Smart Structures and Systems, *Vol. 37, No. 6 (2026) 553-570*
https://doi.org/10.12989/sss.2026.37.6.553

A hybrid approach to using local strain and rotation detected by nonlinear FE analyses as additional threshold values in SHM systems

Varol Koç*[1], Hasan Yılmaz[2]

[1]*Ondokuz Mayis Univercity, Faculty of Engineering, Department of Civil Engineering, Samsun, Türkey*
[2]*Ministry of National Defense, Ankara, Turkey*

(*Received June 1, 2026, Revised June 24, 2026, Accepted June 26, 2026*)

Abstract. Vibration-based Structural Health Monitoring (SHM) systems are susceptible to false alarms, particularly due to environmental influences. This study proposes that nonlinear static pushover Finite Elements (FE) analysis outputs can be used as complementary data to existing methods in Smart Building (SB) decision support systems. The proposed hybrid approach has the potential to reduce false alarm rates compared to decision-making based solely on modal parameter changes, statistical methods, and machine learning. To this end, in addition to these approaches, a secure proposal based on traditional procedures for integrating nonlinear structural analysis results into intelligent SHM systems is presented. A global performance evaluation of a core system was conducted to obtain local damage distribution and degrees at the element level. In the SHM system, the focus was on using element damage level thresholds obtained from system analysis as threshold values, rather than general limits in standards or solely the results of the structural system's specific global performance analysis. Today, thanks to advancements in hardware and software technologies, performing and disseminating these analyses is much easier than in the past. In the near future, the information obtained from these analyses will inevitably be further utilized in SHM systems. Although the study did not include experimental validation and model updating, it was shown that using the proposed physical thresholds in conjunction with existing modal-based SHM methods has the potential to reduce false alarm rates and provides a theoretical basis for rapid decision-making mechanisms after earthquakes.

Keywords: earthquake engineering; finite element modeling; hazard monitoring; nonlinear structural behavior; seismic protection; Structural Health Monitoring (SHM); system identification

1. Introduction

This study proposes integrating nonlinear, time-stepped, static pushover analysis by Finite Elements Method (FEM) structural system analysis with SHM data using a model-based approach. By correlating the analysis results of the FEM model with sensor data, it is possible to derive local element-based damage in the structure. This study focuses particularly on deriving element-based local rotational-strain thresholds. The aim is to contribute to the literature on evaluating nonlinear structural analysis outputs in DT-based intelligent SHM and decision support systems. This study proposes integrating performance-based element evaluation results into SHM systems as additional

*Corresponding author, Ph.D., Associate Professor, E-mail: kvarol@omu.edu.tr
[a] Ph.D., Civil Engineer, E-mail: kosinski06@gmail.com

http://www.techno-press.org/sss/5 ISSN: 1738-1584 (Print), 1738-1991 (Online)

threshold values through decision-oriented indicators. This approach will enable the effective use of behavioral indicators derived from structural analyses in intelligent damage monitoring systems, thus establishing a direct link between structural analysis and SHM. Accurate modeling of structural behavior, as close to reality as possible, is critical for the accuracy of decision-making mechanisms derived from SHM systems.

Moehle and Deierlein [1], who conducted one of the fundamental studies defining the modern performance-based earthquake engineering (PBEE) approach, state that this approach focuses on loss, progressing from hazard to structural response and damage, in contrast to traditional design methods that only aim at strength. Performance is evaluated not only through collapse but also through story displacements, plastic rotations, element damage levels, interruption of use, and economic losses. With the PBEE analyses proposed by FEMA P-58 [2], structural performance after an earthquake is defined through repair costs, downtime, injury risk, and functional loss by obtaining outputs such as story displacement, acceleration, plastic deformation, and element deformations. Turkish Building Earthquake Code [3] and ASCE 41-17: Seismic Evaluation and Retrofit of Existing Buildings [4] adopt approaches that establish a relationship between performance criteria and limit values such as strain-rotation limits. Performance levels such as IO, LS, and CP are specified by damages defined by numerical thresholds. These thresholds, which have a physical meaning based on the element and are calculated specifically for the structural system, can be entered as additional threshold data into the SHM algorithm. Thus, these values, which are generally used only for design and evaluation purposes in the literature, are linked to the decision system. This study proposes to base its analysis not on the performance threshold values given in the regulations, but on the critical values obtained from the system's own analysis. Existing studies in the literature on DT, Artificial Intelligence (AI), SHM, IoT sensor integration, and real-time decision mechanisms generally focus on the questions of where the data should be obtained and how it should be processed. This study, however, focuses on the question of which physical thresholds can be used as additional critical values.

Studies in the literature generally focus on processing SHM data to determine vibration and mode values in structures. Based on changes in these values, attempts are made to detect stiffness reduction and, accordingly, determine the damage status. Doebling et al. [5] demonstrated damage detection methods using natural frequency variations, mode shapes, and modal parameters. Housner et al. [6], examining the development of structural control systems, state that most studies in the literature focus on TMD systems, active control, and semi-active control isolation systems. Spencer and Nagarajaiah [7] state that active and semi-active structural control systems are generally aimed at vibration reduction, comfort improvement, and damage mitigation, and that sensors are mostly used as control devices. Sohn et al. [8], in their studies examining the development of SHM systems and their basic application areas such as damage detection, determination of location and severity, and estimation of remaining life, state that SHM systems often only perform monitoring and have shortcomings in converting data into performance decisions. Worden and Manson [9] noted that SHM research focuses on vibration-based damage detection, modal parameter identification, sensor network design, and pattern recognition, and reviewed data processing methods. According to the authors, SHM data is mostly analyzed based on modal features obtained from vibration data. Sikorska et al. [10], who examined methods for predicting the future behavior of the system (prognostics), compiled studies in which the rate of damage progression, remaining service life, and failure probability were predicted using SHM data.

Korkmaz and Kayhan [11] compared different structural performance evaluation techniques such as capacity spectrum, displacement coefficient method, and time-domain dynamic analysis on a sample reinforced concrete structure, demonstrating the differences between the results of time-domain analysis and classical methods. Tellal [12] performed a statistical analysis of performance characteristics such as maximum displacement and relative story drift obtained from Time History Analysis results with 9 acceleration records belonging to different soil classes. Performance criteria were defined as statistical threshold values. Limongelli and Çelebi [13], in their book compiling SHM theory and applications, addressed topics such as sensor technologies, data processing, earthquake monitoring, damage assessment, and performance evaluation; they established connections between the practical applications of SHM and methodology and theories. Aytulun and Soyöz [14] examined methods of monitoring dynamic properties, story drifts, and wave propagation velocities with SHM systems, focusing on design, data collection, analysis capabilities, and software-based automated data evaluation processes. The system was implemented in three high-rise buildings and tested with a magnitude 5.7 earthquake in 2019.

Nguyen [15], investigating modal analysis-based damage detection methods for the seismic fragility of high-rise buildings, proposed a hybrid procedure integrating mode shape energy, inverse solution, and artificial neural network approaches. Rojas-Mercedes et al. [16] analyzed seismic fragility curves they created for reinforced concrete bridges under the probabilities of structures reaching different damage levels. SHM data were used in the probabilistic evaluation of performance limits. Akbarnezhad et al. [17], generating seismic fragility functions of structures using machine learning, represented performance limits probabilistically with fragility curves and provided uncertainty modeling. Sun et al. [18] conducted a review article on vibration-based damage detection methods used in the SHM literature. Mardanshahi et al. [19] compared the performance metrics of sensor technologies used in SHM, such as sensitivity, deployability, and data quality. The most critical problem in SHM systems is that the measured parameters do not directly represent the damage, and therefore the decision-making mechanism needs reliable threshold values. These thresholds are often based on empirical or global system behavior and do not contain physical significance at the element level. This is because in SHM, damage can be determined not by direct measurement, but by comparison. For this, the correct threshold values need to be defined. This study offers a solution to this problem.

Studies in the literature are generally grouped around data-driven SHM methods such as machine learning and anomaly detection, monitoring approaches based on FE models, and hybrid approaches that evaluate data obtained from physical measurements. However, in the vast majority of these studies, global parameters such as drift and acceleration are used, and these cannot be related to plastic behavior at the element level, establishing weak connections with element failure mechanics. The integration of plastic rotational-strains with SHM is limited, and thresholds are mostly based on physical measurement anomalies rather than critical physical parameters. Therefore, establishing a direct relationship between measured structural responses and element-based failure mechanisms is rare. This study aims to define additional physically based failure thresholds that can be used in SHM systems using element-level deformation data (strain, curvature, etc.) obtained through nonlinear FE analysis, and to use them as decision system inputs. Furthermore, this study is conducted by treating a simple reference model as a test frame. By adopting the Benchmark structure logic, which considers small systems such as single elements and single frames, suggestions have been developed not based on a real building, but on a controlled system. Such simplified systems are widely used in the literature for method development. For example, Liao et al. [20] and Thomoglou and Golias [21] conducted their method development studies based on single elements, single frames, or single floors. Studies using Benchmark structure, reference frame, and test structure can also be exemplified by the works of Silva et al. [22], Castañeda-Saldarriaga et al. [23], and Limongelli et al. [24]. This study conceptually proposes the transformation of analysis outputs into decision indicators and the creation of an analytical basis for automated systems. Therefore, there was no need to consider a real structure. The use of a single reference system provides a basis for scalable methodologies by enabling controlled interpretation of damage localization mechanisms.

As discussed in the literature, processing SHM data for vibration and mode detection can lead to erroneous results. In their study examining the anomaly detection approach in SHM and forming the basis of data-driven SHM studies, Farrar and Sohn [25] created a normal behavior model from sensor data and defined deviations from this model as anomalies. Cornwell et al. [26] showed that environmental effects can cause significant changes in natural frequency and modal parameters. In particular, temperature changes can alter measured vibration characteristics by affecting the rigidity and boundary conditions of the structure. Peeters and De Roeck [27], in their study analyzing data obtained from monitoring a bridge for a year, showed that most of the natural frequency changes were due to temperature changes, not damage. Similarly, Ni et al. [28], examining the effect of environmental factors on long-term bridge monitoring data, showed that factors such as temperature, traffic load, and wind can cause significant changes in sensor data. Sohn [29] conducted one of the important studies that systematically examined the environmental and operational variability (EOV) problem in SHM. The study stated that most of the variations observed in sensor measurements could be caused by factors such as temperature changes, environmental loads, and operating conditions. It was emphasized that this situation increases the risk of false positives. Ditommaso and Ponzo [30] emphasized that the detected self-frequency variations in SHM systems are not always due to damage, but can be a reflection of external factors such as wind, traffic vibrations, and environmental changes. Liang et al. [31] worked on deriving threshold values from sensor data using automated modal parameter determination algorithms and on false modal debugging strategies.

Due to the reasons explained in the paragraph above, many methods have been developed in the literature for anomaly detection and the elimination of false and true alarms. Chandola et al. [32] examined some anomaly detection methods. They compared studies using methods based on learning the normal data distribution and defining deviations from it as anomalies, such as Gaussian mixture models, clustering methods, PCA-based methods, and isolation-based approaches used for anomaly detection. Neves et al. [33], on the other hand, presented a model-independent damage detection approach based on machine learning techniques. The method was applied to data on the structural condition of a fictional railway bridge collected in a numerical experiment using a three-dimensional FE model. Khan et al. [34] determined damage through frequency variations using FRF and modal strain energy methods. Hughes et al. [35] calculated damage probabilities through Bayesian networks using SHM sensor data. Feng et al. [36] describes the processing of SHM data using the Bayesian model updating method for updating modal parameters, probabilistic estimation of damage parameters, and reducing model uncertainty. Plevris's study [37] shows that in ML-based SHM systems, the difference between anomaly detection and actual damage is not always clear, and this can lead to incorrect decisions. Since false positive/false negative problems occur in cases of low probability of damage, the necessity of expert evaluation (human-in-the-loop) is stated. In their study examining the relationship between operational reliability decisions and Bayesian updating in SHM systems, Jia and Papadimitriou [38] first created a prior probability model for the structure. Then, as sensor measurements arrived, the model was revised with Bayesian updating to obtain an updated probability distribution for structure performance and safety. Kamariotis et al. [39] discussed the use of SHM systems as a decision support system supporting operational and maintenance decisions. Luckey et al. [40] state that ML algorithms can detect patterns in sensor data, but engineers often have difficulty trusting the system because the algorithms generally have internal mechanisms with a black-box character. Therefore, justifying engineering decisions in this regard becomes difficult and requires expert interpretation. Similarly, Jia and Li's review [41] focuses on the interpretability problem in the use of ML/DL models in safety-critical systems. They also state that the fact that ML/DL models are generally black-box systems that are difficult to interpret makes it difficult for engineers to trust the algorithm output.

Lu et al. [42] and Zhang et al. [43] state that SC applications aim not only at service optimization but also at urban resilience development, demonstrating that one of the main goals of SC programs is to increase the resilience of cities to disasters and systemic risks. Bertino et al. [44] note that SHM systems are now considered not only as individual building monitoring tools but also as a technology that enhances the resilience of city infrastructure, emphasizing that IoT-based infrastructure monitoring systems are critical data providers for SC applications and disaster management. Aroquipa et al. [45], in their study demonstrating the use of SHM and DT systems for disaster risk reduction within the context of SC, focused on sensor-based SHM systems, real-time data analysis, DT models, and city-scale resilience management. Xu et al. [46] combined a BIM model with a real-time 3D model using sensor data integrated into the model via IoT. Thus, they created a DT integrated with the building's SHM data. Torzoni et al. [47] focused on the contribution of sensor data transmission, processing, and visualization in SHM and DT integration to decision-making processes such as predictive maintenance. Li et al. [48] developed a real-time damage warning system using sensor data and a DT model. Algadi et al. [49] worked on creating DT models from real-world data such as LiDAR so that numerical representations can be as close as possible to the actual physical situation. Cho et al. [50] processed SHM data with AI models to overcome uncertainties in DT. They worked on real-time prediction and reliable decision-making mechanisms with hybrid models they developed using physical data and AI together. Kaveh and Alhajj [51] compiled studies on the use of DTs updated with real-time data in SHM and decision support systems.

Rapid assessment of building safety after an earthquake is critically important, especially in areas with a high building stock. Traditional building assessment methods rely on on-site inspections by expert teams, a process that can be time-consuming. The Applied Technology Council [52] guidelines, developed for rapid building safety assessment after earthquakes, emphasize the importance of quick and accurate decision-making in determining whether buildings are usable after a disaster. The approaches in these guidelines form the basis of the Rapid Visual Screening (RVS) method used worldwide. In intelligent SHM systems and DT approaches, the goal is to automatically evaluate data related to building behavior and transform it into decision-making mechanisms. The condition of a building after an earthquake can be determined by using additional critical thresholds, as proposed in this study. This allows for accurate and rapid assessment of building safety after an earthquake. Even if the structure is damaged during sudden and severe loading such as an earthquake, these proposed thresholds can be compared with instantaneous sensor measurements (strain, rotation) during the earthquake, providing a rapid and physically based reference for evacuation, emergency response, and usability decisions immediately after the event. In this respect, the study aims to provide a numerical infrastructure for post-earthquake rapid building assessment processes. In this sense, the study aims to transform SHM from being merely a 'damage detection tool' into a 'disaster management decision support tool'.

This study does not aim to create a complete digital twin (DT) of any real structure or to replace existing data-driven structural engineering (SEM) methods. The vast majority of current SEM studies rely either on statistical anomaly detection or modal parameter changes. These approaches produce a high rate of false positives due to environmental influences (temperature, humidity, traffic). On the other hand, physical thresholds based on direct strain or rotation measurements can give false alarms due to non-damage causes such as sensor failure or local concrete cracks. The unique contribution of this study is to present a hybrid decision framework that combines these two approaches (modal + local deformation). Instead of relying solely on modal change or solely on strain exceedance, the proposed approach aims to reduce the false alarm rate by increasing the probability of damage when both conditions are met. This hybrid logic has not been presented in the literature with concrete threshold tables on an element basis for reinforced concrete buildings. This study is designed to address this deficiency as well. While the literature focuses primarily on modeling uncertainty, this study proposes the use of nonlinear analysis results in digital monitoring/decision support systems.

2. Method

Since the full-time acceleration, displacement, and vibration values measured by SHM systems can be generated using nonlinear time-stepped, static pushover analysis, the model outputs can be considered as virtual sensor data that also provides the distribution of plastic damage in the structure. Therefore, it is possible to use the structural behavior outputs obtained from modeling in intelligent damage monitoring systems. Structural analyses can be used not only in performance evaluation but also as a behavioral reference in damage monitoring and automated decision support systems by forming the core of the DT system. Thus, structural analyses can be transformed into an integrated digital decision infrastructure that can be used for SB management. Modeling can play a key role in creating a load-bearing subsystem DT of the structure's behavior. This is because component and subsystem DTs are established for single elements, connection points, subframes, shear wall systems, critical modules, etc. In fact, in SHM systems, sensors are not placed on every floor and measurements are not taken for every element. Monitoring is done for critical floors, frames, columns, and shear walls. In reality, structural behavior is attempted to be created using a sampling method. Therefore, model outputs obtained for a subframework, as done in this study, can be evaluated in the SHM system. This is because decision support systems are run on the most critical regions and elements where the most damage is expected. Approaching some of the analysis results previously obtained for the representative framework in the measurements can be interpreted as an indicator of a critical situation. It is also possible to use the analysis results not necessarily for collapse but for earlier stages of damage and use them as critical limit values in SHM. Therefore, with the methodology proposed and exemplified. in this study, inferences can be made about intelligent SHM SHM and ecision support systems through the digital representation of structural subsystems.

The fundamental basis of the proposed approach is independent of the absolute reality of the specific FE model used. This study aims not to capture the exact behavior of a particular building, but to demonstrate the logic of converting physical outputs (plastic rotation, strain) obtained from any nonlinear analysis (whether pushover or time-history) into SHM decision thresholds. In other words, the validity of the method depends on the threshold extraction procedure itself, rather than the absolute agreement of the model with reality. It is clear that model updating with operational modal analysis (OMA) data may be necessary for application in a real field; however, this does not invalidate the conceptual contribution of the proposed complementary threshold strategy.

For these purposes, in this study, a basic reinforced concrete frame was subjected to nonlinear time-stepped, static pushover analysis using three-dimensional solid FEs defined by FEMs in the ANSYS FE program. Displacement-stress distributions and crack maps were obtained, and two elements with critical indicators were selected. The amount of rotational displacement these elements would undergo at different performance levels was determined. These determined values were proposed as additional threshold values for use in the SHM system. In this system, element-based critical thresholds can be determined when designing based on performance analysis. Modeling can be evaluated in both SHM and BIM. As a natural extension of these, it can be used in DT and SB studies. The widespread adoption of this approach will also contribute to SC studies. Because today, it is much more possible to perform and disseminate the analyses mentioned. Performance analysis-based design can be done, at least on some critical subsystems of the structure, with FE-based nonlinear time-stepped, static pushover analysis. In the near future, the evaluation of the information obtained from these analyses in SHM systems will be inevitable.

Current SHM systems perform modal analyses based on natural frequency and mode shape changes, using statistical thresholds. This study proposes comparing strain and rotation data obtained in the field using strain gauge/fiber optic sensors placed on critical elements with εc and εs thresholds derived from analysis. Accepting only stiffness and mode change criteria as thresholds can increase the false alarm rate (FAR) due to environmental effects such as temperature and humidity. Considering only local strains can generate false alarms due to reasons other than sensor failure or damage. Therefore, it can be said that the probability of actual damage is high if both modal anomaly and strain-rotation threshold exceedance occur. However, strain measurements are sensitive to temperature and vibration. Simultaneous measurements should be taken with a temperature sensor. The allowable strain range for each temperature value can be determined with prior thermal analysis, or the strain data can be compared with residual thresholds after regression with temperature. A tolerance band can be established with this approach.

3. Modeling and Analysis

The structural model used in the analysis consists of a three-story, two-span reinforced concrete planar frame system. Beam and column elements were modeled to represent nonlinear behavior, and plastic hinge formations were defined at the element ends. The material properties of the structural elements were determined based on the accepted standard mechanical properties for concrete and reinforcing steel. Element behaviors were defined considering nonlinear moment-curvature relationships, and the modeling of plastic deformations that may occur under seismic effects was ensured. In this study, nonlinear analysis was not only used to determine the structural capacity, but also aimed at converting the obtained global behavior indicators into threshold values that can be used in rapid building assessment processes after an earthquake. In this context, the displacement and force values corresponding to the performance levels were considered as operational classification parameters that can be used in automated decision-making processes.

In the structural analysis of the frame system, whose performance is determined using FEM defined by three-dimensional solid FEs, the story drift ratios and performance level indicators of the system were obtained by considering the damage level assumptions determined by TBDY [3]. The structure consists of 3 axes with a distance of 4 m between them in the x-direction and 4 axes with a distance of 4 m between them in the y-direction. It has dimensions of 12 m in the x-direction and 8 m in the y-direction. The total height of the structure, which consists of 3 floors with a height of 3.25 m each, is 9.75 m. The concrete of the frame system structure, shown with its element

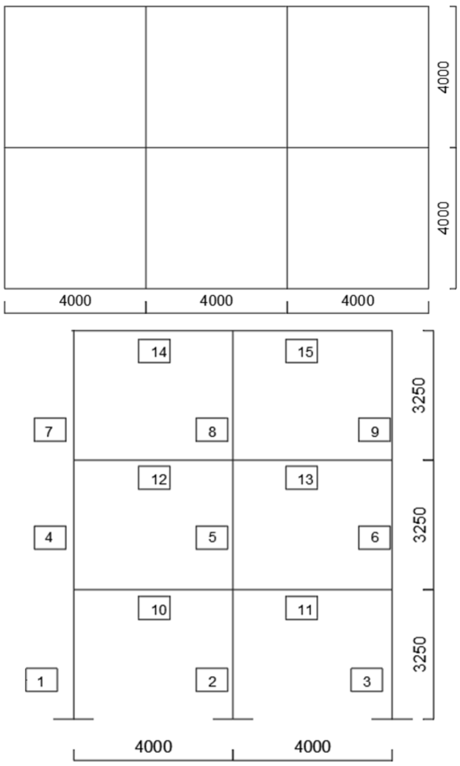

Figure 1. Structural system floor plan, facade view and element numbers

Table 1. Cross-sectional dimensions and reinforcement of structural elements

Element number	Dimensions (m)		Reinforcement	Stirrup
			In the support's region	In the element's middle
		Top	3Ø16	3Ø16
10,11,12,13,14,15	0.5 × 0.3	Bottom	3Ø16	Ø8/125
1,2,3,4,5,6,7,8,9	0.4 × 0.4	Bottom	8Ø16	Ø8/90

numbers in Fig. 1, is C20 and its reinforcement is B420 class [53]. The cross-sectional details and reinforcement information of each element are given in Table 1 [54].

A FE model of a frame in the y-direction of the structure was created using ANSYS, Inc. [55]. The SOLID65 element from the ANSYS library was used to define reinforced and unreinforced concrete; the Link 180 element was used to define longitudinal reinforcement and stirrups. The modulus of elasticity was taken as 21,332 MPa for concrete and 200,000 MPa for reinforcement, with a Poisson ratio of 0.2 [56]. The stress-strain curve of the concrete was defined using the stress-strain model proposed by Saatçioğlu and Razvi [57] for confined and unreinforced concrete. For static push-over analysis, a vertical loading of G+0.3Q was considered.

The solid model modeled with the SOLID65 element is presented in Fig. 2, and the FE model with the reinforcements modeled separately is presented in Fig. 2. Design information and soil parameters for the structural model designed according to TBDY [3] standards for the reinforced concrete load-bearing system were obtained from the AFAD [58] website. Using this information,

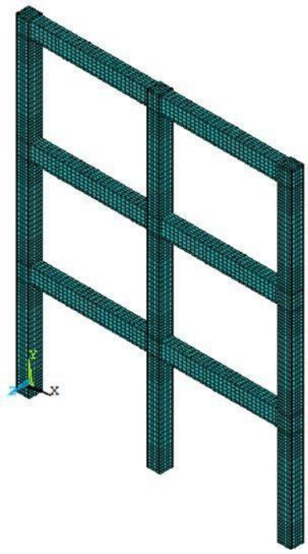

Figure 2. Three-dimensional solid FE model created using the SOLID65 element

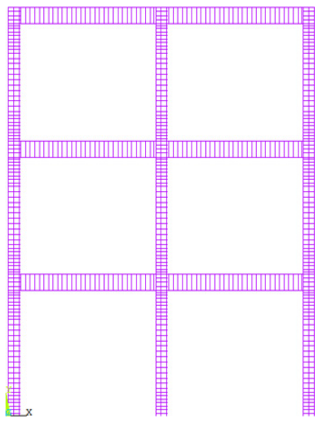

Figure 3. Reinforcement model created using Link 180 elements

an equivalent static earthquake load was applied to the system with horizontal push-over analysis, and to determine the damage levels of the elements, the unit deformations created in the cross-section by the plastic rotations obtained as a result of the push-over analysis were compared with the total unit deformations allowed for concrete and reinforcing steel according to the TBDY [3] standard.

4. Findings: Analysis results

Lateral seismic loads were applied to the floor levels in proportion to the floor heights, and equivalent static push-over analysis was performed using ANSYS. The peak horizontal displacement, base shear force, and concrete-reinforcement strain values obtained from the three-dimensional Solid FE model analysis, corresponding to the damage levels, are given in Table 2.

Table 2. Peak horizontal displacement, base shear force, and concrete-reinforcement strain values at the failure limits of the reinforced concrete frame in the three-dimensional solid model analysis

	Limited damage area	Significant damage area	Advanced damage area	Pre-collapse area
Peak horizontal displacement (mm)	89	190	219	332.3
Base shear force (kN)	210	254.3	259.4	261.9
Concrete strain, ε_c	0.0015	0.0033	0.0039	0.0058
Reinforcement strain, ε_s	0.0075	0.0024	0.0032	0.0059

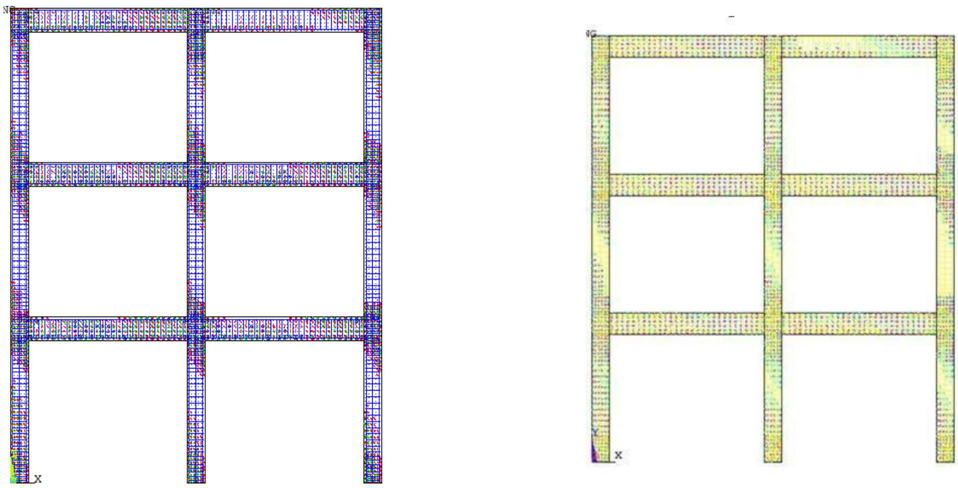

Figure 4. Crack maps for the limited damage zone Δx = 89 mm and the pre-collapse damage limit Δx = 332.3 mm, respectively

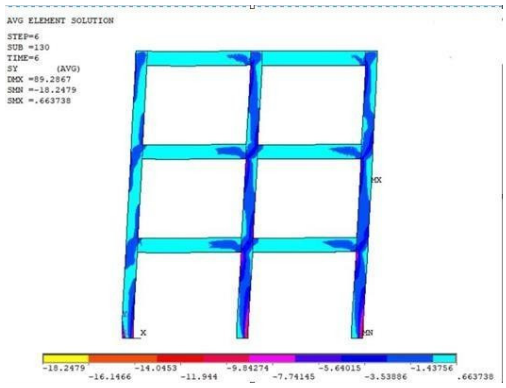

Figure 5. Concrete stress distributions for the limited damage zone Δx = 89 mm and the pre-failure limit Δx = 332.3 mm, respectively

The crack maps for the limited damage zone Δx = 89 mm and the pre-failure limit Δx = 332.3 mm, obtained from ANSYS analyses, are presented in Fig. 4; concrete stress distributions are presented in Fig. 5. Reinforcement strains for the limited damage zone Δx = 89 mm and concrete strains for the pre-failure limit Δx = 332.3 mm are given in Fig. 6. As can be seen from these figures, the two regions with the highest damage level are the bottom support of column 3 and the right support of beam 11. The values for these regions are discussed below. Fig. 7 shows the top horizontal displacement (mm) - base shear force (kN) arranged according to the analysis results.

In the three-dimensional solid FE model, the sum of the unit deformations in the compression and tension regions for the sections at the hinge regions of the columns and beams was divided by the distance between these regions to calculate the average curvatures. Using the relevant equations in TBDY [3], the rotation values corresponding to the curvatures were obtained. Thus, the rotation angles and unit strains obtained in the three-dimensional solid FE model are presented in Table 3 as

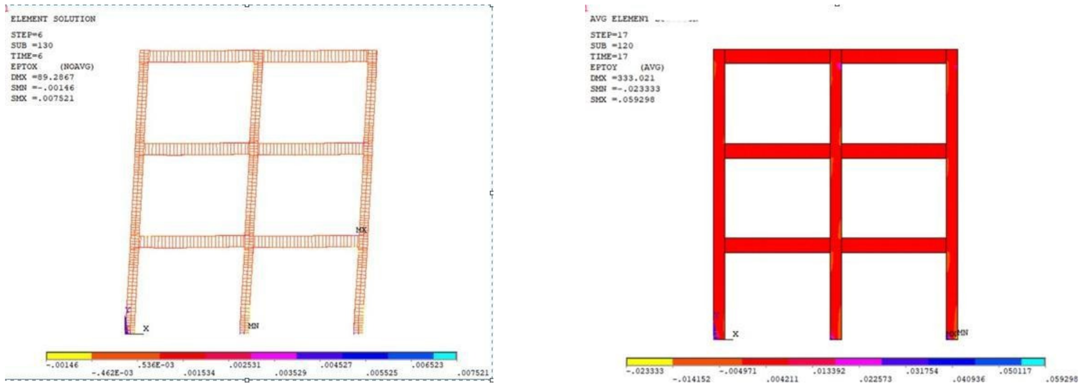

Figure 6. Respectively, the reinforcement strains at the limited damage zone Δx = 89 mm and the concrete strains at the pre-failure limit Δx = 332.3 mm

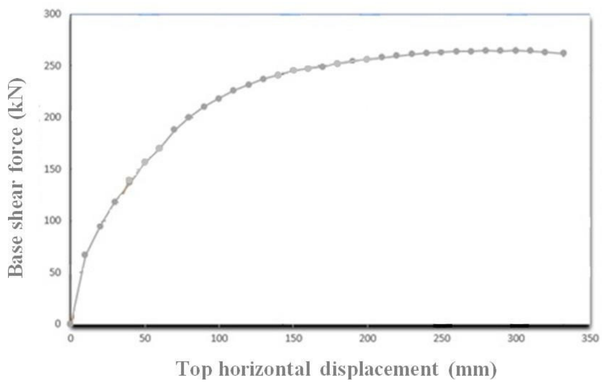

Figure 7. Top horizontal displacement (mm) - base shear force (kN) graph

```
PRINT ITERATION SUMMARY

         ***** POST1 ITERATION SUMMARY *****

LOAD STEP   17  SUBSTEP  120        CUMULATIVE ITERATION 7389
TIME =    17.0000              TIME INCREMENT =   0.833333E-02
 NUMBER OF EQUILIBRIUM ITERATIONS =            3
 CONVERGENCE INDICATOR = 1
 MAXIMUM DEGREE OF FREEDOM VALUE =     332.995
 RESPONSE FREQUENCY FOR 2ND ORDER SYSTEMS =     0.00000
 DESCENT PARAMETER =     1.00000
 FORCE CONVERGENCE VALUE =     1763.24
 MOMENT CONVERGENCE VALUE =     0.00000
 DISPLACEMENT CONVERGENCE VALUE =   0.175430E-01
 ROTATION CONVERGENCE VALUE =     0.00000
 MAXIMUM CREEP RATIO =     0.00000
 MAXIMUM PLASTIC STRAIN STEP =   0.204756E-05
```

Figure 8. Summary of ANSYS analysis iterations

Table 3. Calculated rotation and strain values (0.5 h) of beam 11 and column 3 in the plastic hinge region in the three-dimensional solid model

	Limited	Damage areas: Significant	Advanced	Pre-collapse
Beam number 11 right support area				
Curvature (rad/m)	0.0088	0.037	0.044	0.068
Joint rotation angle, θ_p (rad)	0.0068	0.0149	0.0169	0.028
TBDY 2018 plastic rotation limit value (rad.)	0.0096	0.0144	0.019	
ASCE 41-17 plastic rotation limit value (rad.)	0.01	0.025	0.05	
Concrete strain values, ε_c	0.00085	0.0013	0.0015	0.002
Reinforcement strain values, ε_s	0.0031	0.0156	0.0185	0.0285
Column number 3 bottom support area				
Curvature (rad/m)	0.0125	0.036	0.042	0.058
Joint rotation angle, θ_p (rad)	0.0091	0.0138	0.015	0.018
TBDY 2018 plastic rotation limit value, (rad.)	0.0149	0.022	0.0296	
Concrete strain values, ε_c	0.0017	0.0031	0.0032	0.0037
Reinforcement strain values, ε_s	0.0027	0.0089	0.0116	0.0166

values obtained at half the element height (0.5 h) in the right support of beam 11, where the damage level is highest, and in the lower plastic hinge region of column 3. The iteration summary of the ANSYS analysis is given in Fig. 8. As can be seen from Table 3, the concrete unit strain values are between 0.00085 and 0.0013 in the right support region of beam 11; In the lower support region of column number 3, measurements between 0.0017 and 0.0031 would indicate that a significant level of damage has been reached in those areas. Concrete strain values reaching 0.0015 in the right support region of beam number 11 and 0.0032 in the lower support region of column number 3 would indicate that an advanced level of damage has been reached. In SHM systems, these measurements can be made using Strain Gauges or Fiber Optic Sensors. Curvature and hinge rotations can also be measured using Strain Gauges and Inclinometer-Rotation Sensors. Therefore, these values in Table 3 can also be used in detecting damage zones.

5. Study limitations, discussion, and recommendations

(1) This study does not include field application or validation; however, this does not hinder the applicability of the proposed method. The aim of this paper is not to present an operational sensor-based monitoring system, but rather to propose a conceptual framework for deriving the deterministic reference values—that is, physically meaningful additional threshold values—required by such a system.

(2) The study does not involve real sensor data, multi-structure validation, and probabilistic uncertainty modeling, nor does it utilize real-time data fusion or hardware implementation. Thus, the transformation mechanism between structural analysis outputs and decision support logic is isolated. Furthermore, the study was conducted on a reference basic reinforced concrete frame model that serves as a controlled environment to isolate structural behavior mechanisms and facilitate clear interpretation of analysis outputs. This modeling strategy is consistent with

established practices in SHM and structural identification research, where simplified or canonical systems are frequently used for methodological development and validation.

(3) In this article, a static pushover analysis was performed, but the material models (concrete and reinforcement) were defined as nonlinear. The analysis was carried out using time-step incremental loading in ANSYS software. Increasing horizontal displacement or force was applied to the structure, and material nonlinearity (plasticization, cracking, etc.) was considered at each step. In ANSYS, this is generally done as a "static, nonlinear, time-stepped" analysis; "time" here is not real time, but an artificial time representing the load step. The applied load/displacement is increased in each time step, and the nonlinear equilibrium equations of the system are solved using the Newton-Raphson method. Although this approach is widely accepted in performance-based design due to its computational efficiency and interpretability, it cannot fully capture the cyclic deformation, stiffness reduction, and load reversals naturally present in real earthquake loading. Therefore, extending the framework to nonlinear time-history analyses represents a critical step to improve the accuracy and realism of the proposed decision thresholds. It is suggested that this method be adapted in future studies.

(4) The proposed approach is inherently scalable and system-independent because it is based on fundamental response parameters. Therefore, the proposal can be adapted to smart building environments with different typologies and sizes of structural systems and distributed sensor networks, such as shear wall systems and high-rise buildings.

(5) Typical SHM architectures include data collection, data processing, and decision-making components using sensors. While most current studies focus on the first two components, this study specifically targets the third component through deterministic pre-defined threshold determination. By comparing defined threshold levels, such as service, damage onset, and critical condition, with real-time measurements, it is possible to create automated alarm and intervention mechanisms in building management systems. This approach enables the classification of structural condition without requiring complex model updates or extensive simulations.

(6) A complete probabilistic uncertainty analysis was not performed in this study. However, to partially account for measurement noise and model errors, it is recommended to use the threshold values in Table 3 with a tolerance band of ±10-20%. Monte Carlo simulations for precise uncertainty dispersion are reserved for future work. Furthermore, since cyclic effects such as Bauschinger's effect and stiffness reduction were neglected in the static pushover analysis, it is advisable to reduce the additional threshold values found by 10%.

(7) Another significant limitation of the study is the lack of experimental validation and integration of real sensor data. The proposed framework assumes that structural response quantities such as displacements, accelerations, and strains can be reliably measured and mapped to analytical thresholds. However, real monitoring systems are subject to measurement noise, sensor errors, data loss, and environmental variability. Therefore, although the study defines deterministic threshold values, their practical application in real-time SHM systems requires additional layers, including signal processing, filtering algorithms, and data fusion techniques. In this context, the proposed framework should be interpreted as the analytical core (model-based layer) of a broader DT architecture rather than a complete monitoring system.

(8) Another significant limitation of this study is that the FE model used has not been updated with vibration or displacement data from any real structure. This does not guarantee the absolute predictive accuracy of the model. However, as mentioned above, this study is conceptual method development, and the proposed threshold derivation procedure aims to demonstrate how to derive limit values based on engineering mechanics, rather than the absolute accuracy of the model.

Nevertheless, for the proposed framework to be applicable to a real structure, future studies will require updating the FE model using Bayesian methods with operational modal parameters obtained from sensors and recalibrating the resulting thresholds using this updated model. This step is outside the scope of the current paper and is designated as the subject of subsequent research.

(9) The framework proposed in this study can also be extended to a closed-loop DT architecture where the state of sensor data is continuously updated and thresholds are dynamically evaluated. In such a system, feedback mechanisms can be created to improve threshold values based on observed behavior, enabling adaptive and data-driven decision-making.

(10) The proposed hybrid logic can be illustrated with a simple example: Suppose a modal-based SHM system produces 20% false positives due to environmental influences, while local strain sensors in the same structure, less affected by similar environmental influences, produce a false positive rate of 5%. If the decision mechanism searches for the condition of 'modal anomaly AND strain threshold exceedance', the combination of these two independent indicators reduces the false positive rate to approximately $0.20 \times 0.05 = 1\%$. This simple probabilistic approach demonstrates that the proposed hybrid strategy can produce more reliable results than modal or strain-based decision-making alone. This logic should be tested with real field data in future studies.

(11) Literature shows limited research on reducing false alarms by adding physical thresholds to existing modal/data-driven SHM methods. This study aims to contribute to this limited field.

6. Conclusions

This study focuses on identifying which building elements are at risk by examining damage localization. For this purpose, time-domain nonlinear FE analyses were used to determine crack maps, concrete stress distribution, and reinforcement strains. Elements with concentrated damage were identified to generate evacuation decisions, local strengthening, and rapid intervention outputs in the decision support system. The aim is to generate intervention decisions using element-level damage information. The study proposes that element-level damages, visually summarized with damage maps, be considered as actionable indicators in decision support processes. In the literature, approaches for automatically transferring performance thresholds obtained from analyses to control systems using real-time SHM data are insufficient. With the method proposed in this study, since the performance thresholds determined from the analyses will also be defined as additional threshold values in the SHM system, the analysis results are not only stored during the design phase but also transferred to the SHM system. Comparing these with real-time measurements allows for the determination of the building's instantaneous performance level. This allows for the automatic assessment of the building's condition, enabling control systems to be activated when necessary, and allowing for control, warning, and evacuation decisions to be made.

Most probabilistic, data-driven, or machine learning-base d studies involve statistical inferences from sensor data and the use of artificial neural networks. These studies employ complex, black-box models that are difficult to interpret. They require uncertainty analysis or large training datasets. Specialized sensor infrastructure, large datasets, and training sets are necessary. Moreover, the trained model cannot be transferred to another structure or require s retraining. The proposed deterministic additional thresholds can be used to calibrate or validate the outputs of these methods, thus providing fast, transparent, and regulatory-compliant decision support.

Most SHM studies in the literature are either entirely data- driven (machine learning) or entirely probabilistic (Bayesian networks). Probabilistic methods (Monte Carlo, Bayesian) are computationally expensive, require expertise, and are generally too slow for real-time decision support systems. Smart building systems need simple, fast, understandable, and regulatory-compliant thresholds. Deterministic additional thresholds meet this need.

Structural performance is categorized into discrete operational states based on threshold overshoot logic. Specifically, measured or predicted structural response parameters are compared against predefined limits corresponding to performance levels (e.g., Emergency Use, Life Safety, Collapse Prevention). To reduce the risk of false alarms in real-world applications, a tolerance band can be added around the threshold values, enabling more stable decision-making under uncertain measurement conditions. This rule-based categorization scheme provides a transparent and interpretable decision-making mechanism that can complement more complex data-driven SHM approaches.

This study yielded additional threshold values for the underlying system, as presented in Table 3. Using these thresholds in conjunction with modal analysis can reduce the potential false alarm rates in SHM systems. The study proposes a simple rule base for a hybrid approach. Future studies can expand on this proposal through experimental validation, updating additional thresholds with dynamic analysis, and real-time data fusion.

In conclusion, this study goes beyond the classical push-over analysis known in earthquake engineering, focusing on transforming the outputs of this analysis into complementary and physically meaningful thresholds in intelligent building decision systems. As it stands, the study does not include field application or experimental validation. The FE model has not been updated with real data. This, rather than weakening the claim of the paper, demonstrates that it is the first step that needs to be taken to integrate the proposed hybrid approach into engineering practice. Future studies plan to calibrate the FE model with SHM data (acceleration, strain) from a real structure, dynamically update the proposed thresholds, and test them within a closed-loop digital twin (DT) architecture. In this way, the presented conceptual framework can be transformed into an operational decision support tool.

References

1. Moehle, J., Deierlein, G.G. (2004). A framework methodology for performance-based earthquake engineering. In 13th World Conference on Earthquake Engineering, Vol. 679, p. 12, August, Vancouver, BC, Canada.
2. FEMA P-58 (2012). Seismic Performance Assessment of Buildings, Volume 1 – Methodology, Federal Emergency Management Agency, Washington, DC, USA.
3. TBDY (2018). Turkish Building Earthquake Regulations. Ankara: Disaster and Emergency Management Presidency. (in Turkish)
4. ASCE (2017). ASCE/SEI 41-17: Seismic Evaluation and Retrofit of Existing Buildings. Reston, VA: American Society of Civil Engineers.
5. Doebling, S.W., Farrar, C.R., Prime, M.B., Shevitz, D.W. (1996). Damage identification and health monitoring of structural and mechanical systems from changes in their vibration characteristics: a literature review. Technical Report: Los Alamos National Lab. https://doi.org/10.2172/249299.
6. Housner, G., Bergman, L.A., Caughey, T.K., Chassiakos, A.G., Claus, R.O., Masri, S.F., Skelton, R.E., Soong, T.T., Spencer, B.F., Yao, J.T. (1997). Structural control: past, present, and future. Journal of Engineering Mechanics, 123(9), 897-971. https://doi.org/10.1061/(ASCE)0733-9399(1997)123:9(897).

7. Spencer Jr, B.F., Nagarajaiah, S. (2003). State of the art of structural control. Journal of structural engineering, 129(7), 845-856. https://doi.org/10.1061/(ASCE)0733-9445(2003)129:7(845).
8. Sohn, H., Farrar, C.R., Hemez, F.M., Shunk, D.D., Stinemates, D.W., Nadler, B.R., Czarnecki, J.J. (2003). A review of structural health monitoring literature: 1996–2001. Los Alamos National Laboratory Report LA-13976-MS.
9. Worden, K., Manson, G. (2007). The application of machine learning to structural health monitoring. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 365(1851), 515-537. https://doi.org/10.1098/rsta.2006.1938.
10. Sikorska, J.Z., Hodkiewicz, M., Ma, L. (2011). Prognostic modelling options for remaining useful life estimation by industry. Mechanical Systems and Signal Processing, 25(5), 1803-1836. https://doi.org/10.1016/j.ymssp.2010.11.018.
11. Korkmaz, A., Kayhan, A.H. (2016). Comparison of displacement-based methods with elastic and time history dynamic analysis methods. Trakya Üniversitesi Fen Bilimleri Dergisi, 9(1), 7–13. https://dergipark.org.tr/tr/pub/trakyafbd/issue/22997/245970.
12. Tellal, C. (2017). Statistical evaluation of displacement demands of reinforced concrete buildings obtained by time history analysis. Pamukkale University Institute of Science. https://hdl.handle.net/11499/2227.
13. Limongelli, M.P., Çelebi, M. (Eds.) (2019). Seismic Structural Health Monitoring: From Theory to Successful Applications. Springer. https://doi.org/10.1007/978-3-030-13976-6.
14. Aytulun, E., Soyöz, S. (2020). Monitoring the structural health of a high-rise building before, during, and after an earthquake. Turkish Journal of Earthquake Research. 2(1), 61–75. https://doi.org/10.46464/tdad.735239.
15. Nguyen, Q.T. (2022). Modal analysis-based damage detection and structural health monitoring approach for high-rise buildings. Ph.D. Thesis. Bursa Uludağ University Institute of Science. http://hdl.handle.net/11452/29150.
16. Rojas-Mercedes, N., Erazo, K., Di Sarno, L. (2022). Seismic fragility curves for a concrete bridge using structural health monitoring and digital twins. Earthquake and Structures, 22(5), 503-515. https://doi.org/10.12989/eas.2022.22.5.503.
17. Akbarnezhad, M., Salehi, M., DesRoches, R. (2023). Application of machine learning in seismic fragility assessment of bridges with SMA-restrained rocking columns. Structures, 50, 1320-1337. https://doi.org/10.1016/j.istruc.2023.02.105.
18. Sun, X., Ilanko, S., Mochida, Y., Tighe, R.C. (2023). A review on vibration-based damage detection methods for civil structures. Vibration, 6(4), 843-875. https://doi.org/10.3390/vibration6040051.
19. Mardanshahi, A., Sreekumar, A., Yang, X., Barman, S.K., Chronopoulos, D. (2025). Sensing techniques for structural health monitoring: A state-of-the-art review on performance criteria and new-generation technologies. Sensors, 25(5), 1424. https://doi.org/10.3390/s25051424.
20. Liao, W.I., Hsiao, F.P., Chiu, C.K., Ho, C.E. (2019). Structural health monitoring and interface damage detection for infill reinforced concrete walls in seismic retrofit of reinforced concrete frames using piezoceramic-based transducers under the cyclic loading. Applied Sciences, 9(2), 312. https://doi.org/10.3390/app9020312.
21. Thomoglou, A., Golias, E. (2025). Seismic Response of Reinforced Concrete Structure with Infill Walls for Vertical Forest Applications-Seismic Table Tests, AGHNA, 30,31 OKT.
22. Silva, S.D., Dias Júnior, M., Lopes Junior, V. (2007). Damage detection in a benchmark structure using AR-ARX models and statistical pattern recognition. Journal of the Brazilian Society of Mechanical Sciences and Engineering, 29(2), 174-184. https://doi.org/10.1590/S1678-58782007000200007.
23. Castañeda-Saldarriaga, D.L., Alvarez-Montoya, J., Martínez-Tejada, V., Sierra-Pérez, J. (2021). Toward structural health monitoring of civil structures based on self-sensing concrete nanocomposites: A validation in a reinforced-concrete beam. International Journal of Concrete Structures and Materials, 15(1), 3. https://doi.org/10.1186/s40069-020-00451-8.
24. Limongelli, M.P., Thomson, D., Alampalli, S., Mufti, A., Schumacher, T., Martinelli, L., Lasri, O., Shenton, H., Chen, G., Noori, M. and Raeisi, F. (2025). SCSHM benchmark study on bridge in-service

structural monitoring. Journal of Civil Structural Health Monitoring, 15(3), 849-863. https://doi.org/10.1007/s13349-024-00846-1.
25. Farrar, C.R., Sohn, H. (2000). Pattern recognition for structural health monitoring. In Workshop on Mitigation of Earthquake Disaster by Advanced Technologies. MEDAT.
26. Cornwell, P., Farrar, C.R., Doebling, S.W., Sohn, H. (1999). Environmental variability of modal properties. Experimental Techniques, 23(6), 45-48. https://doi.org/10.1111/j.1747-1567.1999.tb01320.x.
27. Peeters, B., De Roeck, G. (2001). One-year monitoring of the Z24-Bridge: environmental effects versus damage events. Earthquake Engineering & Structural Dynamics, 30(2), 149-171. https://doi.org/10.1002/1096-9845(200102)30:2<149::AID-EQE1>3.0.CO;2-Z.
28. Ni, Y.Q., Xia, H.W., Wong, K.Y., Ko, J.M. (2012). In-service condition assessment of bridge deck using long-term monitoring data of strain response. Journal of Bridge Engineering, 17(6), 876-885. https://doi.org/10.1061/(ASCE)BE.1943-5592.0000321.
29. Sohn, H. (2007). Effects of environmental and operational variability on structural health monitoring. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 365(1851), 539-560. https://doi.org/10.1098/rsta.2006.1935.
30. Ditommaso, R., Ponzo, F.C. (2024). Identifying damage in structures: definition of thresholds to minimize false alarms in SHM systems. Buildings, 14(3), 821. https://doi.org/10.3390/buildings14030821.
31. Liang, Y., Huang, L., Yang, J. (2024). Automated operational modal analysis for supertall buildings based on a three-stage strategy and modified hierarchical clustering. Structures, 62, 106194. https://doi.org/10.1016/j.istruc.2024.106194.
32. Chandola, V., Banerjee, A., Kumar, V. (2009). Anomaly detection: A survey. ACM computing surveys (CSUR), 41(3), 1-58. https://doi.org/10.1145/1541880.1541882.
33. Neves, A.C., Gonzalez, I., Leander, J., Karoumi, R. (2017). Structural health monitoring of bridges: a model-free ANN-based approach to damage detection. Journal of Civil Structural Health Monitoring, 7(5), 689-702. https://doi.org/10.1007/s13349-017-0252-5.
34. Khan, M.W., Akmal Din, N., Ul Haq, R. (2020). Damage detection in a fixed-fixed beam using natural frequency changes. Vibroengineering Procedia, 30, 38-43. https://doi.org/10.21595/vp.2019.21081.
35. Hughes, A.J., Barthorpe, R.J., Dervilis, N., Farrar, C.R., Worden, K. (2021). A probabilistic risk-based decision framework for structural health monitoring. Mechanical Systems and Signal Processing, 150, 107339. https://doi.org/10.1016/j.ymssp.2020.107339.
36. Feng, Z., Lin, Y., Wang, W., Hua, X., Chen, Z. (2020). Probabilistic updating of structural models for damage assessment using approximate bayesian computation. Sensors, 20(11), 3197. https://doi.org/10.3390/s20113197.
37. Plevris, V. (2024). Addressing the pitfalls of image-based structural health monitoring: a focus on false positives, false negatives, and base rate bias. arXiv preprint arXiv:2410.20384.
38. Jia, X., Papadimitriou, C. (2025). Reliability Updating using Monitoring Data. Available at SSRN 5591513.
39. Kamariotis, A., Chatzi, E., Straub, D., Dervilis, N., Goebel, K., Hughes, A.J., Lombaert, G., Papadimitriou, C., Papakonstantinou, K.G., Pozzi, M., Todd, M., Worden, K. (2024). Monitoring-supported value generation for managing structures and infrastructure systems. Data-Centric Engineering, 5, e27. https://doi.org/10.1017/dce.2024.24.
40. Luckey, D., Fritz, H., Legatiuk, D., Peralta Abadía, J.J., Walther, C., Smarsly, K. (2021). Explainable artificial intelligence to advance structural health monitoring. In: Structural health monitoring based on data science techniques, Structural Integrity, 21, 331-346. https://doi.org/10.1007/978-3-030-81716-9_16.
41. Jia, J., Li, Y. (2023). Deep learning for structural health monitoring: Data, algorithms, applications, challenges, and trends. Sensors, 23(21), 8824. https://doi.org/10.3390/s23218824.
42. Lu, J., Liu, L., Lei, Y., Wei, J. (2025). Assessing the Impact of Smart City Development on Urban Resilience: An Empirical Study Based on China's Smart City Pilot Policy. Sustainable Cities and Society, 136, 107029. https://doi.org/10.1016/j.scs.2025.107029.
43. Zhang, X., Liang, W., Yu, X., Xie, B., Liu, C. (2026). Evaluating the impact of artificial intelligence

development on urban resilience: Evidence from Chinese cities. iScience, 29(3), 115083. https://doi.org/10.1016/j.isci.2026.115083.
44. Bertino, E., Jahanshahi, M.R., Singla, A., Wu, R.T. (2021). Intelligent IoT systems for civil infrastructure health monitoring: a research roadmap. Discover Internet of Things, 1(1), 3. https://doi.org/10.1007/s43926-021-00009-4.
45. Aroquipa, H., Hurtado, A., Murga, C., De La Cruz, R., Tarque, N. (2025). Towards Smart Cities: Foundational Methodology for Implementing Intelligent Circular Resilience in Heritage Buildings through Structural Health Monitoring and Digital-Twins–Part A. International Journal of Disaster Risk Reduction, 128, 105749. https://doi.org/10.1016/j.ijdrr.2025.105749.
46. Xu, J., Shu, X., Qiao, P., Li, S., Xu, J. (2023). Developing a digital twin model for monitoring building structural health by combining a building information model and a real-scene 3D model. Measurement, 217, 112955. https://doi.org/10.1016/j.measurement.2023.112955.
47. Torzoni, M., Tezzele, M., Mariani, S., Manzoni, A., Willcox, K.E. (2024). A digital twin framework for civil engineering structures. Computer Methods in Applied Mechanics and Engineering, 418, 116584. https://doi.org/10.1016/j.cma.2023.116584.
48. Li, X., Zhang, F. L., Xiang, W., Liu, W.X., Fu, S.J. (2024). Structural health monitoring system based on digital twins and real-time data-driven methods. Structures, 70, 107739. https://doi.org/10.1016/j.istruc.2024.107739.
49. Algadi, A., Uluutku, B., Cano, J.A., Walters, L., Alqurashi, I., Luleci, F., Catbas, F.N. (2025). Digital twin-oriented generation of structural data and models with LiDAR scan point clouds. Journal of Infrastructure Preservation and Resilience, 6(1), 32. https://doi.org/10.1186/s43065-025-00140-4.
50. Cho, H., Yu, J., Moon, H., Yoon, J., Lee, J., Kim, G., Park, J., Ryu, S. (2025). Real-Time Structural Health Monitoring with Bayesian Neural Networks: Distinguishing Aleatoric and Epistemic Uncertainty for Digital Twin Frameworks. arXiv preprint arXiv:2512.03115. https://doi.org/10.48550/arXiv.2512.03115.
51. Kaveh, H., Alhajj, R. (2025). Advancing civil infrastructure with digital twins: a review of applications and challenges. Journal of Civil Engineering and Management, 31(8), 828-842. https://doi.org/10.3846/jcem.2025.24921.
52. Applied Technology Council, & California. Office of Emergency Services. (1991). Procedures for postearthquake safety evaluation of buildings (Vol. 20). Governor's Office of Emergency Services.
53. Kasımzade, A.A. (2024). Structural Design and Analysis Based on SEM with SAP2000 in Light of Current Regulations. 2nd edition, Nobel Publications, Ankara, Turkey, 356. (in Turkish)
54. Yılmaz, H., Koç, V. (2023). Evaluation of earthquake performance of reinforced concrete frame with direct displacement- based design approach and comparision of rigidity with finite element solution. International Topkapı Congress II, 550-557, October, İstanbul, Türkiye.
55. ANSYS, Inc. (2021). ANSYS Mechanical APDL (Release 2021 R1) [Computer software]. Canonsburg, PA, USA.
56. Yılmaz, H., Koç, V. (2023). Comparison of the damage level of the performance- based design of the reinforced concrete frame obtained by the finite element method with the Turkish earthquake standart. International Topkapı Congress II, 537-549, October, İstanbul, Türkiye.
57. Saatcioglu, M., Razvi, S.R. (1992). Strength and ductility of confined concrete. Journal of Structural Engineering, 118(6), 1590-1607. https://doi.org/10.1061/(ASCE)0733-9445(1992)118:6(1590).
58. AFAD (Disaster and Emergency Management Presidency) (2018). Türkiye Earthquake Hazard Map Interactive Web Application (TDTH). https://tdth.afad.gov.tr (in Turkish)