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Research Paper

Generating Design Spectrum-Compatible Artificial Accelerograms Utilizing Generative Adversarial Networks

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ABSTRACT

Recent advancements in Deep Learning (DL) have significantly expanded its application to address myriad challenges in civil and earthquake engineering. However, a notable challenge persists: the scarcity of reliable data pertinent to earthquake engineering, which may compromise the accuracy of DL-derived results. In response to this challenge, Generative Adversarial Networks (GANs) have emerged as a promising solution. Initially conceptualized to improve the training of generative models, GANs have exhibited exceptional performance and adaptability, particularly in image generation, gaining substantial recognition within the academic community. In structural engineering, the generation of synthetic ground accelerograms that conform to a specified target response spectrum is essential for conducting nonlinear dynamic analyses. This paper introduces an effective algorithm for spectral matching, facilitating the generation of numerous artificial, spectrum-compatible earthquake accelerograms from a limited set of ground motion records. The proposed algorithm represents a significant advancement in the field, addressing the critical need for robust and accurate synthetic data in earthquake engineering. Consequently, the integration of GANs into this domain not only enhances the reliability of DL applications but also paves the way for more precise and comprehensive analyses, thereby contributing to the overall progress of civil and earthquake engineering disciplines.

Keywords:
Artificial accelerograms; GAN; AI; Neural Networks; Deep learning

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1. Introduction

In structural engineering, when engaging in the aseismic design of structural systems, response spectra serve as an invaluable instrument for assessing the maximum responses of such systems. A paramount example of a response spectrum utilized in design is the design spectrum stipulated by seismic regulations. The time-history dynamic analysis is a method commonly applied in the design of structures deemed critical or of high importance, such as skyscrapers. This analysis mandates the availability of multiple ground acceleration records for the execution of nonlinear dynamic analyses, by standards such as ASCE 7-22 (American Society of Civil Engineers, 2022). As a result, there arises a necessity for the generation of accelerograms congruent with a specified target design spectrum.

Scholars have devised multiple methodologies for the generation of artificial spectrum-compatible earthquake accelerograms. In the foundational work by Kanai (1957), followed by Tajimi (1960), the stationary-filtered white noise paradigm was introduced to characterize seismic ground motion. This model has attained extensive application in the domain of random vibration analysis for structural systems, as evidenced by Ahmadi's (1979) work. Additionally, methodologies leveraging nonstationary random process models have been detailed by Mobarakeh et al. (2002). Moreover, stochastic approaches to simulate ground motion time-histories have been advanced by Yang and Zhou (2015). Furthermore, Cacciola and Zentner (2012) proposed an innovative method for the synthesis of artificial spectrum-compatible earthquake time histories employing random joint time-frequency distributions.

Artificial neural networks have been integrally incorporated into various engineering disciplines, as highlighted by Bigdeli et al. (2023), and have notably contributed to the development of innovative techniques for generating artificial spectrum-compatible earthquake accelerograms, such as the approach by Lee and Han (2002). Optimization methods, as an alternative to neural networks, can be utilized to synthesize artificial seismic ground motions that correspond to the specified target spectrum (Tavakoli & Rahami, 2023). However, these optimization techniques often lack the requisite speed or capability to produce an extensive database. As a remedy, Matinfar et al. (2023) utilized deep con-volutional generative adversarial networks (DCGANs), which incorporate convolutional layers in the generation of artificial accelerograms that are compatible with the ASCE design code spectrum. Shi et al. (2023) used a Generative Adversarial Neural Operator (GANO) to develop a data-driven framework for generating ground motion conditioned on various seismic factors, showing promise for efficient broadband ground motion synthesis. Chen et al. (2024) proposed a new deep-learning model to generate realistic seismic waveforms that addresses the challenge of limited labeled field data for training seismic analysis models. Huang et al. (2024) used a conditional generative adversarial neural network (cGAN) to simulate ground motions for earthquakes with varying magnitudes, distances, and local site conditions.

Generative Adversarial Networks (GANs) introduced by Goodfellow et al. (2014) have found numerous applications in contemporary research and technology. Guo et al. (2024) used a generative adversarial neural network (GAN) called ARMGAN to expand the response dataset of single-layer latticed shells (SLRSs) for structural health monitoring by migrating responses from a similar domain while reducing the generation of abnormal data. Shim (2024) used a generative adversarial network (GAN) to synthesize crack images for training a deep learning model for crack detection, reducing the need for a large amount of real-world crack data.

In the present study, dense layers, also termed fully connected layers, have been utilized on account of their superior processing speed in comparison to convolutional layers. Within these layers, each neuron is interconnected with all neurons in the antecedent layer, hence the designation "fully connected." Although convolutional layers are distinguished by their inventive applications and superior output quality, these characteristics can be effectively offset by applying an intricate architectural framework of dense layers. A comprehensive database of accelerograms that adheres to the diverse array of Iranian Standard No. 2800 design spectra is then successfully created (Matinfar & Khaji, 2024).

Generative adversarial neural networks (GANs) are predominantly employed for dataset augmentation, particularly in scenarios where access to original data is limited. This is especially pertinent in cases where datasets must adhere to specific criteria or rules, yet there exists a scarcity of authentic samples. For instance, consider a situation wherein a requisite dataset comprising 5000 high-quality accelerograms conforming to a designated design spectrum is desired. Employing GANs in such contexts not only facilitates the expansion of datasets but also enhances the efficacy of subsequent neural network models (which use GAN data as input) by furnishing them with augmented, relevant data (Hu et al., 2024). The generation of a substantial volume of earthquake records enables robust statistical analyses, facilitating a comprehensive understanding of structural responses under diverse seismic conditions. A larger dataset minimizes the impact of outliers, thereby enhancing the reliability of conclusions drawn from seismic assessments, which is particularly critical in seismic reliability analysis where both epistemic and aleatory uncertainties must be con-sidered. Moreover, the ability to produce thousands of earthquake records supports extensive probabilistic seismic hazard analyses, allowing for more accurate estimations of seismic demand probabilities on structures through a diverse range of simulated ground motions.

Additionally, integrating spectrum-compatible earthquake records into structural design processes ensures that buildings are assessed against a wide array of potential ground motions, thereby improving their resilience. This approach strengthens the ability of structures to withstand unpredictable seismic events, ultimately contributing to more reliable and effective design methodologies.

In several tectonically active regions across the globe, there exist zones characterized by inadequate historical and instrumental seismic data, constraining the availability of empirical ground motion records that structural engineers can utilize as a reference. Under such constraining conditions, there emerges an imperative for structural engineers to generate synthetic ground motion time histories that are congruent with the designated target response spectra. Additionally, the synthesized database of accelerograms must replicate the characteristics of actual seismic records, encapsulating considerations such as soil type, frequency content, and duration, among others. Hence, this study introduces an innovative method for the production of multiple high-quality accelerograms by harnessing the advanced capabilities of Generative Adversarial Networks (GANs). This investigation leverages the distinctive properties of GANs to fabricate artificial accelerograms that are consistent with the design spectrum. The accelerograms generated through this method bear a close visual resemblance to the archetypal recordings within the database while presenting subtle variations in seismic parameters, including peak ground acceleration, peak ground velocity, peak ground displacement, and others.

2. Generative Adversarial Network

A Generative Adversarial Network (GAN) is a deep learning generative model that has been primarily developed to generate high-quality samples (Goodfellow et al., 2014). It characteristically comprises a parameterized generator and discriminator, which may be represented by any form of neural network or a set of predetermined functions. During the training phase of a GAN, the generator and discriminator are pitted against each other in a manner akin to a competitive game. Within this adversarial context, both entities strive iteratively to optimize their outcomes while concurrently attempting to impede the progress of their adversary. The generator, which lacks direct access to the database under consideration, endeavors to produce samples of exceptional quality through a process of trial and error, thus aiming to predict the evaluations of the discriminator. Conversely, the discriminator is schooled by utilizing authentic samples, acquiring the ability to assign a score to the data forwarded by the generator. Elaborating further, imagine a scenario where the generator's objective is to craft synthetic data that will deceive the discriminator. Conversely, the discriminator exerts effort in differentiating between synthetic and genuine data produced by the generator. When the generator effectively confuses the discriminator, the latter adjusts itself to better distinguish synthetic data. Conversely, when the discriminator identifies the synthetic data, the generator revises its approach to once again deceive the discriminator. This iterative process persists until the discriminator can no longer improve its ability to discern the synthetic data. At this juncture, the probability that the discriminator correctly classifies real versus synthetic data approaches 50% (Goodfellow et al., 2014), signifying that the synthetic data closely approximates the real data set.

2.1. Mathematical Principles

From a mathematical perspective, the training of a GAN can be viewed as a MinMax game between the generator and the discriminator. In this game, the generator improves its capability to produce deceptive samples, while the discriminator enhances its ability to distinguish synthetic from real data. This competition culminates in the creation of high-quality samples in various applications where GANs are utilized. The optimization process, however, may present challenges due to nonconvex loss functions and high-dimensional parameter spaces. Therefore, gradient-based algorithms are typically employed to minimize the losses of both the generator and discriminator concurrently. The general structure of a typical GAN is depicted in Figure (1).

In this figure, x represents actual data points, and z denotes a high-dimensional random variable, commonly referred to as a code. We now introduce the probability distributions of the real data, $P_{data}(x)$, the generative model, $P_G(g)$, and the random variable, $P_Z(z)$. The discriminator function $D(.)$ and the generator function $G(.)$ are depicted in Figure (1). To calculate the probability of the discriminator recognizing the real data, $D(x)$ is employed as a sigmoid function (Goodfellow et al., 2014).

Additionally, z generates the synthetic data in accordance with P_G. As previously discussed, the generator is trained to produce synthetic samples $\hat{x}$ that are statistically similar to real samples. Conversely, the discriminator is trained to assign higher scores to x and lower scores to $\hat{x}$ to counteract the generator's attempts (see Figure 1). The value function is provided below (Goodfellow et al., 2014):

$$V(D, G) = V(\theta_D, \theta_G) = \mathbb{E}_{x\sim P_{data}(x)}\left[\log D(x)\right] + \mathbb{E}_{x\sim P_G(x)}\left[\log(1 - D(x))\right] = \mathbb{E}_{x\sim P_{data}(x)}\left[\log D(x)\right] + \mathbb{E}_{z\sim P_z(x)}\left[\log(1 - D(G(z)))\right] \quad (1)$$

In this context, θ_D and θ_G represent the parameters of the discriminator and generator functions, respectively. Additionally, $\mathbb{E}_{a\sim P_\beta(x)}[\cdot]$ signifies the expectation function of the data or random variable α sampled from the distribution P_β. As previously mentioned, the discriminator attempts to distinguish whether the input data are synthetic or actual. Consequently, the cross-entropy can be succinctly expressed in terms of the loss function as follows:

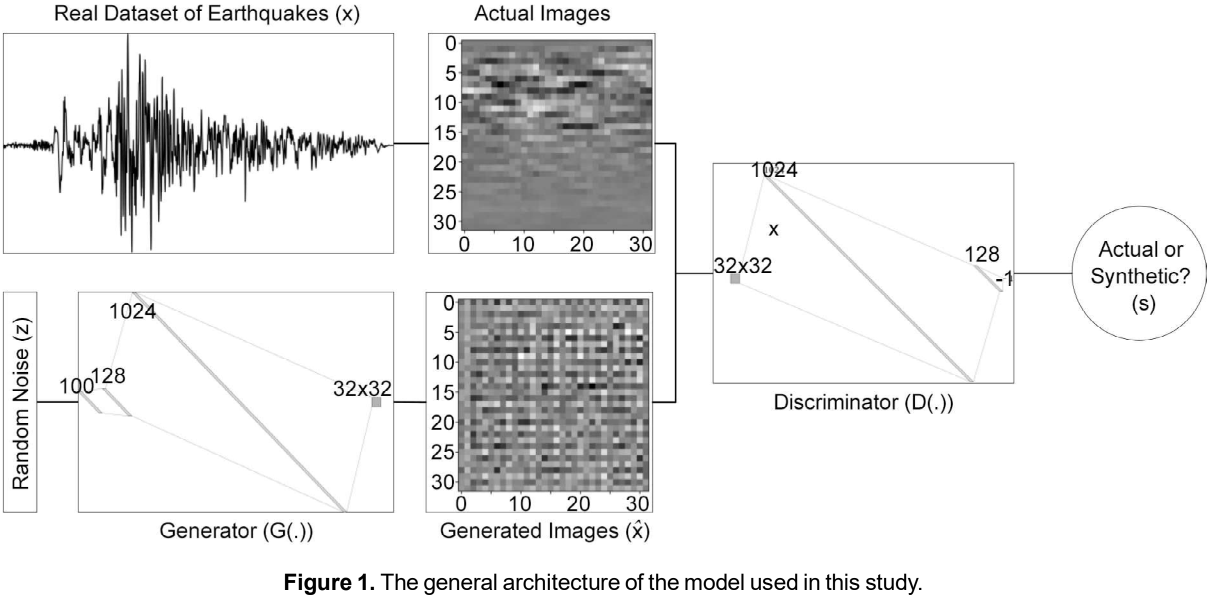

Figure 1. The general architecture of the model used in this study.

$$\mathcal{L}_D = -\frac{1}{N}\sum_{i=1}^{N} y_i \log D(x_i) - \frac{1}{N}\sum_{i=1}^{N}(1-y_i)\log(1-D(x_i)) \tag{2}$$

where N is the number of samples. In this framework, actual data x_i is labeled as 1, while synthetic data $\hat{x}_i$ is labeled as 0. Accordingly, the label y_i is assigned the values of 1 and 0, respectively. Thus, Equation (2) can be simplified as follows:

$$\mathcal{L}_D = -\mathbb{E}_{x\sim P_{data}(x)}\left[\log D(x)\right] - \mathbb{E}_{x\sim P_G(x)}\left[\log(1-D(x))\right] \tag{3}$$

As $D \to \infty$ in Equation (2), the empirical value of $\mathcal{L}_D$ asymptotically converges to its theoretical value. In other words, when optimizing the discriminator by evaluating its parameters, $\hat{\theta}_D$, we effectively minimize the negative value of the value function, $-V(D, G)$. This implies that we are maximizing $V(D,G)$ as shown below:

$$\hat{\theta}_D = argmin_{\theta_D}\mathcal{L}_D = argmax_D V(D, G) \tag{4}$$

Consequently, the game aims to maximize the discriminator's ability to discern the difference between $P_G(g)$ and $P_{data}(x)$ comprehensively. As previously mentioned, during the optimization process, the generator produces synthetic data and endeavors to generate high-quality synthetic data to deceive the discriminator. Since GAN training is a type of MinMax game, the generator strives to minimize the discriminator's gain.

Therefore, the discriminator's gain can be considered the generator's loss function, as follows:

$$\mathcal{L}_D = \max_D V(D,G) \tag{5}$$

for which the parameters are ultimately estimated as follows:

$$\hat{\theta}_G = argmin_{\theta_G}\mathcal{L}_G = argmin_G \max_D V(D,G) \tag{6}$$

The aforementioned MinMax game aims to iteratively optimize the loss functions of both the discriminator and the generator until both functions converge to their respective local minima. The evaluated parameter sets at these points are denoted by $\hat{\theta}_G$ and $\hat{\theta}_D$.

3. Database

The construction or preparation of a database constitutes an essential component within the majority of deep learning methodologies. Pertinently, a formidable challenge is the generation or procurement of databases that are adequately suited for earthquake studies, aligning with the requisite conditions for effective nonlinear dynamic analyses of structural systems. The challenge arises from the scarcity of earthquake incidents that meet the necessary criteria for such sophisticated assessments.

Subsequent segments will elucidate the efficacy of the proposed generative adversarial network (GAN) in synthesizing an extensive array of artificial spectrum-compatible earthquake accelerograms, utilizing a finite set of ground motion records. For the successful application of this technique, it is requisite to begin with a minimal collection of accelerograms that are congruent with the prescribed target spectrum. Such necessary accelerograms can be fabricated using well-documented methodologies found within the scholarly discourse, as expounded in Section 1 (Introduction).

In the present study, the wavelet-based algorithm delineated by Hancock et al. (2006) is employed to calibrate earthquake accelerograms to correspond with a designated target response spectrum.

In order to assess the efficacy and precision of Generative Adversarial Networks (GANs) in generating accelerograms that meet desired criteria, a common illustrative case is selected with a duration of 20 seconds and a sampling interval of 0.02 seconds.

Accordingly, each accelerogram can be represented by an array comprising 20/0.02 = 1000 discrete values. The nearest equivalent square two-dimensional array, or 'image,' accommodating approximately 1000 elements, is one with dimensions of 32^2 = 1024 elements. The discrepancy between these two figures (specifically, 1000 and 1024) can be reconciled by the inclusion of 12 nullified or zero-value elements, strategically positioned at the onset and conclusion of the seismological dataset within the database.

4. Model

As previously mentioned, the foundational architecture of the model presented in the current study is based on the Generative Adversarial Network (GAN) framework, as explicated by Goodfellow et al. (2014). A schematic representation of the model's framework is illustrated in Figure (1). Within this framework, earthquake instances from the database are transmuted into two-dimensional representations, which subsequently serve as input for the discriminator component. Hence, the discriminator is subject to training with the aforementioned representations. Conversely, the generator component endeavors to fabricate images that emulate the characteristics of those originating from the output database, with the intent of devising images indistinguishable from authentic samples by the discriminator. Upon the culmination of the training phase, it is expected that the generator will have the capacity to synthesize images of satisfactory quality. Utilizing this architecture, it is feasible to generate a multitude of accelerograms that possess attributes akin to those cataloged in the database.

4.1. Generator

The configuration of the generator's architecture is contingent upon the temporal extent of the seismic event in question. Specifically, the training of the network for earthquakes with protracted durations necessitates dimensions of greater magnitude within the layers, as opposed to those required for earthquakes of shorter durations. Furthermore, the selection of the number of layers is influenced by the intricacy of the problem at hand. Nevertheless, the researcher's expertise plays a pivotal role in the development of an optimal architectural framework, although empirical methodologies involving trial and error can also yield satisfactory outcomes. An exemplary model of the generator, as employed in the present investigation, is depicted in Figure (2).

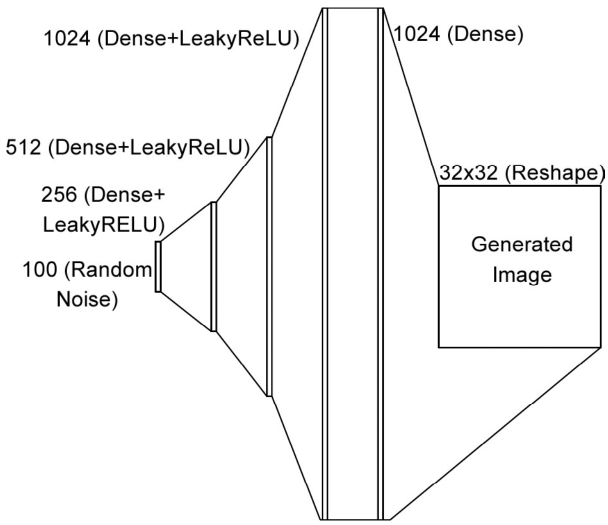

Figure (2). A characteristic generator architecture employed within the model for this investigation.

4.2. Discriminator

The discriminator's role is to evaluate the seismic events it receives and subsequently ascertain the degree of congruence with the database entries.

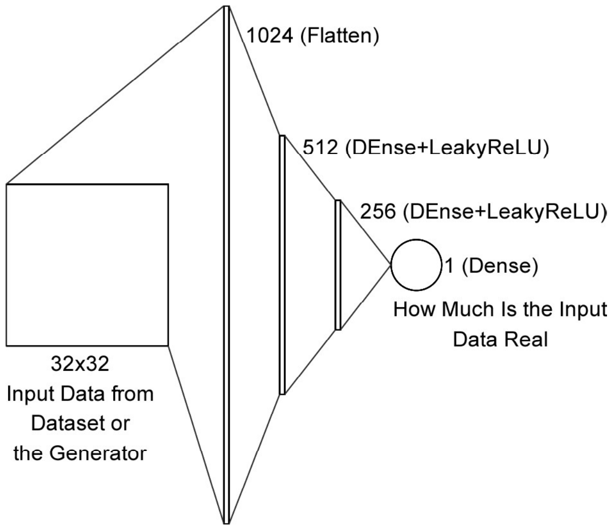

Figure (3). A characteristic discriminator architecture employed within the model for this investigation.

As a result, the terminal layer of this network should ideally be a singular dimension, signifying the classification of an authentic seismic occurrence. Conversely, the input for the discriminator ought to be an exact match to the two-dimensional representations derived from the seismic events documented in the database, ensuring alignment with the generator's output. A representative discriminator model, as utilized in the present analysis, is illustrated in Figure (3).

5. Results

In this section, a series of computational experiments are conducted to determine the efficacy of the Generative Adversarial Network (GAN) model in generating suitable accelerograms.

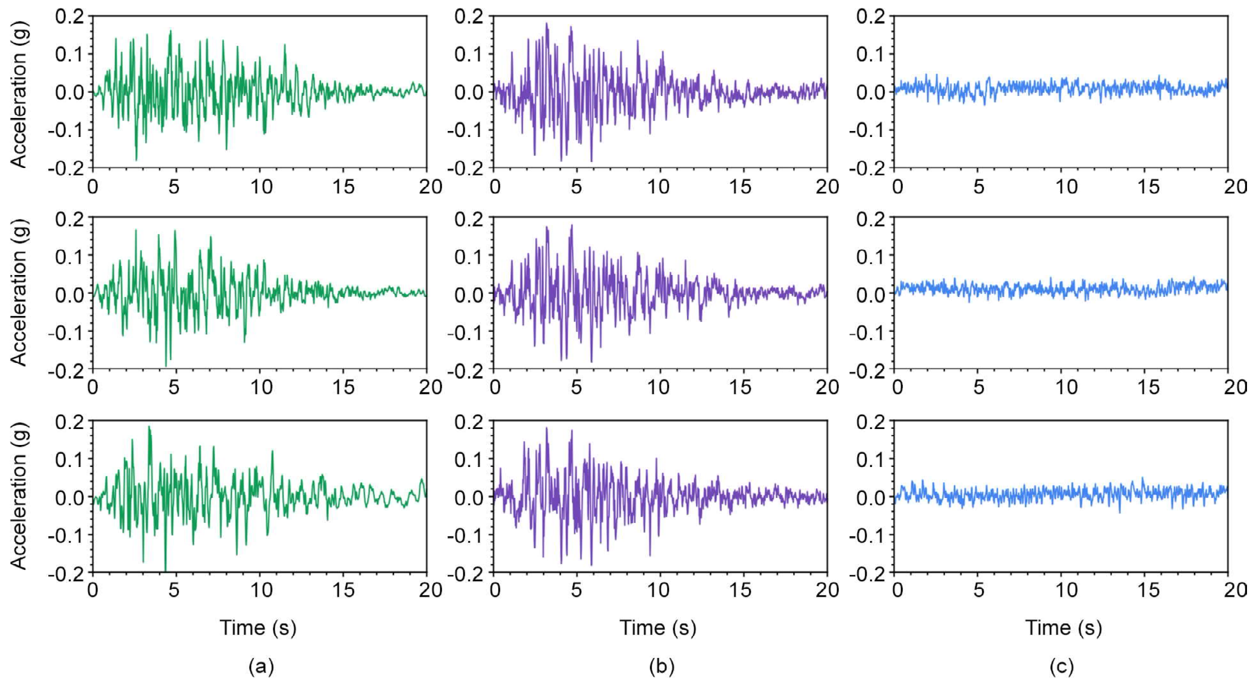

Figure 4. Comparative Study of (a) Dataset Accelerograms Versus (b) Post- and (c) Pre-Training GAN Model Outputs.

5.1. Visual Analysis of GAN-Generated Accelerograms

Upon examining the validation methodologies applied across previous studies in diverse scientific disciplines, visual inspection emerges as one of the foremost approaches. The initial experiment is relatively straightforward, involving a visual observation of the training progression to scrutinize the enhancement in the generator's precision. In Figure (4), three accelerograms from the database are juxtaposed with the outcomes produced by the GAN model pre- and post-training, demonstrating the model's proficiency in synthesizing high-quality samples.

5.2. Comparison of Response and Design Spectra

The second numerical experiment was conducted to assess the coherence between the response spectrum derived from the synthesized accelerograms and the predetermined target design spectrum. As previously noted, a finite assemblage of ground motion records was utilized to synthesize an extensive series of artificial seismic accelerograms that conform to the desired spectrum. Displayed in Figure (5a) is a representative artificially generated accelerogram, with its corresponding response spectrum depicted in Figure (5b). This is set against the benchmark

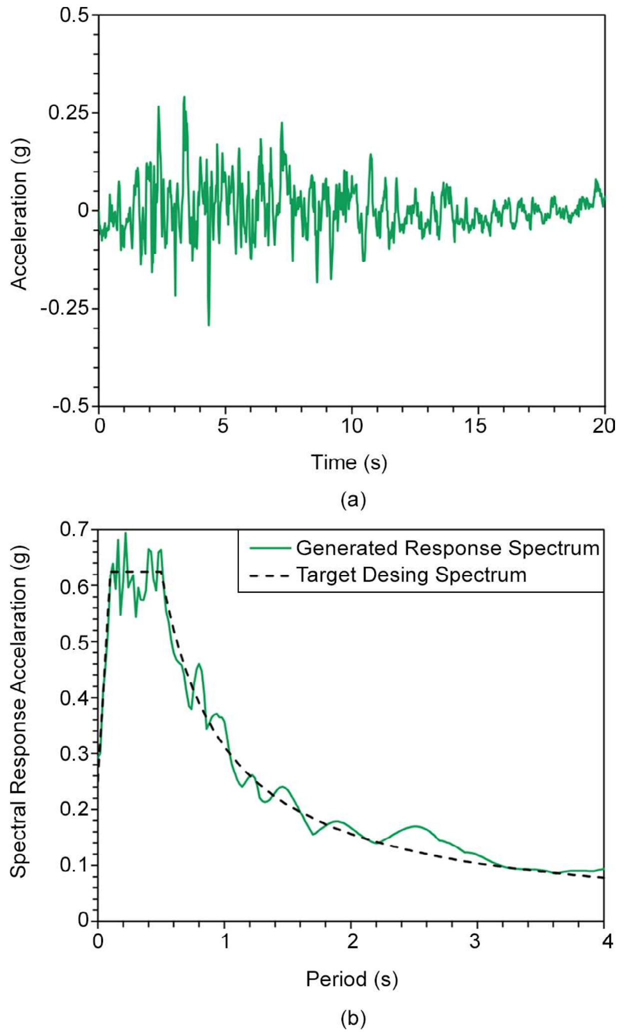

Figure 5. (a) An exemplar of an artificial earthquake accelerogram synthesized via the GAN methodology is presented. (b) The spectral accelerations derived from the aforementioned accelerogram are juxtaposed with the target design spectrum.

target design spectrum specified by Iranian Standard No. 2800 (incorporating 5% damping) for ground type II with a seismic coefficient of A = 0.25. An analysis of Figure (5) reveals that the spectral accelerations of the synthetically produced accelerograms exhibit compatibility with the target design spectrum's stipulations.

5.3. Goodness of Generated Artificial Accelerograms

As first introduced by Arias (1970), the Arias intensity (I_A) stands as a pertinent metric for assessing the cumulative energy imparted by intense ground motion occurrences. This parameter pertains to the spectrum of energy emanating from the subjected ground motion and serves as an indicator of seismic strength with implications for structural integrity. In Figure (6), a comparative analysis is presented between the I_A values derived from the time histories depicted in Figure (5) and those stemming from seismic ground motions utilized as inputs within the GAN database. Evidently, the I_A values of the generated time history align remarkably well with those of the target time history.

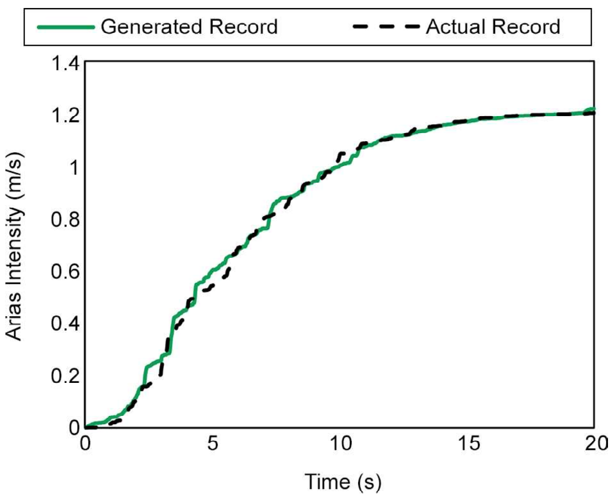

Figure (6). The Arias intensity (I_A) of generated artificial accelerograms of Figure (5) (solid line) and the I_A of input earthquake ground motions (dashed line).

5.4. Comparison of Seismic Parameters

To broaden the investigation into seismic parameters, a comparative analysis is conducted between the accelerogram illustrated in Figure (5) and the actual accelerogram depicted in Figure (6), as presented in Table (1). Analysis of the data

Table (1). Comparing seismic parameters of the actual ground motion with the generated ground motion illustrated in Figure (5).

Seismic Parameter	PGA (g)	PGV (cm/s)	PGD (cm)	A95 Parameter (g)
Actual Record	0.32	34.3	130	0.217
Generated Record	0.29	128.6	1128	0.214

provided in Table (1) reveals that the simulated ground motions demonstrate coherent seismic characteristics. Notably, the generated ground motion has similarities to actual seismic records in its overall characteristics, but it also has noticeable differences in specific features.

6. Conclusions

The scarcity of accessible accelerograms presents a significant impediment to achieving dependable outcomes when employing Deep Learning (DL) algorithms. To surmount this obstacle, the present study introduces a Generative Adversarial Network (GAN) for the training of generative models. Typically, artificial ground accelerograms that accord with a designated target response spectrum are synthesized for implementation in nonlinear dynamic structural analyses. This study delineates an efficacious algorithm wherein the established generative paradigm of the GAN is embraced and applied. By employing this algorithm, it is feasible to produce an abundant quantity of artificial spectrum-compatible accelerograms efficiently, despite the limited availability of ground motion datasets. The subsequent conclusions have been inferred:

- The GAN model possesses the capability to synthesize plausible artificial ground accelerograms by leveraging as few as eight seismic records to train the network. The incorporation of a more extensive array of seismic records as input has the potential to augment the performance of the GAN.
- The algorithm proffered herein demonstrates substantial robustness and is not inherently constrained by specific suppositions concerning the number of seismic records required as input for network training, the duration of said records, or the temporal increments involved.
- Upon visual examination of the output, the results

suggested that the proposed GAN was capable of producing a multitude of accelerograms that were not only compatible with the target spectrum but also exhibited a realistic appearance.

- Scrutiny of the synthesized artificial response spectra disclosed that the response spectral curves, derived from the generated accelerograms, aligned favorably with the predetermined target design spectrum.
- A comprehensive repository of accelerograms has been constituted, ensuring compatibility with the diverse classifications of soils and seismic hazards outlined in the Iranian Standard No. 2800. The outcomes must be scaled by the importance factor (I), as well as the response modification coefficient (R_u), to ensure appropriate application.
- This study employed the methodology proposed by Hancock et al. (2006) to generate the initial dataset. This methodology was selected as a sample to show the applicability of the present study. The integration of multiple methodologies, as well as the adoption of more advanced methods, could further enhance the overall quality of the final results.

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