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NEURAL NETWORK-DRIVEN FORECASTING OF AFTERSHOCK DYNAMICS FOR ENHANCED SEISMIC RESILIENCE IN STRUCTURAL ENGINEERING

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ABSTRACT

This review investigates the application of neural network algorithms in forecasting aftershock dynamics to enhance seismic resilience in structural engineering. Artificial neural networks (ANNs) offer a promising approach for modeling aftershock sequences and predicting their impact on structures, thereby addressing the critical need for accurate and robust seismic evaluations. The study emphasizes the importance of integrating mainshock-aftershock sequences in seismic assessments and highlights the challenges associated with accounting for aftershock influences in structural design. Various methodologies leveraging ANNs are analyzed, accompanied by case studies demonstrating their predictive accuracy and practical benefits. The review underscores key aspects such as advanced data processing techniques, cutting-edge sensor technologies, and the identification of unique frequency patterns essential for precise seismic analysis. The significance of post-yield stiffness ratios, displacement metrics, energy distribution, and plastic hinge behavior in structural performance assessment is also discussed. By synthesizing current research, this review aims to advance seismic engineering practices, enhance structural resilience, and promote safety in earthquake-prone regions.

KEYWORDS: Neural Networks, Aftershock Prediction, Seismic Assessment, Structural Resilience, Seismic Behavior

INTRODUCTION

It is common for mainshock-aftershock sequences to occur after major seismic events (Abdollahzadeh et al., 2019). The mainshock is the initial and typically largest earthquake that releases accumulated stress along a fault line. Aftershocks are smaller earthquakes that occur in the same area following the mainshock. These subsequent tremors can significantly affect structures already weakened by the mainshock (Wen et al., 2017). Aftershocks can pose a significant danger to the stability of buildings and infrastructure, as they can worsen existing damage and weaken the resilience of these structures (Y. Zhang et al., 2022).

It is a widely acknowledged phenomenon that major seismic events are often followed by mainshock-aftershock sequences (Pang et al., 2020). The mainshock, as the initial and typically largest earthquake, releases accumulated stress along a fault line. It is followed by aftershocks—smaller earthquakes occurring in the same area—that can significantly impact structures already weakened by the mainshock. Aftershocks pose a serious threat to the stability of buildings and infrastructure, often worsening existing damage and further compromising structural resilience (Iervolino et al., 2020). It is commonly accepted that after a big earthquake, there are usually aftershocks that follow. The mainshock happens first and is usually the stronger earthquake (Zhao et al., 2020). It releases the tension along a fault line and is then followed by smaller earthquakes known as aftershocks (Song et al., 2016). Aftershocks can significantly impact structures already weakened by the mainshock, further compromising their stability, exacerbating existing damage, and reducing overall resilience (Omranian et al., 2018). It is widely acknowledged among experts in the field that following a significant earthquake, it is not uncommon for a series of subsequent aftershocks to occur (Ding et al., 2021). The initial earthquake, known as the mainshock, typically has the greatest magnitude and releases built-up tension along the fault line. Aftershocks, though often smaller, occur due to continued stress in the surrounding area and can still significantly impact buildings and infrastructure already weakened by the mainshock (Vahedian et al., 2022). They can exacerbate existing damages and ultimately reduce the overall resilience of these structures, thus posing a serious threat to public safety.

The primary aim of this review is to explore the potential of neural network-based algorithms in forecasting aftershock dynamics and enhancing the seismic resilience of structures, thereby contributing to more accurate and comprehensive seismic evaluation methodologies. Given the unpredictable nature of aftershocks and their significant impact on structural integrity, there is a pressing need to develop advanced predictive models. Neural networks, with their capability to process complex datasets and identify patterns, offer an effective solution for improving seismic assessments and ensuring structural safety. The objectives of this review are to examine the importance of mainshock-aftershock sequences in seismic assessments and the challenges associated with incorporating aftershock effects into structural design. It aims to investigate the application of neural networks in predicting aftershock characteristics and their impact on structural integrity. Additionally, the study seeks to analyze existing methodologies employing neural networks for aftershock prediction and present case studies demonstrating their effectiveness. It also aims to identify potential benefits and challenges of integrating neural networks into seismic evaluation frameworks. Finally, the study suggests future research directions for enhancing neural network-based seismic assessment techniques, ultimately contributing to safer and more resilient structural designs in seismic zones. By achieving these objectives, this review paper aims to shed light on the significance of neural network-based predictions of aftershock characteristics, ultimately contributing to more accurate and comprehensive seismic evaluations of structures subjected to mainshock-aftershock sequences.

MAINSHOCK-AFTERSHOCK RELATIONSHIP

Correlation between Mainshock Characteristics and Subsequent Aftershocks:

Understanding the relationship between the characteristics of a main earthquake and its subsequent aftershocks is of utmost importance in the field of seismic activity (Rajabi & Ghodrati Amiri, 2020). The behavior of structures during earthquakes is significantly affected by this connection. Aftershocks are a direct consequence of the stress redistribution that occurs in the Earth's crust after a main earthquake. This redistribution can trigger the activation of new fault segments or reactivate previously existing ones, ultimately leading to aftershocks (Ding et al., 2020). It is essential to comprehend the intricacies of this phenomenon to better prepare for any seismic activity in the future. Several key factors influence the correlation between mainshocks and aftershocks:

- **Magnitude:** Understanding the relationship between a main earthquake and its aftershocks is essential in seismic studies, as it greatly influences structural behavior during seismic events. Aftershocks occur due to the redistribution of stress within the Earth's crust following a primary earthquake, which may activate new fault segments or reactivate existing ones (Rajabi & Ghodrati Amiri, 2022). It is essential to comprehend this phenomenon's intricacies to prepare better for any seismic activity in the future.
- **Distance and Location:** The correlation between the characteristics of a primary earthquake and its subsequent aftershocks is crucial in the study of seismic activity, significantly influencing the behavior of structures during such events. Aftershocks result from the redistribution of stress in the Earth's crust following a primary earthquake, which can activate previously dormant fault segments or reactivate existing ones (Fayaz & Galasso, 2022). It is imperative to grasp the intricacies of this phenomenon to better prepare for any future seismic activity.
- **Time:** It's crucial to deeply understand how the primary characteristics of an earthquake relate to its subsequent tremors, particularly in seismic studies. This connection significantly influences structural behavior during such events. Aftershocks occur due to the redistribution of stress within the Earth's crust following the initial quake (Oh et al., 2020). This redistribution can trigger previously inactive fault segments or reawaken existing ones, leading to aftershocks. Understanding this complex phenomenon is vital to ensure preparedness for future seismic activity.

The authors emphasizes the significance of sequential ground motion pairing in the context of mainshock-aftershock sequences. Their findings reveal that the correlation between ground motions from mainshocks and aftershocks significantly affects the maximum story drift ratio. The study offers practical recommendations for selecting aftershock records based on these insights (Shokrabadi & Burton, 2018). Other authors explores explore the phenomenon of period elongation in deteriorating structures subjected to mainshock-aftershock sequences. They develop inelastic response spectra by considering various parameters, both in terms of ground motion characteristics and structural properties (Di Sarno & Amiri, 2019). The research by authors delves into the impact of modeling uncertainties on the residual drift of steel structures during mainshock-aftershock sequences. Their findings highlight the sensitivity of seismic demands to strength and ductility modeling parameters, particularly during aftershocks (Basim et al., 2022).

Author's work focuses on establishing fragility relationships for reinforced concrete (RC) frames subjected to mainshock-aftershock sequences, using fiber-based finite element models. The research confirms the significant influence of multiple earthquakes on the vulnerability of RC frames (Abdelnaby, 2018). The study investigates the seismic performance of reinforced concrete frames equipped with lead viscoelastic dampers (LVD) under mainshock-aftershock sequences. Despite weakened RC components, the research demonstrates that LVD systems substantially enhance seismic performance during mainshocks and aftershocks (W. Huang et al., 2022). Authors investigate aftershock and mainshock-aftershock risks in reinforced concrete frames. They find post-mainshock seismic hazard and reduced structural capacity significantly impact seismic risk. Aftershocks are shown to significantly increase collapse risk pre-mainshock, necessitating design adjustments (Shokrabadi & Burton, 2018).

It was explored that AP1000 nuclear plant reliability under mainshock-aftershock sequences. Seismic sequences lead to higher dynamic responses and greater plant damage than single mainshocks. Aftershocks reduce plant reliability, especially with increased peak ground acceleration (PGA) (Pang et al., 2023). The study correlations between non-spectral and cumulative-based ground motion intensity measures (IMs) and structural demands in mainshock-aftershock sequences. Optimal IMs for regular systems are identified for efficiency and sufficiency considering various demand parameters (Amiri et al., 2022). It was investigated that aftershock duration and productivity in Greece. Aftershock duration depends on the mainshock rupture process. Other factors like seismic coupling, focal depth, and stress drop also affect aftershock productivity. Regional parameters may aid early aftershock rate predictions (Bonatis et al., 2022).

Authors study how aftershocks impact the seismic vulnerability of transmission towers in mainshock-aftershock sequences. Aftershocks worsen tower damage and raise the likelihood of exceeding damage states (J. Liu et al., 2022). Authors find that longer-duration aftershocks can cause more severe cumulative damage to containment structures damaged by mainshocks. Accounting for aftershocks and their duration is crucial for accurate safety assessments (Zhai et al., 2018). Other study developed a stochastic procedure to simulate synthetic mainshock-aftershock ground motion sequences. This approach simplifies prediction equations and aids in incorporating aftershock effects into seismic analysis and design (Hu et al., 2018). Another study proposed analytical equations to predict residual displacement ratios for structures during mainshock-aftershock sequences. These equations assist in seismic assessments (Amiri & Bojórquez, 2019).

Other study was investigated the relationship between afterslip moment and aftershock productivity. They find that adding afterslip moment to mainshock moment doesn't enhance aftershock predictions (Churchill et al., 2022). Authors assessed the reliability of cantilevered retaining walls considering uncertainty in mainshock-aftershock sequences. They conclude that aftershocks degrade structural reliability, particularly with higher design requirements (Zhou et al., 2022).

Authors present a procedure to estimate the failure probability of mainshock-damaged structures during aftershocks. It considers the spatial location of aftershocks and the time interval between mainshocks and aftershocks. They apply this to the 2021 Yangbi earthquake sequence and investigate how the failure probability of a 5-story concrete frame structure varies over time (Pu & Li, 2023). Other study was focused on aligning the relative locations of mainshock slip and aftershocks using empirical approaches. They find consistent spatiotemporal slip patterns across different empirical Green's functions. Their analysis reveals that large interplate aftershocks within five years of major megathrust earthquakes tend to occur on the periphery or outside the main slip regions (Chang & Ide, 2020). Another study was conducted a risk-based seismic performance evaluation of SMA braced steel frames. They generate seismic demand hazard curves for maximum and residual interstory displacement response (Shi et al., 2020). Authors investigate time-dependent risk assessment of containment buildings subjected to mainshock-aftershock seismic sequences. They conduct parametric studies to quantify the effect of aftershocks on seismic risk. Their findings underscore the importance of considering aftershock contributions in seismic risk management to ensure the safety of containment buildings throughout their service life (Bao et al., 2022).

Frequency Content, Amplitude Decay, and Time Delay between Mainshocks and Aftershocks:

The frequency content, amplitude decay, and time delay between mainshocks and aftershocks play pivotal roles in shaping the seismic behavior of structures and their responses to subsequent events.

1. **Frequency Content:** Seismic waves from mainshocks and aftershocks differ in frequency content. Mainshocks typically encompass both high and low frequencies, while aftershocks exhibit a more limited range. These variations influence structural response, as certain frequencies may align with a building’s natural frequency, amplifying the risk of damage (Gatti et al., 2018).
2. **Amplitude Decay:** Amplitude decay refers to the reduction in the strength of seismic waves as they travel away from an earthquake's origin. Aftershocks generally exhibit lower amplitudes than the main shock due to energy loss while passing through the Earth's crust. This diminishing amplitude affects the impact of aftershocks on structures located farther from the epicenter (Mignan & Broccardo, 2020).
3. **Time Delay:** Amplitude decay is a natural process that occurs as seismic waves move away from an earthquake's epicenter. As they travel through the Earth's crust, these waves gradually lose energy, reducing their intensity. This effect is especially noticeable in aftershocks, which are generally weaker than the main earthquake. The diminishing strength of seismic waves influences the impact of aftershocks on distant structures. Understanding amplitude decay is essential for predicting and minimizing earthquake-related damage.

When seismic waves travel away from the epicenter of an earthquake, they experience a natural occurrence known as amplitude decay. As they pass through the Earth's crust, the waves lose energy and become weaker. This effect is especially noticeable in aftershocks, which are usually less powerful than the initial shock. The results of amplitude decay can greatly influence the potential impact of aftershocks on structures located further from the epicenter. It is essential to comprehend this process in order to predict and reduce the damage caused by earthquakes.

Authors studied hydraulic arched tunnels under mainshock-aftershock ground motion sequences. Aftershocks increase damage in various tunnel sections, emphasizing the need to consider them in seismic tunnel design (Sun et al., 2020). Other authors provide a basis for efficient parameter estimation in near-fault ground motion simulations, improving simulation accuracy and seismic hazard assessment (Dang et al., 2022). Another study was to analyze the statistical correlation between spectral accelerations in mainshock-aftershock ground motion pairs. Aftershock spectral accelerations show mild to weak correlation with mainshock values (Papadopoulos et al., 2019). Other study related to developing a bivariate model to estimate conditional probabilities for offshore mainshock-aftershock intensity measures. The model effectively characterizes statistical characteristics and dependence structures (Bai et al., 2022). Authors explore aftershock triggering mechanisms, including off-fault earthquake swarms associated with atmospheric pressure changes after the mainshock. Multiple triggering mechanisms may influence aftershock occurrence (Meng et al., 2018).

The study was carried out to establish a finite element model for single-layer reticulated domes. They simulate extreme earthquakes through ground motion sequences, finding that even after an extreme mainshock, the structure retains loading capacity and safety despite local plastic damage (H. Huang et al., 2021). Another study was related to examine the performance of damaged viscoelastic dampers during main shocks and aftershocks. The study suggests that although damaged dampers may not perform optimally, they still outperform undamped structures. Proper repair or replacement is essential before the next major earthquake (S.-J. Wang et al., 2021). Others analyze strong-motion data during the Emilia seismic sequence. The mainshock, followed by aftershocks, caused seismic activity in the region, affecting adjacent fault segments (Luzi et al., 2013). A study carried out to present an analysis of acceleration-time histories during the 2015 Gorkha earthquake in Nepal. They use time-frequency decomposition and polarization analysis to assess the earthquake's frequency content (Bhattarai et al., 2015). The study was related to the foreshock sequence preceding the 2010 Yushu earthquake in the Tibetan plateau. They identify 120 foreshocks using advanced techniques, highlighting their characteristics in relation to the mainshock. The sequence follows Omori's law decay with a p-value of 0.73 and a b-value of 0.66 (Chuang et al., 2023).

TRADITIONAL APPROACHES AND LIMITATIONS

Overview of Conventional Methods Used to Consider Aftershock Effects in Seismic Evaluation:

In the field of seismic evaluation, conventional techniques employed to account for aftershock effects have typically relied on simplified methods that strive to capture the influence of aftershocks on structures (Fayaz & Galasso, 2022). The primary objective of these methods is to offer a fundamental comprehension of the potential impact aftershocks can have on buildings and infrastructure (Ahmed et al., 2022). Some traditional approaches frequently utilized include:

1. **Incremental Analysis:** In the area of seismic evaluation, the usual methods used to consider the effects of aftershocks have relied on simple techniques that aim to grasp how aftershocks can affect structures. These methods aim to provide a basic understanding of the possible consequences of aftershocks on buildings and infrastructure (Dhanya & Raghukanth, 2018).
2. **Design Spectra Modification:** A method to adjust the design spectra for aftershocks involves utilizing empirical relationships that exist between the parameters of the mainshock and those of the aftershocks. However, it is important to note that this technique may oversimplify the complexity of aftershock behaviors, which can be quite intricate (RAJABI et al., n.d.).
3. **Time-History Analysis with Synthetic Aftershocks:** To analyze seismic activity, synthetic aftershocks are created using empirical relations and combined with the mainshock record. This method seeks to account for resonance-related amplification effects, but may not perfectly replicate real aftershock traits (Klimasewski et al., 2021).
4. **Highlighting Limitations such as Simplified Models and Lack of Accuracy:** Although traditional methods can offer some initial insights, they have various limitations that may affect the accuracy and dependability of seismic assessment (Gharehbaghi et al., 2021).

i. **Simplified Models:** Many traditional approaches oversimplify the complicated connections between the mainshock and aftershock features. They may ignore the dynamic interaction between the two seismic events and not consider the different frequency content, amplitude decay, and time delays between them (Dhanya & Raghukanth, 2020).

ii. **Limited Data Consideration:** Conventional approaches may overlook numerous historical mainshock-aftershock pairs, resulting in a narrow range of data. This may lead to insufficient diversity in aftershock behaviors being represented (Sreenath et al., 2023).

iii. **Neglecting Uncertainties:** Forecasting aftershocks with precise accuracy can prove to be a daunting task. Conventional methods often overlook the uncertainties associated with the phenomenon, failing to account for the unique characteristics that may precede or follow an aftershock. Consequently, predicting the likelihood of aftershock occurrences remains a challenging feat (Jozinović et al., 2020).

iv. **Inaccurate Response Prediction:** Predicting aftershocks with precise accuracy can be a difficult task. Traditional methods often neglect the uncertainties connected with the event, failing to recognize the distinct features that may come before or after an aftershock. As a result, forecasting the possibility of aftershocks happening remains a challenging achievement (Kuang et al., 2021).

Neural network-based methods offer a promising solution to these challenges by leveraging extensive datasets to identify complex relationships between mainshock and aftershock characteristics. This approach enhances the accuracy of aftershock impact predictions on structures. This review explores the advancements and benefits of artificial neural networks in improving seismic evaluations, addressing the shortcomings of traditional methods.

Authors employ the Epidemic-Type Aftershock Sequence (ETAS) model to decluster Iran's earthquake catalog (1983–2017). They compare the ETAS model's results with other declustering methods, revealing its high potential for declustering Iranian earthquake data. This research highlights the early stages of ETAS model use in Iranian seismological studies, emphasizing the need for further parametric investigations (Davoudi et al., 2018). The study related to utilize experimentally validated models for Shape Memory Alloy (SMA) and Fiber-Reinforced Polymer (FRP) materials to assess the seismic performance of reinforced concrete (RC) frames. They subject these frames to sequential ground motions and analyze damage accumulation and residual drifts. The study compares steel and SMA-FRP reinforcement strategies, providing insights into their seismic performance (Zafar & Andrawes, 2015). Other authors develop a deep learning method for predicting earthquake-induced landslides (EQIL). Their model significantly outperforms conventional methods, achieving an overall accuracy of 91.88%. The study demonstrates that shallow machine learning models capture essential EQIL factors (Y. Li et al., 2021). Other authors explore probabilistic seismic risk assessment, considering seismicity clustering and damage accumulation. They employ the ETAS model to describe earthquake occurrence processes, estimating losses in Central Italy's Umbria region. Their results, based on stochastic event catalogs and damage-dependent fragility functions, are compared with conventional Poisson-based estimates (Papadopoulos et al., 2019).

Other study was carried out to assess the seismic performance of these frames under sequential earthquakes. The study aligns with the Iranian Seismic Code, contributing to the validation of such structures (Mohsenian et al., 2021). In a research, the assumption is that selected mainshocks significantly impact structural responses. They conduct a case study to assess the effects of aftershock record selection on collapse vulnerability. The findings highlight that aftershock fragility can be influenced by record characteristics, particularly response spectral shape (Goda, 2015). Authors explore the aftershock collapse performance of steel buildings equipped with superelastic viscous dampers (SVDs). These SVDs combine shape memory alloy (SMA) cables and viscoelastic compounds to offer self-centering and damping capabilities. Their study analyzes a nine-story steel special moment resisting frame (SMRF) with and without SVDs under seismic sequences through mainshock incremental dynamic analysis (IDA) (Silwal & Ozbulut, 2018).

NEURAL NETWORK APPLICATIONS IN SEISMIC ASSESSMENT

Applications of Neural Networks in Earthquake Analysis Neural networks, an artificial intelligence technique, are becoming more and more useful in many fields such as earthquake engineering and earthquake analysis (R. Zhang et al., 2020). These advanced computational models are capable of analyzing complex data models, making predictions and providing insights that were previously difficult to obtain using traditional methods. Here we examine important applications of neural networks in earthquake measurement (Farfani et al., 2015).

a. Seismic Ground Motion Prediction:

Neural networks will be trained to predict seismic ground motion parameters, including Peak Ground Acceleration (PGA), Peak Ground Velocity (PGV), and Spectral Acceleration. By analyzing historical seismic records, geological data, and other critical factors, they generate precise ground motion estimates. These predictions are essential for seismic hazard assessment and designing earthquake-resistant structures (Di et al., 2020).

b. Health Monitoring:

Neural networks are valuable tools for evaluating the condition of public infrastructure such as buildings, bridges, and dams. By analyzing sensor data from accelerometers, strain gauges, and other monitoring devices, they can identify structural issues or damage resulting from earthquakes. This real-time analysis enables engineers and authorities to make informed decisions regarding structural safety following seismic events (Di et al., 2019).

c. Earthquake damage assessment:

Neural networks can evaluate structural damage following an earthquake by analyzing images, sensor readings, and drone footage. They can identify cracks, deformations, and potential hazards, aiding in prioritizing response efforts and optimizing resource allocation (Iqbal, 2022).

d. Earthquake Risk Assessment:

Neural networks process extensive geological, geotechnical, and structural data to evaluate earthquake risk. They simulate different seismic scenarios, predict potential damage, and assess economic and human impacts. This insight is crucial for urban planning and disaster preparedness (Asim et al., 2020).

e. Ground Motion Simulation:

Simulating earthquake ground motion is crucial for testing designs and assessing seismic performance. Neural networks can generate real-time ground source electrical data using geological and seismic information. These simulations assist engineers in designing and reinforcing structures to better withstand earthquakes (van den Ende & Ampuero, 2020).

f. Earthquake Early Warning Systems:

Neural networks can enhance early warning systems by analyzing seismic data in real time to predict strong earthquakes. These systems utilize advanced predictive models to issue timely alerts, enabling individuals and organizations to take proactive measures to minimize damage and save lives (F. Li et al., 2020).

g. Probabilistic Seismic Hazard Assessment (PSHA):

In PSHA, neural networks enhance the assessment of uncertainty in seismic hazard estimation. They streamline calculations and improve the accuracy of hazard maps, which are essential for building codes and land use planning.

h. Seismic retrofit optimization:

Neural networks can help develop retrofit strategies for existing structures. They can identify a building's weak points and recommend retrofitting to make the building earthquake resistant while reducing construction costs (Xiong et al., 2020).

Authors applied Artificial Neural Networks (ANN) to assess seismic risk and structural damage in masonry buildings. They consider ANN metamodels and data paucity, identifying structure fragility curves that address uncertainties (Ferrario et al., 2017).

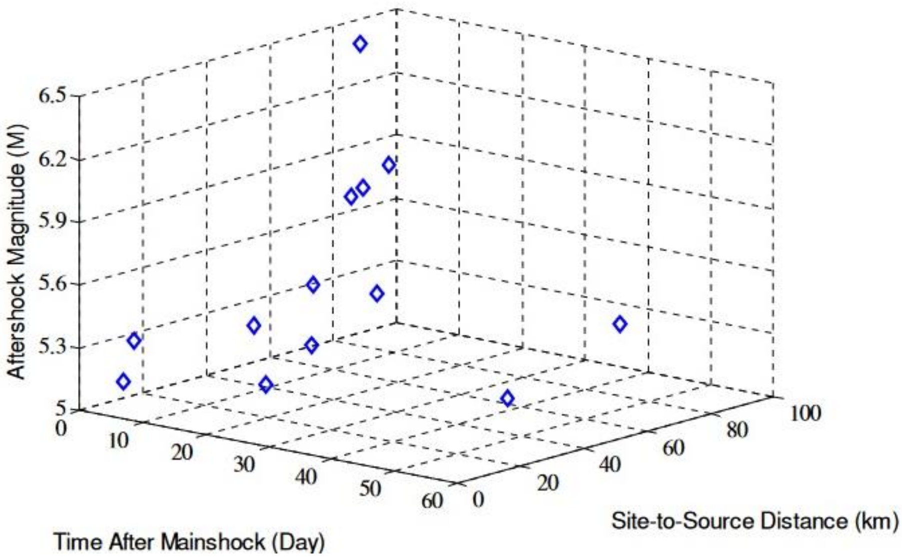

Fig. 1 Simulated Aftershocks (Magnitude ≥ 5) Following a Mainshock of Magnitude 7.5 (Song et al., 2016)

In this simulation, only aftershocks with a magnitude of 5 or greater are taken into account and considered for analysis. Aftershocks are smaller seismic events that follow a larger earthquake and can continue for an extended period after the mainshock. The simulation focuses on these significant aftershocks and their potential impact, often used in seismic risk assessment and preparedness planning.

Estêvão evaluates the accuracy of ANN-based simplified capacity curves for seismic assessments. Precision depends on data quantity, with ANN performing well in domains not well-represented by training data (Estêvão, 2018). The study was carried out compare BP and RBF neural networks for evaluating seismic performance in pier columns. Their results align with hysteresis curves, aiding in reinforced concrete column assessment under various loads (Q. Liu et al., 2020). In other study it was formalized contrastive visual explanations for neural networks. They introduce a methodology to extract contrasts and enhance existing techniques like Grad-CAM for explanation generation (Prabhushankar et al., 2020).

The authors introduce a methodology integrating aleatory and epistemic components into fragility analysis using artificial neural networks (ANNs). Fragility curves are computed with the Monte Carlo method, and the validity of the log-normal assumption is verified. This approach is applied to estimate the failure probability of an electrical cabinet in a reactor building within the KARISMA benchmark (Z. Wang et al., 2018). Other authors the application of ANNs in predicting seismic damage to reinforced concrete (RC) bridges. They emphasize ANNs' effectiveness in damage detection and highlight the significance of reinforcement stresses as a source of uncertainty in RC bridge fragility analysis. ANNs have proven successful in various infrastructure engineering tasks (Shokri & Tavakoli, 2019). It was presented a real-time seismic damage assessment framework based on LSTM neural networks. They analyze LSTM architectures, hyperparameters, and dataset resampling methods. Applying this framework to Tsinghua University campus buildings, the results demonstrate its capability for accurate regional-scale damage assessment in real time (Xu et al., 2021). In the study authors employed a Multilayer Perceptron (MLP) model integrated with GIS for earthquake risk assessment. Their hybrid model demonstrated a 95% accuracy in generating earthquake probability maps (Yariyan et al., 2020).

DATASET COLLECTION AND PREPROCESSING

Extensive datasets are essential for training and validating neural networks in aftershock prediction. These datasets serve multiple purposes, including model training, generalization, and validation. A diverse dataset exposes the neural network to various mainshock-aftershock scenarios, helping it learn complex relationships between mainshock characteristics and aftershock patterns. Additionally, a well-curated dataset enables the model to apply its predictions to a broader range of seismic events beyond the training data. Furthermore, the dataset provides a benchmark to assess the model's accuracy by comparing its predictions with observed aftershock behaviors.

Data for aftershock prediction is sourced from multiple channels. Seismological organizations provide earthquake data, including mainshock and aftershock magnitudes, epicenter locations, ground motion, and time histories. Historical earthquake databases, such as the USGS Earthquake Catalog and the Global Centroid Moment Tensor (CMT) database, offer extensive records of seismic events worldwide. In some cases, Structural Health Monitoring (SHM) systems installed in infrastructure capture structural responses to earthquakes, supplementing seismological data for a more comprehensive dataset.

To compile a dataset, mainshock-aftershock pairs are systematically integrated, ensuring aftershocks are correctly linked to their respective mainshocks. The data then undergoes preprocessing, which includes aligning records in time, filtering frequency content, and normalizing data to enhance suitability for neural network training. However, dataset development comes with challenges. High-quality aftershock data may be scarce, particularly for smaller events or underexplored regions. Ensuring the accuracy and consistency of data is crucial, as errors or inconsistencies can affect prediction reliability. Additionally, geological and tectonic variations influence aftershock behavior, making it difficult to create a dataset that represents all possible scenarios. Data imbalance is another issue, as the distribution of mainshock-aftershock pairs may be uneven across different regions or time periods, potentially limiting the model's ability to generalize effectively.

In conclusion, building reliable datasets for neural network-based aftershock prediction requires careful data selection, integration, and preprocessing. Ensuring accuracy and consistency in these datasets is crucial for developing models that enhance aftershock forecasting and seismic risk assessment.

Neural Network Framework:

For predicting aftershock characteristics, a neural network model is typically built using a feedforward neural network or a recurrent neural network (RNN). These models consist of multiple interconnected layers, allowing them to analyze complex seismic patterns effectively.

Input Features:

The network processes diverse input features, including mainshock parameters (such as magnitude, depth, and location), ground motion records (accelerograms), and geological data. These inputs provide essential context for refining aftershock predictions.

Predicted Outputs:

The model generates predictions related to key aftershock properties, such as spectral characteristics, amplitude attenuation, and the time interval between mainshocks and aftershocks. These insights contribute to a better understanding of aftershock behavior and its structural impact.

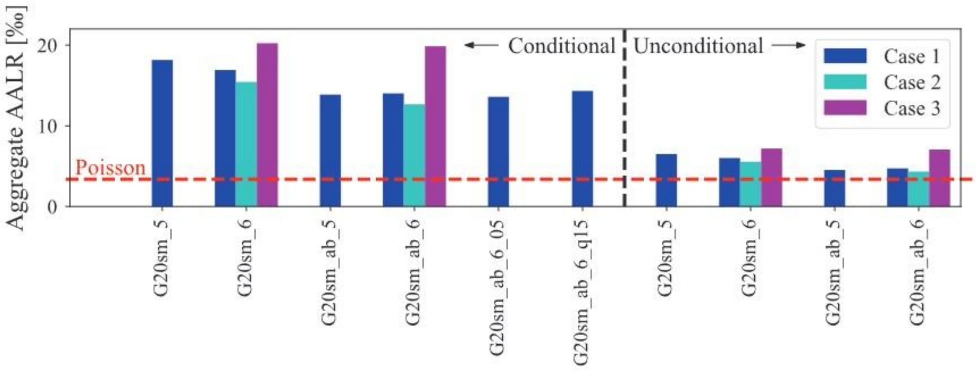

Fig. 2 Comparison of average annual loss ratio (AALRs) Across Various ETAS Models and Loss Estimation Scenarios (Papadopoulos & Bazzurro, 2021)

By integrating advanced neural network architectures with relevant seismic features, researchers aim to enhance aftershock prediction accuracy, ultimately supporting improved seismic risk assessment and structural retrofitting strategies.

In regard to the overall Average Annual Loss Rates (AALR) calculated for the entire portfolio of exposures, Figure 2 provides a comparison of estimates generated by various models using three distinct loss estimation methods (referred to as Cases 1-3) as described earlier. Once more, we observe a notable difference: in the conditional scenario, the AALR for the year following the seismic sequence in Central Italy is approximately four times greater than in the Poisson scenario, which doesn't account for past events in its prediction.

A potent tool for describing aftershock sequences and, more crucially, for assessing the projected aftershock decay rate, which can be extremely critical for disaster management following a major earthquake. Aftershock frequency (Mm) at time t following a mainshock is expected to be (Bonatis et al., 2022):

$$\lambda(t) = \frac{10^{a+b(M_m - M_{min})}}{(t+c)^p} \tag{1}$$

In the context of the frequency-magnitude distribution, the variable 'b' represents the slope, indicating how the frequency of seismic events (such as aftershocks) changes concerning their magnitude. Meanwhile, 'a' serves as a parameter signifying the productivity of aftershocks. Additionally, 'p' and 'c' stand as parameters for the Modified Omori Law (MOL), which describes the temporal decay of aftershock activity and the time shift before this activity commences, respectively. 'Mmin' denotes the minimum magnitude threshold below which seismic events are not considered part of the sequence in question.

The data processing was meticulous, aiming for precision and resolving modeling uncertainties. Here used Episensors (Kinemetrics) for ground acceleration within our 0.25–16 Hz range. Data was converted to ground velocity, and it was visually inspected each seismogram. Problematic recordings were discarded, and then verified P- and S-wave arrival times for the rest (Bodin et al., 2004). The analysis identified unique frequency patterns: 0.25 Hz for the mainshock and 0.3 Hz for the aftershock, with notable horizontal amplification. Past studies rarely explored sub-0.5 Hz data, hampering comparisons. A more detailed site response analysis is warranted for deeper insights into these frequencies (Bhattarai et al., 2015). The post-yield stiffness ratio impacts the response spectrum. At -0.03 and 0.03 ratios, spectral amplitudes at soil sites increased by 18.5% to 34%. Repeated earthquake ground motions had little impact at rock sites but significantly affected SDOF systems at soil sites (Bastami & Jonaidi, 2021). The study investigates how mainshock-aftershock sequences affect steel moment frames designed with ED and PBPD methods. Here it was assessed structural performance using parameters like lateral displacement, hysteretic energy distribution, and plastic hinge placement. The analysis involves nonlinear time-history simulations under these sequences (Abdollahzadeh et al., 2019).

In this study, authors create fragility curves using numerical simulations of frame models exposed to various earthquake ground motion sequences with varying parameters. These curves are described by two key parameters: the median and log-standard deviation. The equation for this function is a log-normal distribution (Abdelnaby, 2018).

$$P(Exceedance_i\ GMI) = \phi\left[\frac{1}{\beta_I} In\left(\frac{GMI}{Ls_I}\right)\right] \tag{2}$$

Here, 'P' represents the probability that the i^{th} limit state will be exceeded based on a ground motion intensity measure (GMI), such as PGA (Peak Ground Acceleration). We use 'φ' to denote the probability density function of a normal distribution. 'βi' stands for the normalized log-normal standard deviation, while 'LSi' corresponds to the median value representing a GMI level where there is a 50% probability of the i^{th} limit state occurrence.

CGAN model underwent training using 80% of the complete dataset. To assess the model's performance, we decided to validate it using the remaining, previously untouched 20% of the dataset. In this validation process, it was introduced 20% of the mainshock (MS) data that had never been seen by the CGAN model. Subsequently, it was compared the aftershock (AS) intensity measures predicted by the CGAN with the actual, observed intensity measures for this previously unseen data (Ding et al., 2020). The maximum rotation angle (θmax) observed in masonry structures tends to rise as the intensity of aftershocks increases. Notably, this effect is more pronounced when masonry structures are in the plastic phase rather than the elastic phase. Moreover, it becomes apparent that the impact of aftershocks on θmax in masonry structures can be disregarded when the relative intensity of the aftershock remains below 0.5. However, when the relative intensity reaches 1.0, θmax in masonry structures can increase by approximately 19.0% (Y. Zhang et al., 2022). The author’s method uses GPS station data from the mainshock day as its sole input. It employs a Convolutional Neural Network (CNN) to capture spatial correlations within the data. Despite having limited data, our approach shows strong performance. However, its accuracy is contingent on the GPS station density. It performs best when mainshocks are close to measurement stations, less so in offshore areas (Schimmenti et al., 2023).

In the study, authors gauge the accuracy of the CNN model using the coefficient of correlation (r), which is defined as follows (Moscoso Alcantara et al., 2021):

$$r = \frac{\frac{1}{N}\sum_i^N (y_{pred,i} - \overline{y_{pred}})(y_{ref,i} - \overline{y_{ref}})}{\sqrt{\frac{1}{N}\sum_i^N (y_{pred,i} - \overline{y_{pred}})^2}\, x \sqrt{\frac{1}{N}\sum_i^N (y_{ref,i} - \overline{y_{ref}})^2}} \tag{3}$$

Here, 'y_{pred}' represents the output predicted by the CNN model, while 'y_{ref}' signifies the reference output generated by structural analysis. We calculate the means of 'y_{pred}' and 'y_{ref}' as 'y_{pred}' and 'y_{ref}', respectively, by summing all values and dividing by the number of samples, represented as 'N'.

CHALLENGES AND FUTURE DIRECTIONS

1 Challenges in Neural Network-Based Aftershock Prediction

Despite the significant potential of neural networks in aftershock prediction, several challenges must be addressed. One of the primary issues is the availability and quality of seismic data. In certain regions or specific events, high-quality data, particularly for aftershocks, may be limited, which affects the model’s ability to generalize. Additionally, the number and intensity of aftershocks vary greatly across different sequences, leading to data imbalances that can hinder accurate model training.

Another critical challenge is handling the inherent uncertainty in aftershock events. Neural networks must be designed to account for this uncertainty to improve the reliability of their predictions. Furthermore, models trained on data from one region may struggle to adapt to other areas with distinct geological conditions, making generalization across different locations a complex task. The intricate behavior of aftershocks, including variations in amplitude decay, frequency content, and temporal patterns, further complicates the development of accurate predictive models. Capturing these complexities within neural networks remains a significant challenge.

2 Future Research Directions

To overcome these challenges and advance neural network-based aftershock prediction, several key research areas require further exploration. Enhancing data collection efforts is crucial, particularly for aftershocks. Expanding sensor networks, creating standardized data-sharing platforms, and integrating information from multiple sources can significantly improve the availability and quality of datasets. Additionally, data augmentation techniques, such as generative adversarial networks (GANs) and synthetic data generation, can help mitigate issues related to data scarcity and imbalance.

Another essential area of research involves developing methods for uncertainty quantification. Creating techniques to assess and visualize uncertainty in aftershock predictions will improve model reliability and interpretability. Transfer learning strategies also hold promise, as they can help extend the applicability of neural networks trained on data from one region to other locations with different geological characteristics.

Incorporating geological and geophysical data into neural networks can enhance their ability to model the complexities of aftershock behavior. Furthermore, the development of real-time prediction systems could provide valuable early warnings, improving disaster preparedness and response. Establishing standardized validation methods and benchmarks for aftershock prediction models is also critical to ensuring model robustness and enabling fair comparisons.

Addressing these challenges and exploring these research directions will contribute to the continued advancement of neural network-based aftershock prediction. Ultimately, these efforts will enhance our ability to assess and mitigate seismic risks more effectively, leading to improved disaster preparedness and response.

CONCLUSIONS

In conclusion, the reviewed articles collectively underscore the critical importance of meticulous data processing in seismic analysis, emphasizing precision and the resolution of modeling uncertainties. The utilization of advanced sensor technology, like Episensors from Kinemetrics, in capturing ground motion data within specific frequency ranges provides invaluable insights into seismic behavior. Notably, the identification of unique frequency patterns, often below 0.5 Hz, reveals the need for a more comprehensive exploration of these lower-frequency phenomena. Furthermore, the studies highlight the substantial impact of factors such as post-yield stiffness ratios on structural response, demonstrating the complexity of seismic effects on various building types. The research on mainshock-aftershock sequences underscores the significance of evaluating structural performance using parameters like displacement, energy distribution, and plastic hinge behavior, reaffirming the need for nonlinear time-history simulations to better understand these dynamic events. Overall, these findings collectively contribute to the advancement of seismic assessment and engineering practices, highlighting the multifaceted nature of seismic studies in ensuring structural resilience and safety.

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