

AI AND MACHINE LEARNING IN SEISMIC DESIGN OF BUILDINGS

Temirlan Bakhytzhan

Structural Engineer, USA

ABSTRACT	KEYWORDS
This article presents an analytical review of the application of artificial intelligence (AI), machine learning (ML), and deep learning (DL) in seismic design, assessment, and optimization of buildings. Five interrelated areas are considered: machine learning for seismic response prediction, deep learning of nonlinear time histories, damage and seismic risk assessment, the direct application of ML in design and multi-criteria optimization, and physically enhanced ML approaches. It is shown that research is evolving from individual regression and classification models to surrogate models capable of reproducing the complex dynamic response of a structure and participating in an iterative search for design solutions. Of particular importance is the ability of ML models to significantly reduce the number of costly nonlinear calculations in multivariate design. However, analysis shows that the model's accuracy on the test set does not guarantee its reliability for a new building. Key limitations remain its dependence on training data, the problem of transferring to structural models not included in the training set, sensitivity to the range of seismic impacts, physical interpretability, and the need for independent engineering verification. In this article, based on the conducted analysis, it is proposed to consider AI in seismic design not as an independent alternative to traditional calculations, but as a surrogate-optimization layer of the digital engineering process . The scientific and methodological novelty of the proposed concept lies in the unification of five functions in a single cycle: digital representation of the building; formation of a calculation base; ML/DL forecasting of seismic behavior; intelligent optimization of design parameters; mandatory physical and regulatory verification. In contrast to studies that apply machine learning only to predict individual parameters or classify damage, the proposed concept considers prediction as an intermediate computational layer that enables iterative generation of design options, which allows for changes in the structure of seismic design. The proposed concept thus shifts AI from the role of an auxiliary analysis tool to that of an intelligent design layer , but does not eliminate engineering calculations from the final decision-making cycle. Based on	Artificial intelligence, machine learning, deep learning, seismic design, seismic response, nonlinear analysis, surrogate model, seismic vulnerability, optimization, physically informed learning.

the analysis, a conceptual model of AI-oriented seismic design is proposed, in which AI is viewed as a surrogate optimization layer between the digital building model and traditional calculations. It is concluded that the most viable direction for development is not replacing engineering calculations with artificial intelligence, but rather the formation of a hybrid digital framework combining numerical modeling, ML/DL, optimization, and mandatory physical and regulatory verification.

Introduction

Seismic design of buildings is one of the most complex problems in structural engineering due to the uncertainty of seismic impact, the nonlinearity of structural behavior, and the need to consider a large number of possible combinations of structure parameters and earthquakes. Unlike static problems, in which the calculated relationship between the load and the structural response can be represented relatively concisely, seismic analysis requires consideration of time dynamics, the interaction of various vibration modes, the nonlinear behavior of materials and structural elements, and the variability of the earthquake itself.

The computational load is particularly high when using nonlinear time history analysis. Multivariate design requires considering various geometric parameters, material characteristics, design schemes, and sets of accelerograms. As a result, a traditional approach can require running hundreds or thousands of calculation scenarios.

This very problem creates the preconditions for the use of machine learning methods. Their basic idea is to create a sufficiently representative database once through high-precision numerical or experimental calculations, and then construct an ML/DL model capable of quickly approximating the relationship between building parameters, seismic impact, and the analysis results.

In general, this approach can be represented as follows: **building characteristics + seismic impact → nonlinear calculation → training base → ML/DL model → rapid forecast.**

A review by H.-T. Thai shows that machine learning has already become a rapidly developing area of structural engineering by the early 2020s and is used for structural analysis and design, damage detection, material property assessment, and other tasks.

In seismic engineering, this trend has been further developed. Research has shifted from simply predicting individual parameters to modeling time histories, assessing damage, seismic risk, and optimizing design solutions.

In the work of Torky and Ohno, a deep learning approach was proposed for predicting nonlinear multi-component seismic response using hybrid ConvLSTM models.

Wen, Zhang, and Zhai developed a CNN model, StruNet, to quickly predict interstory displacements and peak accelerations of RC frame buildings based on limited information about the existing building. The training dataset included 162 typical frames and 200 seismic events, and the model was further validated on four real buildings.

Research has now expanded to include damage, fragility, and vulnerability assessment. Kazemi, Asgarkhani, and Jankowski used ML to predict the seismic response and performance of reinforced concrete buildings, and in another study by the same authors, to construct seismic fragility and vulnerability models.

Thus, the modern question is no longer just **whether AI can replace a single calculation step**, but **how to integrate AI into the engineering cycle in such a way as to preserve the physical validity, verifiability, and regulatory reliability of design solutions.**

Machine learning as a surrogate for traditional seismic calculations. The most fundamental application of AI is the creation of surrogate models capable of approximately reproducing the results of expensive numerical analysis. The traditional scheme involves: **model formation → earthquake selection → nonlinear calculation → analysis of results.**

When a large number of design options need to be explored, this process is repeated multiple times. ML restructures the computational process: **numerical modeling → database generation → training → rapid prediction of a large number of options.**

Thus, the main computational burden is shifted from the stage of each individual design option to the preliminary stage of training sample generation. This concept can be considered the foundation of AI-driven seismic design.

In a study by Wen, Zhang, and Zhai, this logic was implemented for RC frame buildings. The authors compiled a database of nonlinear analysis results for 162 buildings and 200 earthquakes and developed the StruNet CNN model. The outputs included interstory displacements and peak floor accelerations. An important result was the use of a limited number of relatively easily retrievable building parameters, which increases the practical applicability of the model to existing building stock.

The significance of this work extends beyond the specific CNN model. It demonstrates a shift from the idea of "AI calculating a building" to a more realistic concept: **AI approximating an expensive computational procedure within a predefined domain of applicability.** This approach is particularly useful for preliminary analysis of a large number of options.

Deep learning and nonlinear seismic response prediction. The next stage of development involves using deep neural networks to model the temporal structure of seismic responses. Instead of predicting a single value, such as maximum interstory displacement, the model can receive a time series of seismic impacts as input and generate a time history of the structure's response.

Torky and Ohno developed a deep learning model based on a hybrid ConvLSTM architecture for predicting the nonlinear multicomponent seismic response of buildings. The authors examined the relationship between foundation acceleration time series and superstructure response and used a discrete wavelet transform for signal processing. This approach is crucial because time history contains significantly more information than a single integral characteristic. In traditional calculations, time history is a direct result of dynamic analysis. In the DL model, it becomes the learning object.

Another example is provided by a study by Huang et al., in which 1D-CNN and LSTM were used to predict the nonlinear seismic response of an underground power station. The authors demonstrated the ability to significantly reduce the computational cost of stochastic analysis. Furthermore, 1D-CNN demonstrated higher accuracy and extrapolation capability compared to LSTM and the baseline MLP model in this problem.

In 2023, Ning, Xie, and Sun expanded their architecture matching by exploring LSTM, WaveNet, and 2D-CNN for nonlinear time history prediction. Testing was conducted on an SDOF system, a steel frame, and a multi-component bridge structure.

Thus, an important trend has emerged: **ML regression of individual parameters → DL modeling of the full dynamic response**. However, increasing model complexity simultaneously increases the requirements for training data and control of the applicability domain.

ML for seismic damage assessment. A separate area of research concerns structural damage prediction. The task differs from predicting a direct physical response. The engineer is now interested not only in the magnitude of the displacement or acceleration, but also in its possible consequences: **seismic action → structural response → damage state**.

Bhatta and Dang investigated K-nearest neighbors, Random Forest, Decision Tree, Support Vector Machine, and Artificial Neural Network for forecasting damage reinforced concrete buildings. Both the structure's characteristics and the earthquake's parameters were considered as input parameters. A key advantage of the study was the use of not only calculated data but also actual data on building damage after the 2015 Nepal earthquake to evaluate the models.

This aspect is particularly important. If a model is trained solely on numerical calculations, it essentially learns to reproduce the specific features of the computational model being used. Testing on actual damage provides additional information about the algorithm's ability to handle a real object. However, the issue of data quality also arises. Actual damage catalogs are typically significantly smaller than synthetic calculation databases. Therefore, the most promising combination appears to be: **numerical data + experimental data + real earthquake data**.

ML for seismic fragility, vulnerability, and risk. The next level of analysis involves moving from an individual building to a probabilistic risk assessment. Kazemi, Asgarkhani, and Jankowski developed ML models to predict seismic fragility and vulnerability curves for reinforced concrete structures. The work was published in *Soil Dynamics and Earthquake Engineering* in 2023. The authors viewed ML as a means of accelerating a computationally intensive procedure and created a tool to support seismic risk assessment.

This approach is important for design and reconstruction, as it allows for a faster evaluation of a large number of options.

Even earlier, Tanga and co-authors proposed an ML approach for rapid seismic risk analysis of buildings. The model used seismic hazard parameters and building characteristics, and outputs included continuous risk indicators and discrete risk levels. In a study for steel frames, neural networks demonstrated the ability to solve both regression and classification problems.

Thus, ML is capable of working not only with a single calculation indicator, but also with a probabilistic chain: **seismic hazard → response → damage → economic or functional risk**. This expands the application of AI from the design of individual buildings to the seismic stability management of the building stock.

Machine learning directly in seismic design. The application of AI becomes especially interesting when the model is used not only after the design stage to evaluate the building, but also directly **in the design decision-making process**.

Noureldin and co-authors proposed a machine learning procedure for seismic assessment and design that takes safety and serviceability into account. The approach combines an artificial neural network, a fuzzy inference system, and the bagged trees ensemble algorithm. Over 60,000 nonlinear time-history

analyses were performed to generate a training set. The fundamental significance of this work lies in the shift in the role of machine learning. The model is no longer limited to answering the question, "How will a building perform under a given load?" It is used to answer a more project-specific question: "Does a given building variant meet the required safety and serviceability criteria?" Consequently, machine learning becomes an element **of the design filter**, allowing for the rapid elimination of undesirable variants before performing costly detailed calculations.

Machine learning and optimization of design solutions. The next step is using AI to find design solutions. The traditional process can be represented as follows: **design** → **calculation** → **verification** → **parameter change** → **new calculation**. With a large number of variables, this iterative procedure becomes computationally expensive.

ML allows you to build a reverse cycle: **design parameters** → **surrogate forecast** → **assessment** → **optimizer** → **new option**.

Fang and co-authors proposed a machine learning-based multi-objective optimization framework for hybrid structures. The framework integrated design parameter selection, database generation, machine learning models, cost calculations, and NSGA-II genetic optimization. The authors demonstrated that a large number of nonlinear calculations could be replaced by a faster machine learning layer. The architectural principle itself is particularly important:

1. determine optimization parameters;
2. set their acceptable range;
3. form a calculation base;
4. train ML model;
5. replace part of the NLTHA with surrogate forecasts;
6. perform a multi-criteria search;
7. check the obtained solutions using traditional calculations.

This approach is the closest to full-fledged AI-oriented design.

Physically enhanced machine learning. One of the central challenges of ML in engineering remains the gap between statistical accuracy and physical correctness. A typical ML model optimizes for data fit. However, an engineering model must simultaneously satisfy the laws of physics. Therefore, it is developing direction of physics-enhanced or physics-informed machine learning.

In 2023, Yang and co-authors proposed physically enhanced ML algorithms for optimizing tuned mass damper parameters under seismic impact. Single-objective optimization was considered for a linear system, while multi-objective optimization was used for a nonlinear structure. In the proposed framework, physical assessment was directly integrated into the model data generation and update cycle. This approach is fundamental to seismic design. A conventional ML model can be represented as: **data** → **pattern** → **prediction**. A physically enhanced model: **data + physical information** → **limited prediction** → **engineering-interpretable result**. This does not automatically eliminate all errors, but it does reduce the risk of obtaining a statistically plausible but physically questionable result.

Table 1. Main areas of AI application in seismic engineering

Source	Year	Task	Method	Main meaning
Torky, Ohno	2021	Nonlinear response multicomponent	ConvLSTM, DWT	Forecast of time histories
Huang et al.	2021	Nonlinear response of underground structure	1D-CNN, LSTM	Reducing computational costs
Thai	2022	General ML in structural engineering	ML Review	Methodological basis
Wen et al.	2022	Fast response of RC frames	CNN / StruNet	IDR and PFA forecast with limited information
Tanga et al.	2022	Seismic risk	ANN and ML	Rapid risk assessment
Noureldin et al.	2022	Seismic assessment and design	ANN, FIS, EBT	Safety and serviceability
Fang et al.	2022	Multicriteria optimization	ML + NSGA-II	Search for constructive solutions
Kazemi et al.	2023	Seismic response of RC buildings	ML	Rapid performance forecasting
Kazemi et al.	2023	Fragility and vulnerability	ML	Accelerating risk analysis
Bhatta, Dang	2023	Damage to RC buildings	KNN, RF, DT, SVM, ANN	Use of structural and seismic parameters
Ning et al.	2023	Nonlinear time histories	LSTM, WaveNet, 2D-CNN	Comparison of DL architectures
Yang et al.	2023	TMD Optimization	Physics-enhanced ML	Single- and multi-criteria optimization

The comparison shows that AI development is not simply a matter of expanding the number of algorithms used. More significant is **the evolution of the model's engineering function : regression → dynamic prediction → damage assessment → risk assessment → design filter → optimization**. This sequence characterizes the transition from an auxiliary computational tool to an integrated design support system.

A conceptual model of AI-oriented seismic design. Based on the analysis of the studies presented in this article, it is proposed to consider AI in seismic design as **a surrogate-optimization layer of digital design** . The proposed model consists of six interrelated stages.

Stage 1. Formation of seismic context.

The following are determined:

- estimated seismicity;
- soil characteristics;
- calculated accelerograms;
- intensity range;
- regulatory restrictions;
- safety and serviceability requirements.

Stage 2. Formation of a digital model of the building.

The model includes:

- geometry;
- number of storeys;
- design scheme;
- materials;
- weight;
- rigidity;
- characteristics of elements;
- damping;
- design constraints.

Stage 3. Formation of the learning space.

Based on numerical analysis, experimental data and, if possible, real seismic observations, a database is formed:

building parameters + impact parameters → calculated response.

Stage 4. AI forecasting.

The ML/DL model predicts:

- acceleration;
- movements;
- interfloor drifts;
- temporary stories;
- damage;
- fragility indicators;
- probabilistic risk indicators.

Stage 5. Generation and optimization of design options.

Based on the forecast, the design parameters are changed:

- sections of elements;
- rigidity;
- weight;
- design scheme;
- connection parameters;
- parameters of damping devices;
- other design variables.

The optimizer generates a new set of options taking into account several criteria.

Stage 6. Engineering and regulatory verification.

The most promising options are fed back into the physical calculation model.

The following are being carried out:

- nonlinear dynamic analysis;
- finite element modeling;

- verification according to standards;
- checking restrictions;
- sensitivity analysis.

Only after this stage can the design solution be considered as engineeringly sound.

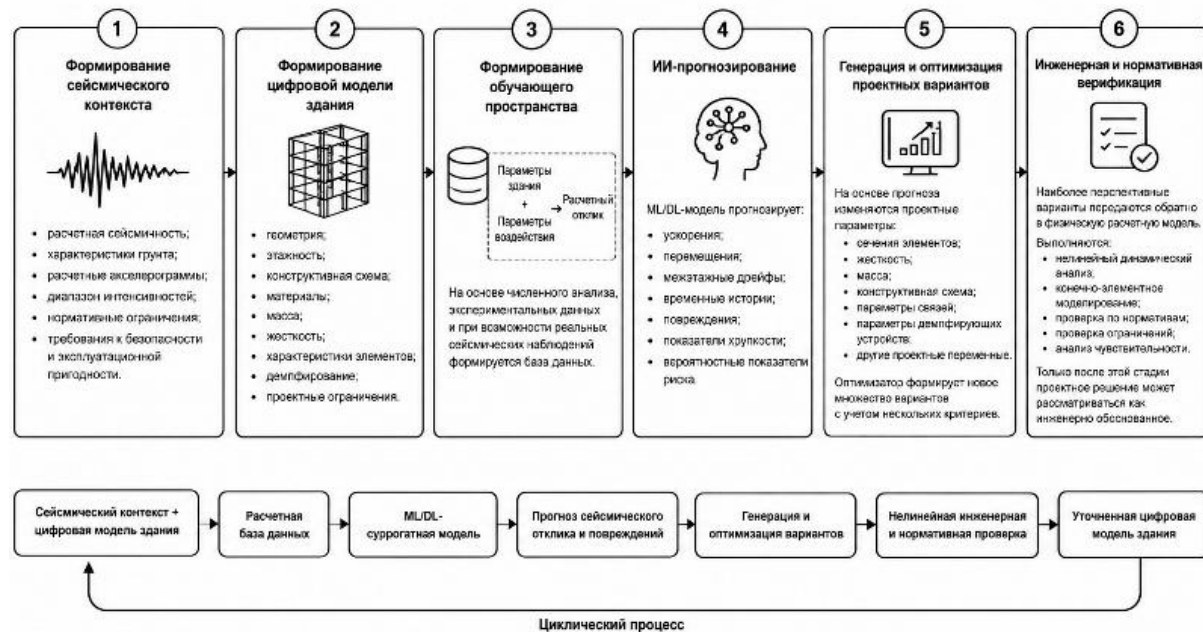


Figure 1. Conceptual model of AI-based seismic design of buildings.

Thus, the process becomes cyclical rather than linear.

Several stages of AI development in seismic engineering can be distinguished.

The first stage is accelerating calculations. ML is used as an approximate model to quickly obtain results that traditionally require extensive numerical calculations.

The second stage is dynamic modeling. DL begins working directly with time series and forecasting nonlinear time histories.

The third stage is the transition to damage and risk. The model links seismic impact and building characteristics not only to the physical response but also to probable damage states and risk.

The fourth stage is the incorporation of AI into design. ML is beginning to be used as a tool for preliminary safety assessments, operational suitability, and the selection of design options.

The fifth stage is optimization. AI becomes part of the search algorithm, which simultaneously considers design parameters, seismic response, cost, and other criteria.

The sixth stage is physically enhanced models. Physical constraints begin to be incorporated directly into machine learning. This evolution allows us to formulate a more general principle:

AI in seismic engineering is evolving from a predictive model to a design decision support model.

The most promising approach is not an isolated ML model, but an integrated system. Such a system can be conceptualized as follows: **digital model** → **surrogate forecast** → **evaluation** → **optimization** → **physical verification** → **model update**.

Conclusion

It is clear that artificial intelligence and machine learning are gradually becoming a significant tool in seismic engineering. The most developed areas include: seismic response prediction; modeling of nonlinear time histories; damage assessment; construction of models of fragility and vulnerability; accelerated seismic risk assessment; seismic design support; multi-criteria optimization; physically enhanced machine learning.

The main advantage of AI lies in the ability to construct fast surrogate models capable of approximately reproducing the results of a large number of expensive numerical calculations. This is a gradual transition from standalone predictive models to a more comprehensive use of AI in the engineering cycle. However, high statistical accuracy of a model should not be equated with the engineering reliability of a design solution.

Key limitations include: dependence on training data; limited applicability; risk of extrapolation; complexity of nonlinear behavior; lack of interpretability; and the need for independent verification.

Therefore, the most feasible approach is a hybrid architecture in which artificial intelligence performs rapid forecasting, preliminary selection, and optimization, while traditional physical calculations and regulatory verification retain the function of final engineering verification. In this case, a promising seismic design model can be represented as follows: **digital building model → calculation base → ML/DL forecast → response assessment → variant generation → optimization → nonlinear engineering verification → digital model update.**

Thus, the main promising direction is not in replacing the engineer with artificial intelligence, but in the formation of a **hybrid intelligent system of seismic design**, in which the computational speed of ML is combined with the physical validity of numerical analysis and the engineering responsibility of the designer.

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