Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

Reinforcement Learning for Enhancing Earthquake Resistance in Concrete Structures Using Artificial Intelligence

Dr. SenthamaraiKannan. K[1], Andal. L[2], Vishnukumar Kaliappan[3], l. Ponraj sankar[4], T. Lakshmanan[5]

[1]*Professor,Civil & Architectural Engineering, University of Technology and Applied sciences-Al Musanna, South Al Batina, Sultanate of Oman, senthamarai.kulanthaivelu@utas.edu.om*
[2]*Professor,Civil Engineering, Velammal College of Engineering and Technology, Madurai, Tamil Nadu, India, la@vcet.ac.in*
[3]*Department of Computer Science and Engineering, KPR Institute of Engineering and Technology, Coimbatore, Tamilnadu,India,vishnudms@gmail.com*
[4]*Concrete & Structural Consultant, Former Professor in Civil Engineering, Madurai, Tamil Nadu, India, ponrajresearch@gmail.com*
[5]*Professor,Department of Mechanical Engineering, SRMIST, Kattankulathur, Tamilnadu, India, lakshmat@srmist.edu.in*

In civil engineering, the seismic durability of building materials is still a major concern, particularly in areas where earthquakes are common. To improve the seismic resistance of concrete structures, this article investigates the use of artificial intelligence (AI) approaches, particularly reinforcement learning (RL). By using structural responses to seismic stresses as a source of information, reinforcement learning presents a viable method for optimizing the parameters of design and reinforcement tactics. The study simulates and assesses the behavior of building materials subjected to stresses caused by earthquakes by integrating finite element analysis with reinforcement learning methods. In comparison to conventional design methodologies, a case study is provided to show how well the suggested RL-based methodology improves seismic performance indicators including displacement, speed, and integrity of the structure. The results demonstrate how AI-driven reinforcement learning approaches can progress the field of resistance to earthquake design and help create concrete structures that are more durable and safe.

Keywords: Seismic resilience, Reinforcement learning (RL), Concrete structures, Artificial intelligence (AI) techniques, Earthquake resistance.

1. Introduction

In many parts of the world, reinforced concrete (RC) frame buildings are a common structural technology. 38 RC frames experiencing seismic stresses may exhibit nonlinear behavior in high seismic zones. As the seismic demand and endurance of the RC frames may be measured from the expected nonlinear seismic response, it is essential to precisely predict the nonlinear 39 response of RC frames during upcoming earthquakes. People can take the required steps (e.g., reinforcing and retrofitting) to lessen the collapse 42 risk before an earthquake by using the expected seismic demand and capacity of the RC 41 frames. Performing nonlinear time-history studies utilizing current physics-based 44 techniques is one of the most popular methods for predicting the nonlinear 43 seismic reaction of an RC frame [1]. The structural stiffness of RC frame buildings has a direct bearing on the accuracy of the forecast of their nonlinear seismic response, as it connects external forces to the building's deformations. 46 In the scenario of structural systems with multiple degrees of freedom (MDOF) 48 for dynamic analysis, structure stiffness is a matrix form. However,the current physics-based modeling techniques typically don't strike a suitable balance between computing efficiency and predictive performance.

After analysing 20 distinct building configurations, an empirical formula was presented for determining the fundamental period of reinforced concrete (RC) constructions. The structures were modeled using six degrees of freedom finite elements (FEs), and the SSI effect was taken into consideration by utilizing the Winkler base type (springs fastened to the structure's foundation) and the impact of infill walls[2]. A key challenge in structural engineering has been the creation of a computationally effective model for reinforced concrete structures that can yield precise responses under dynamic nonlinear loading circumstances. The nonlinear mechanical behavior of reinforced concrete (RC) constructions is extremely complicated and demanding to simulate and capture. This complexity is further compounded by the interaction between the concrete and reinforcing bars. To prevent numerical disturbances in the absence of nonlinearities and lower the computational cost of the study, researchers typically use simpler 1D and 2D numerical models to simulate RC structures while dealing with material irregularities.

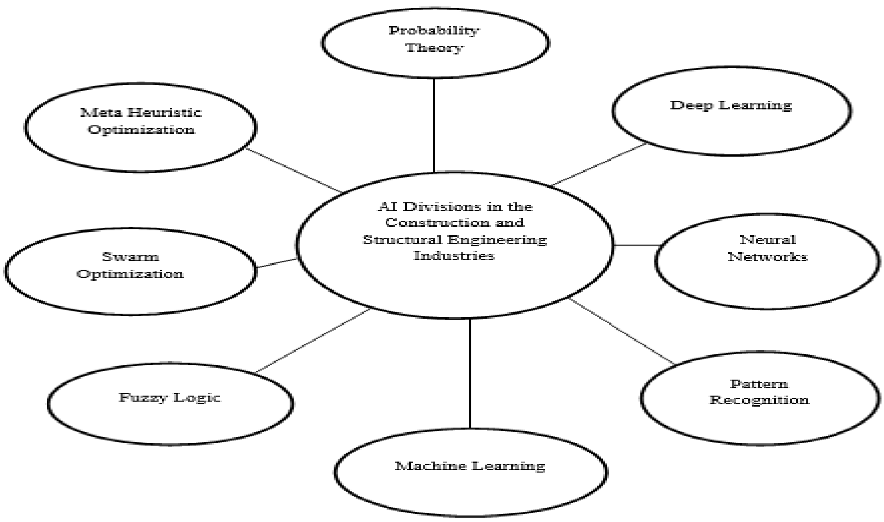

Fig. 1.1. Developmental AI Fields in the Concrete and Structural Engineering Sectors

Figure 1.1 depicts tShe growing trends of the various AI disciplines in the field of building and structural engineering over the past ten years. Taking into consideration the various AI disciplines like Deep Learning, Pattern Recognition, Machine Learning, Fuzzy Logic, Swarm Optimization, Decision Trees, and Evolutionary Computation; all can find uses in the areas of building industry structural engineering.

Sorting items into distinct classes, teams, or categories is the primary goal of pattern identification or PR. Signals, voice, pictures, and other types of data may be the primary basis for classification, depending on the application area. The qualities of PR are represented by a set of features [3]. The empirical decision theory's results are used to establish the crucial borders among the pattern classes.

The structure of the paper is as follows. The method used to choose the evaluated literature and carry out the content analysis is presented in Section 2. In Section 3, which elaborates on the distinctions between these techniques, new AI techniques (ML, PR, and DL) are presented and highlighted. A summary of these approaches used in structural engineering is given in Section 4. In addition, the present shortcomings of the mentioned AI techniques while outlining future research directions and trends for utilizing them in innovations. Ultimately, Section 5 offers conclusion.

2. Related Works

ETABS2000 software is used to analyze and design structures utilizing elastic limits. However, the most recent version of the nonlinear dynamic analysis application (IDARC software-ver6.0) has been used to analyze the vulnerability of the researched buildings, compute input and hysteric forces, and investigate the behavior of the structures based on nonlinear limits [4]. The earthquake accelerogram that is used in a seismic study is one of the most effective parameters on the input energy to buildings. Input accelerogram has a greater effect on the pace of energy input into structures than do structural features. For this purpose, a range of accelerogram qualities are taken into consideration while choosing accelerograms, in addition to the notion of restricting adaptation to structural circumstances.

A unique kind of fiber-reinforced concrete (FRC) with promising deflection-hardening behavior under deformation is called high-performance fiber-reinforced concrete (HPFRC). The flexural strength is significantly higher than that of high-performance concrete (HPC) and is comparable to that of engineering cementitious composites (ECC) and high-performance fiber-reinforced cementitious composites (HPFRCC). While it is less than ultra-high-performance concrete, HPFRC has a better compressive strength than HPFRCC, ECC, and HPC [5]. For example, oxidation of steel rebar from chloride and moisture seeping through cracks greatly affects the loading capacity and longevity of concrete components. The deterioration of concrete members caused by the corroded rebars increases the likelihood of structural failure.

While the aforementioned review articles discussed the use of AI in civil engineering buildings and infrastructure, they mostly covered older approaches and neglected more modern ones like PR, ML, and DL [6]. However, during the past few years, there have been significant advancements and a rise in the application of these clever techniques in structural engineering. Consequently, throughout the past ten years, research on the application of these cutting-edge AI techniques in structural engineering has been extensively covered in this review paper. Owing to space constraints, the focus of each paper's review was on the problem or issue being tackled, the field and case structure under consideration, and the AI approach being employed.

This paper issue statement aims to find the best design and placement techniques for Fiber-Reinforced Polymer (FRP) composites and examine the shear strength of RC beams that have been retrofitted with them. Since shear failure offers no prior warning, it is considered the most catastrophic failure mechanism for RC beams. When compared to conventional approaches, the accuracy and efficiency of shear strength prediction can be increased by using artificial neural networks (ANNs) [7]. This could lead to an improvement in the strength and longevity of reinforced concrete structures and a decrease in the need for expensive repairs or replacement. Four RC beams will be used in the investigation, and they will be subjected to both shear and torsion in experiments.

The analysis of wave propagation in solids served as the foundation for the identification process. The input data used to train neural network models for structural damage detection is the observed frequency response functions (FRF). Neural networks were utilized by Harpula and Ziemianski to identify damage in bar structures by analyzing alterations in their dynamic properties. In this work [8], the seismic damage imposed on various reinforced concrete MRF model structures is evaluated using the damage index.Several earthquake datasets of varying intensities were used in extensive nonlinear time history studies. Next, several artificial neural networks are trained to estimate the damage index using the generated database. Additionally, numerical examples are provided to show how well the suggested strategy works.

The impact of natural calamities like earthquakes is taken into consideration in this study on high-rise structure earthquake resistance [9]. By designing an earthquake-resistant framework as the structure's primary body, high-rise buildings can better withstand earthquakes. When creating high-rise structures, architects typically choose steel structures with excellent performance because of their good deformation capability and bearing capacity, which minimize damage and help prevent casualties and financial loss during natural catastrophes. High-rise building model structures are created mathematically, and the computerized simulation of each building component subjected to seismic energy waves is examined.

One or more intermediary (hidden) layers, an output layer, and an input layer of terminals (neurons) make up the layout [10]. Any kind of ANN usually results in the building of a physical system model from the information, as opposed to knowing the analytical relationship between the variables beforehand.To do this, a training procedure is used to determine the ANN's variables (heavy objects), beginning with a set of values that are allocated at random. The training process is an iterative process that looks for a performance function's minimum. The majority of employed algorithms consist of first- or second-order reduction processes, where the difference between the measured (target) values and the output is the performance function, typically expressed by the average squared error of the network's output.

3. Methods and Materials

3.1 IoT-powered smart cities

The IoT is crucial for further research application given the industry's rapid growth and concentration on the concept and use of smart cities across numerous engineering disciplines. Smart cities are conceptualized to reduce operating costs while simultaneously improving public service utilization [11]. As a result, it may be regarded as a discipline that emphasizes the successful and effective utilization of the resources at hand. This specific goal can only be accomplished by appropriate installation and data collection using wireless sensors that can be placed across a city. Sensors are utilized for data collecting, analysis, and classification in the context of IoT applications and smart city concepts in Figure 3.1.

Maintaining and interpreting the massive amounts of data that are gathered from a single city can be challenging. Furthermore, as every city is unique and faces various issues, technical breakthroughs in the areas of data gathering, classification, and interpretation are imperative. DL design can be employed for the gathering and analysis of the information in such situation.The idea of deep learning is used to train different systems to identify patterns in a wide range of networks and to identify patterns that might arise from problems in terms of network efficiency. Consecutive data analysis has shown how effective DL design is [12].

Consequently, this system provides an answer to the optimization problem related to smart buildings and cities. Smart city concepts rely on the use of sensors to guarantee efficiency and environmental sustainability [13], and safety of the city's infrastructures. The most recent advancements in nanotechnology have led to the provision of self-sensing substances in cities to track the state of the buildings within them. Another important development in concrete technology that could make any concrete structure self-sufficient is smart concrete. Carbon nanotubes sensors added to the concrete mix make it easy to follow cars and assess an object's structural risk. The development of new methods for spotting corrosion in building materials early on is another noteworthy instance.

The rationale for this method of keeping an eye on the state of the concrete while it cures. The sensors that are incorporated into the building material also enable precise temperature and strength monitoring of the concrete during the curing process. Through IoT, cellphones can facilitate the easy storage and communication of related data. When it comes to using AI for data collection and interpretation in structural evaluation, ML and DL are seen to be the two most popular applications.

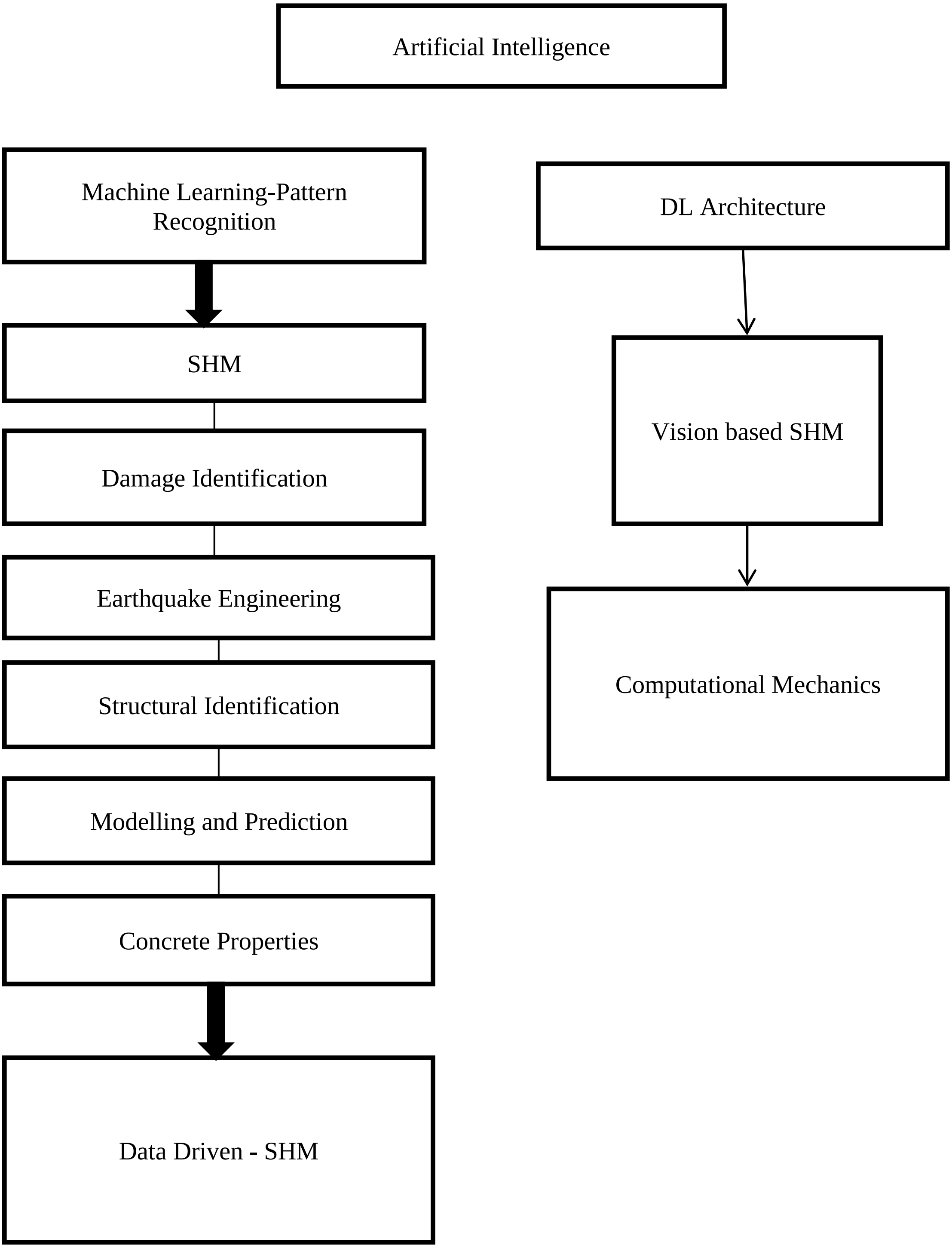

Fig. 3.1. AI Subdisciplines in Architectural Engineering

3.2 IoT-based SHM System

One of the primary problems that the frame and construction sectors are experiencing is the lifetime of the structures. The most recent modification requirements of the Indian Standard Coal Rules must be followed when examining and evaluating the existing designs, which now include additional clauses and directions addressing the manufacturing of concrete, the computation of wind loads, and seismic susceptibility. The construction industry is being forced to adopt the Internet of Things concept and expertise due to this specific predicament.

The structure monitoring field applies the idea of IoT.

The major objective of this approach is to effectively and efficiently monitor devices by improving machine-to-machine interaction via the use of integrated sensors. Data collecting, information transmission, and collaborative information processing using cloud computing techniques are all accomplished with smart devices. Furthermore, SHM can benefit from the combined use of ML and the IoT.

On the other hand, one of the most important issues that come up when doing SHM on structures—typically bridges—is that it is difficult to promptly monitor the sensors that are installed and to compare the most recent readings with the historical data. Consequently, keeping an eye on all of the installed sensors is a difficult task, as they may be situated at different distances from one another. Since all of the mounted sensors' recordings can be recorded simultaneously, an innovative method that connects the sensors is therefore required for the present purpose.

It is also essential to link all of the data collected from the sensors over the web. Some IoT and AI fields can effectively be combined and employed towards the same goal. Using the IoT, information collected by the numerous sensors positioned on a long-span bridge may be gathered. Afterward, structural examination and interpretation can be performed with the use of machine learning. The structural evaluation offers a precise, economical, time-saving, and effective option with IoT. When IoT, SHM, and online computing principles are combined, a potent database may be created and examined in contrast to the conventional method of conducting structural health assessments. Additionally, the SHM system benefits from the cloud computing platform's ability to store data and use it for the creation and application of smart monitoring gadgets. The server receives the structure's "good health" status, stores it, and uses ML to decode the information and enable remote monitoring via mobile devices.

4. Implementation and Experimental Results

Preparing the datasets based on key attributes is the most crucial component of prediction models. Plotting was done for the seven key characteristics associated with each kind of prediction, such as Sa(T1) or IDRmax. These targets indicated that 93,500 data points from IDAs were included in the training dataset. Put differently, to create the sizable database for prediction [14, 15], 93,500 linear time's history studies were conducted based on raising the magnitude of measurements (i.e., IDA).

To illustrate the estimation accuracy of M-IDA curve models, it is not enough to only have higher values of R2, given the connections among the numbers of the before and after point data.

Plotting both the real and anticipated curves is therefore the best approach to demonstrate the algorithm's power. Figure 4.3 shows the predicted and real M-IDA curves for the three-story and seven-story RC MRFs with five distinct kinds of bays that are subject to PL recordings. The study's projection models' reliability was demonstrated by the plotting of the two most accurate predicted M-IDAs, which may also be utilized to make preliminary predictions for the M-IDA slopes ofRC MRFs.

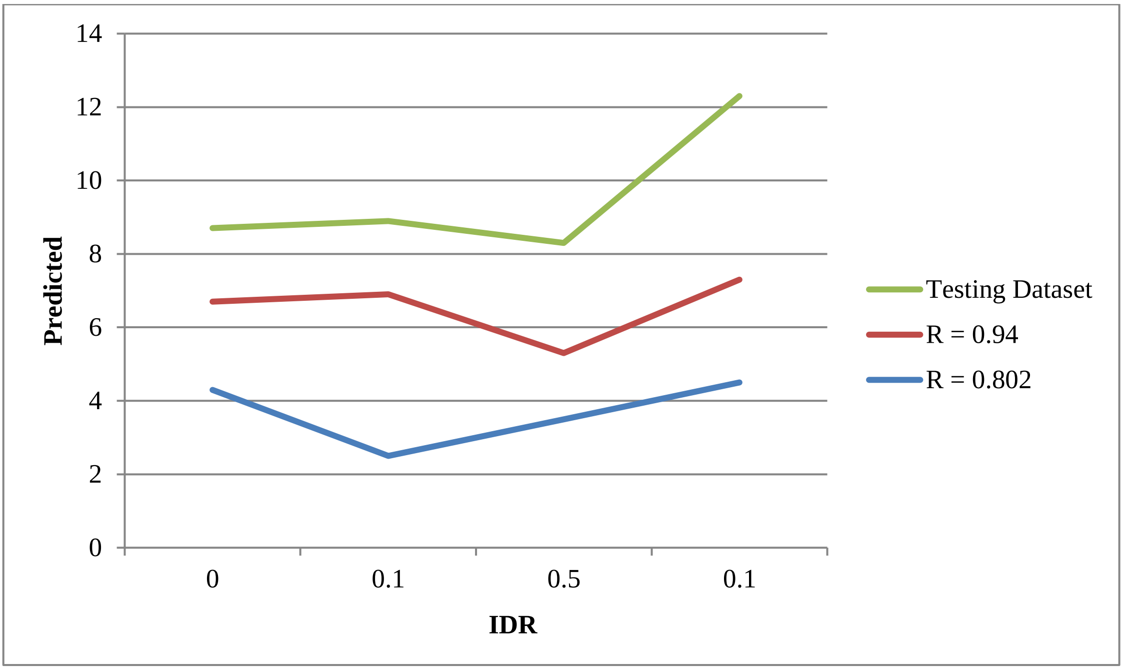

Fig. 4.1.Results of the IDRmax prediction for the 6-Story RC MRFs as testing datasets with PL records included

Seismic response forecasting models were created using the chosen machine learning algorithms (see Tables 1) that had the highest prediction accuracy after appropriate datasets were prepared. Figures 4.1 and 4.2 display the IDRmax forecast outcomes for the 6-Story and 8-Story RC MRFs, assuming five different types of bays, include PL recordings. It should be noted that the selected RC MRFs were removed from the original training datasets during the prediction procedure. Consequently, for all varieties of RC MRFs, the aforementioned algorithms can be employed as an accurate prediction model for IDRmax less than 4.0%.

Table 1. Comparison of statistical metrics assuming the 3-Story RC frame with three bays having bay lengths of 6.0 m as test data for predicting IDRmax

Model	R^2	MSE	RMSE	MAE	MARE	MSRE
XGBoost	0.819	2.59	1.62	1.25	0.53	0.87

RF	0.902	3.43	1.86	1.36	0.22	0.09
BReg	0.899	2.07	1.45	1.05	0.17	0.05
ETReg	0891	2.26	1.51	1.11	0.19	0.06
GBM	0.819	3.04	1.75	1.35	0.29	0.29
HistGBR	0.889	2.29	1.52	1.08	0.16	0.05
HistGBR(FN)	0.831	2.77	1.67	1.25	0.49	0.64
AdaBoost	0.865	5.1	2.25	1.75	0.48	0.40
KNR	0.796	3.18	1.79	1.18	0.17	0.06
PLSReg	0.385	6.62	2.58	2.08	1.12	5.10
SReg	0.387	6.61	2.58	1.90	0.34	0.24
VReg	0.586	3.15	1.78	1.39	0.53	0.87
LReg	0.351	6.76	2.61	2.06	0.94	3.33
GReg	0.161	7.68	2.78	2.37	1.99	19.37
MLPReg	0.206	8.01	2.81	2.23	0.74	4.71

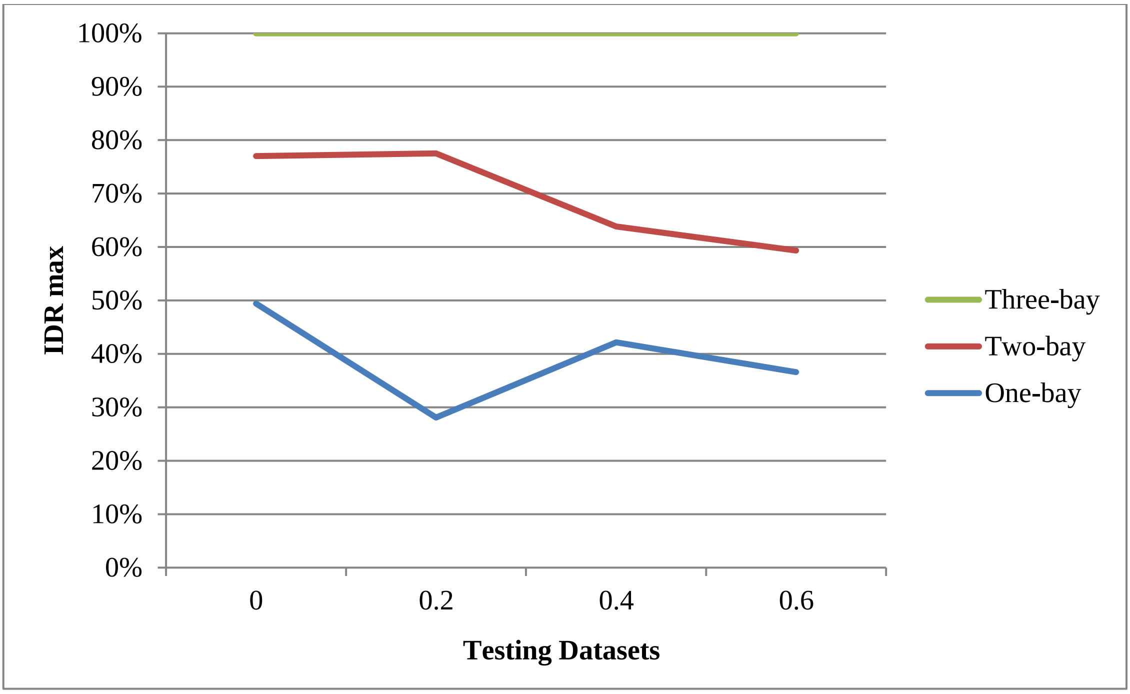

Fig. 4.2. Results of the IDRmax forecast for the 6-Story RC MRFs as test datasets with PL Records Included

The fitting forecast M-IDAs by upgraded ML techniques are displayed in Figure 4.3. The most reliable prediction models are the ANNs and XGBoost techniques, which have the best-fitting curves. The seismic resistance levels of the five-story RC frameworks were assumed to be established by the structural performance levels that were defined based on the permitted IDRmax values of 1.0%, 2.0%, and 4.0%, which correspond to Immediate

Occupancy (IO), Life Safety (LS), and Collapse Prevention (CP) performance levels, respectively.

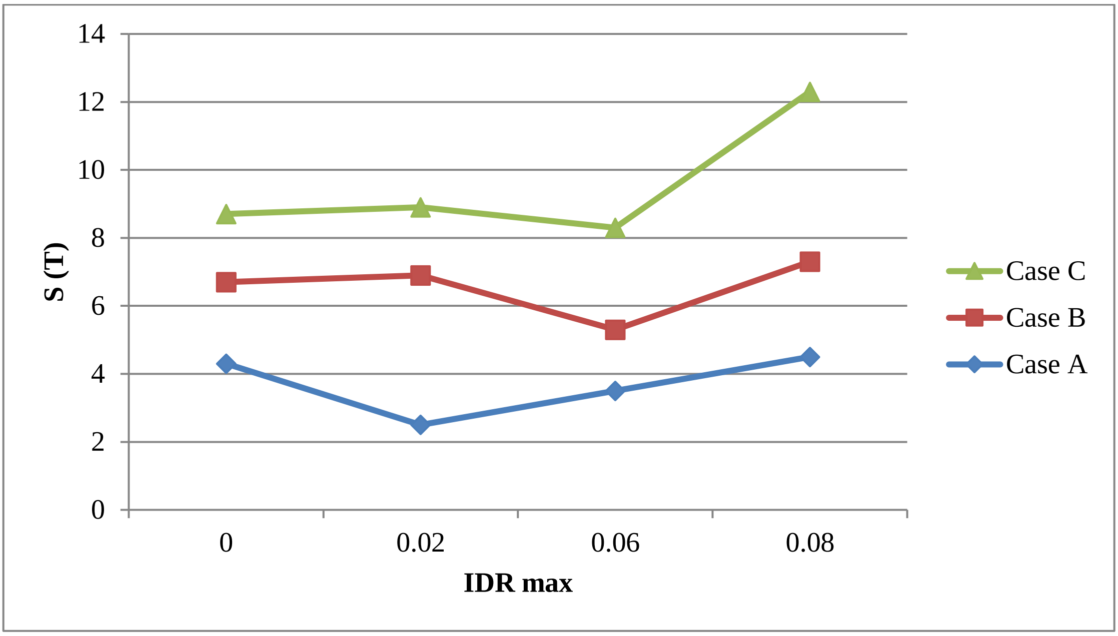

Fig. 4.3. The five-Story RC frames' projected M-IDA curves using the greatest machine learning techniques, incorporating PL datasets

Remarkably, the limit states for restricting the damage states of the main structural components of the lateral force-resisting device were outlined in accordance with Table 2 in FEMA 356. Table 2 shows the actual values obtained by M-IDAs of the RC frames and those predicted by enhanced ML algorithms, categorized by permissible performance levels. Researchers can use the prediction models to reliably anticipate RC frames because, the predicted values in all performance levels are relatively similar to the actual values.

Table 2. Seismic efficiency levels of the five-story reinforced concrete frames predicted using M-IDA curves that include PL recordings

M-IDA curve	**Case A**			**Case B**		
	IO	**IS**	**CP**	**IO**	**LS**	**CP**
Actual value	0.206	0.358	0.551	0.225	0.391	0.595
XGBoost prediction	0.198	0.352	0.538	0.214	0.379	0.603
ANNs Prediction	0.194	0.347	0.549	0.223	0.383	0.601
M-IDA Curve	**Case C**			**Case D**		
	IO	**IS**	**CP**	**IO**	**LS**	**CP**
Actual value	0.258	0.445	0.674	0.282	0.493	0.752
XGBoost predicted	-	-	-	0.278	0.479	0.753
NuSVR predicted	0.238	0.416	0.666	-	-	-
ANNs predicted	0.245	0.430	0.670	0.280	0.496	0.749

Designers can utilize the preliminary performance level estimation data to examine the vulnerability of their structures, as it can greatly assist them in identifying the weaknesses of the buildings they have constructed. A graphical user interface (GUI) was developed to collect input parameters related to the RC frame and the seismic constraint of performance levels in order to improve the accessibility of the research findings. The recently introduced GUI might be able to generate the expected machine learning-based M-IDA curve with less complicated modelling and analysis needed. It's noteworthy that it's easy to meet the input requirements for the expected build. Moreover, the duration of the structure can be ascertained using the calculations supplied by the seismic regulations (such ASCE 07-16).

5. Conclusion

According to recent research, in order to ascertain the seismic reactions and seismic performance requirements of reinforced concrete (RC) structures, intricate modelling and analysis must be carried out. The majority of these analyses need the use of high-speed computer systems and take a considerable amount of time. A further aspect influencing the accomplishment of seismic performance is the unpredictability of seismic events. In order to address this problem,the work proposed to compute the IDR max and Sa(T1) for the M-IDA curvature of the RC frames using machine learning (ML)-based predictive models..

The investigation concentrated on the numerous applications of AI in the structural engineering and construction sectors. It has been observed that in order to address structural issues related to damage assessment or health surveillance, conventional methods are used in conjunction with technological improvements in the form of devices and software for data gathering, installation, and analysis. Also, new applications of artificial intelligence in civil engineering are yielding commendable outcomes, whether they are linked to structural design and analysis or construction management. When these innovations are used, accuracy and performance improve.

References

1. Luo, H., &Paal, S. G. (2022). Artificial intelligence-enhanced seismic response prediction of reinforced concrete frames. *Advanced Engineering Informatics*, *52*, 101568.
2. Gravett, D. Z., Mourlas, C., Taljaard, V. L., Bakas, N., Markou, G., &Papadrakakis, M. (2021). New fundamental period formulae for soil-reinforced concrete structures interaction using machine learning algorithms and ANNs. Soil Dynamics and Earthquake Engineering, 144, 106656.
3. Hooda, Y., Kuhar, P., Sharma, K., &Verma, N. K. (2021, August). Emerging applications of artificial intelligence in structural engineering and construction industry. In Journal of Physics: Conference Series (Vol. 1950, No. 1, p. 012062). IOP Publishing.
4. Nikoo, M., Zarfam, P., &Nikoo, M. (2012). Determining displacement in concrete reinforcement building with using evolutionary artificial neural networks. World Applied Sciences Journal, 16(12), 1699-1708.
5. Jiao, P., Roy, M., Barri, K., Zhu, R., Ray, I., &Alavi, A. H. (2019). High-performance fiber reinforced concrete as a repairing material to normal concrete structures: Experiments, numerical simulations and a machine learning-based prediction model. Construction and Building Materials, 223, 1167-1181.

6. Salehi, H., &Burgueño, R. (2018). Emerging artificial intelligence methods in structural engineering. Engineering structures, 171, 170-189.
7. James, S., &Thiagi, T. T. (2024). Enhancing Shear Strength in Retrofitted Reinforced Concrete Beams with Fiber-Reinforced Polymers: An Artificial Neural Network Approach. International Journal of Researches on Civil Engineering with Artificial Intelligence, 1(1), 1-20.
8. Rofooei, F. R., Kaveh, A., &Farahani, F. M. (2011). Estimating the vulnerability of the concrete moment resisting frame structures using artificial neural networks. International Journal of Optimization in Civil Engineering, 1(3), 433-448.
9. Mukhopadhyay, Saibal, et al. "Heterogeneous integration for artificial intelligence: Challenges and opportunities." IBM Journal of Research and Development 63.6 (2019): 4-1.
10. Xia, W. (2022). Electrochemical Seismic Design and Artificial Intelligence System Modeling of High-Rise Steel Structure Buildings. Journal of Chemistry, 2022.
11. Li, S., Liew, J. R., &Xiong, M. X. (2021). Prediction of fire resistance of concrete encased steel composite columns using artificial neural network. Engineering Structures, 245, 112877.
12. Li, S., Liew, J. R., &Xiong, M. X. (2021). Prediction of fire resistance of concrete encased steel composite columns using artificial neural network. Engineering Structures, 245, 112877.
13. Chen, C. S. (2020). Seismic performance assessments of school buildings in Taiwan using artificial intelligence theories. Engineering Computations, 37(9), 3321-3343.
14. Arslan, M. H. (2010). An evaluation of effective design parameters on earthquake performance of RC buildings using neural networks. Engineering Structures, 32(7), 1888-1898.
15. Falcone, R., Ciaramella, A., Carrabs, F., Strisciuglio, N., &Martinelli, E. (2022, July). Artificial neural network for technical feasibility prediction of seismic retrofitting in existing RC structures. In Structures (Vol. 41, pp. 1220-1234). Elsevier.
16. Souza, L., &Savoikar, P. (2022). Need for Artificial Intelligence in Geotechnical Earthquake Engineering. Earthquake Geotechnics: Select Proceedings of 7th ICRAGEE 2021, 425-434.