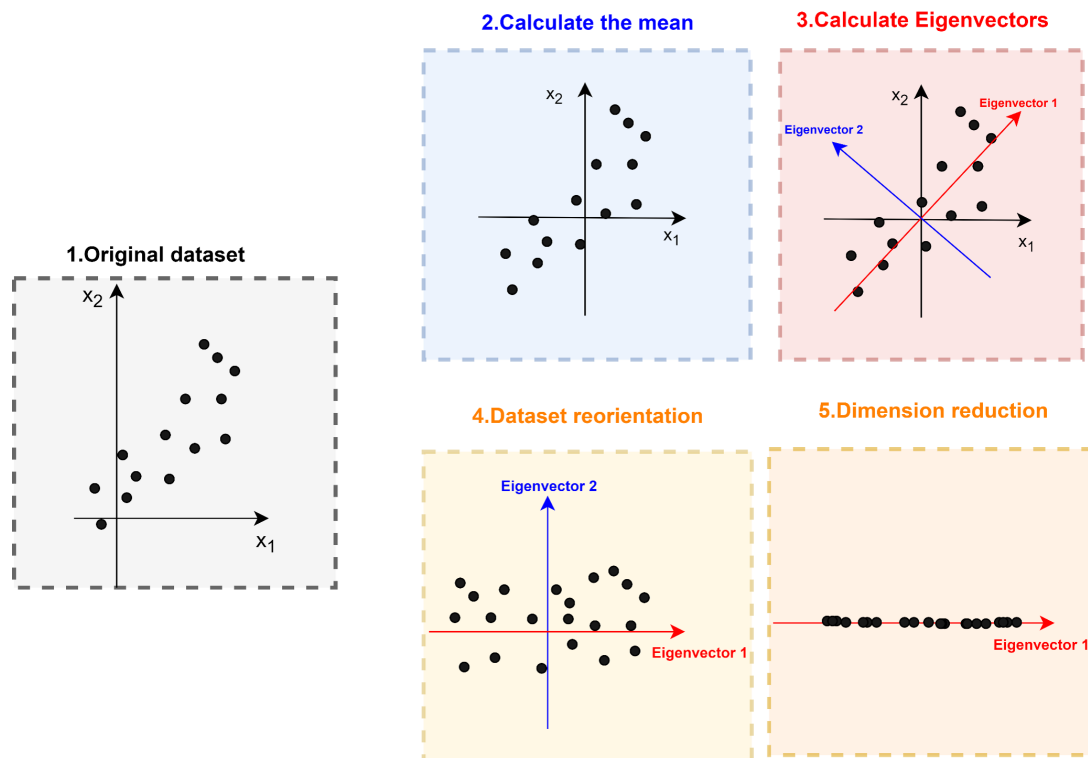


Figure 6.10: Steps to perform PCA.

the last PC has the lowest. Based on the cumulative variance, the analyst can select a desired threshold, such as 90% of variance. This means selecting all PCs where the cumulative variance reaches or exceeds 90%.

- **Dimensionality reduction:** If the analyst selects the number of principal components based on an information threshold, it is possible to remove other principal components that have less variance. By doing so, the dataset can be projected onto a new axis (such as PC1) without losing much of the original dataset's information (variance). However, it is important to note that this step is irreversible, and it will be impossible to recreate the original dataset from the selected principal components.

6.3.2.2 K-means clustering algorithm

K-means clustering is a widely used unsupervised machine learning algorithm to group similar data points. The algorithm partitions a given dataset into K clusters as shown in Figure 6.11, where K is a pre-defined number decided by the user. To start the process, the algorithm chooses K centroids randomly and then iteratively assigns each data point to the nearest centroid. Then, the centroids are recalculated as the mean of all the data points assigned to that cluster. This process continues until there is no change in the centroids or the maximum number of iterations is reached. K-means clustering is a simple yet powerful algorithm that can efficiently handle large datasets and is commonly

used in pattern recognition, image segmentation, and data mining [104]. The K-means is

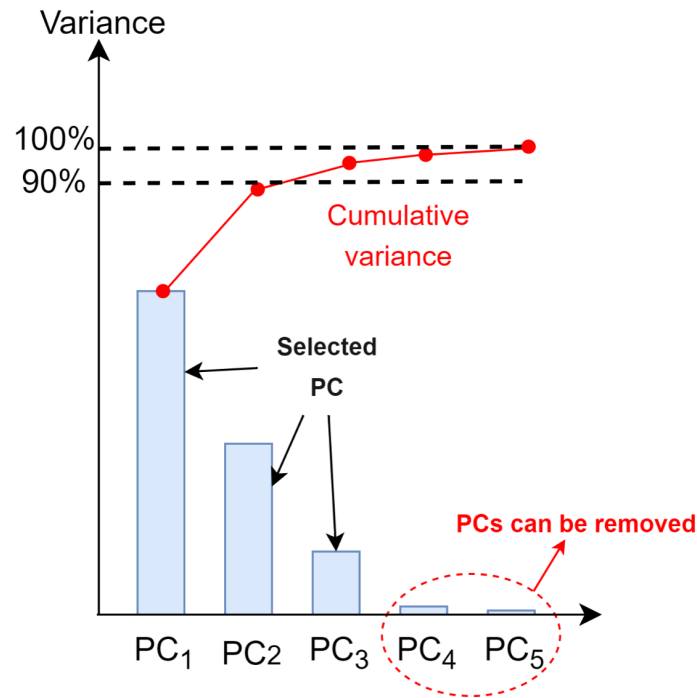


Figure 6.11: PC selection and dimension reduction in PCA.

based on seven main steps illustrated in Figure 6.12 explained as follows:

- *Step-1*: selection of the number of clusters (K). A high number of clusters means multiple clusters of the dataset should be calculated and it requires more time to perform.
- *Step 2*: After selecting the number of clusters (K) a random selection of K-points will be performed and these points will be considered as the centroids of each cluster.
- *Step 3*: the closest points of the dataset to the centroid will be considered as a part of the cluster.
- *Step 4*: The variance should be calculated for each new centroid.
- *Step 5*: step-3 should be repeated.
- *Step 6*: if the reassignment of the selected occurs then step-4 shall be calculated, else the algorithm will stop.
- *Step-7*: The clusters are defined and the model is ready.

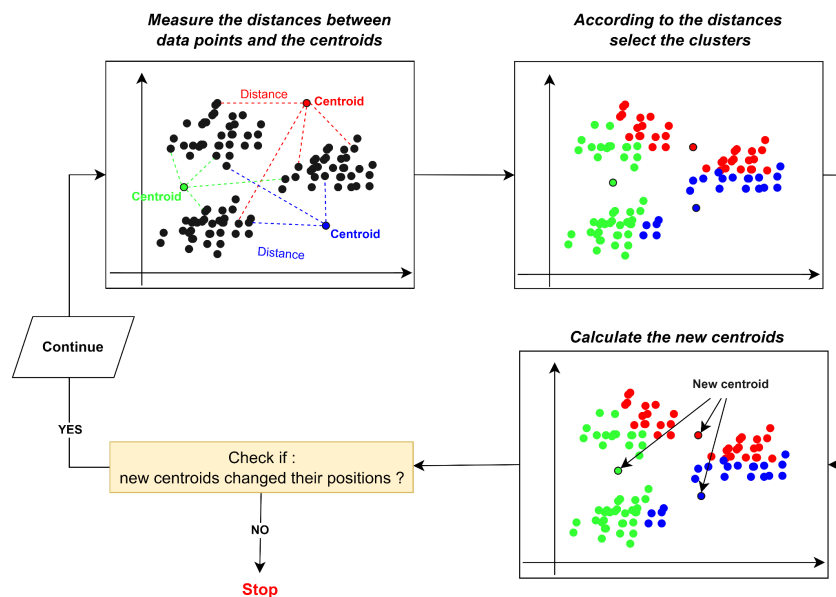


Figure 6.12: K-means algorithm for clustering.

6.3.2.3 Autoencoder for dimensionality reduction

The autoencoder is a type of unsupervised machine-learning algorithm that is commonly used to reduce the dimensionality of a dataset. While it is similar to PCA, it can handle nonlinear problems thanks to the implementation of nonlinear activation functions in the hidden layers. By compressing the dataset into a smaller one, the autoencoder can identify and isolate the most important features while simultaneously eliminating any extraneous noise [106].

The autoencoder is composed of two main networks as illustrated in Figure 6.13:

- *Encoder:* A neural network compresses high-dimensional features of the dataset into a lower-dimensional bottleneck. The dimension of the compressed data depends on the acceptable level of information loss.
- *Decoder:* The decoder network performs the opposite function of the encoder network. It attempts to recreate the input features of the encoder layer from the compressed data. As the compressed data becomes smaller, more information is lost. The quality of the decoding process is evaluated by computing the difference between the original data and the reconstructed data.

The autoencoder is a versatile machine-learning technique that finds applications in various fields such as time series, image analysis, and convolutional layers. Its performance is dependent on optimizing the hyperparameters of the neural networks, which includes determining the number of layers for both encoder and decoder layers, the number of neurons in each layer, the activation function used in each layer, and the number of neurons in the bottleneck (output dimensions). Several Auto-encoder types exist:

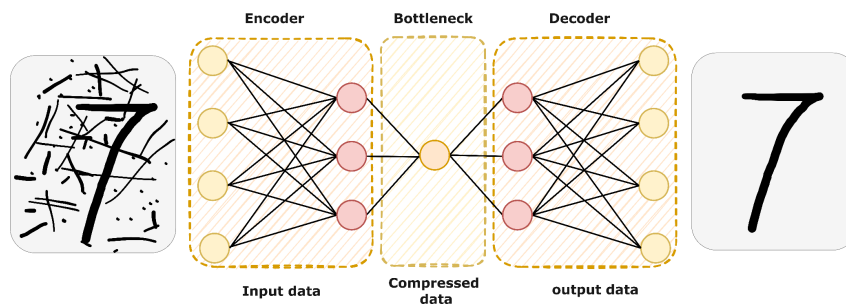


Figure 6.13: Auto-encoder architecture.

- **Undercomplete Autoencoder** : This type of autoencoder is more effective than the PCA as it captures the nonlinearity of the dataset. It is considered as the simplest type of algorithm. It ensures that the bottleneck has always a lower dimension than the inputs to avoid overfitting [107].
- **Sparse autoencoder**: This type of autoencoder is quite similar to the previous type. However, the difference is the sparse uses another technique to avoid overfitting by activating and deactivating neurons instead of reducing the dimension of the bottleneck [108].
- **Denoising autoencoder**: Image enhancement is a technique that is commonly used to improve the quality of images. It involves taking inputs to remove any noise present in an image or to enhance the details in a low-quality image. To compare the performance of the model, a labeled clean image is required.
- **Variational Autoencoder**: The Variational Autoencoder (VAE) differs from traditional Autoencoders in that it employs a probabilistic approach. Instead of the encoder generating a single value for each dimension, VAEs create a probability distribution for each dimension. This distribution allows the decoder to sample values and describe the various dimensions, ultimately constructing an input vector that can be used to reconstruct the original input data. VAEs are particularly valuable for generative tasks, as the decoder can create previously impossible outputs by sampling the latent model from these distributions [109].

6.3.3 Reinforcement learning

Reinforcement learning is a highly effective machine learning technique that involves an agent engaging with its environment by taking actions and receiving feedback in the form of rewards or punishments [110]. The ultimate objective of the agent is to maximize the total reward it receives over time. Unlike supervised learning, reinforcement learning does not require labeled examples. Instead, the agent learns through trial and error by exploring the environment and receiving feedback on its actions. As the agent continues

to learn, it gradually improves its ability to take actions that lead to the highest rewards. Reinforcement learning has a wide range of applications, including game playing, robotics, and autonomous driving, and has proven to be extremely successful in each of these areas. Reinforcement learning can be applied to a variety of real-world scenarios where an agent needs to learn from experience to perform a task. Here are some examples:

- **Game playing:** Reinforcement learning has been successfully applied to game playing, where the agent learns to make decisions based on the current state of the game and the possible actions it can take. For example, AlphaGo, an AI system developed by Google, uses reinforcement learning to play the game of Go at a superhuman level.
- **Robotics:** Reinforcement learning can be used to train robots to perform tasks such as grasping objects, navigating through a space, or performing complex manipulation tasks. The robot learns to take actions that maximize the reward it receives from the environment.
- **Autonomous driving:** Reinforcement learning can be used to train autonomous vehicles to make decisions in complex traffic situations. The vehicle learns to take actions that maximize safety and efficiency.
- **Resource management:** Reinforcement learning can be used to optimize the allocation of resources in a system. For example, it can be used to optimize the use of energy in a smart grid or to optimize the use of computing resources in a data center.
- **Personalized recommendation:** Reinforcement learning can be used to provide personalized recommendations to users based on their past behavior. The system learns to recommend items that maximize the user's satisfaction.

There are several types of reinforcement learning algorithms. Here are some of the most commonly used ones:

- **Q-Learning:** Q-Learning is a simple yet powerful algorithm that is used to learn the optimal action-value function. It works by updating the Q-values of the state-action pairs based on the reward received and the maximum Q-value of the next state.
- **SARSA:** SARSA is another simple algorithm that is used to learn the optimal policy. It works by updating the Q-values of the current state-action pair based on the reward received and the Q-value of the next state-action pair.

- **Deep Q-Networks (DQN):** DQN is a deep learning-based algorithm that is used to learn the optimal action-value function. It uses a neural network to approximate the Q-function and learns from experience by updating the network parameters using a variant of stochastic gradient descent.
- **Policy Gradient Methods:** Policy Gradient Methods are a class of reinforcement learning algorithms that learn the optimal policy directly. They work by updating the policy parameters in the direction of the gradient of the expected reward concerning the parameters.
- **Actor-Critic Methods:** Actor-critic methods combine the advantages of both value-based and policy-based methods. They use two networks: one to learn the value function and the other to learn the policy. The actor network is used to select actions, while the critic network is used to evaluate the value of the selected actions.

6.3.4 Optimization algorithms

6.3.4.1 Genetic Algorithm (GA)

Genetic Algorithm is an optimization algorithm inspired by the process of natural selection and genetics. It generates a population of candidate solutions and iteratively improves them through mutation, crossover, and selection. In each iteration, the algorithm evaluates the fitness of each candidate solution and selects the fittest ones to generate the next generation [111–113]. Genetic Algorithms are particularly useful for complex optimization problems that have a large number of variables and constraints and have been applied to a variety of fields, including engineering, finance, and healthcare. The general steps to perform a genetic algorithm as shown in Figure 6.14:

1. **Define the problem:** This involves defining the objective function that the algorithm will try to optimize, as well as the constraints and boundaries of the problem.
2. **Generate the initial population:** This involves creating a set of random solutions that will serve as the starting point for the algorithm. The size of the population and the range of values for each parameter are defined by the user.
3. **Evaluate fitness:** Each solution in the population is evaluated using the objective function to determine its fitness score. This is a measure of how well the solution performs concerning the objective function.
4. **Select parents:** The fittest solutions are selected as parents for the next generation. The selection process can be done using different methods such as tournament selection, roulette wheel selection, or rank-based selection.

5. **Crossover:** The selected parents are combined to create new offspring solutions. This is done by exchanging genetic information between the parents to create new solutions that inherit traits from both parents.
6. **Mutation:** Random changes are made to some of the offspring solutions to introduce diversity into the population. This helps prevent the algorithm from getting stuck in local optima.
7. **Evaluate the fitness of the new population:** The fitness of the new population is evaluated using the objective function.
8. **Repeat:** Steps 4 to 7 are repeated until a stopping criterion is met. This could be a maximum number of generations, a minimum fitness score, or a time limit.

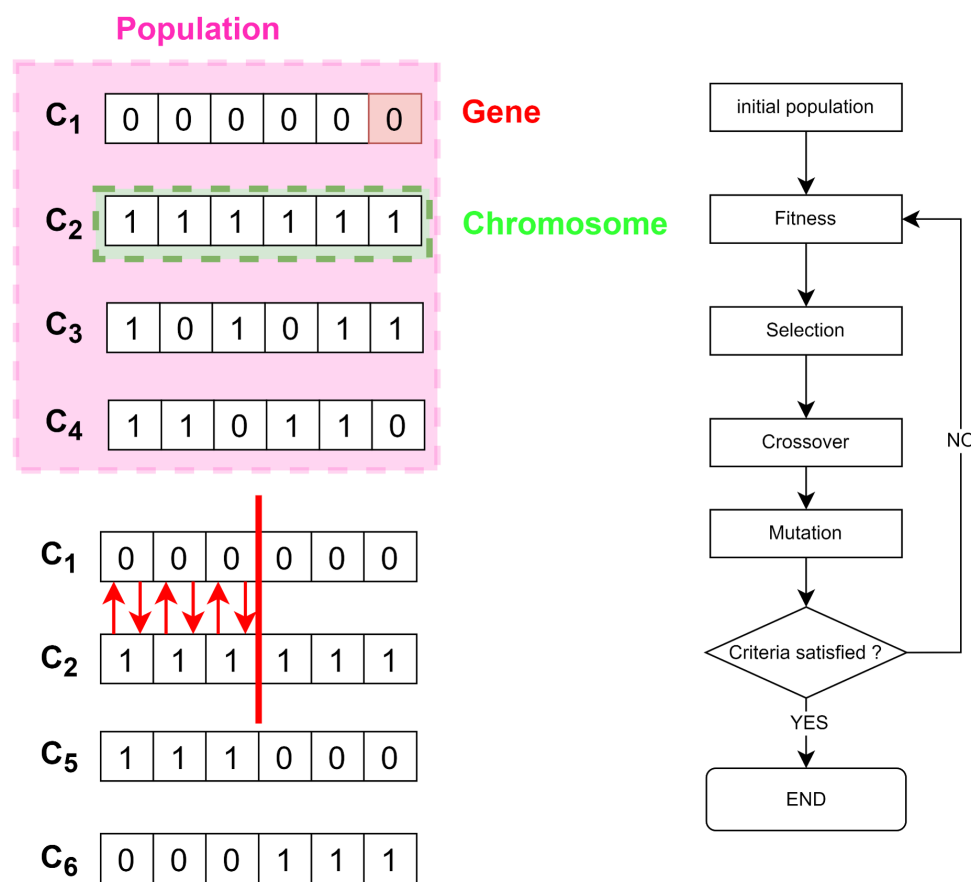


Figure 6.14: Genetic algorithm Algorithm.

6.3.4.2 Particle Swarm Optimization (PSO)

Particle Swarm Optimization is an optimization algorithm that draws inspiration from the social behavior of birds flocking or fish schooling. It works by updating the position and velocity of a population of particles iteratively based on the best position found by

the particles themselves and the entire population. PSO is especially useful for continuous optimization problems that have a large number of variables, and it has found applications in different fields, including engineering, finance, and image processing [114] .

The following are the steps involved in the PSO algorithm:

1. **Initialization:** Initialize the population of particles randomly within the search space. Each particle is a potential solution to the problem, and its position and velocity are represented as vectors.
2. **Evaluation:** Evaluate the fitness of each particle in the population. The fitness function evaluates how good or bad a particular solution is.
3. **Update Personal Best (pbest):** Assign the best position of each particle to its pbest vector. The pbest vector stores the best position a particle has visited so far.
4. **Update Global Best (gbest):** Select the particle with the best fitness value among all particles and assign its position to gbest. The gbest vector stores the best position in the entire population (See Figure 6.15).
5. **Update Velocity:** Update the velocity of each particle using the following Equation (V.13):

$$\vec{v}_i(t+1) = \omega \cdot \vec{v}_i(t) + C_1 (\vec{P}_i(t) - \vec{x}_i(t)) + C_2 (\vec{g}(t) - \vec{x}_i(t)) \quad (6.17)$$

where:

- $v_i(t)$ is the velocity of the i th particle at time t .
 - ω is the inertia weight that controls the impact of the previous velocity on the new velocity.
 - C_1 and C_2 are the acceleration constants that control the impact of the cognitive and social components.
 - $\vec{P}_i(t)$ is the personal best position of the i th particle.
 - $\vec{g}(t)$ is the global best position in the population.
 - $\vec{x}_i(t)$ is the current position of the i th particle.
6. **Update Position:** Update the position of each particle using the following Equation (6.18):

$$\vec{x}_i(t+1) = \vec{x}_i(t) + \vec{v}_i(t+1) \quad (6.18)$$

where:

- $\vec{x}_i(t)$ is the current position of the i th particle at time t .

- $\vec{v}_i(t+1)$ is the updated velocity of the i th particle at time $t+1$.
- $\vec{x}_i(t+1)$ is the new position of the i th particle at time $t+1$.

7. **Termination:** Repeat steps 2 to 6 until the termination criterion is met. The termination criterion can be a maximum number of iterations or a threshold value of the fitness function.

Overall, the PSO algorithm uses the concept of swarm intelligence to search for the optimal solution in a multi-dimensional search space.

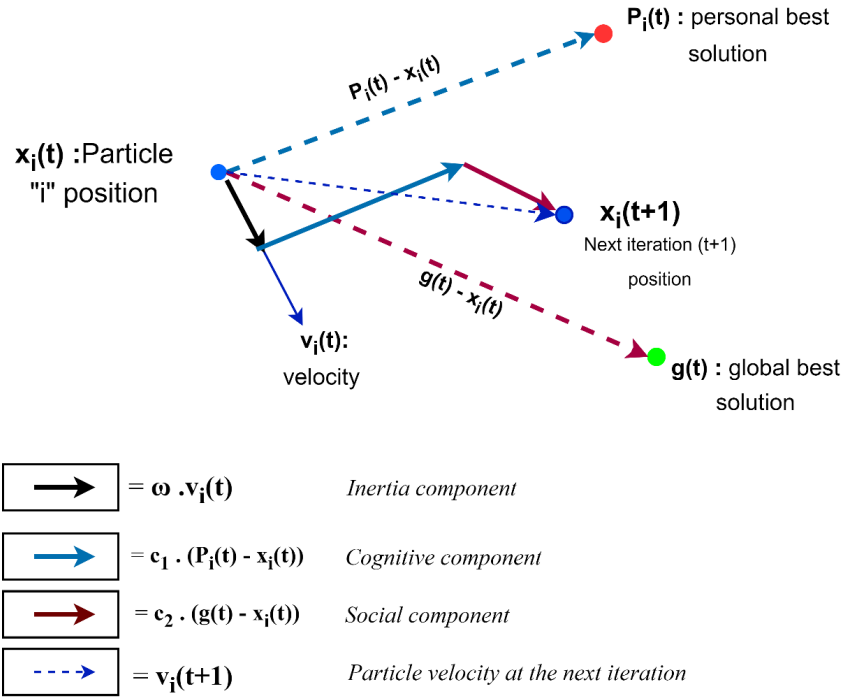


Figure 6.15: PSO updating the velocity and position of a particle.

6.3.4.3 Ant Colony Optimization (ACO)

Ant Colony Optimization is an optimization algorithm inspired by the behavior of ants searching for food. It works by iteratively updating the pheromone trails left by the ants and the probability of choosing a path based on the amount of pheromone. ACO is particularly useful for discrete optimization problems, such as the traveling salesman problem, and has been applied to a variety of fields, including logistics, transportation, and telecommunications [115].

It is a metaheuristic algorithm that is used to solve combinatorial optimization problems. The steps of the ant colony algorithm are as follows:

1. **Initialization:** Create a set of artificial ants and place them randomly on the problem space.

2. **Ant movement:** Each ant moves through the problem space, choosing the next location based on a pheromone trail left by previous ants. The probability of an ant choosing a particular path is proportional to the amount of pheromone on that path.
3. **Updating pheromone trail:** After each ant completes its tour, the pheromone trail is updated. The pheromone on the paths taken by successful ants is increased, while the pheromone on the paths taken by unsuccessful ants is decreased. This reinforces the successful paths and discourages the unsuccessful ones.
4. **Termination:** The algorithm continues until a stopping criterion is met. This can be a maximum number of iterations, a fixed amount of time, or a predetermined level of pheromone.
5. **Solution construction:** The best solution found by the ants is returned as the final solution.
6. **Parameter tuning:** The parameters of the algorithm, such as the pheromone evaporation rate and the importance of the pheromone trail, are adjusted to improve the performance of the algorithm.

6.3.4.4 Multi-objective Optimization algorithm

Multi-objective optimization (MOO) is based on the simultaneous optimization of two or more fitness functions $f = f_1, f_2, \dots, f_n$. Its goal is to find the best solution that satisfies the imposed restraints and objectives. In the real world, the MOO can be used to minimize the cost and maximize the comfort of cars or to reduce fuel consumption and maximize the performance of a jet engine. In summary, the MOO aims to find the balance between the fitness function and to help in the decision-making process. In mathematics, the MOO problem can be written as Equation (6.19) :

$$\min_{x \in X} (f_1(x), f_2(x), \dots, f_n(x)) \quad (6.19)$$

Where $n > 1$ is the number of fitness functions and X is the solutions space of the input variables ($X \subseteq \mathbb{R}^n$).

In MOO there is no unique solution that optimizes all the fitness functions at the same time. The group of solutions that cannot be improved in any activation functions is called the Pareto front or Pareto frontier. It is said $x_1 \in X$ dominates another solution $x_2 \in X$ if:

$$\forall i \in \{1, 2, \dots, n\}, f_i(x_1) \leq f_i(x_2) \quad \text{and} \quad \exists i \in \{1, 2, \dots, n\}, f_i(x_1) < f_i(x_2)$$

A solution vector is called a Pareto optimal vector if there are no other solutions that dominate it. Figure 6.16 illustrates the Pareto frontier.

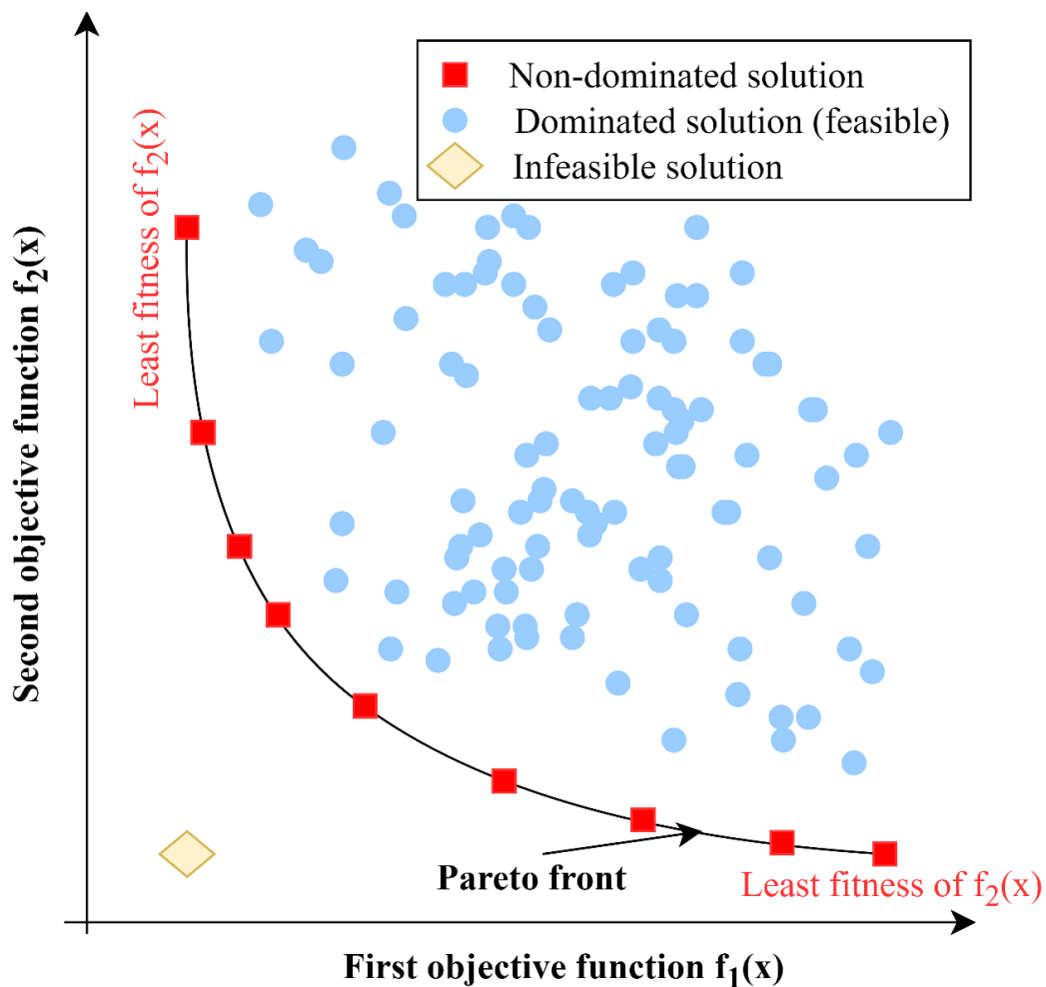


Figure 6.16: Pareto front for two objective functions.

Several popular algorithms to achieve these challenges. Evolutionary Algorithms, such as GA and PSO, are population-based search algorithms inspired by natural processes. An example of GA in MOO is the NSGA-II, which uses fast non-dominated sorting and crowding distance to preserve diversity. Similarly, MOPSO incorporates Pareto dominance and uses an external archive to maintain optimal solutions.

Mathematical programming provides many methods for solving multi-objective problems. One such method is the Weighted Sum Method, which simplifies a multi-objective problem into a single-objective one by assigning weights to each objective. However, it may need help with non-convex Pareto fronts. Another approach is the ϵ -Constraint Method, and it optimizes one objective while treating the others as constraints with permissible deviations. It is more flexible in handling non-convex Pareto fronts.

Decomposition-based algorithms, such as *MOEA/D* (Multi-Objective Evolutionary Algorithm based on Decomposition), decompose the MOO problem into several scalar op-

timization sub-problems. they are optimized simultaneously, providing a good balance between convergence and diversity. To evaluate the performance of MOO algorithms, several metrics are used:

- **The Hyper-volume Indicator:** it measures the volume of the objective space dominated by the Pareto front.
- **Generational Distance:** it assesses the average distance between the obtained and true Pareto front.
- **The spread metric:** it evaluates how well the solutions are distributed along the Pareto front.

6.4 Conclusion

In conclusion, artificial intelligence (AI) and machine learning (ML) have become integral parts of various fields, including civil engineering, automation, and data analysis. AI has various applications, including automation and data analysis, that increase efficiency and minimize the possibility of human error. ML uses data to create a model capable of predicting outcomes for new scenarios, enabling computers to learn from previous experiences automatically, without any human intervention. The primary objective of ML is to increase accuracy and predictability in performance. Due to their accuracy and predictability, supervised learning, including linear regression, logistic regression, and the K-nearest neighbor algorithm, are popular ML methods used in civil engineering, particularly in earthquake engineering. Lastly, various optimization algorithms were introduced, including concepts for single or multi-objective optimization.

Chapter 7

Fast and accurate seismic response prediction using Machine Learning

7.1 Introduction

Earthquake engineering researchers face the challenging task of accurately predicting non-linear responses. Being able to capture valuable information about structural behavior makes it an important field of study. Previous studies suggest that solving the equation of motion through NLTHA is the most reliable way to calculate inelastic response. However, this approach is time-consuming, and researchers are looking for equally good alternatives that require less time. Pushover analysis is one of the most commonly used methods to estimate a building's capacity and performance.

In recent years, the use of AI in earthquake engineering has become increasingly popular due to the ability of AI models to learn and their high performance in predicting outputs. This chapter will introduce a proposed methodology for calculating inelastic seismic response using machine learning, and their accuracy, limitations, and performance will be discussed.

7.2 Methodology

The proposed approach uses AGM to perform NLTHA on a random RC frame structure. The resulting seismic responses of the buildings and the ground motion parameters will be recorded. This data will then be used as a dataset for the machine learning model. Figure 7.1 demonstrates the steps involved in this proposed approach.

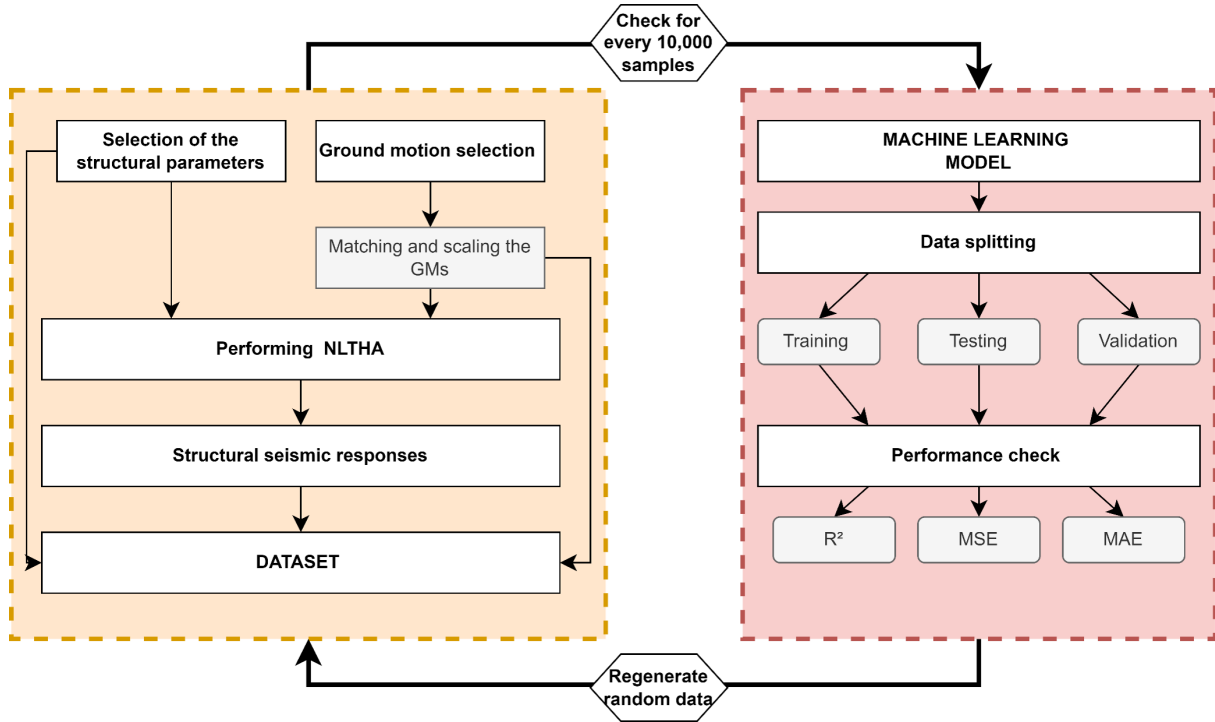


Figure 7.1: The proposed methodology for seismic response prediction.

7.2.1 generating the dataset

1. **Structure characteristics selection:** The study randomly selected the geometrical and material characteristics of 1,500,000 RC frame buildings from a range listed in Table 7.1. These buildings were subjected to 80 AGMs.
2. **Ground motions selection:** A dataset of 80 AGMs was created using "SeismoArtif" software to match a specific response spectrum. Each AGM's parameters were saved in the dataset, including 33 calculated parameters for each AGM. To determine the seismic response spectrum, a zone response spectrum should be used to generate the appropriate AGMs to the studied zone
The generated AGMs are matched to a target response spectrum. An ASCE response spectrum was selected for this study as shown in 7.2. however, any response spectrum can be used to generate AGMs or to match real GMs.
3. **Material characteristics:** Two materials have been used in this study, concrete and steel as shown in Figure 7.3. The steel of the reinforcement bars has a bilinear behavior that is defined by the elastic modulus, yielding force limit, and the post-yield stiffness ratio (in this study is assumed zero). For the concrete, a Mander et al reference model is used to model the effect of the longitudinal and transversal reinforcement on the confined concrete strength as shown in Figure 7.4.

Table 7.1: The geometric and material characteristics used to generate the dataset

Parameter	Symbol	Unit	Min	Max
Number of bays	N_b	-	1	7
Number of stories	N_s	-	1	15
Bay's length	L_b	cm	300	700
Ground floor height	H_e	cm	300	400
Floor's height	H_s	cm	300	400
Column dimension	h_{column}	cm	30	100
Reinforcement ratio	ρ_{column}	%	1	8
Beam depth	h_{beam}	cm	25	70
Beam width	b_{beam}	cm	25	70
Upper reinforcement ratio	$\rho_{\text{upper}}^{\text{beam}}$	%	1	4
Lower reinforcement ratio	$\rho_{\text{lower}}^{\text{beam}}$	%	1	4
Compressive concrete strength	f_{c28}	MPa	20	65
Steel yielding stress	f_y	MPa	400	600
Transversal reinforcement area	A_{transv}	mm ²	50	400
Transversal reinforcement spacing	spacing	mm	50	200
Cover	c	mm	25	50
Dead load	G	KN/m	0.2	7
Live load	Q	KN/m	0.2	7

7.2.2 NLTHA using OpenSEES

OpenSEES is open-access software used in earthquake engineering to perform various types of analysis, including static, quasi-static, and dynamic analysis. Unlike other software used in civil engineering, OpenSEES allows users to program their scripts and semi-automate or fully automate the process. This gives users full control over the analysis process, including analyzing and generating structures or performing different types of analysis. This software performs an NLTHA. The process is illustrated in Figure 7.5.

The analysis will end by saving all the seismic responses of the structures (i.e., MISD, MRDR, maximum base shear, period) and the seismic ground motion parameters. The resulting dataset will then be used to train a machine learning algorithm for each of the 10,000 analyzed structures to determine if the desired performance is achieved or not.

7.2.2.1 Dataset collection

The dataset included structural characteristics, ground motion parameters, maximum base shear (MBS), inter-story drift (MIDR), and roof drift ratios (MRDR). The structures were randomly selected using a uniform distribution.

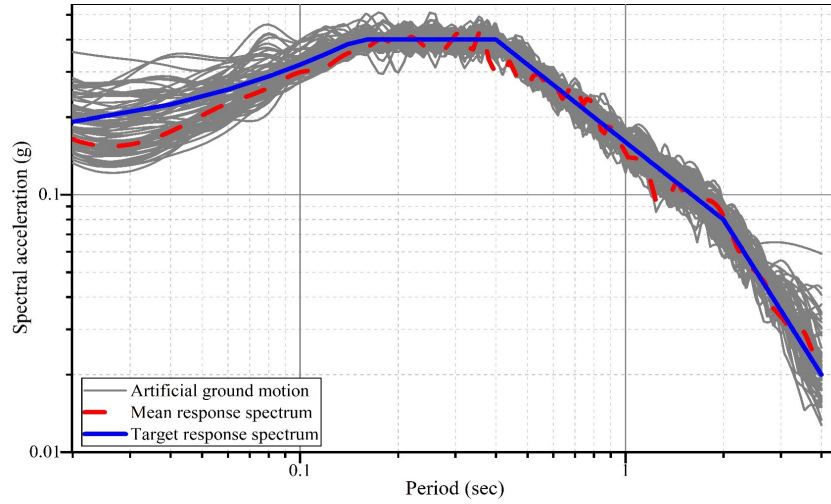


Figure 7.2: The generated artificial ground motions and the target response spectrum.

7.2.2.1.1 Dataset statistical description

This section presents a statistical analysis of the dataset to describe its features. *The structural features:*

Figure 7.6 illustrates in a bin plot the frequency of each feature among the generated dataset. It can be noted that N_b , N_s , L_b , h_{column} , As_{trans} , G , and Q , have a uniform distribution.

Ground motion features Figures 7.7 and 7.8 summarize the frequency of each GM feature in the dataset and its statistical distribution.

7.2.2.1.2 correlation between Input and output features

The correlation between the input features and the seismic responses (fundamental period, MBS, MIDR, MRDR) are illustrated in Figures 7.9 and 7.10. According to the mentioned Figures, several points can be obtained:

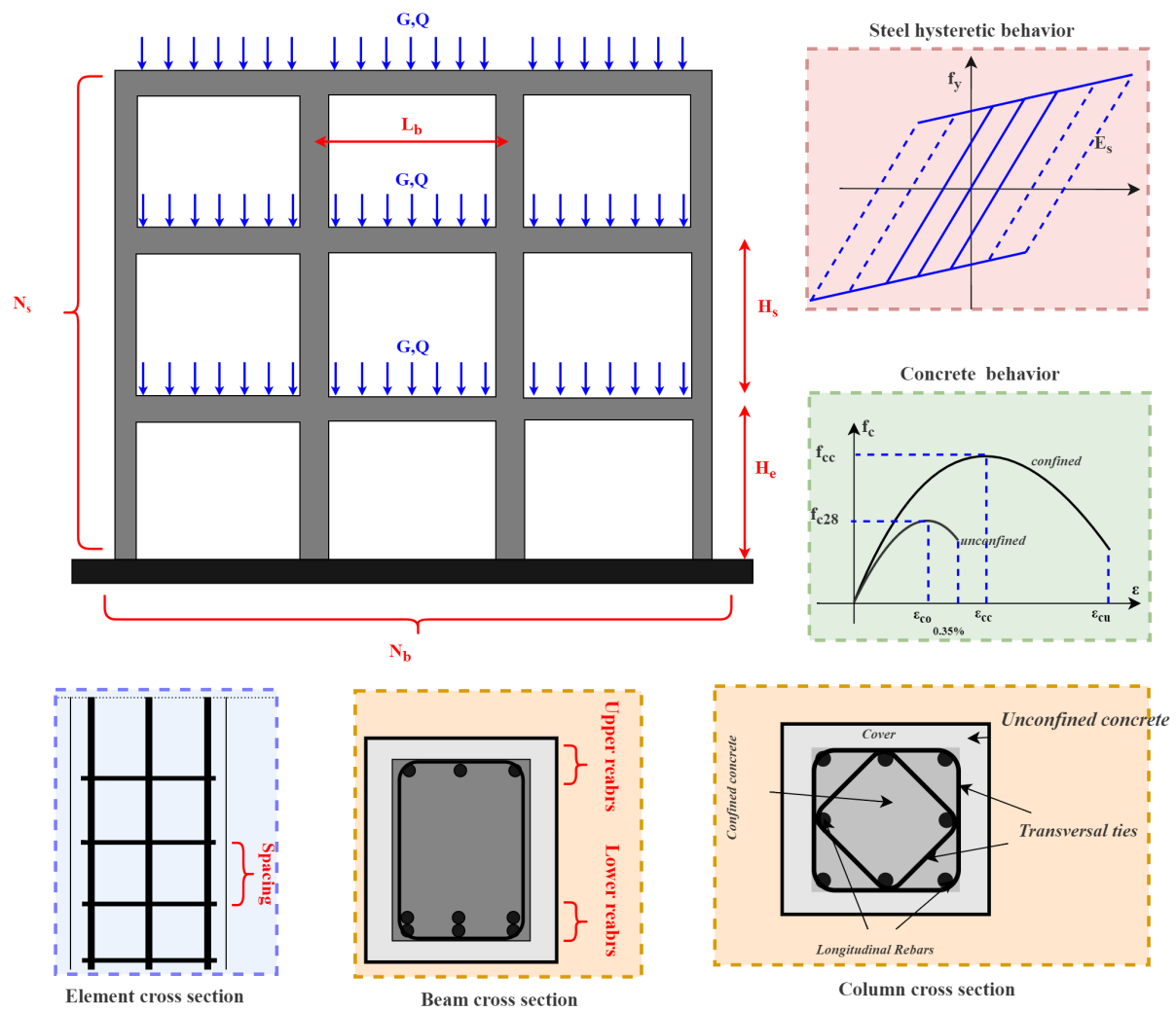
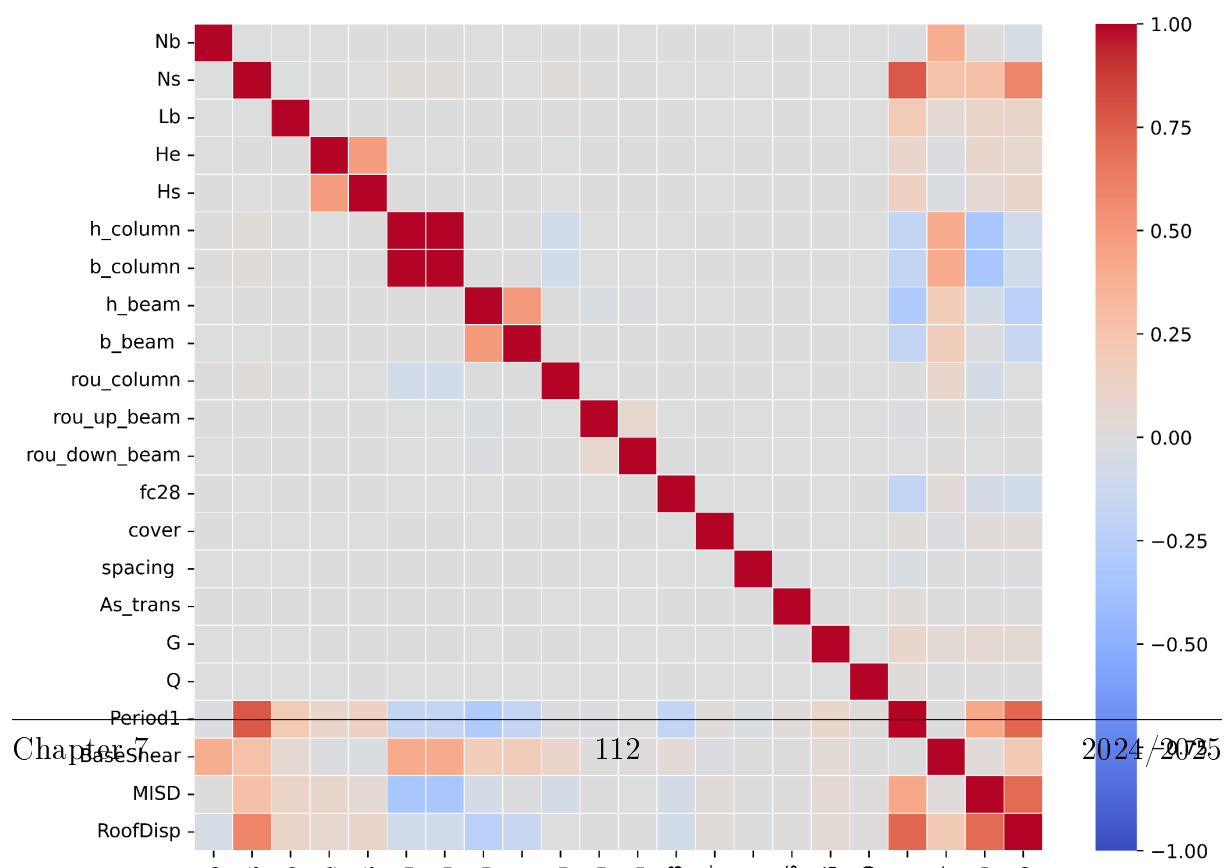


Figure 7.3: The structural, geometric, and material characteristics of the RC frame buildings.



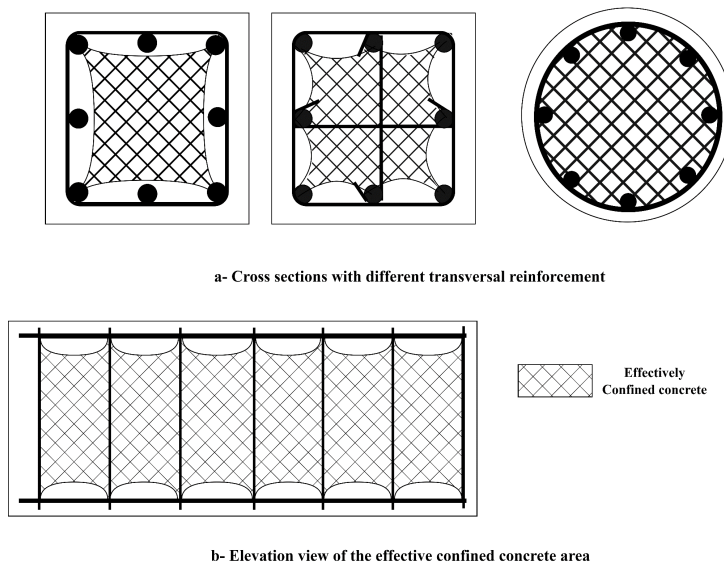


Figure 7.4: Confined and unconfined area of RC elements.

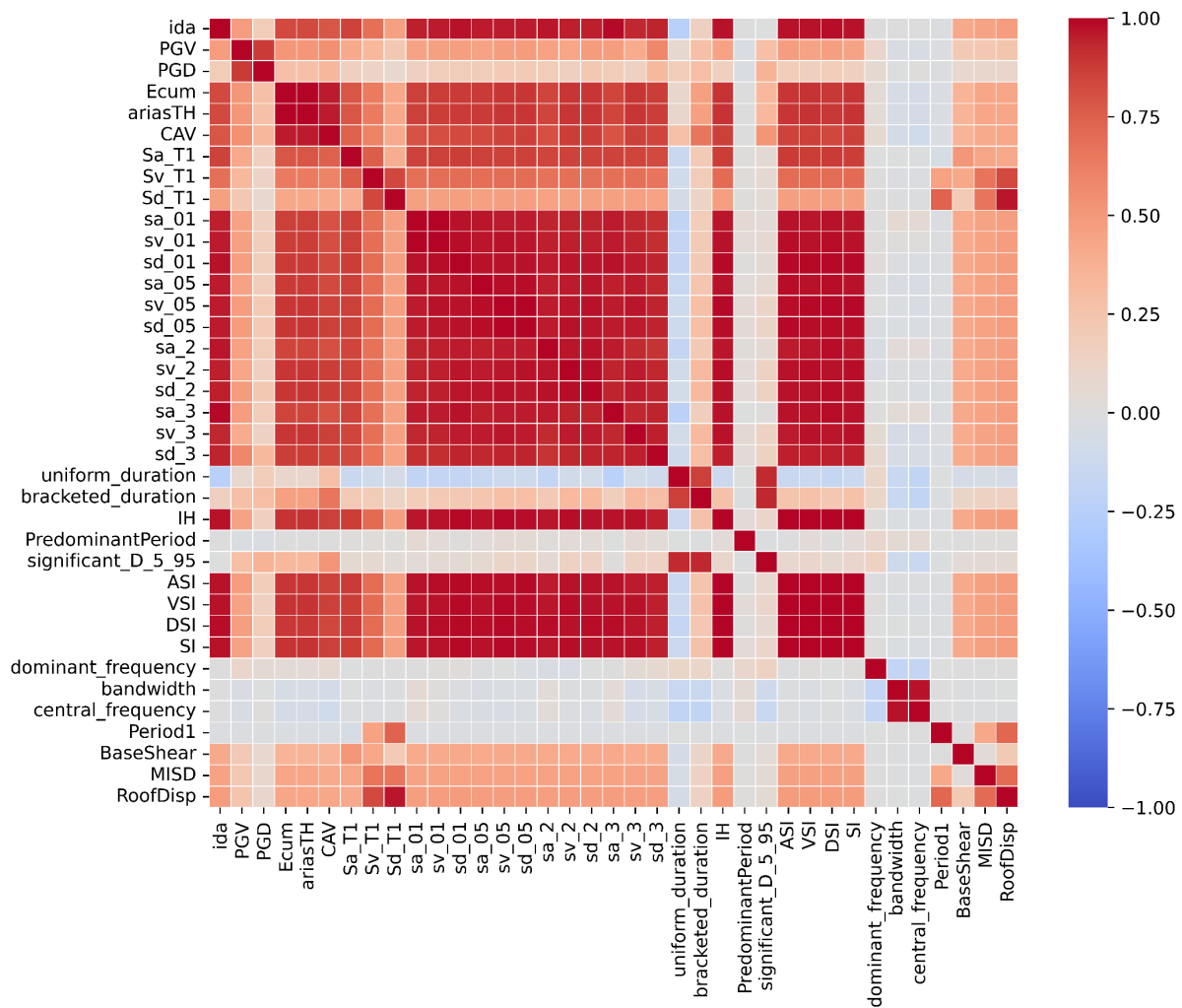


Figure 7.10: Ground motion parameters and the seismic responses heatmap .

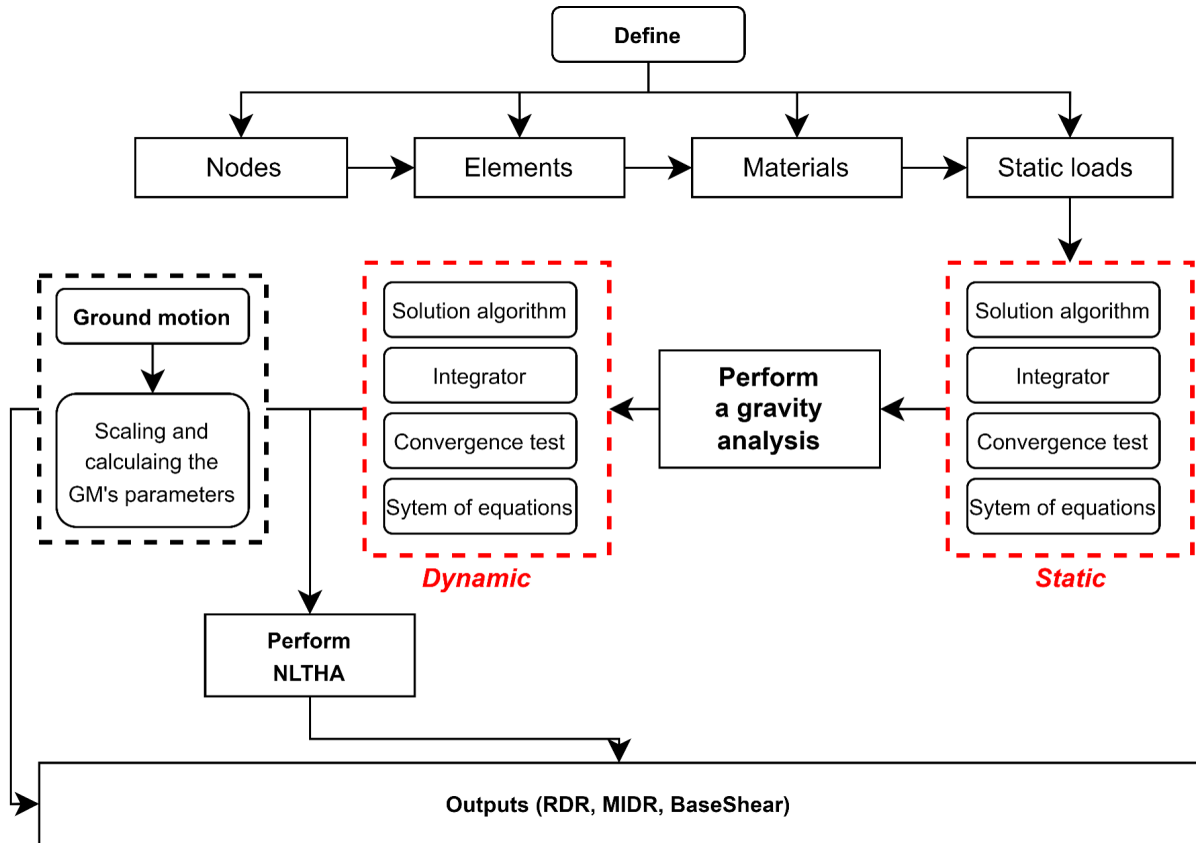


Figure 7.5: The process to perform NLTHA on OpenSEES.

- **Fundamental period:** there is a high correlation between the fundamental period and the structural features (number of stories, story heights, element dimensions, and concrete compressive strength).

Maximum base shear: The MBS is correlated with N_b , N_s , and column dimensions for the structural features. It is also correlated with the ground motion parameters except duration (e.g., uniform duration, predominant period, and significant duration), and frequency content properties (e.g., bandwidth and central frequency).

- **MIDR:** The MIDR is correlated with N_s , and column dimensions for the structural features. It is also correlated with the ground motion parameters except duration (e.g., uniform duration, predominant period, and significant duration), and frequency content properties (e.g., bandwidth and central frequency).
- **MRDR:** The MRDR is correlated with N_s , and the fundamental period for the structural features. It is also correlated with the ground motion parameters except duration (e.g., uniform duration, predominant period, and significant duration), and frequency content properties (e.g., bandwidth and central frequency).

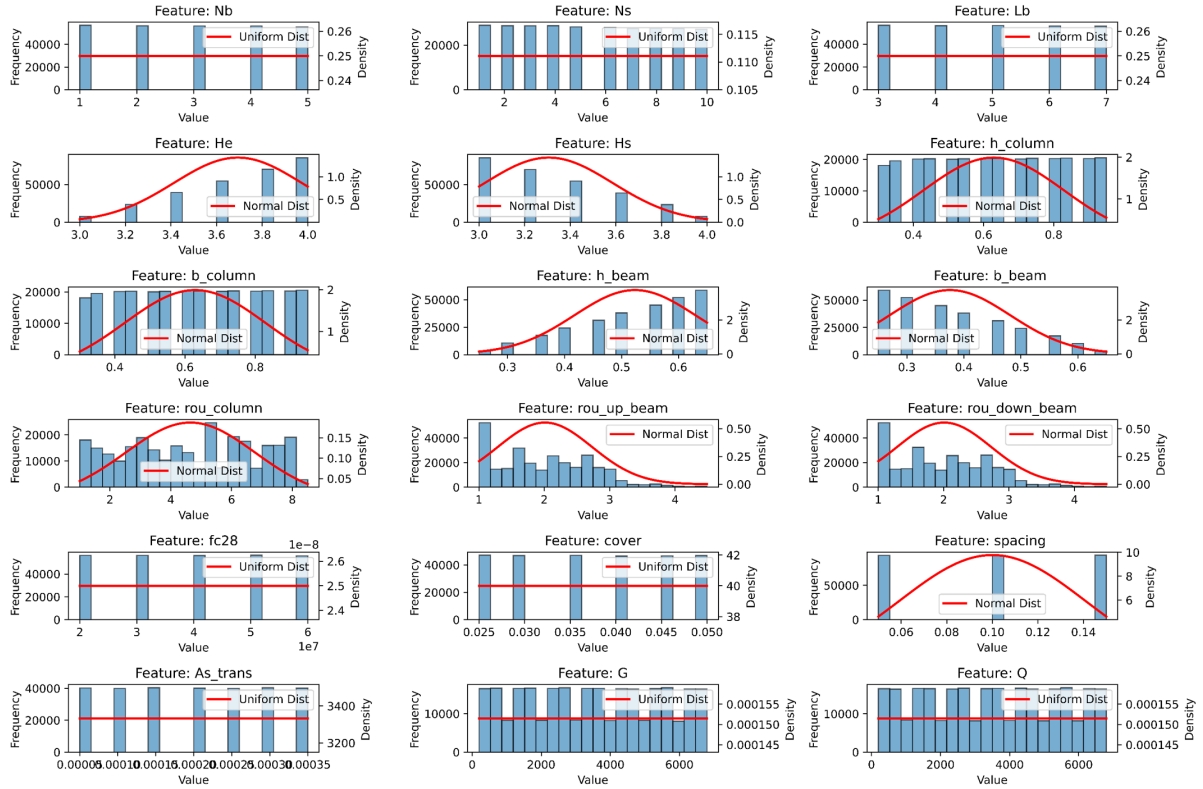


Figure 7.6: The structural input features and their distribution in the dataset.

7.2.2.2 Input features ranking

A ranking algorithm called RReliefF was used to identify the most important features in the dataset. RReliefF is a preprocessing technique that reduces the number of less important input features. This helps to improve training time and reduce overfitting. Figures 7.11, 7.12, 7.13 are the important score results of the RReliefF algorithm for the MBS, MIDR, and MRDR.

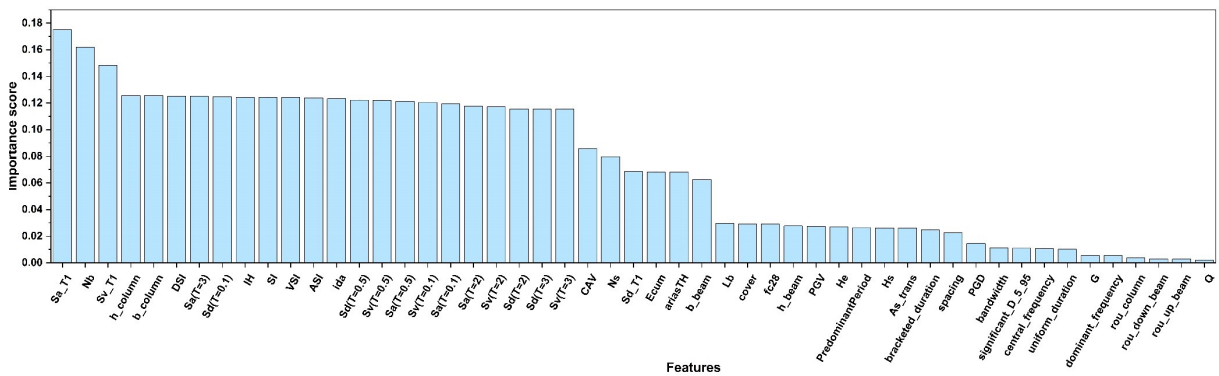


Figure 7.11: The input features ranking using RReliefF for MBS as an output .

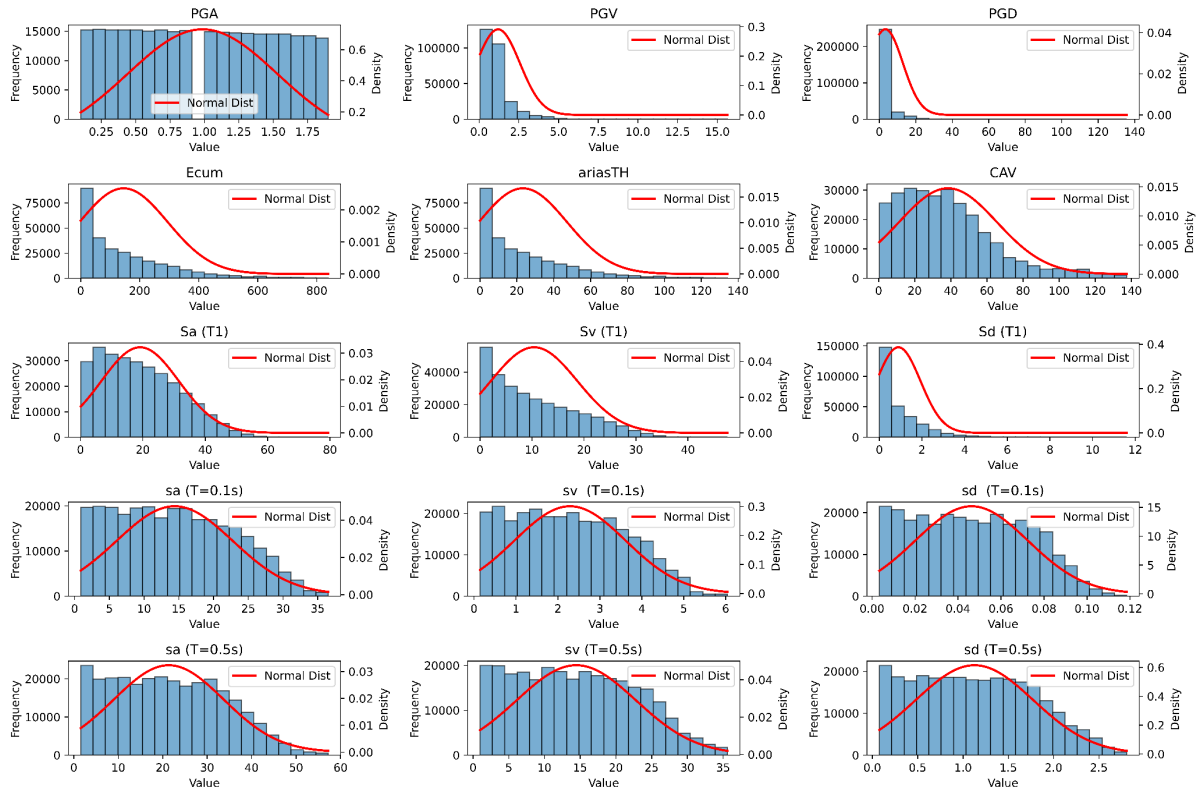


Figure 7.7: Ground motion parameters, frequencies, and their statistical distribution (Part 1).

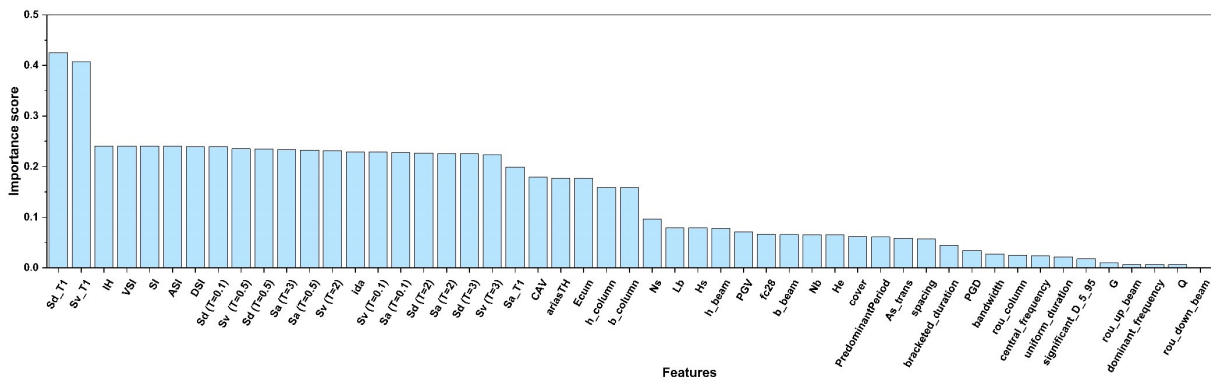


Figure 7.12: The input features ranking using RReliefF for MIDR as an output .

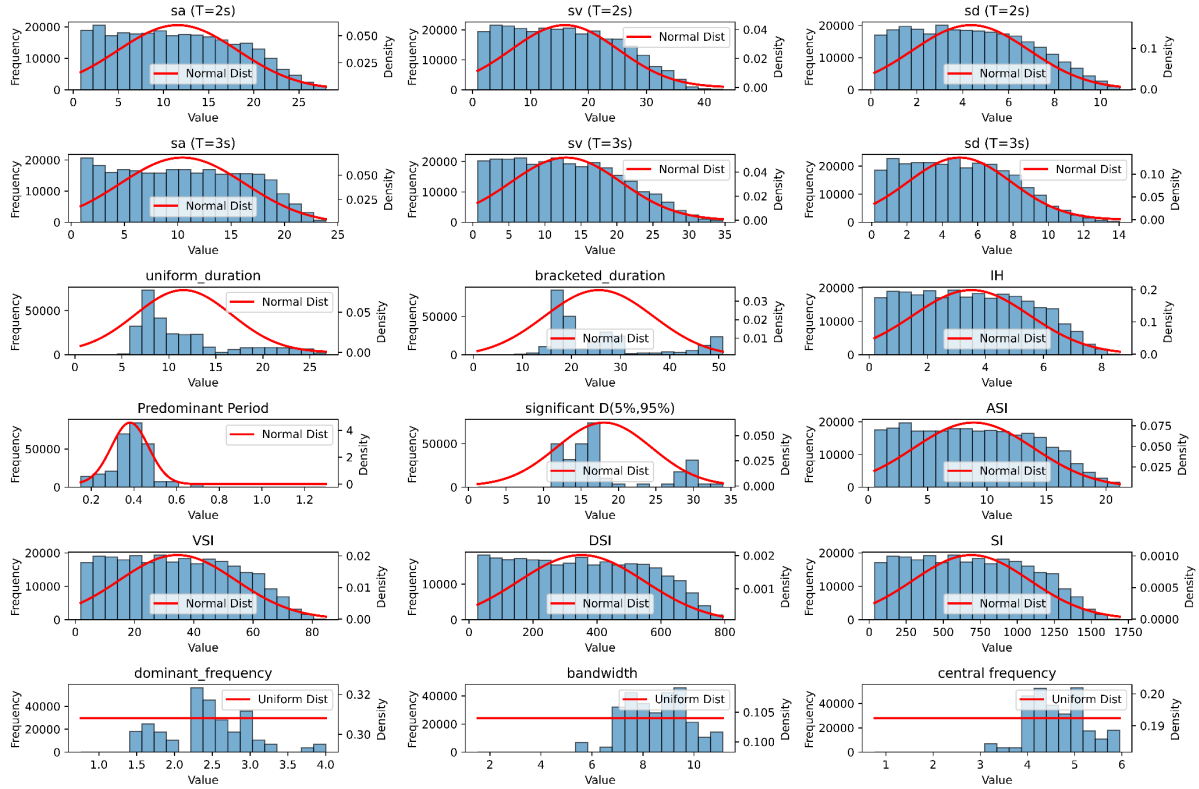


Figure 7.8: Ground motion parameters, frequencies, and their statistical distribution (Part 2).

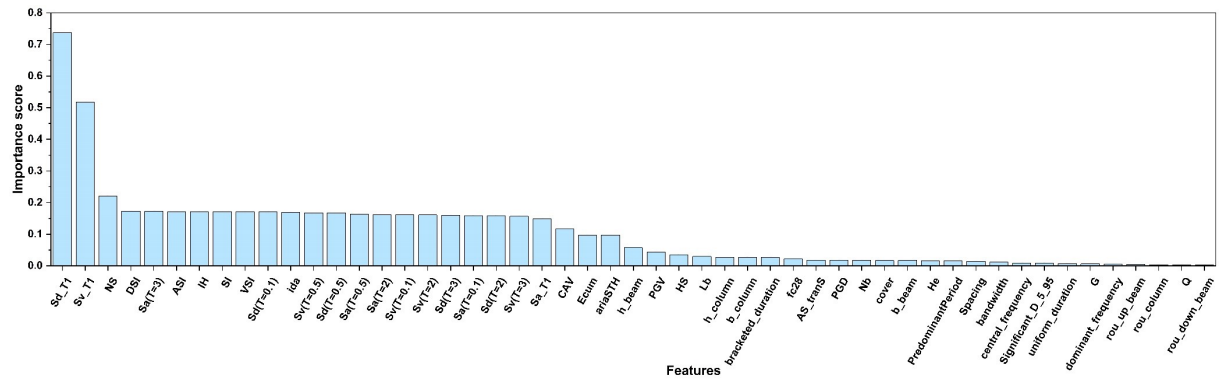


Figure 7.13: The input features ranking using RReliefF for MRDR as an output .

- **MBS:** Per Figure 7.11, numerous seismic parameters affect the MBS more than the structural characteristics. However, it was found that the spectral response $S_a(T_1)$ is the most influential. On the other hand, the number of bays (N_b) and the column geometry are the most influential structural parameters. Additionally, the reinforcement and loading intensity have less influence on the MBS.
- **MIDR:** Based on Figure 7.12, the seismic parameters have the highest importance scores compared to the structural characteristics, indicating that they are the most

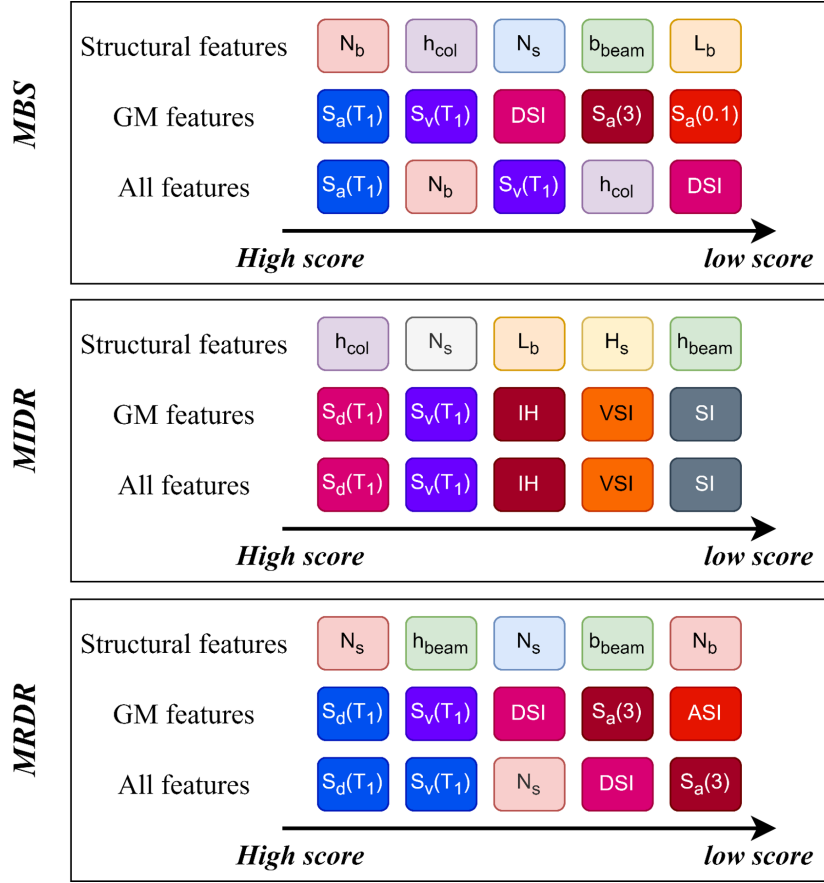


Figure 7.14: The 5 highest importance score features of MBS, MIDR, and MRDR.

influential features of the MIDR. The dimensions of the columns and the number of stories are the most influential structural features. The reinforcement and the loading intensities have the lowest important scores.

- **MRDR:** Figure 7.13 illustrates that the seismic parameters have a greater impact on the MRDR than the structural characteristics. All the structural features have lower importance scores than the seismic parameters. Additionally, the reinforcement and loading intensities have the lowest scores.

Figure 7.14 summarizes the best 5 top importance scores of structural features, GM features, and combined features.

7.3 Proposed methodology for seismic response prediction using hybrid algorithms

Different methods, approaches, and equations have been suggested for estimating a building's response to an earthquake. To simplify the process and reduce processing time, a

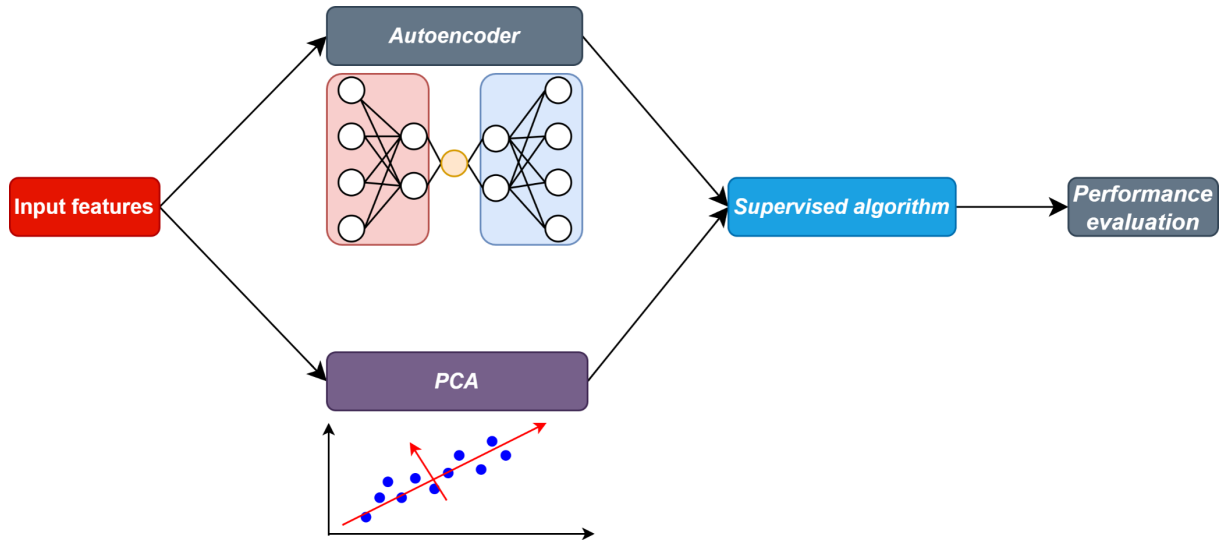


Figure 7.15: The proposed hybrid methodology for seismic response prediction.

static procedure called pushover analysis is used instead of the more complex NLTHA. With the advancement of the IA technique, the use of machine learning in earthquake engineering has become increasingly interesting, particularly for predicting seismic responses. To address this, efforts are being made to improve prediction performance and minimize errors by transitioning from unsupervised algorithms to supervised ones. The main objective is to reduce the dimensionality of the input features and enhance predictability, decrease training time, and simplify the network to avoid overfitting.

Two unsupervised algorithms (PCA and Autoencoder) [116] were selected to be used as a dimensionality reduction technique. A comparative study will be conducted to choose the best hybrid model representing the highest performance (correlation coefficient, and MSE).

Figure 7.15 illustrates a summary of the proposed methodology to predict the seismic response.

The unsupervised algorithms capture the most influential and significant features of the input features and make the dataset less complex.

This study will compare the use of supervised algorithms' performance with hybrid algorithms. The comparison will be done by calculating the correlation coefficient (R^2) and MSE between the NLTHA results and the predicted results.

7.3.1 Hyperparameters optimization

The hyperparameters are the most influential factors that affect the model's predictability and control the type of fitting that may occur during and after the training (overfitting and underfitting). Therefore, it is essential to conduct a parametric analysis to search

Table 7.2: Hyperparameters of each supervised algorithm

Algorithm	Hyperparameters
AdaBoost	<ul style="list-style-type: none"> • Number of estimators • Learning rate • Regression loss function
ANN	<ul style="list-style-type: none"> • Activation function • Learning rate • Solver • Number of hidden layers • Number of neurons
SVM	<ul style="list-style-type: none"> • Regression cost • Complexity bound
Tree	<ul style="list-style-type: none"> • Minimum number of instances in leaves • Minimum splitting limit • Maximum tree depth

for the best hyperparameters that will lead to the highest (R^2) and the lowest MSE. The training model uses the early stopping technique (i.e., the model will stop learning as soon as overfitting occurs) and saves the best performance weights and biases. A PSO algorithm is chosen to perform this type of optimization problem. Tables 7.2 and 7.3 summarize the hyperparameters of each model that should be optimized using PSO. This process should be repeated for all the outputs (MBS, MIDR, and MRDR).

Tables 7.4, 7.5, and 7.6 summarize the optimal hyperparameters for supervised and hybrid learning algorithms used for each model.

7.3.2 Performance of supervised and hybrid learning for seismic response prediction

A comparative study will be conducted to investigate the effectiveness of emerging dimensionality reduction algorithms on the performance of supervised learning.

Tables 7.7 and 7.8 summarize the training performance (R^2 , MSE) of the hybrid mod-

Table 7.3: Hyperparamters of each supervised algorithm

Algorithm	Hyperparameters
Autoencoder	<ul style="list-style-type: none"> • Number of hidden layers • Number of neurons • Activation function • Size of the bottleneck.
PCA	<ul style="list-style-type: none"> • Number of principal components • Cumulative variance threshold.

Table 7.4: The hyperparameters of supervised learning regression algorithms

Algorithm	Hyperparameter	MBS	MIDR	MRDR
Adaboost	Number of estimators	50	65	43
	Learning rate	1	1	1
	Regression loss function	Square	Square	Square
ANN	Activation function	Relu/linear	Relu/linear	Relu/linear
	Learning rate	0.01	0.02	0.001
	Solver	Adam	Adam	Adam
	Number of hidden layers	4	4	5
	Number of neurons	70	60	60
SVM	Regression cost	1	1.25	1
	Complexity bound	0.5	0.5	0.45
Tree	number of instances in leaves	2	5	4
	Minimum splitting limit	5	5	5
	Maximum tree depth	100	100	100

Table 7.5: The hyperparameters of PCA + supervised learning regression algorithms

Algorithm	Hyperparameter	MBS	MIDR	MRDR
Adaboost	Number of estimators	47	63	50
	Learning rate	1	1	1
	Regression loss function	Square	Square	Square
ANN	Activation function	Relu/linear	Relu/linear	Relu/linear
	Learning rate	0.04	0.05	0.01
	Solver	Adam	Adam	Adam
	Number of hidden layers	3	4	4
	Number of neurons	50	40	40
SVM	Regression cost	1.05	1.15	0.95
	Complexity bound	0.5	0.5	0.45
Tree	number of instances in leaves	2	2	3
	Minimum splitting limit	5	5	5
	Maximum tree depth	70	80	85

Table 7.6: The hyperparameters of Autoencoder + supervised learning regression algorithms

Algorithm	Hyperparameter	MBS	MIDR	MRDR
Adaboost	Number of estimators	40	55	48
	Learning rate	1	1	1
	Regression loss function	Square	Square	Square
ANN	Activation function	Relu/linear	Relu/linear	Relu/linear
	Learning rate	0.03	0.055	0.02
	Solver	Adam	Adam	Adam
	Number of hidden layers	2	3	2
	Number of neurons	45	35	40
SVM	Regression cost	1.1	1.1	1
	Complexity bound	0.5	0.5	0.45
Tree	number of instances in leaves	2	2	3
	Minimum splitting limit	5	5	5
	Maximum tree depth	65	70	75

els and the supervised model to predict MBS, MIDR, and MRDR.

It's important to note that (R^2) represents the average performance across the training, testing, and validation datasets, as well as the mean squared error (MSE). The optimization of hyperparameters demonstrated that the use of hybrid learning algorithms improved training performance and reduced the mean error between the exact and predicted solutions. It also significantly reduced the training time for each model (from 5 minutes to 1-2 minutes) due to dimensionality reduction. It was also observed that the best-performing models were the Autoencoder and the ANN model. The autoencoder's capability to capture both linear and nonlinear relationships, as well as the most influential features in the dataset, resulted in a faster and less complex training process for the ANN. For these reasons, this model will be used for seismic design in the next chapter.

Table 7.7: The correlation coefficient (R^2) with and without the unsupervised learning algorithms.

	Without			PCA			Autoencoder		
	MBS	MIDR	MRDR	MBS	MIDR	MRDR	MBS	MIDR	MRDR
ANN	0.972	0.912	0.979	0.985	0.971	0.983	0.989	0.989	0.9901
TREE	0.875	0.823	0.89	0.889	0.9	0.923	0.901	0.932	0.933
SVM	0.812	0.7687	0.901	0.856	0.815	0.915	0.895	0.901	0.927
AdaBoost	0.951	0.907	0.965	0.978	0.927	0.966	0.988	0.956	0.976

Table 7.8: The mean squared error (MSE) with and without the unsupervised learning algorithms.

	Without			PCA			Autoencoder		
	MBS	MIDR	MRDR	MBS	MIDR	MRDR	MBS	MIDR	MRDR
ANN	0.0029	0.0096	0.0021	0.0015	0.0030	0.0017	0.0007	0.0008	0.0001
TREE	0.0143	0.0215	0.0124	0.0125	0.0111	0.0083	0.0011	0.0007	0.0007
SVM	0.0232	0.0301	0.0110	0.0168	0.0227	0.0093	0.0012	0.0011	0.0008
AdaB	0.0052	0.0103	0.0036	0.0022	0.0079	0.0035	0.0001	0.0005	0.0002

7.3.3 effect of the proposed approach on the dataset size and performance

As the previous section demonstrated hybrid learning made the performance better and more accurate. This section will investigate the effect of hybrid learning on the dataset size required to train the model.

To achieve this goal, four datasets with different sizes (25%, 50%, 75%, and 100% of one million samples) are selected to train two models (ANN and the hybrid Autoencoder+ANN). The performance will be compared in terms of (R^2), PBias, and RSR. PBias and RSR can be calculated using Equations (7.1) and (7.2).

$$PBias = \frac{\sqrt{\sum_{i=1}^n (Y_{Pred,i} - Y_{NLTHA,i})^2}}{\sum_{i=1}^n (Y_{NLTHA,i})} 100 \quad (7.1)$$

$$RSR = \frac{\sqrt{\sum_{i=1}^n (Y_{Pred,i} - Y_{NLTHA,i})^2}}{\sqrt{\sum_{i=1}^n (Y_{Pred,i} - \bar{Y}_{NLTHA,i})^2}} 100 \quad (7.2)$$

Where :

- Y_{pred} : the predicted output (MBS, MIDR, or MRDR) using machine learning algorithms.
- Y_{NLTHA} : the calculated outputs (MBS, MIDR, or MRDR) using NLTHA. $\bar{Y}_{NLTHA}$: is the mean value of the outputs obtained from NLTHA.

The RSR and PBIAS are two statistical coefficients used to measure the dispersion and the percentage of bias of errors between the predicted and reference values. Low values of RSR and PBIAS indicate low variability of estimation and high agreement between the prediction using machine learning (ML) and the exact solution using NLTHA, and vice versa.

The results are presented in Figure 7.16, 7.17, and 7.18, illustrating the training performance in terms of R^2 , RSR, and PBIAS using ANN and the hybrid models for MBS, MIDR, and MRDR respectively.

Based on these results, we can draw several conclusions from them:

1. **Correlation coefficients:** The hybrid models improved the prediction of all the outputs (MBS, MIDR, MRDR). When 25% of the dataset was used with hybrid learning ($> 75\%$), the performance exceeded the threshold to be considered a "**Very Good**" prediction according to Table 7.9. In contrast, the performance of the ANN was less than the hybrid ($\leq 75\%$).
2. **RSR:** The hybrid learning resulted in less dispersed predictions compared to the ANNs for all the dataset sizes. The RSR for the 25% dataset in the hybrid model is below the "very good" threshold. The lowest RSR (indicating the lowest dispersion) is observed at the 100% dataset size.
3. **PBias:** The hybrid learning resulted in less biased predictions compared to the artificial neural networks (ANNs) across all dataset sizes. The percentage bias

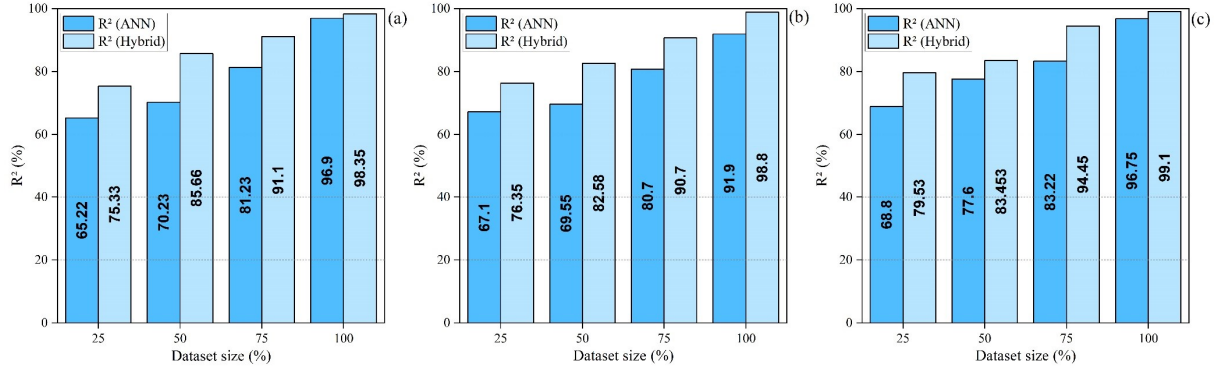


Figure 7.16: The correlation coefficients of ANN and Hybrid models to predict: a) MBS, b) MIDR, and c) MRDR.

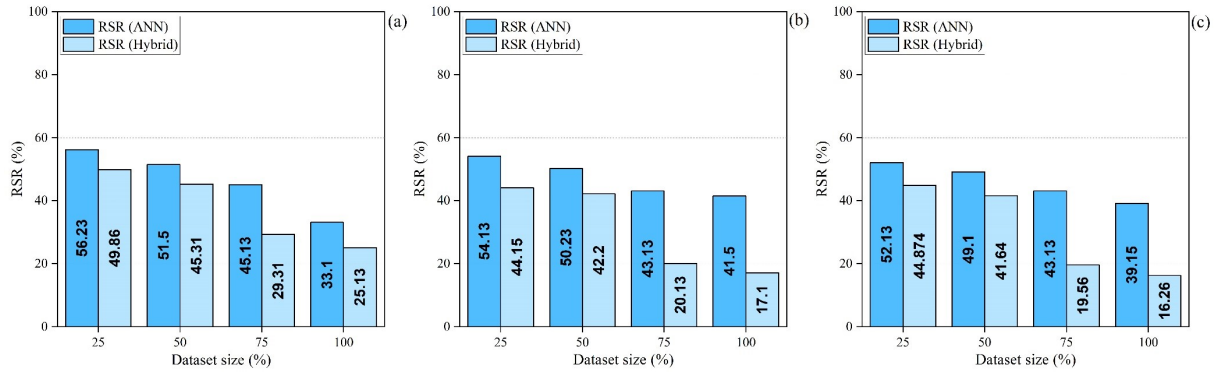


Figure 7.17: RSR of ANN and Hybrid models to predict: a) MBS, b) MIDR, and c) MRDR.

(PBias) for the hybrid model with a 50% dataset is lower than the threshold for a "very good" prediction. The lowest PBias, or bias error, is observed with the 100% dataset size.

Table 7.9: Statistical criteria for the performance evaluation

Evaluation	R^2	PBIAS	RSR
Very good	$75 \leq R^2 \leq 100$	$0 \leq PBIAS \leq 10$	$0 \leq RSR \leq 50$
Good	$65 \leq R^2 < 75$	$10 \leq PBIAS < 15$	$50 \leq RSR < 60$
Satisfaction	$50 \leq R^2 < 65$	$15 \leq PBIAS < 25$	$60 \leq RSR < 70$
Unsatisfaction	$0 \leq R^2 < 50$	$100 \leq PBIAS < 25$	$100 \leq RSR < 70$

7.4 conclusion

The prediction of seismic response is an important aspect of earthquake engineering as it helps in assessing how structures will react to ground motions during an earthquake. This

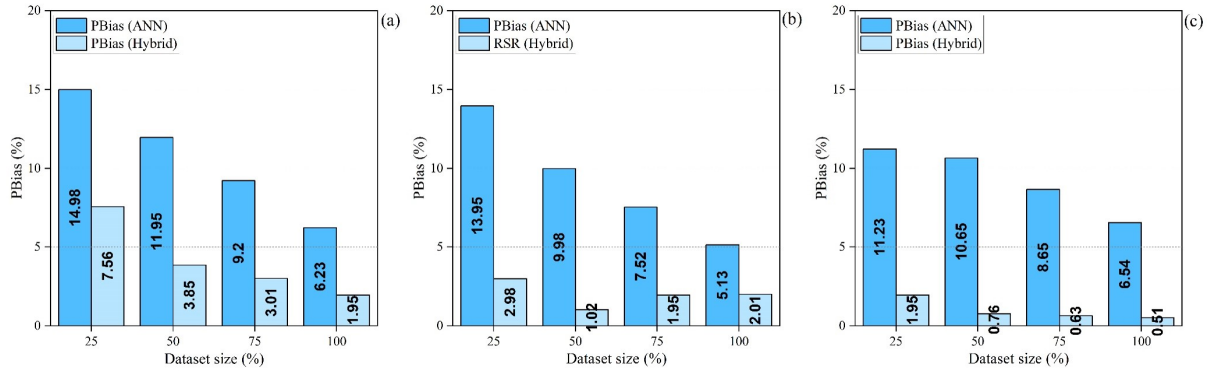


Figure 7.18: PBias of ANN and Hybrid models to predict: a) MBS, b) MIDR, and c) MRDR.

can be determined through complex and accurate methods like NLTHA or less complex and less accurate static nonlinear analysis such as pushover analysis. The use of ML has improved the accuracy and reduced the complexity of seismic response prediction, making it a necessary tool in this field. A hybrid model combining an Autoencoder with an ANN was found to be the most effective. The findings revealed that the hybrid model enhanced prediction accuracy, reduced error biases, and minimized prediction variations, particularly for smaller datasets. In conclusion, ML-based methods offer a fast and accurate alternative to NLTHA for seismic response prediction.

Chapter 8

AI-based seismic design

8.1 Introduction

The choice of an appropriate seismic design approach depends on the objective and desired behavior of the structure. Designing a structure only as it can resist a ground motion, as in force-based design, in some cases is not adequate. For example, the functionality of some strategic structures must be assured, where the performance has the first priority than the stability. For these reasons, engineers must adopt performance- or displacement-based design. However, the complexity of both of them may limit the use by engineers, and in some cases, the processing time will make the process take a long time to converge to the best design that fulfills the target response. This chapter presents a new methodology for seismic design; this methodology uses an AI algorithm that predicts seismic responses and correctly optimizes structural parameters. That is a way to find design combinations that satisfy all the necessary performance, cost, and fragility criteria. Also, the selection will consider the seismic intensity (moderate and extensive seismic intensity) simultaneously to check the performance not only in one performance level but two. The approach uses a previously developed hybrid machine learning model for predicting MIDR and MBS and an optimization algorithm to find the best solution.

The chapter will end with a case study, where three special moment frames (4-, 8-, and -12 stories) named SMF4, SMF8, and SMF12 will be designed using the proposed AI-based methodology and using the force-based design (FBD). A comparative study will be conducted in terms of, static and dynamic analysis, fragility assessment, and damage rate.

8.2 The proposed AI-based methodology

The main goal of the methodology is to find the best design of structures that meets the following criteria:

1. Low construction cost (only volume of concrete and steel will be included).
2. Low damage losses during extensive seismic events.
3. Desired performance level for both moderate and extensive seismic scenarios.
4. The structure design meets the code requirements in terms of capacity and stability according to ACI318-19.

1-3 criteria will be considered as objectives function that will be used in the multi-objective optimization (MOO). The 4th criterion will be considered as a constraint during the optimization process.

The following procedure will be composed of two parts:

1. Optimized structures generator.
2. Best design selection.

8.2.1 Define the structural inputs and the control variables

The first part as illustrated in Figure 8.1 begins with selecting the control variables and their limit boundaries that shall be used in the optimization algorithm. The input features consist of structural parameters, including unchangeable factors such as the number of bays, and the number of stories, as well as their length and height. These parameters are associated solely with the architectural design. However, dimensions and reinforcement are the two primary factors that need to be carefully controlled and designed to ensure that the structure remains stable, safe, and performs as expected during an earthquake event, and they are illustrated in Figure 8.2.

8.2.2 Ground motion selection and scaling

This step involves selecting suitable ground motions for the site and seismicity and then matching them to the target response spectrum. The seismic intensity should also be determined by identifying the most probable maximum intensity measure that may occur during a specific return period as shown in Figure 8.3. This determination depends on the site's seismology and soil class. Moreover, the seismicity also relies on the structure's significance and the desired performance or damage limit state.

The seismic hazard analysis, as discussed in Chapter II, will ascertain the maximum probable intensity in terms of peak ground acceleration (PGA), for example, using the seismic hazard curve. The most commonly used return periods are outlined in Table 8.1.

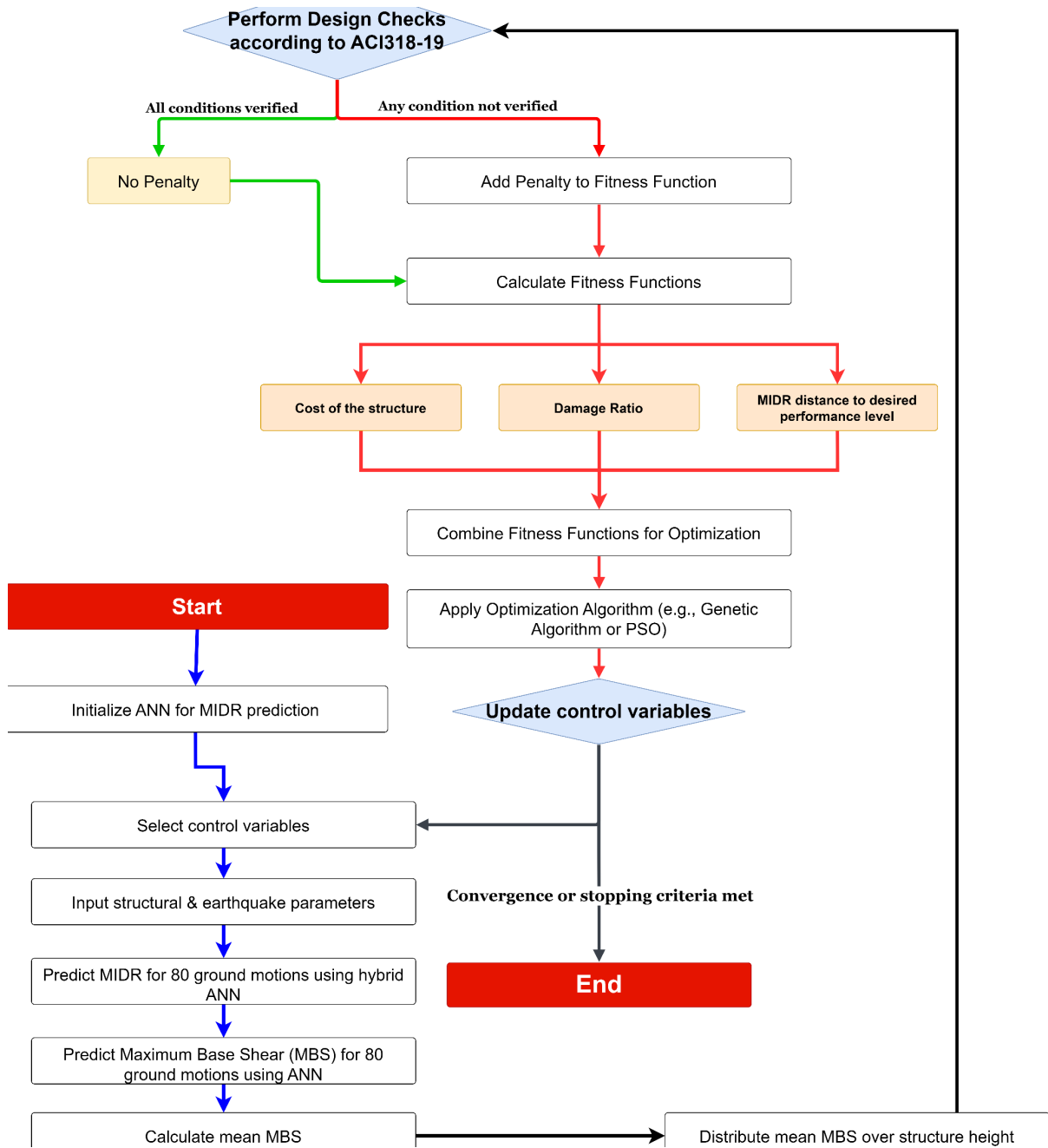


Figure 8.1: The proposed methodology for seismic design (part I)

Table 8.1: Return period and the annual frequency of exceedance.

Probability	Return period (TR)	Aannual frequency of exceedance
2% in 50 years	2475 years	4.04e-4
5% in 50 years	975 years	1.0e-3
10% in 50 years	475 years	2.1e-3

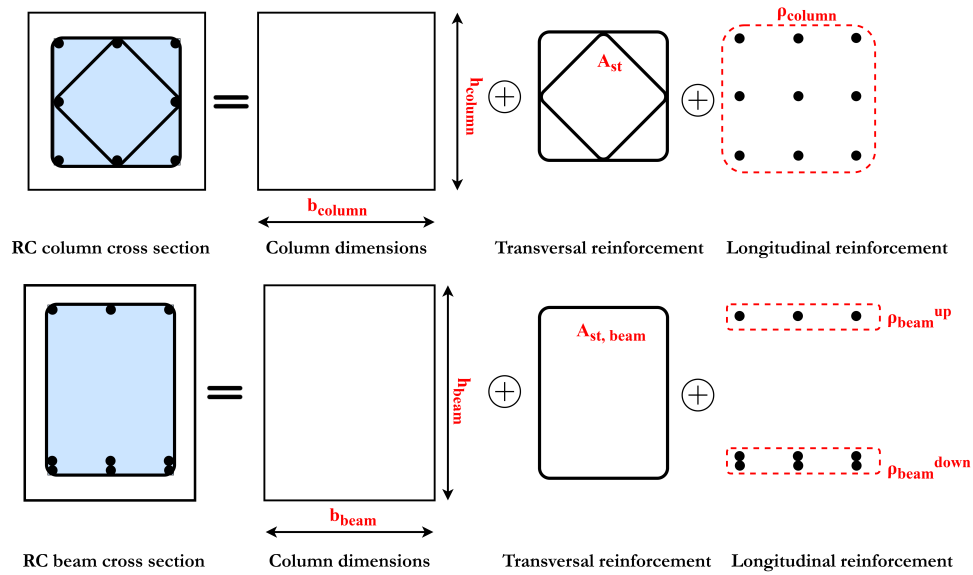


Figure 8.2: The control variables used for this approach

		Design performance level		
		Immediate occupancy (IO)	Life safety (LS)	Collapse prevention (CP)
Earthquake intensity level	Low seismic activity region (TR = 475 years)			
	Moderate seismic activity region (TR = 975 years)			
	High seismic activity region (TR = 2475 years)			

The table is divided into three regions by diagonal lines:

- Low importance structure:** Red shaded region (top-right).
- Moderate importance structure:** Blue shaded region (middle).
- High importance structure:** Green shaded region (bottom-left).

Figure 8.3: The seismic activity and the design performance level.

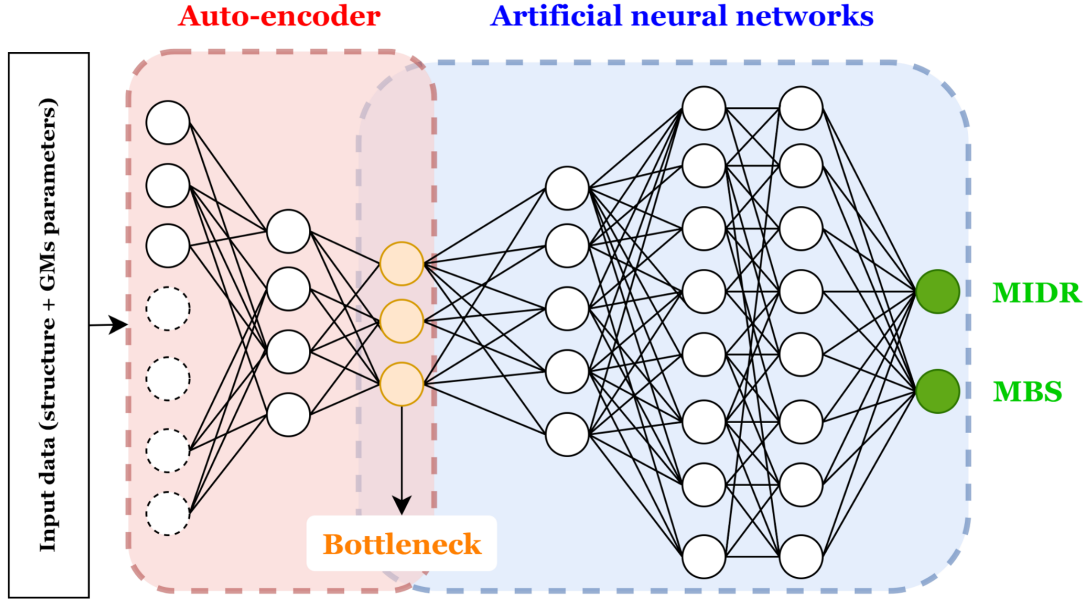


Figure 8.4: Hybrid Machine learning model for seismic response prediction.

8.2.3 Seismic responses prediction using Machine learning

It is crucial to accurately predict the seismic response as it greatly influences the performance of seismic design. The response is typically determined either through static nonlinear analysis (to estimate the performance point as discussed in Chapter II) or dynamic nonlinear analysis.

A hybrid model that combines Autoencode and ANN to predict two parameters maximum inter-story drift ratio (MIDR) and maximum base shear (MBS) for several GMs, and then a mean value shall be calculated for both outputs, as illustrated in Figure 8.4.

The estimated MIDR for constant seismic intensity would estimate the damage loss by including the damage/performance levels and estimating the exceedance probability for each damage/performance level, further followed by computing the mean MIDR to be employed as an objective function, which needs to be maximized. It is noteworthy to mention that two mean MIDR values are to be attained, one of which shall be calculated for the moderate seismic intensity for the checking of the building's performance not to exceed the performance/damage level; whereas the second mean MIDR shall be for the building's performance/damage check with severe seismic intensity, as depicted in Figure 8.3.

Furthermore, the MBS will also be predicted and the mean value will be used to check the structural design and stability of the building, as well as the reinforcement. The MBS should be distributed throughout the height of the building using Equation (8.1).

$$F_i = MBS \frac{w_i H_i^k}{\sum w_j H_j^k} \quad (8.1)$$

Where:

- F_i : the applied force in the i th story.
- MBS: the maximum base shear.
- w_i : the weight of the i th story
- H_i : the height of the i th story.
- k is defined as $k = 1$ or 2 for vibration period $T < 0.5$ sec, or $T > 2.5$ sec. A linear interpolation is needed for the period between 0.5 sec and 2.5 sec.

8.2.4 Structural design verification according to ACI 318-19

The seismic design is based on finding the best combination of dimensions, and reinforcement of all the elements (columns, beams, joints). It is necessary to check the PSO's selection of the control variables for each iteration. The idea behind this step is to add a penalty value to the fitness function in case of undesired design. In this way, the algorithm will only converge when it finds a control variables combination that fulfills the seismic responses (MIDR, cost, and GD_r) and the engineering requirements at the same time. After selecting the control variables in the i th iteration, the PSO will calculate the distance of cost, MIDR, and GD_r to their thresholds. If the condition is not verified, then PSO will update the particles' position and velocity and it changes the control variables. Otherwise, the MBS will be predicted using the proposed hybrid model using the structural variables and the control variables to perform a static analysis and check the design. The algorithm should check several engineering requirements to approve the design:

8.2.4.1 Beams Flexural strength

In OpenSEES, five integration points were used as shown in Figure 8.5 to calculate the bending moments in the beginning, mid, and endpoints. The flexural beam capacity will be calculated according to ACI 318-19.

To calculate the beam's moment capacity (M_{bn}), Figure 8.6 illustrates the stress-strain diagram that will be used to develop the used equations.

It should be noted that:

When the compression steel is not yielding ($\epsilon'_s < \epsilon_y$) the stress is calculated using Equation (8.2):

$$f'_s = E_s \cdot \epsilon'_s \quad (8.2)$$

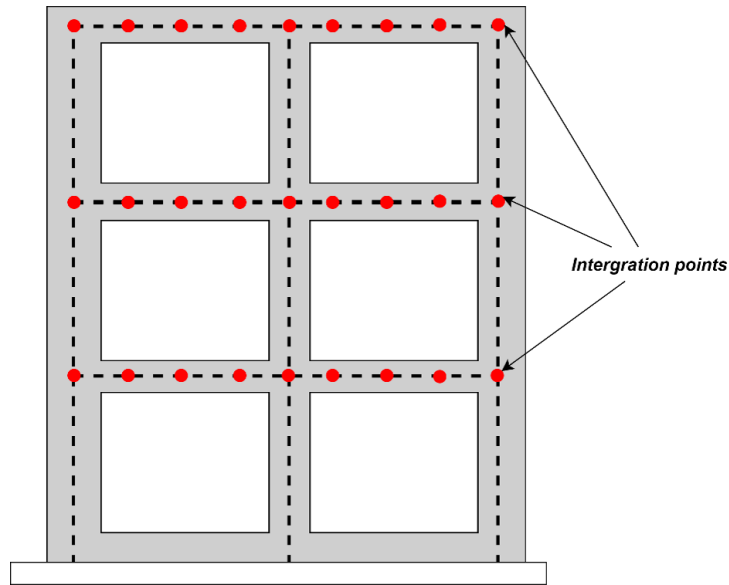


Figure 8.5: Integration points of beams.

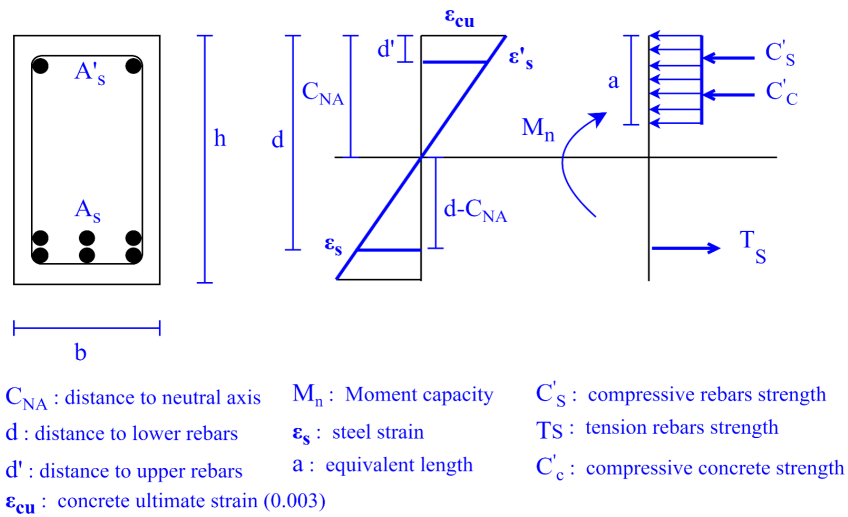


Figure 8.6: stress-strain diagram for beam moment capacity.

f_{c28} (MPa)	β
$17.23 < f_{c28} < 27.57$	0.85
$27.57 < f_{c28} < 55.15$	$0.85 - 0.05 \frac{(f_{c28} - 27.57)}{6.89}$
$55.15 < f_{c28}$	0.65

Table 8.2: Factor relating the depth of the rectangular concrete stress diagram to the C_{NA}

Otherwise, the stress is calculated using Equation (8.3):

$$f'_s = f_y \quad (8.3)$$

According to Figure 8.6, the neural axis distance can be calculated using Equation (8.4) by satisfying the equilibrium between the tension and compression forces of steel and concrete.

$$T_s = C'_s + C_c \rightarrow A_s f_y - A'_s f_s - 0.85 f_{c28} a b \quad (8.4)$$

The compression steel strain (ϵ'_s) is calculated using the strain diagram as shown in Equation (8.5).

$$\epsilon'_s = \frac{\epsilon_{cu} \cdot (C_{NA} - d')}{C_{NA}} \quad (8.5)$$

Knowing that: $a = \beta \cdot C_{NA}$. where β can be calculated using Table 8.2.

The neutral axis can be determined by substituting all factors of the equilibrium Equation (8.4) into Equation (8.6) to calculate the neutral axis.

$$A_s \cdot f_y - \frac{A_s \cdot E_s \cdot \epsilon_{cu} \cdot (C_{NA} - d')}{C_{NA}} - 0.85 \cdot f'_c \cdot \beta \cdot C_{NA} \cdot b = 0 \quad (8.6)$$

So finally the beam moment capacity can be calculated using Equation (8.7).

$$M_{bc} = A'_s \cdot E_s \cdot \epsilon_{cu} \cdot \frac{(C_{NA} - d')}{C_{NA}} \left(\frac{a}{2} - d' \right) + A_s \cdot f_y \cdot \left(d - \frac{a}{2} \right) \quad (8.7)$$

The moment capacity will be compared to the moment calculated from the static analysis where the base shear represents the predicted MBS and the condition in Equation (8.8) must be fulfilled.

$$M_{demand} < M_{b capacity} \quad (8.8)$$

8.2.4.2 Beam shear capacity

According to ACI 318-14, the base shear capacity of a beam with stirrups can be calculated as follows in Equations (8.9):

$$V_{beam} = \varphi V_c + \varphi V_s, \varphi V_c = 0.75 \quad (8.9)$$

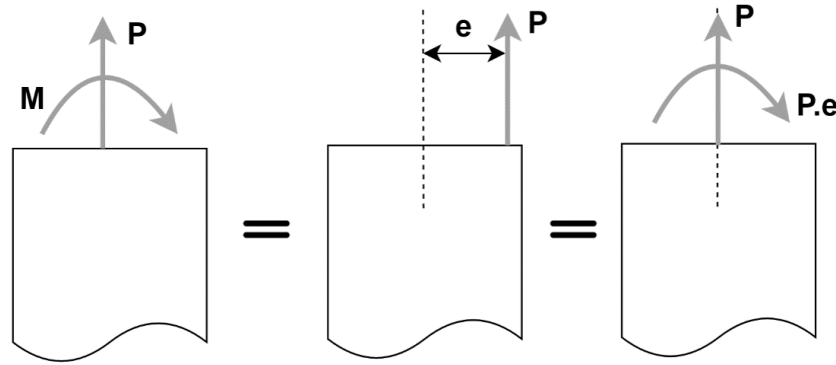


Figure 8.7: Axial load eccentricity.

$$V_{cbeam} = 2 * \sqrt{f_c} \cdot b_w \cdot d \quad (8.10a)$$

$$V_s = \frac{A_v \cdot f_y \cdot d}{s} \quad (8.10b)$$

Where :

- V_s : the stirrup shear strength (See Equation(8.10b)).
- V_c : the concrete shear strength (See Equation(8.10a)).
- A_v : the transversal reinforcement area.
- b_w : beam's width.
- d : the distance between the upper concrete layer and lower rebar layer.

8.2.4.3 Columns capacity

Unlike beams, columns are subjected to axial and bending moments combined, due to dead, live, and seismic loads. The axial load and bending moment can be also represented as an axial load (P) and an eccentricity (e) applied on a cross-section, as shown in Figure 8.7.

The different positions of the axial load will cause various column's behavior and the stress distribution diagram. The different scenarios can be plotted in a curve called an M-N interaction diagram, as shown in Figure 8.8:

- **Point A**: This point represents pure compression, where the load is entirely axial, and it denotes the maximum compression load that the column can support.
- **Point B**: This point represents compression with a minor bending moment due to a large axial load applied with a small eccentricity.

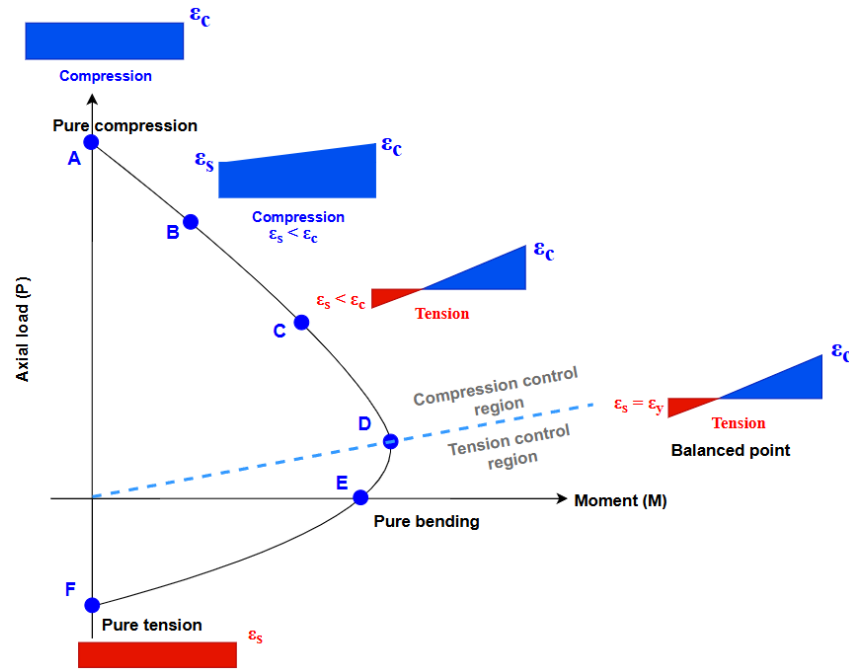


Figure 8.8: M-N interaction curve.

- **Point C:** At this point, two zones appear as tension and compression, with the tension strains in the steel being less than the steel yielding strain.
- **Point D:** This point is called a balance point, where the concrete compression strain reaches the ultimate limit and the steel strain reaches the yielding limit.
- **Point E:** Pure bending occurs when the axial load is zero (eccentricity is infinite). The steel strain is now larger than the yielding limit.
- **Point F:** This point represents the largest tension load that the column can support.

The corresponding M and N values can be obtained using the forces equilibrium between the steel and concrete, as shown in Figure 8.9.

8.2.4.4 Column capacity ratio

As depicted in Figure 8.10, the M-N demand combination should always fall inside the curve, otherwise, it will result in a column failure. The capacity ratio, which represents the ratio between the capacity and the demand, can determine if this condition is met. If the ratio is less than 1, it means that the capacity is greater than the demand, and the column can support this load. If the ratio is greater than 1, then the column's capacity cannot support the demand load.

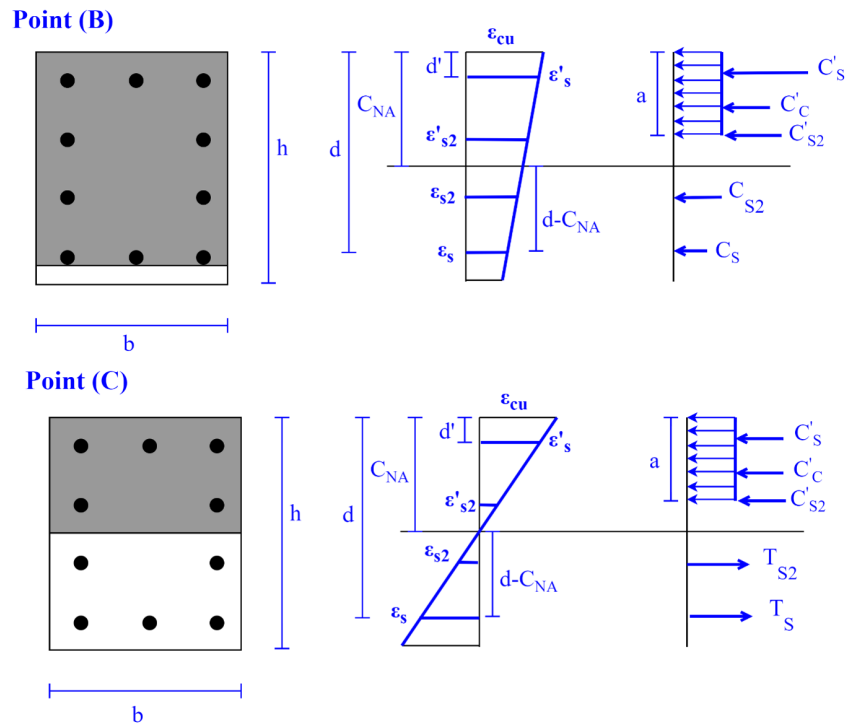


Figure 8.9: Strain- stress diagram of a column.

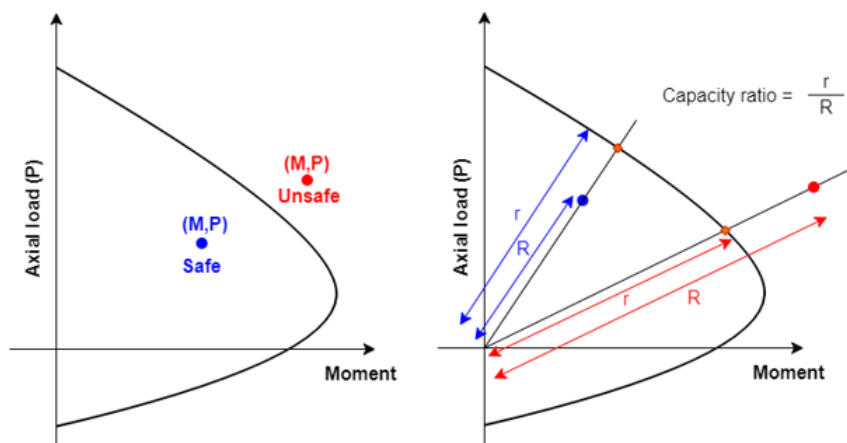


Figure 8.10: Safe and unsafe capacity ratio in the M-N interaction curve.

8.2.4.5 Column shear capacity

Gravitational and earthquake forces create significant base shear stress. The columns are the first components to experience this stress. Their size and the transverse reinforcement will determine the failure mechanism, deformation behavior (flexural, shear), and structural ductility, which will impact the dissipation of energy.

The process of checking the shear capacity of columns is based on calculating the concrete capacity and the steel capacity. The M-N diagram will also be modified to account for the shear capacity limitations. The shear span ratio will also be included to limit the column's dimensions based on the story height.

The concrete shear capacity can be calculated (see Equation (8.11)):

$$V_c = (2.\lambda.\sqrt{f_c} + \frac{N_c}{6.A_g}.b_w.d \leq 5.\lambda.\sqrt{f_c} \quad (8.11)$$

Where :

- f_c : concrete compressive strength.
- N_c : the axial load capacity of the M-N interaction curve.
- A_g : gross area of column
- b_w : the column's width
- d : the effective column height (0.9 H).

if $V_c > 5.\lambda . \sqrt{f_c}$ then $V_c = 5.\lambda . \sqrt{f_c}$. To integrate V_c shear limit capacity in the M-N interaction curve, $M_c = \frac{V_c L}{2}$.

When $\phi \frac{V_c}{2} < V_u$, then a steel reinforcement (V_s) is required to support the ultimate shear (V_u), as written in Equation (8.12).

$$V_s = \frac{A_v.f_y.d}{s} \leq 4.\sqrt{f_c} \quad (8.12)$$

where:

- A_v : the transversal reinforcement area. $A_{vmin} = \max(0.75\sqrt{f_c} . \frac{bs}{f_y}; 50. \frac{bs}{f_y})$
- f_y : the steel yielding limit stress
- d : the effective depth
- s : stirrups spacing ($s_{max} < \min(d/2, 60\text{cm})$).

To consider V_s in the M-N interaction curve, $M_s = \frac{V_s.L}{2}$. the factored shear capacity (ϕV_n) should be greater than three times the ultimate shear demand (see Equation (8.13)).

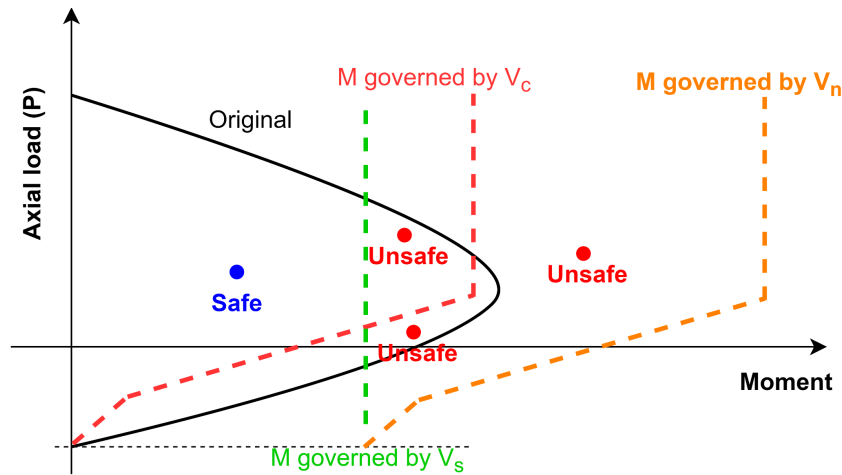


Figure 8.11: M-N interaction curve considering shear capacity and slenderness effect.

$$\phi V_n = \phi(V_s + V_c) > 3V_c. \text{ Where : } \phi = 0.75 \quad (8.13)$$

The final M-N interaction curve considering the shear capacity is illustrated in Figure 8.11.

8.2.4.6 Recommendation for a good design

Table 8.3 summarizes several design aspects to have good behavior and to avoid shear failure and low ductility.

Table 8.3: recommendations to obtain a desirable column design

		Aspect Ratio (L/h)	
		>3.5 to 4.0	<3.5 to 4.0
Axial load ($\frac{N}{f_c A_g}$)	<1/3	Good energy dissipation and flexural behavior	The column will slowly degrade, with limited ductility.
	>1/3	Flexural behavior, but limited ductility	The column will fail rapidly in shear. Very low ductility.

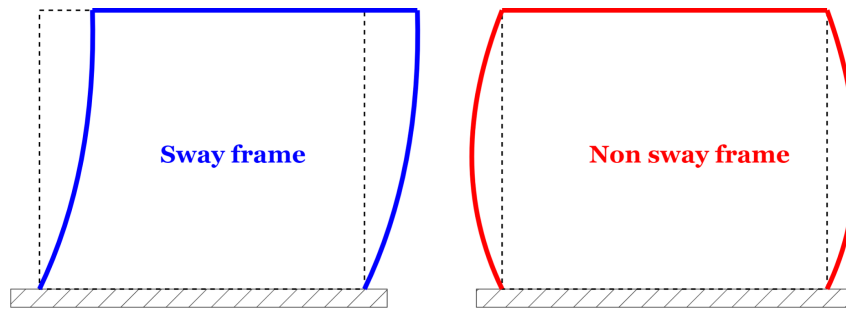


Figure 8.12: sway and non-sway mode in RC frames.

8.2.4.7 Slenderness in columns

In the column's design or investigation, the slenderness is an important factor that affects the capacity of columns. When the columns are not short, the slenderness effect must be considered when designing columns.

Two types of frames are considered, sway and non-sway frames as shown in Figure 8.12.

The column in a structure is non-sway if the stability index (See Equation (8.14)) is less than or equal to 0.05.

$$Q = \frac{\sum P_c \Delta_0}{V_{us} l_c} \quad (8.14)$$

where:

- $\sum P_u$: sum of the factored vertical load in the story.
- Δ_0 : the drift between the top and bottom displacement of the story due to V_u .
- V_u : the factored story shear.
- l_c : is the column's height from joint to joint.

Thus, The columns of a story are considered as a sway frame.

8.2.4.8 Slenderness ratio

The slenderness ratio determines whether the column is short or slender using Equation (8.15).

$$\text{slenderness ratio} = \frac{K l_u}{r} \quad (8.15)$$

where:

- k : is the effective length factor, it depends on the end conditions of the column.
- L_u : the unsupported length of the column.

- r : the radius of gyration $r = 0.288 h$ (h : dimension of the column).

For a sway frame : $k = 2, 0 + 0, 3.min(\Psi_A, \Psi_B) \leq 1, 0$

where Ψ can be calculated using Equation (8.16):

$$\Psi = \frac{\sum E_c I_c / l_c}{\sum E_b I_b / l_b} \quad (8.16)$$

where:

- E_c, E_b : Elasticity modulus of the column and beams concrete.
- I_c, I_b : The moment inertia of cross-section according to the axis perpendicular to the plane of buckling column and beams concrete.
- l_c, l_b : The column, beam length center-to-center of the joints.

For a non-sway frame: $k = 0.85 + 0, 05.min(\Psi_A, \Psi_B) \leq 1, 0$

The columns are considered short when their slenderness ratio satisfies the following criteria:

- For sway frames: $k.l_u < 34 - 12 (M_1/M_2) < 40, 0$.
- For non-sway frames: $k.l_u / r < 22$.

In addition, the frames are considered non-sway frames if the stiffness of the bracing elements resisting lateral movement is larger than 12 times the stiffness of the columns of the same story.

8.2.4.9 Euler critical buckling load (P_{cr})

It shall be calculated using Equation (8.17)

$$P_{cr} = \frac{\pi^2 (EI)_{eff}}{(kl_u)^2} \quad (8.17)$$

EI_{eff} is the effective flexural stiffness of the column, it can be calculated using Equation (6.6.4.4.4) in ACI 318-14.

8.2.4.10 Moment Magnification factor: For non-sway frames

it can be written as shown in Equation (8.18).

$$M_c = \delta M_2 \quad (8.18)$$

Where:

- M_c : the amplified moment for designing the columns.
- M_2 : the first-order factored moment obtained from the analysis.
- δ : the magnification factor, can be calculated using Equation (8.19)

$$\delta = \frac{C_m}{1 - \left(\frac{P_u}{0.75P_{cr}} \right)} \quad (8.19)$$

- P_{cr} : the Euler critical buckling load.
- C_m : correction factor that relates the actual moment diagram to an equivalent diagram. It shall be calculated as Equation (8.20):

$$C_m = 0.6 + 0.4 \frac{M_1}{M_2} \quad (8.20)$$

- M_1 and M_2 are the factored top and bottom bending moments. If the column is bent in a single curvature, then $\frac{M_1}{M_2}$ is negative, and positive if it is bent in double curvature.

8.2.4.11 Moment magnification for sway-frames

M_1 and M_2 will be calculated individually. Where M_1 and M_2 represent the bending moment at the ends of the column. They can be calculated using Equation (8.21) and Equation (8.22) .

$$M_1 = M_{1ns} + \delta_s M_{1s} \quad (8.21)$$

$$M_2 = M_{2ns} + \delta_s M_{2s} \quad (8.22)$$

where:

- M_{1ns} and M_{2ns} are unmagnified non-sway frames bending moment at the end of the column using the first-order analysis.
- $\delta_s M_{1s}$ and $\delta_s M_{2s}$ are the magnified sway frames bending moment at the end of the column using the second-order analysis
- δ_s is the magnification factor in sway-frames, it shall be calculated using Equations (8.23), (8.24), or (8.25)

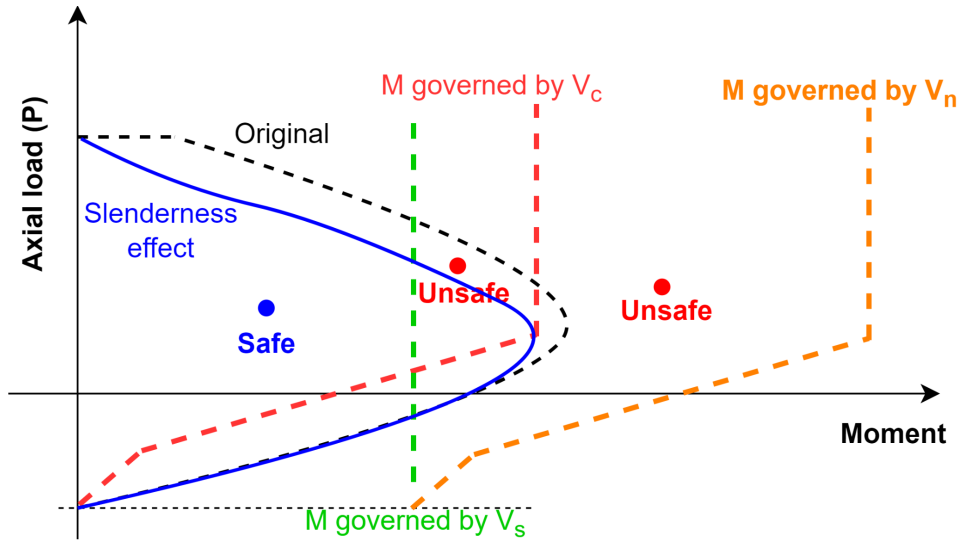


Figure 8.13: M-N interaction curve considering slenderness and shear capacity.

$$(a) \quad \delta_s = \frac{1}{1 - Q} \geq 1.0 \quad (8.23)$$

$$(b) \quad \delta_s = \frac{1}{1 - \left(\frac{P_u}{0.75 P_{cr}} \right)} \geq 1.0 \quad (8.24)$$

$$(c) \quad \text{second-order analysis} \quad (8.25)$$

if δ_s exceeds 1.5, only equations (8.24), and (8.25) can be used.

8.2.5 M-N Interaction Diagram considering slenderness and shear capacity

The modified moments and axial loads are used to plot the interaction diagram. The ACI 318 code provides guidelines for constructing the M-N interaction diagram, which illustrates the relationship between the axial force and bending moment capacity of the column. By combining slenderness and the shear capacity of columns in the M-N interaction curve, a new M-N curve can be plotted in 8.13

8.2.6 Weak beams strong columns

The columns are an important part of the building's ability to withstand earthquakes. The beams must yield before the columns do, which is known as "weak beams, strong columns". If the columns yield before the beams, the building can suffer from undesirable deformation and less energy dissipation during an earthquake. The worst-case scenario is when all the columns on one story or more yield, leading to local failure, as shown in

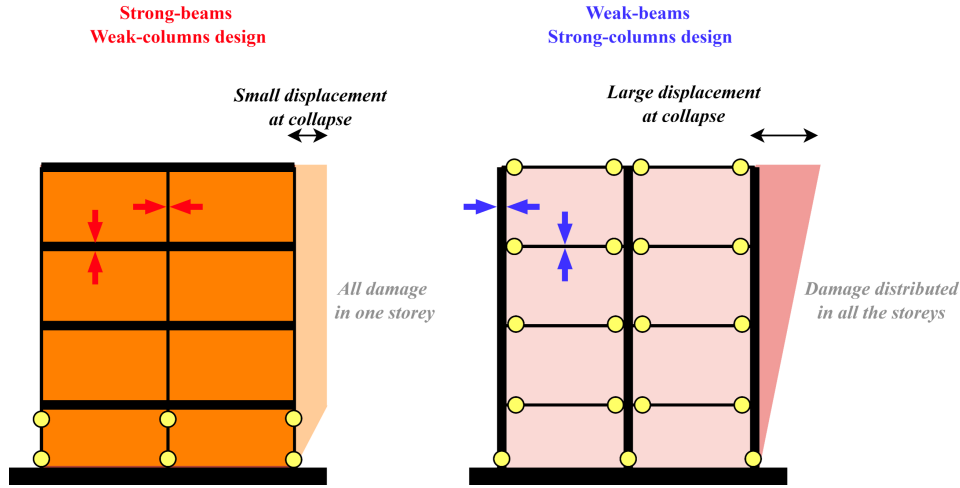


Figure 8.14: Weak-beams Strong-columns design and its effect on the global deformation.

Figure 8.14.

To ensure that plastic hinges will form in beams instead of columns, the flexural strength of beam-columns as expressed in Equation 8.26 should be satisfied.

$$\sum M_{nc} \geq \frac{6}{5} \sum M_{nb} \quad (8.26)$$

Where:

- $\sum M_{nc}$: is the sum of the nominal flexural moment capacity of columns. It is calculated using the factored axial load P_u , corresponding to the direction of the lateral force.
- $\sum M_{nb}$: The sum of the nominal flexural moment capacity of beams. Considering the bending direction (Hogging or sagging). Figure 8.15 illustrates the details of $\sum M_{nc}$ and $\sum M_{nb}$.

The factored P_u is calculated using OpenSees obtained from each combination load for each column. For each P_u value, the moment capacity will be calculated using the M-N interaction curve. The moment capacity represents the nominal flexural strength (unfactored moment capacity) without using the reduction factors. Equation (8.26) should be satisfied, except for columns with an axial load P_u under a seismic effect that is less than $A_g f_c / 10$.

The use of MOPSO requires a fitness function to be optimized. If a structural failure occurs or any previously mentioned condition does not meet the requirements, the selected design should be penalized by adding a large value (e.g., $1e6$) to the fitness function. By doing this, the algorithm will ignore this selection and consider it unsuitable.

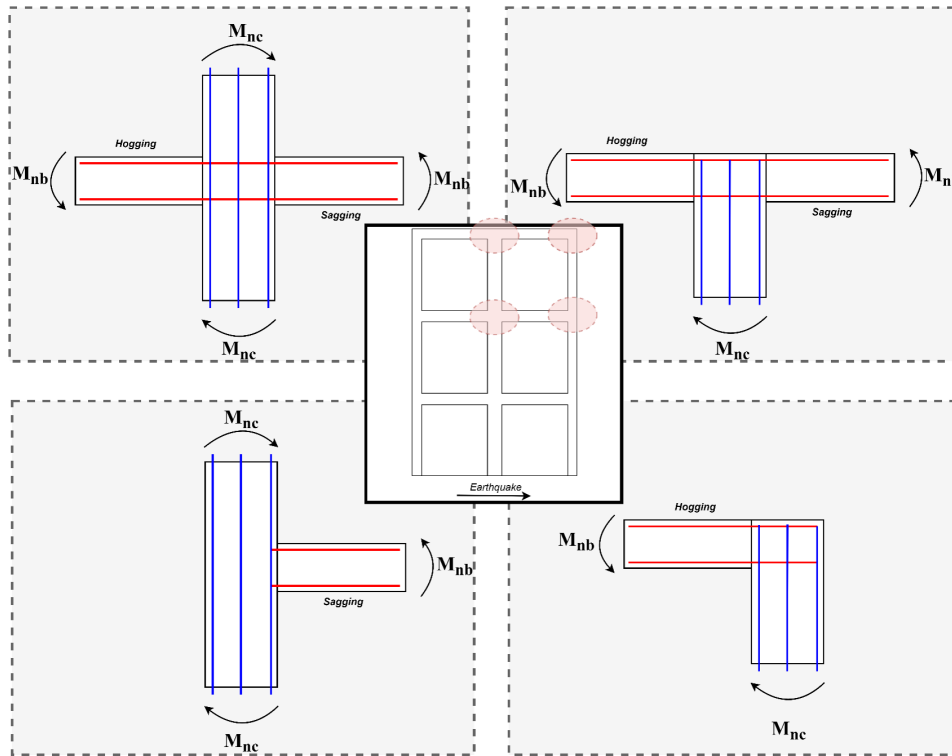


Figure 8.15: Beam-columns capacity for different beam-column connection points.

8.2.7 Joint shear strength

In RC frame structures, joints are the most susceptible elements that are affected by the shear forces. Their strength and shear capacity should be enough to resist the seismic shear joint demand.

According to ACI 318-19 18.4.4.7.1 the joints should satisfy the following condition: $\phi V_n \geq V_u$ Where:

- V_u represents the calculated joint shear value as written in Equation (8.30). (ACI 18.4.4.7.2)
- V_n is the nominal shear strength of the joint as written in Equation (8.27), , or . (ACI 18.4.4.7.4)
- ϕ : shear reduction factor ($\phi=0.75$). (ACI 18.4.4.7.3)

To calculate the nominal joint shear strength, the joint's condition should be defined according to table ACI 18.8.4.3. for simplification, the seismic code ASCE 7 -16 is used to calculate V_n :

$$\text{Confined joints: } V_n = 20\sqrt{f_{c28}}A_j \quad (8.27)$$

$$\text{Continuous-unconfined joints: } V_n = 15\sqrt{f_{c28}}A_j \quad (8.28)$$

$$\text{Unconfined joints: } V_n = 12\sqrt{f_{c28}}A_j \quad (8.29)$$

Where: A_j is the effective joint area, it is calculated as depicted in Figure 8.16. f_{c28} is the concrete compressive strength. The joint shear forces applied in the panel zone are

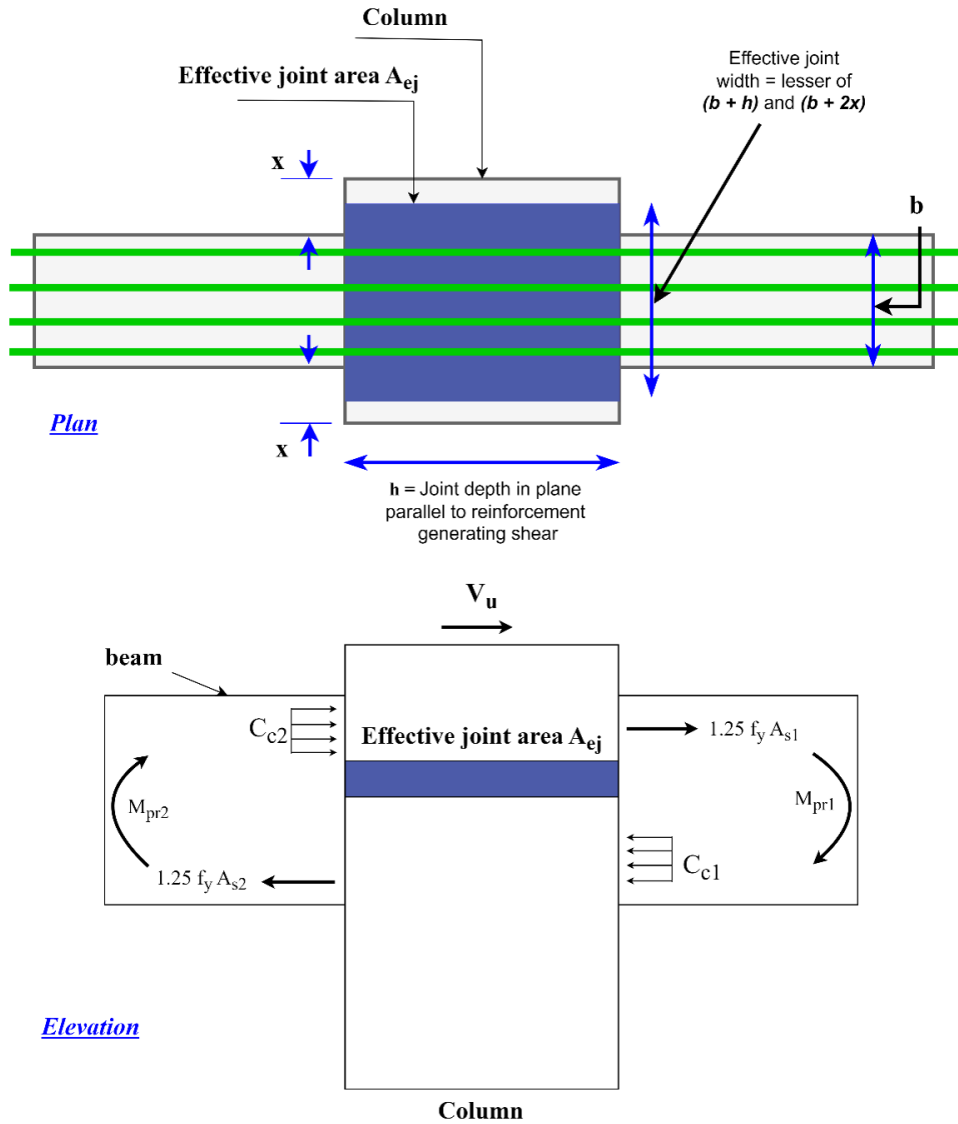


Figure 8.16: Effective area of a shear joint according to ACI 318.

calculated using the tensile and compressive beam forces obtained from the column shear and the flexural of beams. ACI 318-19 assumes the stress in the longitudinal reinforcement of beams is $1.25f_y$. According to the depicted Figure 8.16, the joint shear demand is

calculated using Equation 8.30.

$$V_u = 1.25f_y(A_{s1}^+ + A_{s2}^-) - \frac{(M_{pr}^+ + M_{pr}^-) + (V_{ul} + V_{ur}) \frac{h}{2}}{l} \quad (8.30)$$

Where: A_{s1}^+ and A_{s2}^- : are the upper and lower reinforcement area of beams. M_{pr} is the probable flexural strength of beams. V_{ul} and V_{ur} : are the shear forces generated in the left and right beams. h is the column's height. l is the distance between the mid- to mid-height of the column above and the bottom of the joint.

8.2.8 Multi-objective optimization algorithm for seismic design

This section aims to identify the control variables (the structural characteristics of buildings) that meet the desired performance level at a fixed intensity of seismic hazard. The output of the MOO is the Pareto front, which represents the fitness function of initial cost, GDR, and MIDR (for two seismic intensities). Multi-objective particle swarm optimization (MOPSO) algorithm will be employed to determine the control variables using the hybrid ML model for forecasting the seismic responses, and OpenSEES for checking the code requirements, i.e., element strength and joint strength. Such structures that will fail to meet the code requirement or standard will be eliminated. However, those structures satisfying the standards will be preserved and used to define the Pareto front and select the best design.

The flowchart in Figure 8.1 illustrates the first part of generating the best designs and the optimized objective functions. The second part as illustrated in Figure 8.17 demonstrates the next procedure to select the best design from the optimized solutions.

After the data generation from MOPSO, a selection of the damage/performance levels should be made: their number depends on the building's importance. For low-importance structures, such as residential buildings, should be designed to have slight damages/immediate occupancy performance during low-intensity earthquakes, moderate damages/life safety performance in case of moderate-intensity earthquakes, and not collapse for high seismic intensities. However, the high-importance structures should remain functional with slight damages for high seismic intensities due to their importance and impact on society. Next, all the points under the performance limits should be selected then two plots should be performed that illustrate the relationship between the MIDR and initial costs and consider the damage rate.

The best design that is recommended to select is that how is on the Pareto front on both plots and has the lowest initial cost as illustrated in step 4 Figure 8.17.

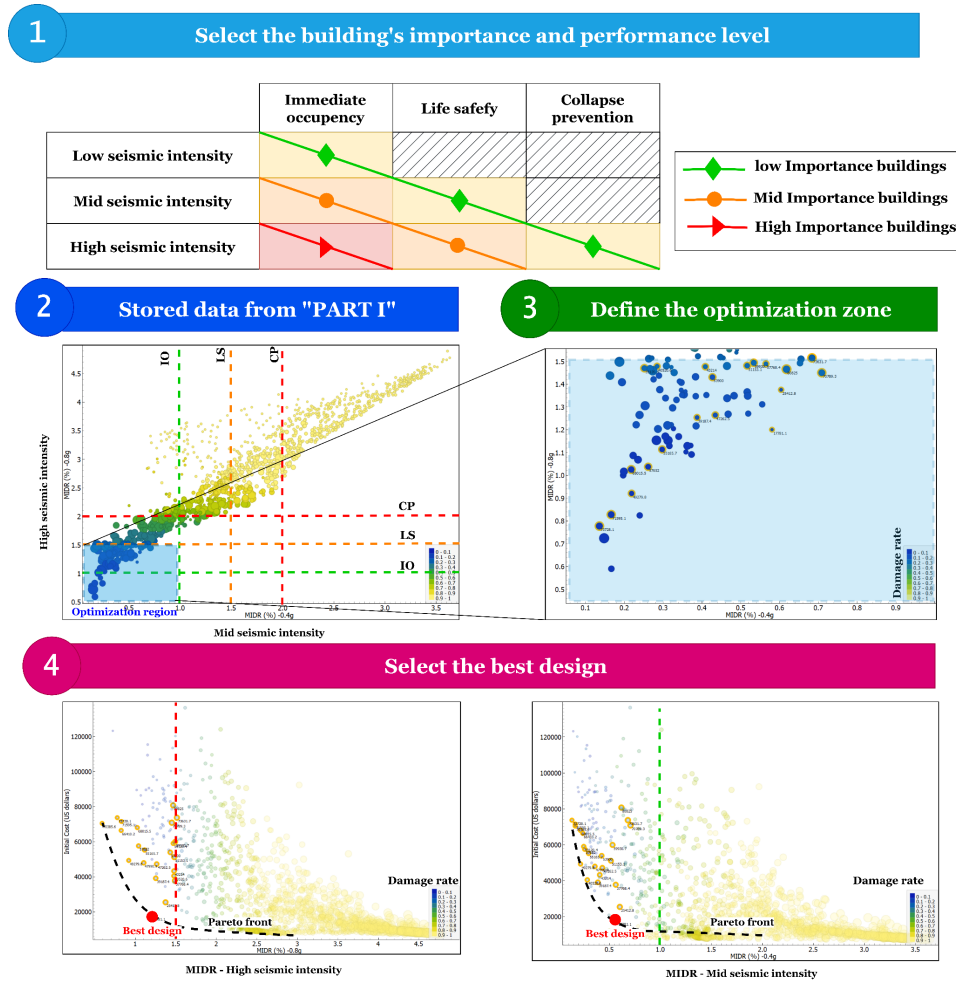


Figure 8.17: Best design selection using the collected data (Part II).

8.3 Case study: Special moment RC frame (SMF) design using the proposed methodology

This section discusses the design of special moment RC frame (SMF) structures with varying heights (4, 8, and 12 stories). Unlike ordinary moment frames (OMFs), SMFs are more ductile and are typically used in areas with medium to high levels of seismic activity due to their ability to dissipate more energy. However, designing these structures requires a thorough understanding of standards and code requirements. Additionally, they are more sensitive to design details such as transverse reinforcement and joint strength.

Low-, Mid- and high-rise RC SMF buildings will be designed using the proposed ML approach by limiting their behavior, and their initial cost ($C_{initial}$) where only the cost of material volume will be considered and the damage ratio assuming that they are located in a high seismic activity zone with two different return periods (2% and 10% in 50 years). The PGAs used in the case study are 0.4g and 0.8g.

The initial cost is calculated by assuming that the concrete cost of 1-meter cube 1 m³ =

75 *US dollar* and for the steel $1\text{m}^3 = 7457.50\text{ US dollar}$, as shown in Equation (8.31).

$$\begin{aligned} C_{\text{initial}} &= C_{\text{steel}} + C_{\text{concrete}} \\ &= 75 \cdot V_{\text{concrete}} + 7457.50 \cdot V_{\text{steel}} \end{aligned} \quad (8.31)$$

$$\begin{aligned} V_{\text{concrete}} &= V_{\text{beams}} + V_{\text{columns}} \\ &= b_{\text{beam}} \cdot h_{\text{beam}} \cdot N_b \cdot N_s + b_{\text{column}} \cdot h_{\text{column}} \cdot (N_b + 1) \cdot (N_s + 1) \end{aligned} \quad (8.32)$$

$$V_{\text{steel}} = \rho_{\text{column}} \cdot V_{\text{column}} + (\rho_{\text{beam, upper}} + \rho_{\text{beam, lower}}) \cdot V_{\text{beam}} \quad (8.33)$$

Where: V_{column} and V_{beam} are the steel and concrete volumes, ρ_{column} , and ρ_{beam} are the reinforcement ratio for columns and beams. N_b and N_s are the number of bays and stories.

8.3.1 Loss function: Damage ratio

The direct losses from structural damage can include damage to structural components, while the indirect losses can involve social-economic impacts, casualties, and non-structural component damages. The damage ratios which is a form of loss function estimator are obtained from HAZUS MR4 for each performance level and they are summarized in Table 8.4. The thresholds of each performance level are determined by the corresponding MIDR (%) according to HAZUS MR4.

Table 8.4: Performance level threshold and the corresponding damage ratio according to HAZUS MR4.

Performance level	MIDR (%)	damage ratio
Immediate occupancy (IO)	0.01	0.1
Damage control (DC)	0.015	0.4
Life safety (LS)	0.02	0.8
Collapse prevention (CP)	0.025	1

8.3.2 Structural characteristics

The case study structures will be conducted on three SMF RC frame buildings. Their structural characteristics, materials, and architectural plan are illustrated in Figure 8.18. The control variables and their lower and upper bounds are summarized in Table 8.5.

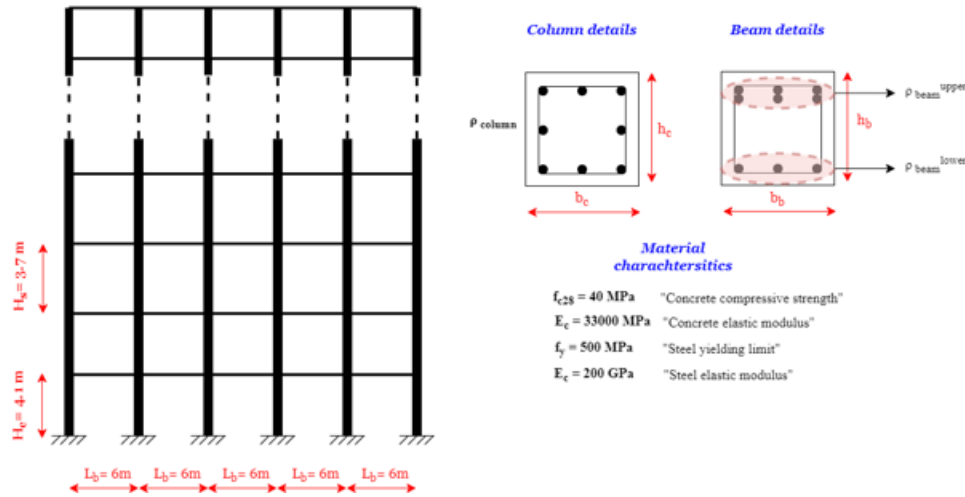


Figure 8.18: The architectural plan and material characteristics.

Table 8.5: Control variable lower and upper bounds.

Variable	Lower bound	Upper bound
Column's width ($b_c = h_c$)	0.3 m	1.0 m
Beam's width (b_b)	0.25 m	0.5 m
Beam's depth (h_b)	0.3 m	0.7 m
Reinforcement ratio (ρ_{column})	0.8%	8%
Reinforcement ratio (ρ_{beam})	200/fy	2.5%
Transversal reinforcement	$50e - 5 \text{ m}^2$	$700e - 5 \text{ m}^2$
Stirrups spacing	0.05 m	0.20 cm

8.3.3 Region seismic activity

The case study is located in a high-seismicity region. Based on the seismic hazard curves in Figure 8.19, the design of the structure will use $PGA_{TR=2475yr} = 0.8g$, and $PGA_{TR=975yr} = 0.4g$ will be used to check the design. The hazard curve, response spectra, selected ground motions, and their characteristics are summarized in Figure 8.19. Additionally, Appendix A.1 provides detailed seismic activity parameters for the selected zone located in California at coordinates as depicted in Figure A.1.

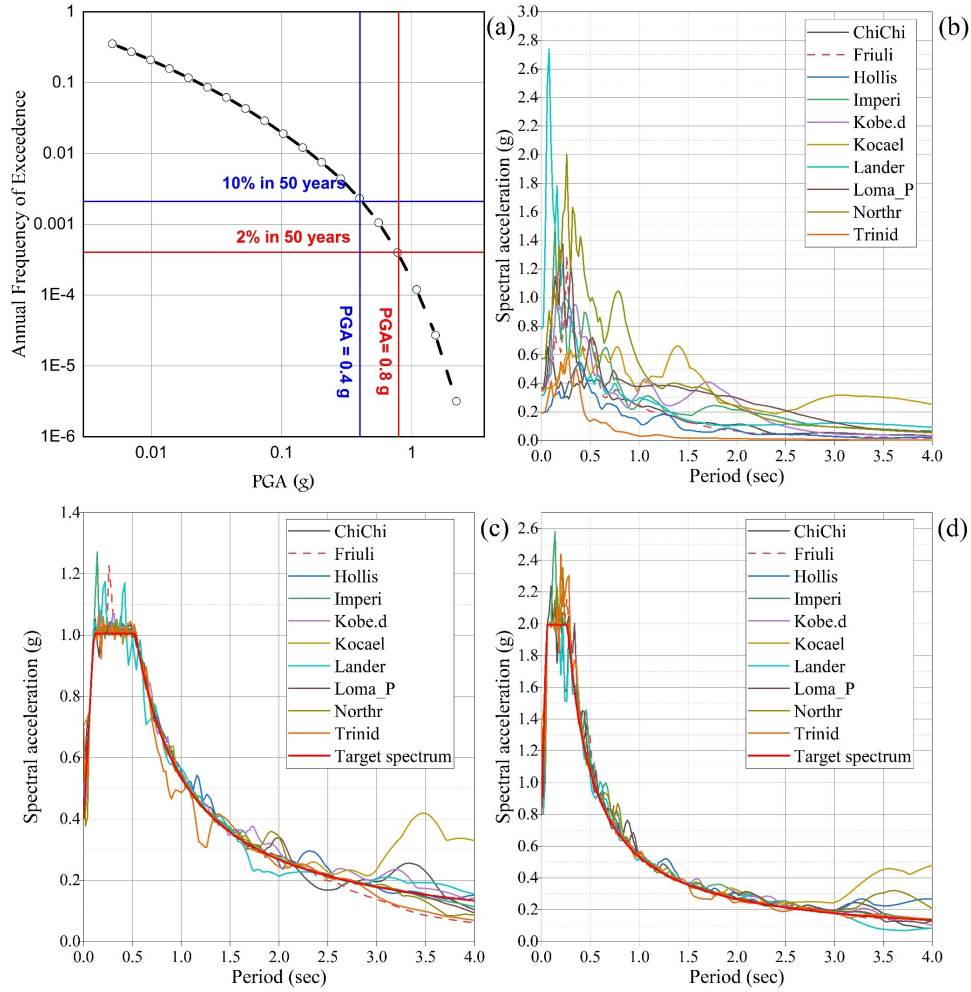


Figure 8.19: Seismic activity characteristics: a) Seismic hazard curve, b) unmatched selected ground motions, c) matched GMs to PGA=0.4g target response spectrum, d) matched GMs to PGA=0.8g target response spectrum.

8.3.4 Load combinations

ASCE 7 specifies the seismic load combinations for designing SMF beams and columns, requiring consideration of horizontal seismic effect, dead load, live load, and other loads (wind, snow, or fluid) as outlined in Equations (8.34) and (8.35).

$$1.2 \text{ Dead} \pm E_h + 1.0 \text{ Live} \quad (8.34)$$

$$0.9 \text{ Dead} \pm E_h \quad (8.35)$$

The load combinations are also used to calculate the column capacity that corresponds to the minimum and maximum axial forces as illustrated in Figure 8.20.

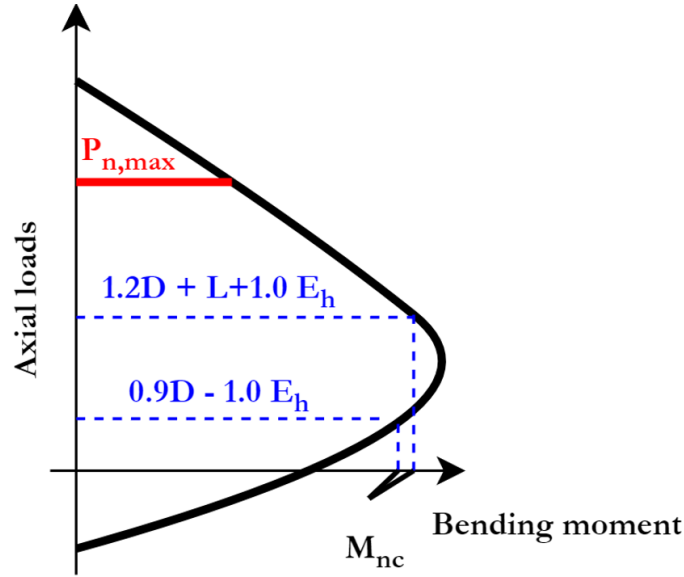


Figure 8.20: Column capacity calculation using minimum and maximum axial loads.

8.3.5 Seismic analysis

the three SMF buildings mentioned previously shall be designed using the proposed AI-based methodology and FBD. The obtained designs will be compared to check the performance of the proposed methodology in terms of :

- Static nonlinear analysis (NSA).
- Dynamic nonlinear time history analysis (NLTHA).
- Performance checks
- Fragility assessment.

8.3.6 Force-based design according to ASCE 7-22

The equivalent lateral force method (ELF) is one of the simplest methods that is used to design structures based on seismic demand forces. It is based on assuming that the lateral seismic force equals a portion of the structural weight, as written in Equation (8.36).

$$V_{base} = C_s \cdot W \quad (8.36)$$

Where: W is the effective building's weight. C_s is the seismic response coefficient as explained in ASCE 7-22 (eq 12.8.1.1).

The calculated base shears using ELF according to ASCE 7-22 of the case study buildings are illustrated in Table 8.6.

SMF	G+4	G+8	G+12
Base shear (KN)	330.8691	1136.492	2350.906

Table 8.6: Base shear SMFs using ELF

The corresponding design of the columns and beam of each SMF are summarized in Table 8.7.

Table 8.7: Columns and beams design

SMF	G+4		G+8		G+12	
Column cross-section (mm^2)	450 * 450		700 * 700		850 * 850	
Column reinforcement (%)	1.37		1.57		2.31	
Beam cross-section (mm^2)	300 * 250		500 * 300		550 * 300	
Beam reinforcement (%)	upper	lower	upper	lower	upper	lower
	2.00	1.24	1.12	1.25	1.02	1.04

8.3.7 AI-based seismic design

The proposed methodology uses MOOPSO to find multiple potential designs that meet the structural requirements and minimize the MIDRs, initial cost, and GDr. Figure 8.21 shows the optimization results obtained from the MOOPSO. The MOOPSO minimized also MIDR for the seismic intensity of PGA= 0.4g and PGA =0.8g. The SMFs' results are illustrated in Figure 8.21 -a, -b, and -c. The performance level that corresponds to each PGA is plotted and the acceptance region is determined. All the points belonging to this region are considered as a possible solution. The solution selection will be based on finding the lowest cost possible. Figure 8.21-d demonstrates that all the structures with MIDR lower than 1.5% have a maximum of 20% damage rate for all the SMFs.

After selecting the possible solutions do not exceed 1% and 1.5% for PGA=0.4g and 0.8g. A Pareto front will be plotted to represent the non-dominated solutions. The Pareto plot is between the initial cost and MIDR- PGA =0.8g. the non-dominated solutions then will be selected and plotted in other plots where initial cost and MIDR-PGA=0.4g are plotted. This step is crucial because it can capture the best solution that fulfills the performance levels in both seismic intensities with the minimum initial cost. Figure 8.22, 8.23, and 8.24 illustrate the Pareto front and the best design selection for all the SMFs. It can be noted that the best solution corresponds to the lowest cost that does not exceed the performance limits.

The best designs of the three SMFs are summarized in Table 8.8.

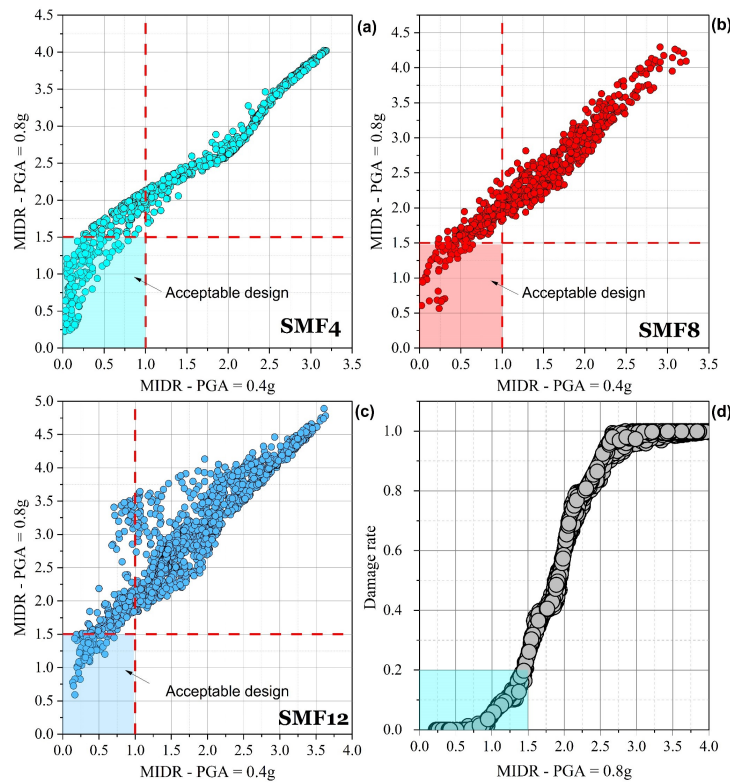


Figure 8.21: Optimization cloud of points: a) MIDR of PGA=0.4g versus MIDR of PGA= 0.8g for SMF4, b) MIDR of PGA=0.4g versus MIDR of PGA= 0.8g for SMF8, c) MIDR of PGA=0.4g versus MIDR of PGA= 0.8g for SMF12, and d) MIDR of PGA=0.8g versus damage rate of all the SMFs.

8.3.8 Comparative study between FBD and AI-based designs of SMF

In this section, a comparative study will be conducted between the found design using the traditional FBD and the proposed AI-based design of three SMFs. The study will compare capacity curves, hysteretic curves, inter-story drift ratio using NLTHA, and fragility curves.

8.3.8.1 Pushover analysis

The capacity curve provides a wealth of information about structural performance such as:

Base shear capacity, roof displacement, yielding limit, ultimate capacity, ductility, energy dissipation. It can also be used to estimate the structure's performance for a given earthquake event. Figure 8.25 illustrates the pushover curves of SMF4, SMF8, and SMF12 using FBD and the proposed methodology. Table 8.9 summarizes the bilinear curves' values and the obtained performance points (seismic demand).

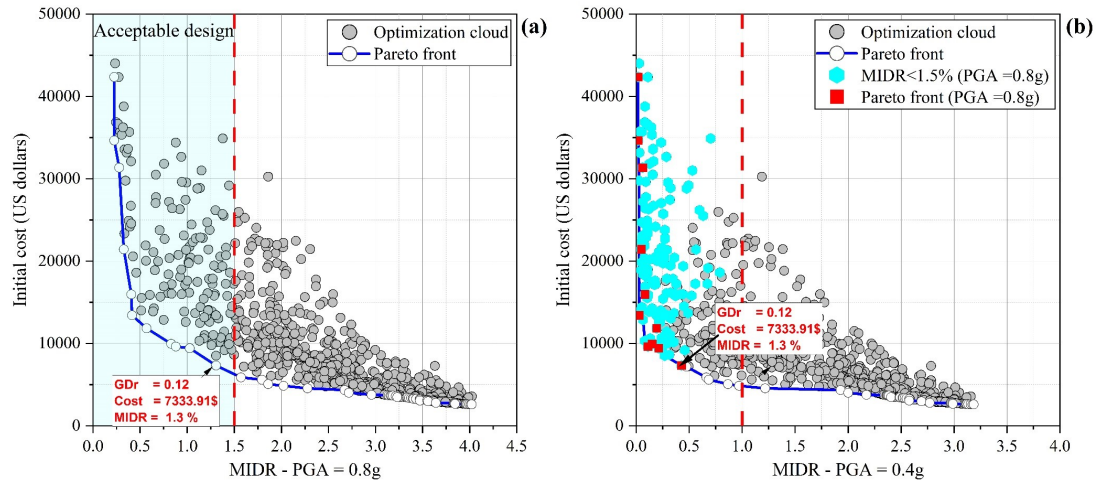


Figure 8.22: Pareto fronts and best design selection of SMF4: a) MIDR-PGA = 0.8g versus initial cost, b) MIDR-PGA = 0.4g versus initial cost.

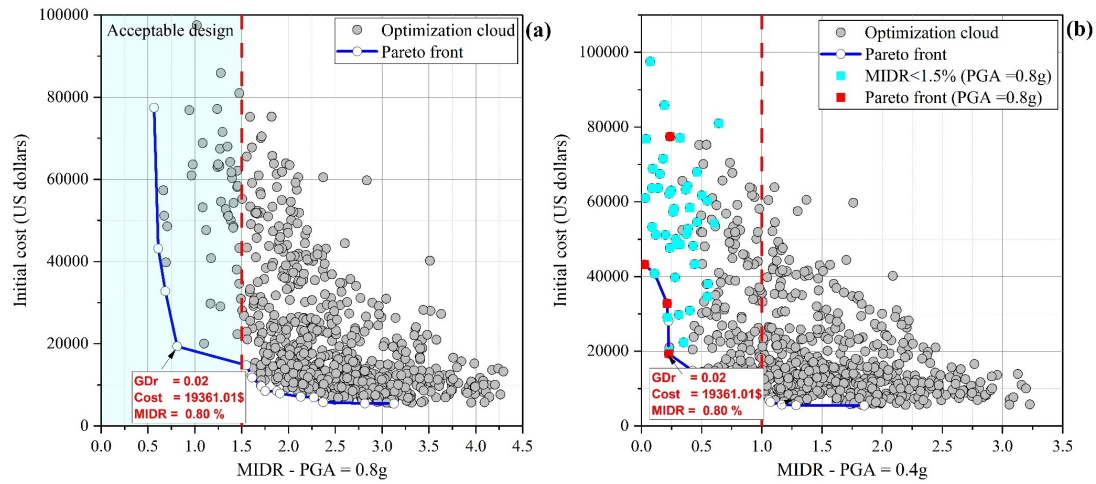


Figure 8.23: Pareto fronts and best design selection of SMF8: a) MIDR-PGA = 0.8g versus initial cost, b) MIDR-PGA = 0.4g versus initial cost.

Table 8.9: Theoretical solutions of SMF designs using the proposed methodology

	SMF4		SMF8		SMF12	
	Proposed	FBD	Proposed	FBD	Proposed	FBD
δ_y	79.740	78.587	119.591	88.247	351.670	185.089
δ_u	425.120	340.062	658.091	475.950	1250.000	670.290
V_y	476.559	637.585	908.922	1360.481	2283.004	2517.558
V_u	524.030	656.336	957.075	1674.697	2479.890	2923.824
μ_u	5.331	4.327	5.503	5.393	3.554	3.621
δ_d	144.631	129.735	267.348	197.592	353.163	300.223
V_d	483.702	593.318	937.607	1472.529	1797.833	2850.482

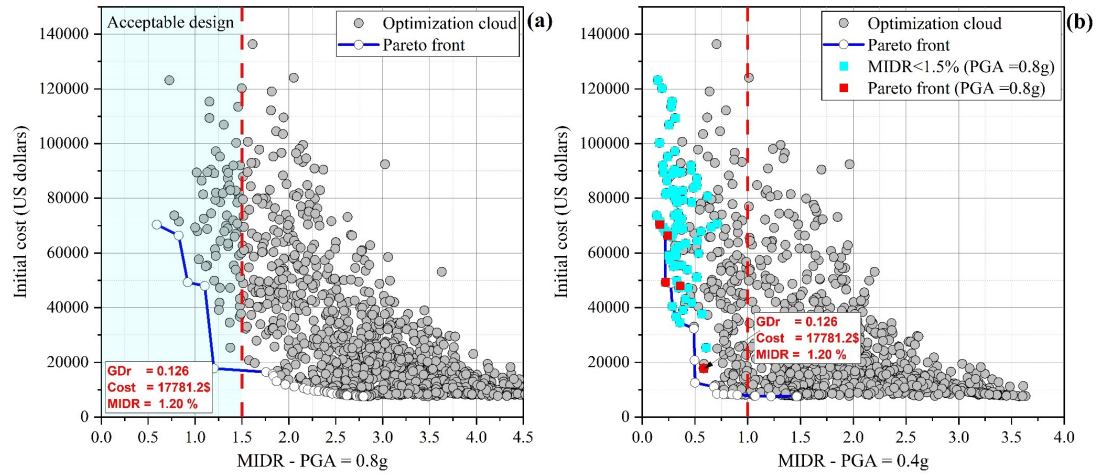


Figure 8.24: : Pareto fronts and best design selection of SMF12: a) MIDR-PGA =0.8g versus initial cost,b) MIDR-PGA =0.8g versus initial cost.

Table 8.8: Theoretical solutions of SMF designs using the proposed methodology

SMF	G+4	G+8	G+12
Column cross-section (mm^2)	417 * 417	652 * 652	793 * 793
Column reinforcement (%)	1.37	1.72	1.61
Beam cross-section (mm^2)	258 * 250	400 * 250	478 * 289
Beam reinforcement (%)	upper: 0.9 lower: 1.03	upper: 1.02 lower: 1.04	upper: 1.92 lower: 1.82
Column Shear reinforcement			
Area (mm^2/m)	701	770	2927
Spacing (mm)	75	110	80
Beam Shear reinforcement			
Area (mm^2/m)	480	1025	1753
Spacing (mm)	100	75	112

8.3.8.2 Nonlinear time history analysis

The NLTHA evaluates the structural nonlinear dynamic behavior when exposed to ground motion. Utilizing multiple ground motions on the same structure enhances our understanding of the overall response of the structure. This method boosts the accuracy and generalization of the investigation. Since the frequency content of each ground motion varies, the response to one ground motion will never be identical to another. In this section, we will calculate each story's maximum inter-story drift ratio and determine the mean response. The main objective of this section is to compare the responses of the structures designed using FBD and the proposed methodology.

The design should fulfill the performance levels for moderate and high-intensity earthquakes (2% and 10% in 50 years). The allowed performance level/ damage states are shown in Table 8.10

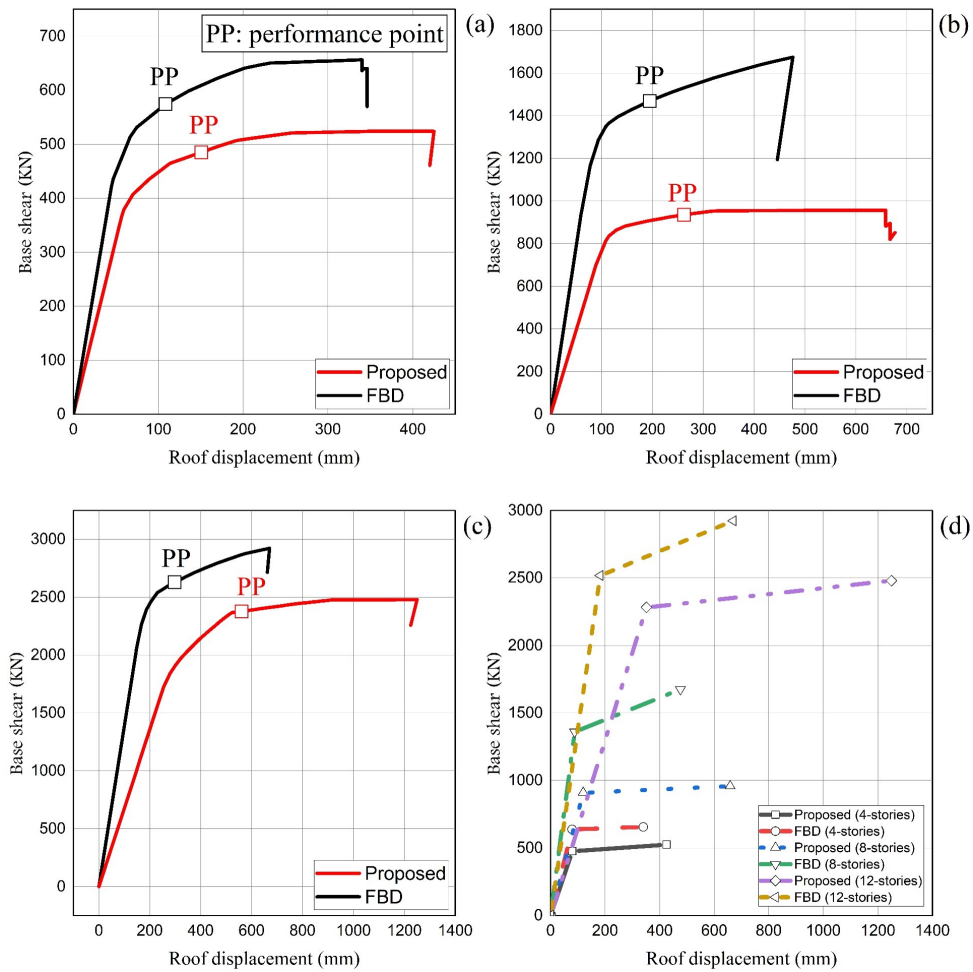


Figure 8.25: Pushover curves using FBD and the proposed methodology: a) SMF4, b) SMF8, c) SMF12, d) Idealized curves.

Table 8.10: MIDR thresholds for moderate and high-intensity earthquakes.

Earthquake intensity	Performance/damage thresholds (MIDR)	
	Slight damages (immediate occupancy)	Moderate damages (Life safety)
Moderate intensity (975 years)	1%	-
High intensity (2475 years)	-	1.5%

Figure 8.26, Figure 8.27, and Figure 8.28 depict the MIDR of each story and the mean response compared to the performance threshold (MIDR = 1.5%). On the other hand, Figure 8.29, Figure 8.30, and Figure 8.31 depict the MIDR of each story and the mean response compared to the performance threshold (MIDR = 1.0%).

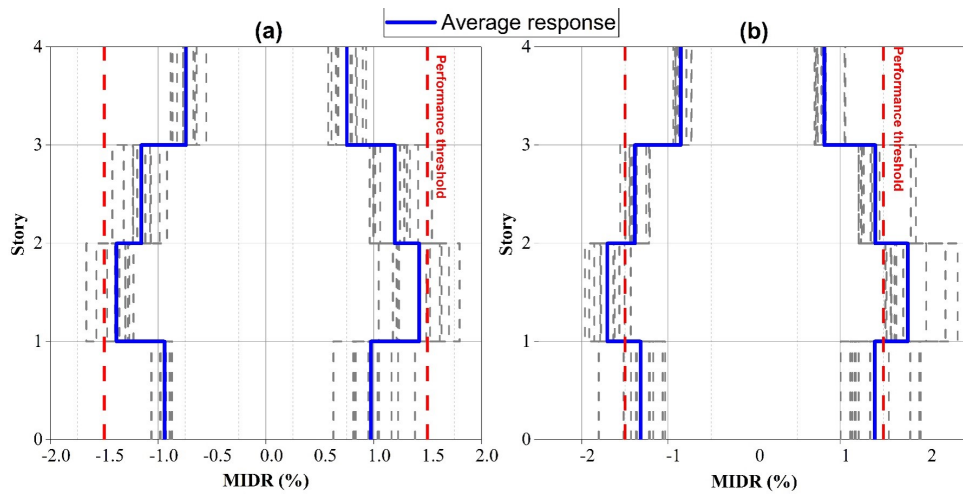


Figure 8.26: MIDR of each story of SMF4 designed using: a) AI-based, b) FBD, at $\text{PGA}=0.8g$.

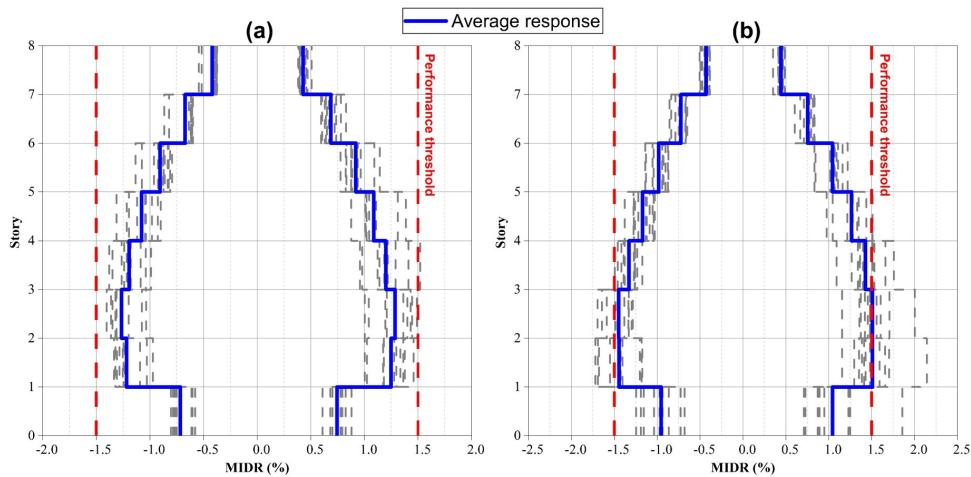


Figure 8.27: MIDR of each story of SMF8 designed using: a) AI-based, b) FBD, at $\text{PGA}=0.8g$.

The best design should satisfy two performance /damage conditions: The structure should face slight damages ($\text{MIDR} < 1.0\%$) under earthquakes with intensity less than $0.4g$ and moderate damages for earthquakes under $\text{PGA} = 0.8g$, which corresponds to a 975 and 2475 years return period respectively.

8.3.8.3 Fragility assessment

Fragility assessment aims to describe the amount of damage a building may experience during an earthquake using probabilities. It gives extra information about how fragile the building is. Figure 8.32 compares the fragility curves of structures designed using the proposed methodology and the traditional FBD. These curves show two main things: how quickly damage happens and the chance of reaching each level of damage or performance. Statistically, the likelihood of damage is high when it goes over a 50% chance. Figure 8.33

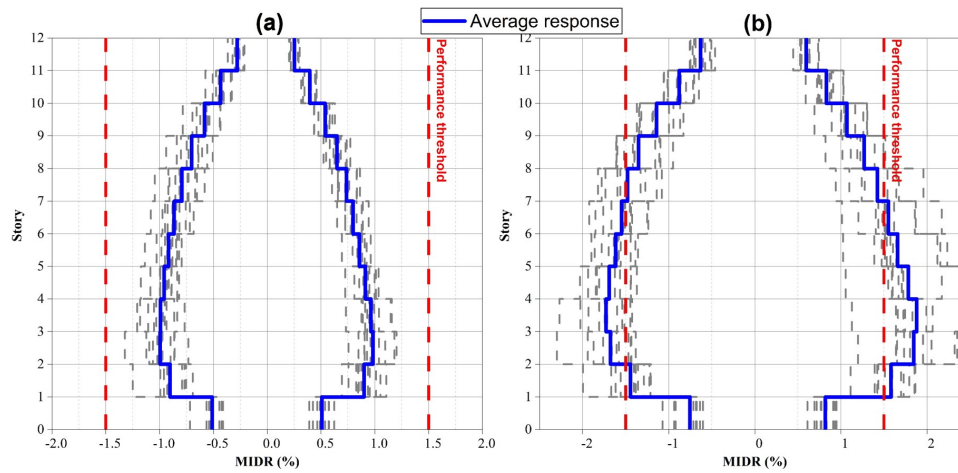


Figure 8.28: MIDR of each story of SMF12 designed using: a) AI-based, b) FBD, at $PGA=0.8g$.

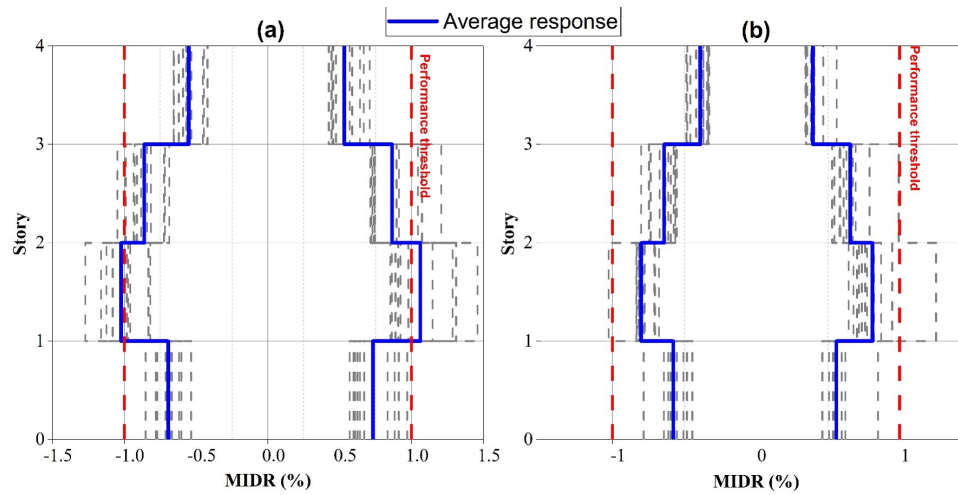


Figure 8.29: MIDR of each story of SMF4 designed using: a) AI-based, b) FBD, at $PGA=0.4g$.

illustrates the probability comparison of FBD and AI-based SMFs and the corresponding DG_r at $PGA=0.8g$. This section will examine how design changes may impact the building's fragility.

8.3.8.4 Initial and global cost

Since one of the objectives is the building cost initially and the probable damage loss. Figure 8.34 summarizes the DG_r and the DG_r at $PGA=0.8g$ of all the SMFs in both design methodologies.

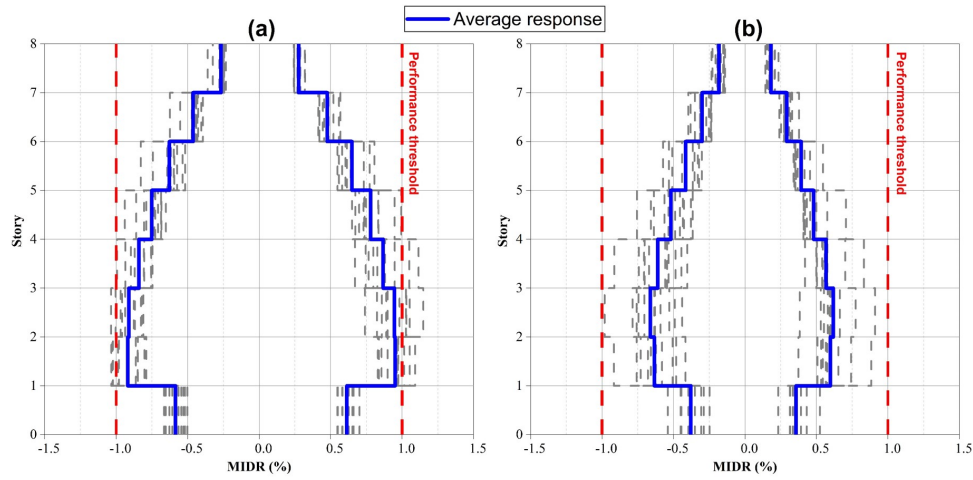


Figure 8.30: MIDR of each story of SMF8 designed using: a) AI-based, b) FBD, at $\text{PGA}=0.4g$.

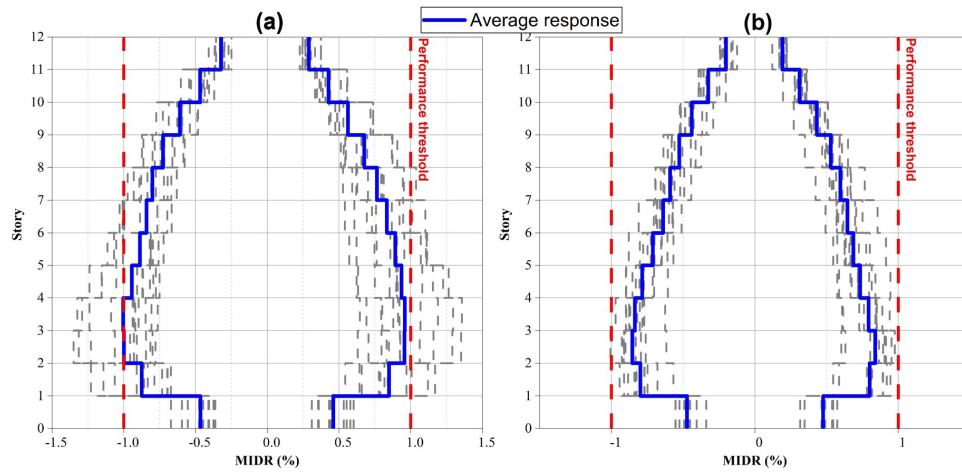


Figure 8.31: MIDR of each story of SMF12 designed using: a) AI-based, b) FBD, at $\text{PGA}=0.4g$.

8.4 Discussion and Results

8.4.1 Pushover analysis

The pushover analysis results and seismic demands for three different structural models (SMF4, SMF8, and SMF12) using the proposed method and the Force-Based Design (FBD) method are presented in Table 8.8 and Figure 8.24. The key findings are discussed below.

1. *Yield Displacement and Ultimate Displacement:*

- For all models (SMF4, SMF8, and SMF12), the proposed method results in higher ultimate displacements compared to the FBD method. Specifically, the

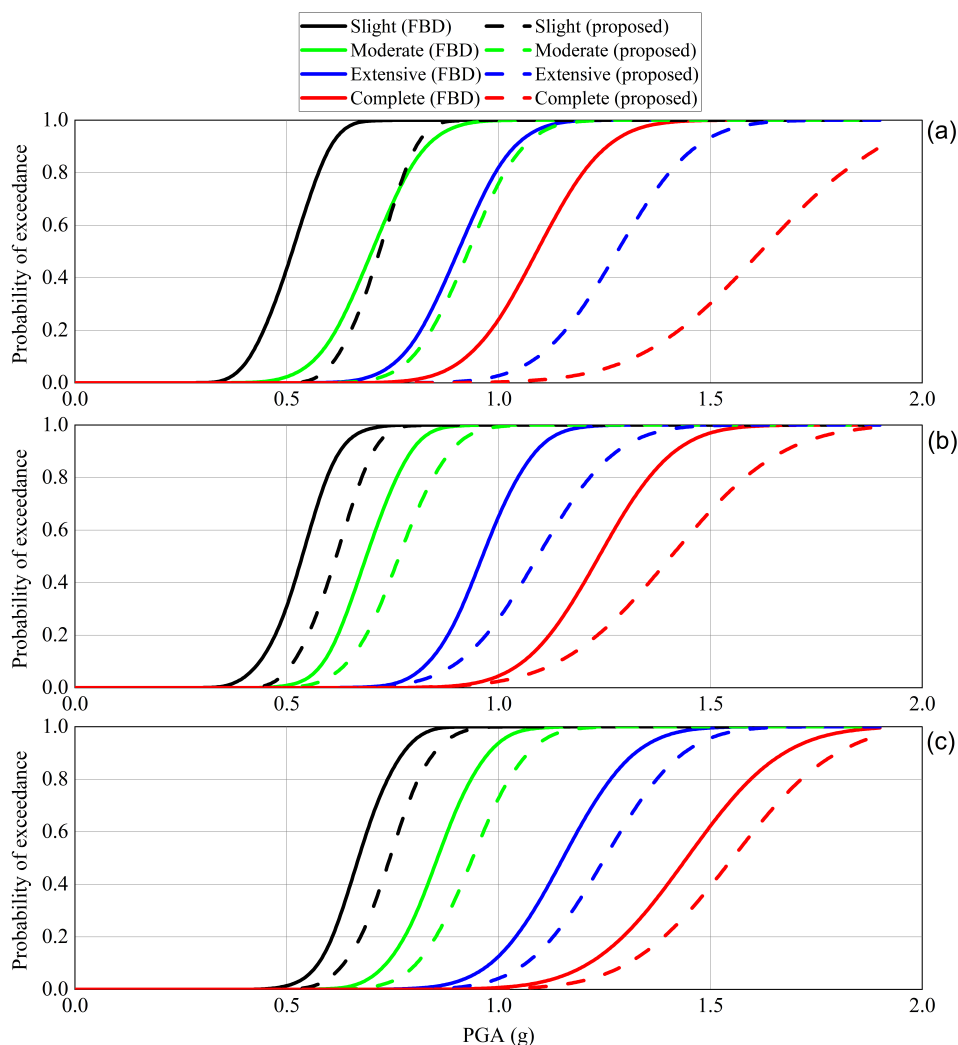


Figure 8.32: Fragility curves comparison between FBD and AI-based: a) SMF4, b) SMF8, and c) SMF12.

ultimate displacement for SMF12 using the proposed method (1250.000 mm) is significantly higher than that of the FBD method (670.290 mm), indicating a greater deformation capacity before failure.

- Yield displacements show a slight increase with the proposed method compared to the FBD method. For example, in SMF8, the yield displacement is 119.591 mm for the proposed method and 88.247 mm for the FBD method.

2. Yield Shear and Ultimate Base Shear:

- The yield shear values are consistently lower for the proposed method compared to the FBD method. For instance, in SMF8, the yield shear for the proposed method is 908.922 kN, whereas for the FBD method, it is 1360.481 kN.
- Similarly, ultimate base shear values follow the same trend, with the proposed

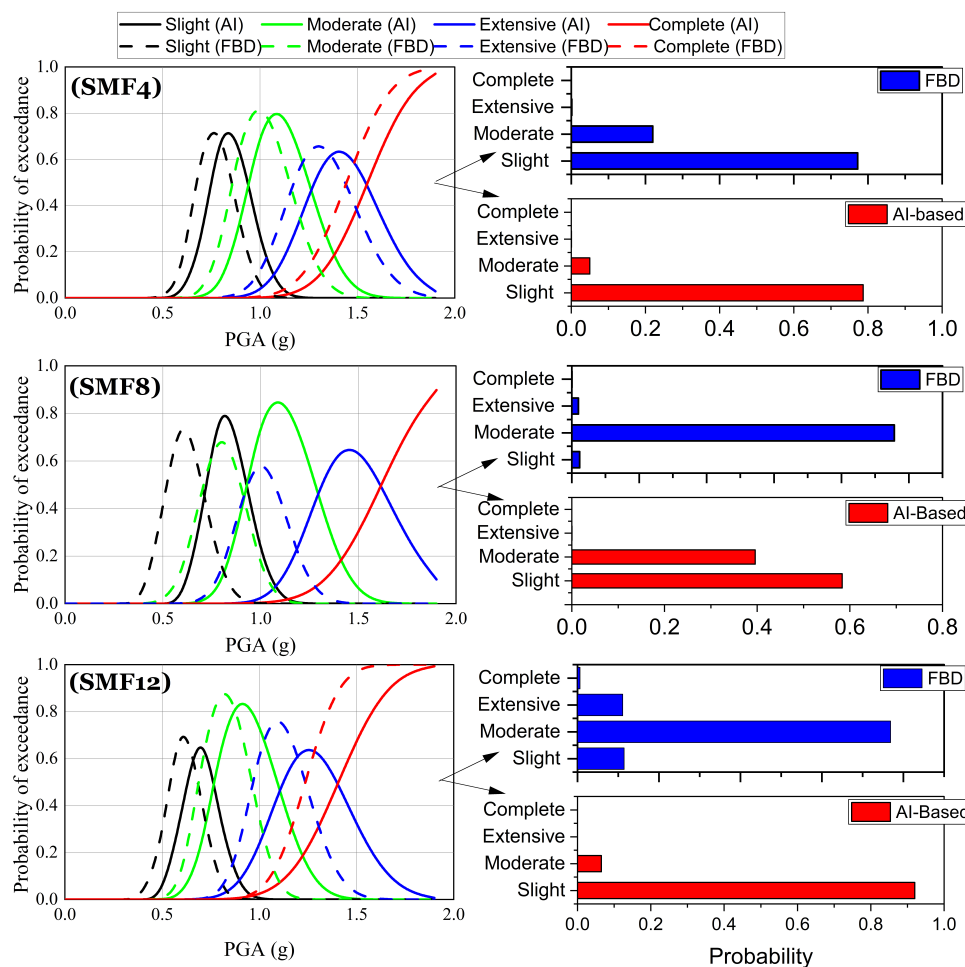


Figure 8.33: Probability of each damage state at PGA= 0.8g of SMFs designed using FBD and the AI-Based.

method yielding lower values. In SMF12, the ultimate base shear is 2479.890 kN for the proposed method, compared to 2923.824 kN for the FBD method.

3. *Ultimate Ductility:*

The ultimate ductility, defined as the ratio of ultimate displacement to yield displacement, is higher in the proposed method across all models. For instance, in SMF12, the ultimate ductility is 3.554 for the proposed method, compared to 3.621 for the FBD method, indicating an enhanced ability to undergo plastic deformations.

4. *Displacement Demand and Shear Demand:*

- Displacement demand is higher for the proposed method in all models. For SMF4, the displacement demand is 144.631 mm for the proposed method, compared to 129.735 mm for the FBD method.
- Shear demand also follows a similar trend, with the proposed method showing lower values. In SMF12, the shear demand is 1797.833 kN for the proposed

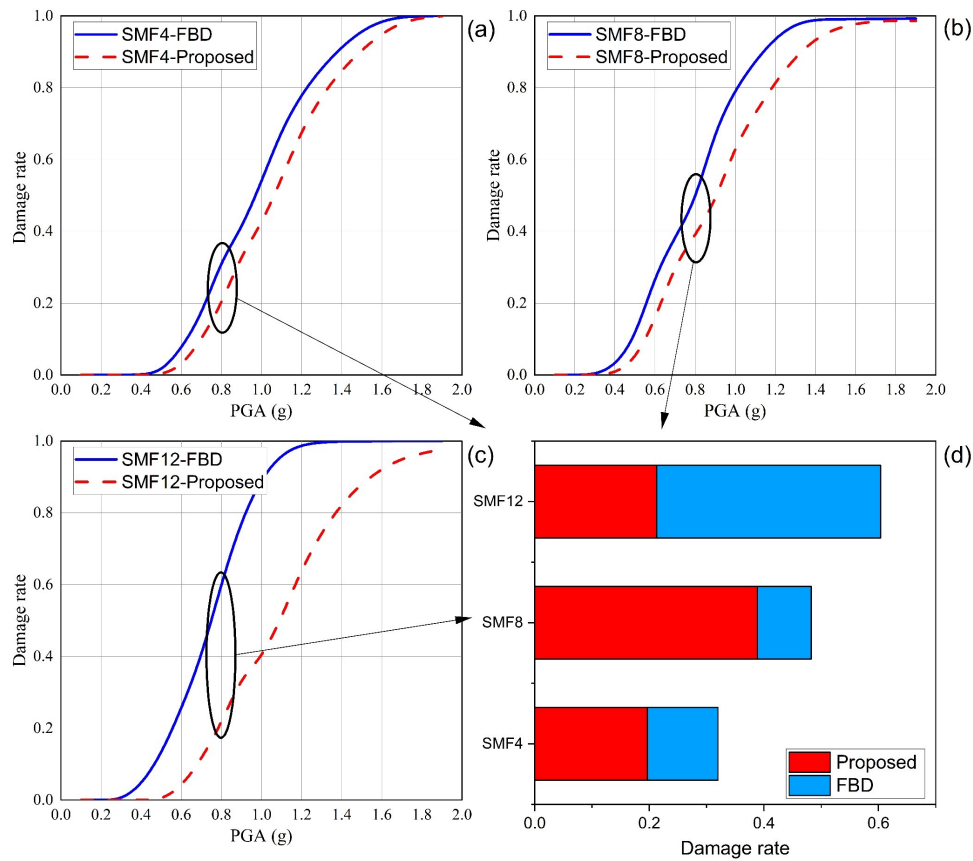


Figure 8.34: DGr comparison between the FBD and the proposed methodology: a) SMF4, b) SMF8, c) SMF12, and d) DG_r at $PGA=0.8g$.

method, whereas it is 2850.482 kN for the FBD method.

5. Performance Points and Capacity Curves:

Figures 8.25-(a),-(b), and-(c) illustrate the capacity curves and performance points for SMF4, SMF8, and SMF12, respectively. The following observations can be made:

- The proposed method exhibits a higher roof displacement at the performance point than the FBD method. This is evident in SMF12, where the proposed method's roof displacement at the performance point is significantly greater.
- The base shear capacity is higher for the FBD method across all models, as indicated by the sharper peaks in the capacity curves. This trend suggests that the proposed method may lead to designs with slightly reduced base shear capacity but higher ductility and displacement capacity.
- Figure 8.25-(d) summarizes the performance points of all models, illustrating the relative positions of the proposed and FBD methods. The proposed method consistently shows a balance between increased displacement and adequate base shear capacities.

8.4.1.1 Discussion

The proposed AI-based design selects smaller cross-sections, resulting in reduced stiffness, which lowers the seismic forces that need to be absorbed by the structural elements. This design strategy achieved a reduction in ultimate base shear by 20%, 42%, and 15%, while increasing ultimate displacement by 125%, 138%, and 186% for SMF4, SMF8, and SMF12, respectively.

A comparison of ductility parameters reveals that the AI-based design offers greater ultimate ductility for low- and mid-rise structures (SMF4 and SMF8) compared to the force-based design (FBD), with only a slight difference observed for SMF12 (high-rise structure).

In terms of demand ductility, the AI-based design demonstrates superior performance for SMF4 (1.81 vs. 1.65) and similar values for SMF8 (both 2.23). However, for SMF12, the demand ductility is lower (1.00 vs. 1.62) than that of the FBD.

These results highlight the objectives of the AI-based approach: for low-rise structures, the design prioritizes increased ductility, while for high-rise structures, it aims to reduce ductility. This differentiation stems from the inherent characteristics of the buildings. Low-rise structures, being stiffer, are better equipped to dissipate seismic energy and can accommodate greater deformation with slight stiffness reductions. Conversely, high-rise structures, which are inherently more flexible, are susceptible to excessive lateral deformation. To address this, the AI-based design reduces both ultimate and demand ductility for high-rise structures.

In summary, the AI-based approach autonomously optimizes key factors such as ductility and base shear demand, striking a balance that promotes efficient and resilient structural behavior across different building heights, without requiring human intervention.

8.4.2 Nonlinear dynamic analysis

This sub-section involves the use of dynamic analysis where 10 real and matched ground motions were used to investigate the mean response of the MIDR. The analysis was conducted to determine the MIDR for each story of the studies SMFs subjected to two intensities. a mean response is calculated to study the average response of the structures. According to Figure 8.26, 8.27, and 8.28, The SMFs designed using the AI-based showed a better performance in terms of MIDR, where the maximum MIDR does not exceed the MIDR threshold ($MIDR = 1.5\%$) for all the SMFs. On the other hand, FBD designs showed in desired performance where the mean MIDR exceeded the performance limit for SMF4 and SMF12.

For $PGA = 0.4g$, the performance limit was changed to ($MIDR = 1\%$). The results from Figures 8.29, 8.30, and 8.31 illustrate the AI-based design was better than the FBD, and

the MIDR for all the SMFs didn't exceed or reach the performance limit.

8.4.2.1 Discussion

NLTHA provides more realistic results as it employs actual ground motions to evaluate seismic behavior. Unlike static analysis, NLTHA results are influenced by the characteristics of the selected ground motions, including their duration and frequency content.

The results shown in Figures 8.26, 8.27, 8.28, 8.29, 8.30, and 8.31 demonstrate that the AI-based design method outperforms the traditional FBD in nonlinear response analysis. For all SMFs, the mean responses remain below the performance thresholds specified by standards for moderate and extensive seismic intensities (0.4g and 0.8g).

As discussed earlier, the AI-based approach aims to optimize stiffness and seismic force demands to ensure that the MIDR does not exceed predefined thresholds. While some ground motion responses exceed the threshold for the AI-based design, the mean response, representing a 50% probability of exceedance, consistently falls below the desired performance level. This outcome is directly attributable to the algorithm and its fitness function, which is intentionally designed to optimize the average responses.

In contrast, the FBD method often fails to meet the desired seismic performance in terms of MIDR. This is because the FBD approach, as adopted by many standards (e.g., ASCE), focuses primarily on ensuring structural stability rather than explicitly addressing seismic performance during the design process. The estimated seismic base shear derived from FBD ensures stability but does not necessarily optimize performance.

Moreover, optimizing seismic performance under both moderate and extensive seismic intensities simultaneously is an innovative application of AI techniques within PBD. This approach ensures that the building is designed to behave as intended under varying seismic conditions.

The AI-based design successfully identifies the optimal configuration to achieve superior dynamic performance and resilience across different seismic intensities. Unlike traditional methods, the AI-based approach does not rely on iterative processes. Instead, it directly selects the most suitable design that simultaneously satisfies performance, cost, and global damage rate objectives.

8.4.3 Fragility assessment and global damage rate

The fragility curves represent the probability of reaching or exceeding a given damage state or performance level, serving as a critical tool in probabilistic or uncertainty studies. As shown in Figure 8.32, the fragility curves obtained for the studied SMFs illustrate that the AI-based methodology consistently achieves a lower probability of exceedance across all damage states compared to the FBD approach. To provide a more detailed comparison, Figure 8.33 highlights the probability of each damage state by subtracting

one cumulative fragility curve from the next.

For a seismic intensity of $PGA = 0.8g$, the results reveal notable differences between the two methods. In terms of slight damage, the probabilities for the AI-based design are 78%, 59%, and 91% for SMF4, SMF8, and SMF12, respectively, compared to 79%, 3%, and 12% for the FBD design. For moderate damage, the AI-based methodology maintains probabilities of 8%, 41%, and 9% for SMF4, SMF8, and SMF12, while the FBD approach results in significantly higher probabilities of 21%, 97%, and 79%, respectively. For extensive damage, the AI-based design demonstrates superior performance with a 0% probability of occurrence across all structures, whereas the FBD method shows probabilities of 0%, 2%, and 11% for SMF4, SMF8, and SMF12, respectively.

The box plot in Figure 8.33 confirms that moderate damage is effectively controlled by the AI-based methodology, with probabilities never exceeding 50%. Conversely, the FBD results indicate a higher likelihood of moderate damage, especially for mid- and high-rise structures. Furthermore, as illustrated in Figure 8.34, the damage rate analysis underscores the advantages of the AI-based approach. At $PGA = 0.8g$, the global damage rates for the AI-based design are 19%, 39%, and 21% for SMF4, SMF8, and SMF12, respectively, compared to 27%, 43%, and 59% for the FBD approach. Figure 8.34(d) emphasizes these differences, showcasing the consistently lower damage rates achieved by the proposed AI-based methodology.

These findings highlight the effectiveness of the AI-based design in reducing the probability of moderate and extensive damage while maintaining a comparable likelihood of slight damage. By delivering lower damage rates and probabilities of exceedance, the AI-based methodology enhances structural resilience and offers significant improvements over the traditional FBD approach.

8.4.3.1 Discussion

The obtained results demonstrated that the AI-based approach effectively incorporates the fragility factor and controls the probable damages that may occur during an earthquake. The fragility curves illustrated in Figure 8.32 highlight the AI-based methodology's ability to produce designs with lower vulnerability to seismic actions. In contrast, the FBD method does not influence structural fragility, as its approach merely estimates seismic forces to ensure structural safety and prevent collapse, without addressing performance or potential damage.

Figure 8.33 reveals two key findings: first, it confirms that the probability of exceedance is significantly reduced at a seismic intensity of $0.8g$ for all SMFs; second, it shows that moderate damages are controlled, with no exceedance into higher damage states. This indicates that the mean building response remains within the performance thresholds, a result corroborated by NLTHA analysis.

Regarding the damage rate, the proposed AI-based methodology achieves consistently

lower damage rates compared to FBD designs across all SMFs. This underscores the effectiveness of the multi-objective optimization process and the high-accuracy predictions of the AI model in identifying the best designs that meet all performance, cost, and damage reduction requirements—factors not addressed by the FBD approach.

8.5 Conclusion

The following paragraph describes a new AI-based method for designing structures to withstand seismic events. The method involves using a hybrid artificial neural network (ANN) model to predict seismic responses, such as MIDR and MBS, and then using multi-objective optimization algorithms (MOOPSO) to design the structures to minimize cost, performance, and global damage rate. The study also involved testing the performance of the AI-based methodology on three different structures. Additionally, traditional methods like FBD were compared with the proposed methodology, and the performance of the AI-based seismic design was evaluated through static, dynamic, and fragility analysis.

Conclusion

Seismic design is essential for creating sustainable and resilient structures. Various seismic design philosophies, such as Force-Based Design (FBD), Capacity-Based Design (CBD), Performance-Based Design (PBD), Displacement-Based Design (DBD), and Energy-Based Design (EBD), offer different approaches depending on performance, displacement, dissipated energy, and capacity requirements. For strategic and high-importance buildings, it is crucial to design structures that can not only withstand seismic forces but also maintain functionality during and after earthquake events.

Performance-Based Design (PBD) aims to achieve designs that meet specific performance criteria. However, nonlinear static or dynamic procedures, like Nonlinear Time History Analysis (NLTHA) or pushover analysis, can be time-consuming, often taking hours or days to converge to acceptable results.

This research addresses this challenge by leveraging artificial intelligence (AI) algorithms to propose a novel, fast, and accurate methodology for seismic design. The AI-based methodology involves two key components:

1. A machine learning (ML) model establishes the relationship between structural inputs and seismic responses, specifically Maximum Inter-story Drift Ratio (MIDR) and Maximum Base Shear (MBS). The performance of the ML model is enhanced using a hybrid technique that combines unsupervised and supervised algorithms, demonstrating that hybrid algorithms outperform purely supervised ones. The results have shown an improvement of predictability performance compared to the traditional ANN technique. The dataset size comparison confirmed that even when less data was used the performance in term of R^2 , PBIAS and RSR were acceptable and better than the ANN.
2. A multi-objective optimization algorithm identifies the optimal design control variables, balancing initial cost, damage rate, and performance. These objectives are crucial as they significantly influence structural performance, fragility, and cost.

A case study is conducted to apply the AI-based approach to three special moment frames (SMFs) of varying heights (4-, 8-, and 12-stories). These frames are particularly susceptible to seismic design considerations, requiring multiple checks for capacity, joint

strength, and ductility. The investigation includes static and dynamic nonlinear analysis and fragility assessments. Comparative analysis between the proposed methodology and traditional FBD evaluates structural behavior under both approaches. Structures are assumed to be located in a high seismic activity region with two return periods (975 years and 2475 years), corresponding to PGAs of 0.8g and 0.4g. The results indicate that the proposed methodology achieves designs with lower costs, better performance, and reduced seismic fragility and damage rates. The proposed AI-based method was able to balance between the structural behavior and the seismic demand that will effect as a result its performance in two different intensities. In addition, the high performance and rapid prediction of the seismic response was a crucial key to converge rapidly to the solution, which make the technique useful to be applied by engineers.

8.6 Key Findings

- **Accuracy and Efficiency:** The hybrid model combining an Autoencoder with an ANN was found to be the most effective, enhancing prediction accuracy, reducing error biases, and minimizing prediction variations, particularly for smaller datasets. This model provided a fast and accurate alternative to NLTHA for seismic response prediction.
- **Pushover Analysis:** The proposed method resulted in higher ultimate displacements and ductility compared to the FBD method, indicating more resilient structures capable of sustaining larger deformations without failure.
- **Nonlinear Dynamic Analysis:** The AI-based design outperformed the FBD method in terms of Maximum Inter-story Drift Ratio (MIDR), with the AI-based designs consistently remaining below performance thresholds.
- **Fragility Assessment:** The AI-based methodology effectively controlled the probability of exceeding fixed damage states and recommended designs that met desired performance levels. It also resulted in a consistently lower damage rate than the FBD method.

8.7 Implications

The use of machine learning, particularly hybrid models, in seismic design offers significant improvements in the accuracy, efficiency, and resilience of structures. These models provide a viable and superior alternative to traditional methods like NLTHA and FBD, enhancing the overall performance and safety of buildings in seismic regions. The findings underscore the potential of AI-driven methodologies to revolutionize seismic design,

making it more robust, reliable, and economically feasible. This advancement contributes to structural engineering and promotes socio-economic stability and safety in earthquake-prone areas.

8.8 Further research

Further research should explore more complex structures with varying material properties and different lateral force-resisting systems. Additionally, incorporating soil-structure interaction effects will provide a more comprehensive understanding of seismic behavior. Structural irregularities should also be considered to enhance the robustness and applicability of the AI-based seismic design methodology across diverse building types and conditions.

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Appendix A

Artificial intelligence-based for optimized seismic design

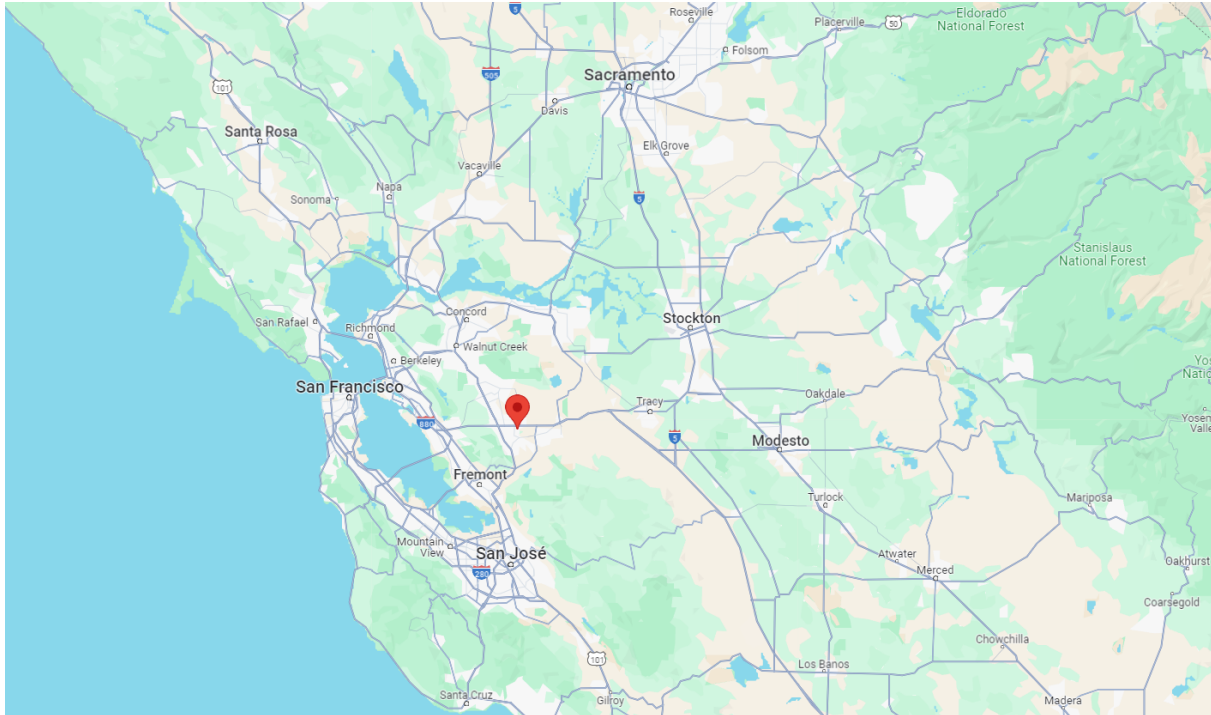
A.1 Location coordination on Google Earth

A.2 Seismic Hazard Parameters

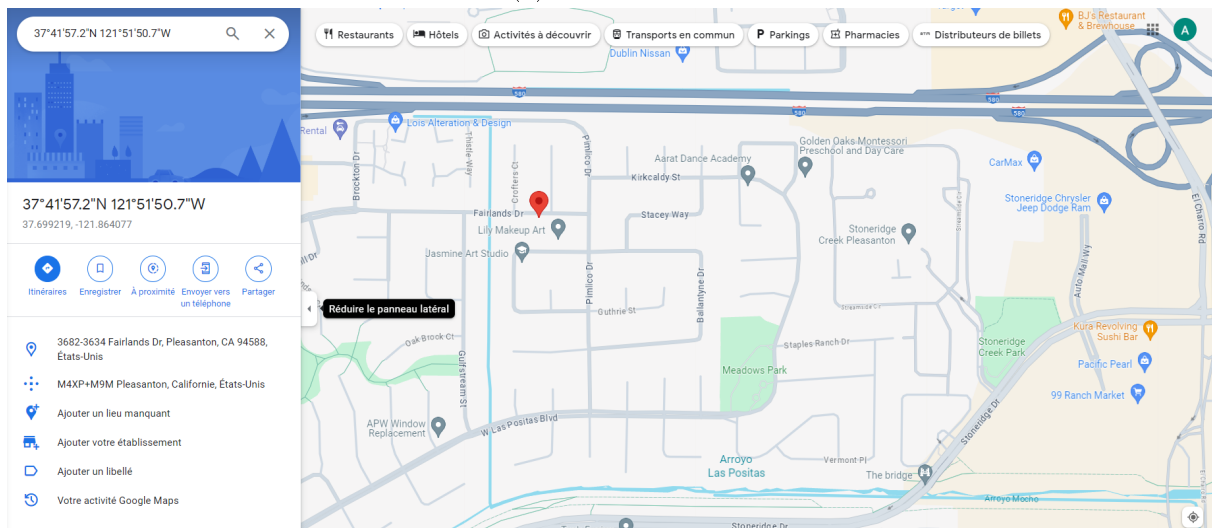
The following table provides the seismic hazard parameters used for the design and analysis of the structure according to ASCE 41-17 guidelines. The parameters are based on a site class of "A - Hard Rock" with a custom probability of 0.01 and 0.1.

Table A.1: seismic hazard parameters used to generate the seismic response spectrum

Return period (years)	975	2475	
Probability	10%	1%	In 50 years
Ss	0.21	2.606	MCER ground motion (period=0.2s)
Fa	0.8	0.8	Site amplification factor at 0.2s
Sxs	0.968	2.085	Site modified spectral response (0.2s)
S1	0.428	0.983	MCER ground motion (period=1.0s)
Fv	0.8	0.8	Site amplification factor at 1.0s
Sx1	0.342	0.787	Site modified spectral response (1.0s)



(a) Site location



(b) Site coordinates

Figure A.1: Site location on Google Earth