A New Approach in Structural Control: An Industrial Application for the Tallest Building in the Caucasus

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Abstract. For the Baku Tower (BT), the tallest building in the Caucasus region, constructed in Baku, the capital of Azerbaijan, controlling dynamic behavior is critical for both safety and user comfort. The structure is equipped with a Tuned Mass Damper (TMD) system with a mass of 400 tons to reduce vibrations caused by wind and earthquakes. In this study, the dynamic analysis results of the BT with and without the damper were compared using the Finite Element Method (FEM). The results show that the use of TMDs increases the period.

In the second phase of the study, the Structural Health Monitoring (SHM) system installed on the building is examined. Through accelerometers and sensors placed on critical floors, the dynamic behavior of the structure is continuously monitored, and warning signals are sent to the building management and power control systems when critical threshold values are exceeded, based on real-time comparisons of the obtained data. Therefore, the structural control system performance and the indicators obtained from numerical dynamic analyses are correlated with the real-time SHM system. Thus, the analysis results are evaluated beyond their use in design and verification, and integrated into building operation and safety decision-making processes. Critical parameters such as story displacements, vibration characteristics, and peak displacements obtained from dynamic analyses are used as monitorable threshold values by the SHM system. In this way, this data is transformed into operational decision criteria that can be transferred to the building control system. The integrated use of structural control systems and SHM applications in a high-rise building has been examined through analyses and applications.

Keywords: Structural control, Tuned mass damper (TMD), Structural health monitoring (SHM), High-rise buildings, Wind effect, Seismic behavior, Dynamic analysis, Vibration control, Decision support system, Smart building systems

1 First Section

In this study, the Baku Tower (BT) building was subjected to nonlinear and time-date interval dynamic analyses using finite element methods in both its normal and Tuned Mass Damper (TMD) system configurations, and its response values under free and forced vibrations were compared. The critical values obtained from the TMD system configuration were evaluated by a decision support system designed to determine the necessary maintenance or intervention for the structure. This system generates a warning signal when it detects that critical threshold values have been reached due to the stress of dynamic factors such as wind and earthquakes. The information is sent to the building's power control system via a transmission line, enabling the implementation of emergency safety procedures in the water, electricity, and natural gas systems. A Structural Health Monitoring (SHM) supported decision system was used in the building. SHM is a system that continuously monitors the dynamic effects of earthquakes and wind; vibrations caused by various devices or vehicles that may affect the structure inside or around it; and long-term damage developments that may occur in the structure due to ground or load effects, as well as the structural behavior under these factors, using sensors. In SHM, data from accelerometers positioned at critical points in the building are continuously monitored by real-time analysis software. This allows for tracking the long-term damage development of the structure. Whether the building has sustained damage after an earthquake can be quickly determined, enabling decisions to be made regarding the safe use of the building.

In this study, stages that are often carried out independently between analysis, monitoring, and building management processes are integrated into a single decision support chain. Therefore, structural performance evaluation is viewed not only as a process used in the design-review phase, but also as an active component in the continuous evaluation of the building's comfort of use and operational safety. Thus, the integrated use of structural control systems and smart building management applications in a high-rise building is examined through analysis and applications, and structural control systems, smart building management technologies, and smart building management applications are made usable in an integrated manner in engineering practice.

Currently, intensive research is being conducted on transferring data obtained from structural analysis (SAM) to building operation processes (Kamariotis et al., 2023; 2024). However, studies focusing on integrated approaches to integrating performance limits obtained from structural analysis results into building control and operation systems through real-time evaluation via the SAM system should be increased. While there are studies on performance-based SAM and control systems in the existing literature (Spencer and Nagarajaiah, 2003; Hughes et al., 2021), approaches for automatically transferring performance thresholds obtained from analysis to control systems using real-time SAM data are lacking. With the method proposed in this study, performance thresholds determined from analyses are defined in the SAM system, and sensor data are compared with the threshold values. The building safety status is automatically determined, and control systems are activated when necessary. In other words, the analysis, monitoring, decision, and control chain is integrated. Performance-based analysis during the design phase (Moehle and Deierlein, 2004; FEMA P-58, 2012), which is discussed separately in the literature, and vibration reduction studies carried out with SHM and control systems during the service life (Connor, 2003; Kareem, 1999) are used together as a chain. By addressing the gap in the real-time evaluation of performance thresholds obtained from analyses via the SHM system and their transfer to the control system, the analysis results are not only kept at the design stage but are also transferred to the SHM system, compared with real-time measurements, and subsequently the structural performance level is determined. This allows for the automatic evaluation of the structural condition and, when necessary, the activation of control systems to generate control, warning, and evacuation decisions. In the literature, modal analysis-based SHM studies aim to detect damage through frequency and mode changes (Wang et al. 2008; Khan et al., 2020), generate damage probabilities using vibration measurements (Hughes et al., 2021; Del Pozo et al., 2023), but do not link these to performance levels. Data-driven SHM approaches, on the other hand, aim to detect anomalies in the structure (Worden et al., 2007; Zacharakis and Giagopoulos, 2022), generate damage alarms using sensor data (Wang and Ke, 2024; Li et al., 2024), but maintain a weak relationship with analyses.

Numerous studies in the current literature on reducing vibrations caused by wind and earthquake effects in high-rise buildings mostly focus on the design and performance of TMD or seismic isolation systems and various passive, semi-active, or active damping methods (Housner et al., 1997; Kelly, 1993; Soong and Dargusg, 1997; Kareem, 1999; Spencer and Nagarajaiah, 2003; Connor, 2003). Similarly, research on SHM systems focuses on issues such as sensor placement, vibration-based damage detection, determination of modal parameters, and rapid post-earthquake damage assessment (Doebling et al., 1996; Sohn et al., 2003; Li et al., 2004; Worden et al., 2007; Farrar and Worden, 2012). There is a need for studies that intersect these two areas, which are generally considered independently. Comprehensive studies should be conducted that combine research on the performance of structural control systems examined during the design phase with research on SHM systems used as monitoring and reporting tools. In particular, there is a significant gap in the literature regarding the conversion of the performance of vibration control systems used in high-rise buildings under real operating conditions into decision support mechanisms. This study includes an application for performance-based real-time building management in high-rise buildings by integrating analysis, monitoring, and operation processes.

2 Problem Statement

Traditional SHM (Survey Management) applications involve a system where sensor data is interpreted by experts, leading to subjective decision-making risks and slow post-disaster decision delays. Therefore, it is crucial to generate automatic damage indicators by detecting threshold exceedances from SHM data to create alarms and warnings. In a typical automated decision-making process, feature extraction from sensor data is used to perform threshold checks and generate alarms, but usually only a decision of whether damage exists or not is made (Farrar and Worden, 2012; Worden and Manson, 2007; Ni et al., 2009; Sun et al., 2023; Riveros et al., 2014). More advanced systems attempt to determine whether the structure can continue to be used after damage detection. For this purpose, the probability of a specific measurement corresponding to damage is calculated. The risk level is determined as the product of this damage probability and the severity of the damage. The results are evaluated in terms of loss of use, economic loss, and safety risk. Decision levels are generally classified as safe use, restricted use, and evacuation requirement (Sohn et al., 2003; Farrar and Worden, 2012; Lynch and Loh, 2006). Most systems base these decisions on measurement statistics rather than analytical data. Therefore, current studies adopt a probabilistic decision approach. Instead of deterministic thresholds, Bayesian updates, probabilistic damage models, and reliability indices are used. In these approaches, the structural performance is expressed as a probability distribution, the distribution is updated with sensor data, and risk levels are recalculated (Hughes et al., 2021; Feng et al., 2021; Jia and Papadimitriou, 2025; Straub and Der Kiureghian, 2010). However, the models are often complex and their real-time application is limited. The fact that SHM measurements make risk predictions by generating damage indicators means that the decision-making process is not related to structural analyses. In other words, threshold values are mostly empirical or statistical. They do not depend on the actual analytical performance of the structure. Decision-making mechanisms and control processes, developed by comparing performance thresholds obtained from structural analyses with SHM measurements, ensure that thresholds are grounded in analyses derived from structural modeling, that performance-based decisions determine performance levels rather than just alarms, and that control systems can be triggered by decision outputs directly transferred to building systems. Currently, SHM systems detect damage but lack performance-based decision-making and control integration (Kamariotis et al., 2023; 2024; Limongelli, 2020).

While SHM systems classically relied on physics-based analyses, data-driven approaches have come to the forefront in the last 20 years due to the increasing amount of data. This transformation is seen in the application areas of damage detection, anomaly detection, and prediction/prognosis (Farrar and Worden, 2012; Worden et al., 2007; Farrar and Sohn, 2000; Sikorska et al., 2011). In this context, machine learning approaches such as artificial neural networks, support vector machines, random forests, k-nearest neighbors, and deep learning models are used to classify structural condition by extracting features such as frequency variations, acceleration records, mode shape differences, and vibration characteristics from sensor data (Worden and Manson, 2007; Farrar and Worden, 2012; Avci et al., 2021). These systems operate on the principle of creating damage classes by using sensor data for feature extraction and model training. The fundamental problem with these methods, which allow learning from data even if the damage mechanism is not explicitly modeled, is that the model only works as well as the training data and may not always correctly interpret new situations (Worden et al., 2007; Farrar and Worden, 2012; Avci et al., 2021).

In many cases, since damage data is unavailable, the system learns normal behavior using techniques such as autoencoder networks, Gaussian mixture models, PCA-based methods, isolation forests, and clustering algorithms, and identifies deviations from this behavior as anomalies (Farrar and Sohn, 2000; Chandola et al., 2009; Avci et al., 2021). Another problem here is that an anomaly does not always mean damage. Factors such as temperature changes, wind conditions, and changes in land use can also create anomalies (Peeters and De Roeck, 2001; Sohn, 2007; Cornwell et al., 1999; Ni et al., 2012). Further studies on model-based prediction (prognosis) methods not only detect damage but also make inferences about how the damage will develop in the future. Farrar and Lieven (2007), Eleftheroglou et al., 2018; Li and Noman (2025) state that at this point, techniques such as time series prediction models, LSTM and RNN networks, Kalman filters, and Bayesian update methods are used. These approaches produce outputs such as remaining service life estimation, performance degradation prediction, and maintenance planning (Yang et al., 2022; Zhang et al., 2021; Zhang et al., 2024; Kamariotis et al., 2023; Lai et al., 2024). However, the fact that the prediction is mostly not related to physical performance levels leads to problems in AI-machine learning based SHM studies, such as the inability to link the results to engineering performance criteria, relate them to analysis-based thresholds, and integrate them into control systems, especially in the damage detection, anomaly identification, and prediction generation phases. In other words, the algorithm learns from the data but cannot produce engineering decisions. At this point, expert review becomes necessary (Luckey et al., 2021; Jia and Li, 2023; Plevris, 2024). This study aims to complete the decision and control chain by combining analysis-based performance thresholds with SHM and data-driven approaches.

Today, modern cities are evaluated not only in terms of their physical characteristics but also in terms of their digital infrastructure. Thus, decision-making mechanisms based on real-time data are created in areas such as energy management, transportation, security, infrastructure monitoring, and disaster management throughout the city (Batty et al., 2012; Zanella et al., 2014; Bibri and Krogstie, 2017; Kitchin, 2014). Indeed, the goal of the smart city approach is not only energy and transportation optimization. One of the critical goals is to create cities that are resilient to disasters and capable of rapid recovery. Therefore, efforts are being made to use SHM systems not only as individual building monitoring tools but also as an integral part of city management (Lu et al., 2025; Zhang et al., 2026; Bertino et al., 2021; Aroquipa et al., 2025; Rodríguez-Antuñano et al., 2022). However, it is necessary to advance studies on integrating the information obtained from SHM (Strategic Engineering Monitoring) data of structures considered as passive components in smart city systems into the smart city management mechanism. In particular, high-rise buildings, bridges and viaducts, metro systems, hospitals, critical public buildings, energy and communication infrastructures should be monitored as parts of a network system. Thanks to this integration, damaged and at-risk areas, as well as inoperable infrastructure, can be seen instantly. However, in most applications, only damage maps are produced, and performance evaluation remains limited (Bertino et al., 2021; Jahanshahi and Masri, 2012). The most critical problem after an earthquake is the rapid identification of buildings that are unsafe and should not be used, as well as safe areas that need to be evacuated (Applied Technology Council, 1991). The traditional method, where engineers go to the site to inspect buildings, causes the process to take weeks. Although speed has been achieved with SHM systems, most systems only provide warnings about potential damage. The actual performance level is not determined (Sohn et al., 2004; Worden and Farrar, 2007).

The goal of modern disaster management is to direct search and rescue teams to the right places, protect hospital and transportation infrastructure, and rapidly restore city functions. In current systems, building performance levels cannot be directly linked to city management decisions. While damage maps can be generated from post-disaster data, the inability to automatically determine performance levels, the lack of correlation between decision-making mechanisms and analysis, and the limited evaluation of existing data in decision-making indicate the shortcomings of current data. However, the use of performance thresholds obtained through analysis, especially when applied at the city level, automates and accelerates the identification of safe areas, the closure of buildings, and the optimization of emergency response plans. The potential of this study, extending from the building scale to the city scale, can provide a revolutionary improvement in multi-disaster management systems. In the traditional approach, performance evaluation is largely limited to the design and construction phases, and behavioral changes under various factors are identified through post-damage inspections. Thanks to advancements in sensor technologies, data processing capacity, and communication infrastructures, buildings should now be considered as systems that continuously generate data, and this data must be effectively utilized in smart city approaches. Just as structural engineering (SHM) systems become not merely a monitored parameter but an active component guiding operational decisions when integrated into smart building management, the integration of city-scale building data into central disaster and infrastructure management systems can create holistic emergency response and service sustainability. By integrating analysis, monitoring, and operation processes, chaotic post-disaster decision-making processes can be replaced by data-driven management strategies, leading to significant advantages in multi-disaster management. This study presents the building-scale engineering equivalent of data-driven management approaches developed for smart cities and offers a framework for the future integration of SHM-supported performance management with city-scale disaster and infrastructure management systems.

3 SHM and TMD Systems Installed in the Baku Tower Building

Baku, the capital of Azerbaijan, located on the Caspian Sea coast and affected by varying degrees of winds daily, derives its name from the word "bakı," meaning "windy place." This meaning alone highlights the challenges of constructing high-rise buildings in Baku. As the building gets higher, the increasing wind intensity causes vibrations and oscillations. Even low-acceleration oscillations of 10-20 milli-g, if sustained for a period, can be felt by people, creating a "seasickness" effect. Therefore, it is necessary to dampen the oscillations caused by wind in high-rise buildings for comfort. Especially in high-rise buildings like the Baku Tower (BT), which was constructed between 2014 and completed in 2020, and is the tallest building in the Caucasus region at 276.3 m, it is essential to prioritize comfort as well as safety and functionality, given the constant and sometimes very strong wind effects. For this purpose, floor rigidities, damping ratios, and mass distributions must be optimized. BT, with its roof and observation platform, has 50 above-ground floors and 2 larger underground floors. As with all high-rise buildings, shear forces are high in the lower floors and displacements are high in the upper floors. To limit these displacements, a 400-ton Tuned Mass Damper (TMD) is used in BT to dampen wind and seismic effects. The mass block, consisting of a large steel box filled with in-situ concrete, undergoes controlled horizontal movement of 1.3 m in each direction due to wind and seismic effects. Thus, the TMD reduces accelerations from the lower limit of 10 milli-g to 7 milli-g. This reduces the dynamic loads acting on the structure and ensures living and working comfort in BT, which consists of office centers, commercial and service areas (Structurae, 2020).

Figure 1 shows a view from the top of the tower towards the interior compartments of the steel box before the concrete was poured. The reinforced concrete reinforcement is also visible at the bottom. The block has four suspension systems, each containing three cables, the housings of which are shown in Figure 1. Although four cables would normally suffice according to calculations, twelve cables were used to ensure the highest level of safety. These pendulum cables are manufactured as smooth-surfaced, fully interlocking cables. As can be seen in Figure 2, the cables are used in sets of three at each of the four suspension points. In this way, the cross-linked hydraulic dampers are also visible. Figure 3 shows the TMD system and some of its features. Views from the construction phase of the BT are given in Figure 4. The TMD system effectively produces benefits when its vibration period is aligned with the natural period of the structure. Therefore, natural frequency measurements had to be taken after the tower was completed. TMD adjustment was made through cables extended to coincide with the natural frequency. For this purpose, an adjustment block, which acts as a mechanical compression device, was used. This block, easily movable downwards within the steel box, allows for the extension of the free pendulum length at the top, thereby slowing down pendulum vibrations. Following vibration testing, a total of ten hydraulic dampers were installed, mounted diagonally around the mass block. These dampers ensure that pendulum deflection caused by hurricane and earthquake effects is limited to a maximum of 1.3 m. Since hydraulic dampers react according to speed, they show almost no reaction under effects that would cause relatively small pendulum movements, such as strong winds. TMD reduces large seismic effects by 10-15% overall. In addition, Anti-buckling Braces (BRBs) have also been installed on the tower as additional seismic protection (Structurae, 2020).

Both passive and adaptive TMD systems require a suitable and simple design to minimize costs and installation space. In this context, the slope of the oil dampers, the design of the TMD mass as simply as possible to minimize processing costs, cable anchors with variable compression units, and a robust suspension beam structure are critical. The secondary mass added to the structure with the TMD moves in phase opposite to the vibration of the main structure, damping some of the energy and thus reducing the acceleration acting on the main structure. Wind analyses performed for BT have shown that ISO 10137 comfort limits cannot be achieved without TMD (Weber et al., 2019). Since actual wind loads are broadband and a purely frequency-tuned, undamped system is only effective at a single frequency, TMD systems with internal damping are required for high-rise structures under severe wind loads. In BT, with dampers placed at a 60° angle, excessive displacements are limited and the system occupies less space as the damping force increases proportionally with the load. However, controlling vibrations affecting structures today is not only a design problem aimed at reducing structural damage, but also a performance problem concerning user comfort and operational safety (Weber et al., 2019). Wind effects on high-rise buildings and bridges, human-induced vibrations on overpasses, and ground vibrations from vehicles and machinery can cause unacceptable accelerations in terms of user comfort, even if they do not exceed the structural strength limits. The modern engineering approach is based not only on preventing structural damage and collapse, but also on controlling service performance. Although the use of TMD and isolation systems serving these purposes has become widespread, the performance of these systems is generally considered at the design stage. However, the performance of these systems should also be continuously monitored during operation. Therefore, today, it is becoming increasingly important to convert performance thresholds obtained from structural analysis into operational decisions via SHM (Strategic Maintenance and Control).

Fig. 1. Internal compartments of the steel box (Structurae, 2020).

Fig. 2. Cross hydraulic dampers and pendulum cables.

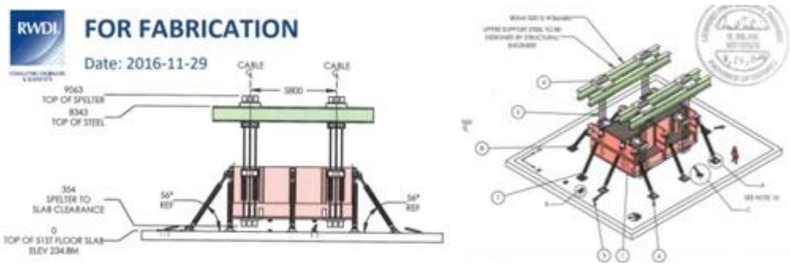


Fig. 3. TMD system.

The primary goal when establishing an SHM (Surface-to-Surface Hydraulic Works) system is to accurately capture the dynamic behavior of a building using the minimum number of accelerometers and sensors placed at critical floors that can represent this behavior. Initially, accelerometers are placed at the base of the foundation/basement, the first point where the actual seismic motion reflected from the ground to the building can be detected. This allows for a comparison of the ground motion with the upper floor movements, and the amplification effect of the structure can be determined from the measured difference. However, for this, sensors and accelerometers capable of measuring the maximum response of the structure are also placed at the top of the highest floor. This is because horizontal displacement, acceleration, and oscillation values are at their maximum at this point. Thus, the total oscillation of the building, the natural vibration period, and damping ratios can be obtained. Furthermore, the maximum wind speed the structure may be subjected to is also measured by a sensor placed at the top. In addition to all this, it is necessary to detect the different oscillation modes that occur, especially in high-rise buildings, due to their lack of a single, unified block movement under seismic influence. For this purpose, accelerometers should also be placed at critical middle floors. This allows us to obtain information such as the distribution of motion between floors, vibration modes, and where damage is concentrated or may be concentrated. In soft stories, transfer floors, floors where the floor height changes, or where shear walls are reduced, the change in stiffness increases the floor displacement, thus increasing the risk of damage. Torsional motion can also be captured by placing more than one accelerometer on some floors. The aim of SHM is not to place sensors and accelerometers on every floor, but to place sensors and accelerometers at the minimum number of points that can represent the dynamic behavior of the structure.

In addition to accelerometers, a wind sensor has also been installed at the top of the structure. Thanks to both 2-axis and 1-axis accelerometers placed at the mezzanine floors, displacements in directional orientation and torsional effects can be detected. Examples of the application and planning stages of the accelerometer system installation are presented in Figure 6.

In the study by Sevgen et al. (2025), which describes the planning phase of the SHM system installation in the IT building, the control of power systems is not addressed. This is because the study describes the planning required for the SHM system to send warning signals to the control unit when critical threshold values are detected. It is assumed that the necessary subsequent actions will be performed by the power control system according to the specified protocol in emergency mode. In smart building systems, in any disaster or emergency, the building's power system control unit performs many defined tasks related to building safety depending on the type of warning. For these actions to be performed effectively, an accurate and reliable warning signal must be transmitted to the power control unit, and the control unit must be properly informed. At this point, this study includes analyses aimed at analytically determining critical threshold values.

Fig. 4. Views of the IT construction phases (Council on Vertical Urbanism, n.d.)

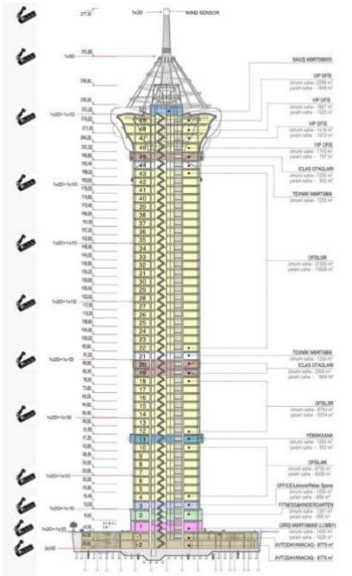


Fig. 5. General and usable area characteristics of floors in the CT system and location characteristics and number of accelerometers used for SHM.

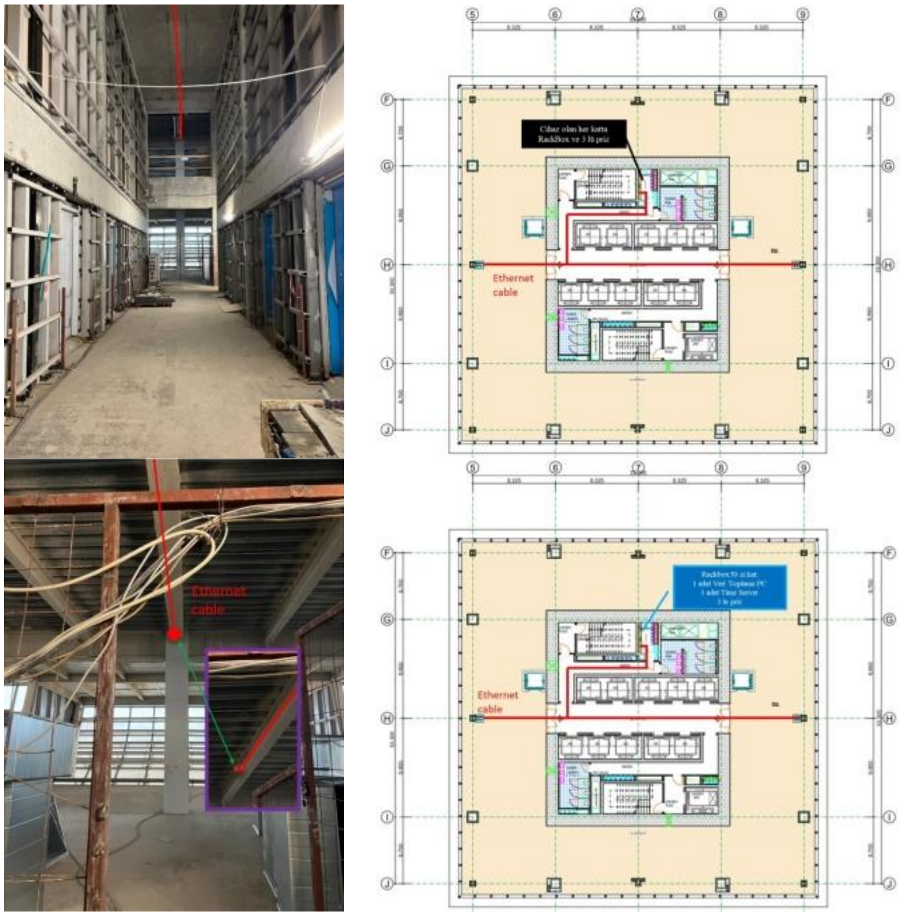


Fig. 6. Examples of implementation and planning for accelerometer placements on some floors.

4 Method

In this study, the method proposed is to determine the alarm thresholds to be used in the SHM system based on the peak acceleration, peak displacement, and maximum story displacement values obtained from time-domain nonlinear analyses performed on the numerical model of the structure. This study essentially presents a methodological proposal. Therefore, only two earthquake records were used. For more comprehensive studies, calibration can be performed with more earthquake records. In this study, Chi-Chi and Kobe earthquake records were selected as reference earthquake records due to their different frequency contents and strong ground motion characteristics, and the structural responses obtained under these records were evaluated as threshold values representing the reference demand levels for the system. For this purpose, modal analyses were performed for the damped and undamped cases of the BT building using the Etabs V9.7.4 FEM program. In the modeling of the TMD-equipped BT structure with ETABS, the structure mass was taken as 80,688,774.55 kg, the TMD mass as 400,000 kg, and the structure mass/TMD mass = 201.6, using the IBC 2012 Regulation. The dead load of the viscous damper, steel beam, and other elements used to fix the TMD's Mass Box was taken as 80,771.8 kg. Antenna mass of 156,000 kg was added. The total length and width of the cover on which the loads rest was taken as 16,625 x 19.80 m; the total area was taken as 329,175 m^2.

For damper case analyses, the lateral stiffness (k) of the TMD system was taken as 544.32 kN/m and the period as 5.3835 sec. To obtain the design-based behavior spectrum, acceleration spectra (uniform hazard spectra) obtained based on soil-dependent spectral amplitudes at periods Ss= 0.2s and S1= 1s in the IBC (2012) seismic code were used. In this stage, the spectral acceleration modification coefficients included in the code were used to calculate the effect of local soil conditions on spectral accelerations. A D-type soil class was assumed for the local soil conditions in the project area. Therefore, there is a modification in the spectral accelerations obtained under the reference soil conditions. The spectral accelerations calculated according to the periods are given in Figure 7. Based on these calculations, the SS=1.18 and S1=0.7 information specified in the BT Calculation Report were entered into the Seismomatch software.

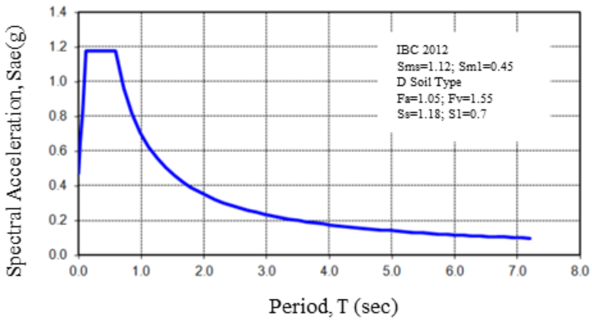


Fig. 7. Period- Spectral Acceleration Graphic

5 Findings

According to the analysis results, the period values for the modes are given in Table 1, and the peak horizontal displacement values are given in Table 2. The period value for the first mode was obtained as 4.393 seconds in the undamped case and 4.705 seconds in the damped case. The period value for the second mode was obtained as 4.023 seconds in the undamped case and 4.3 seconds in the damped case. Thus, it was observed that the period of the structure could be increased by 7.1% in the first mode and 6.88% in the second mode with the TMD system. The peak horizontal displacements were 0.193 m in the undamped case and 0.181 m in the damped case, and it was observed that the peak displacements could be reduced by 6.17% thanks to the TMD system (Table 2). The comparison of the forced vibration responses of damped and undamped BT structures under the Kobe earthquake is given in Table 3. The comparison of the forced vibration responses of the damped and undamped BT structure under the Chi-Chi earthquake is given in Table 4. Forced vibration ETABS BT analysis results are given in Figures 8-12 for the Kobe earthquake and in Figures 13-17 for the Chi-Chi earthquake. The maximum drift in the Kobe EQ with damper, story 37 - drift in the X direction was obtained as 0.005199 m; the maximum drift in the Kobe EQ without damper, story 41 - drift in the X direction was obtained as 0.007977 m. This shows that a 35% reduction in maximum drift was achieved in the damped system. The maximum drift in the Chi-Chi EQ with damper, story 37 - drift in the X direction was obtained as 0.002808 m; the maximum drift in the Chi-Chi EQ without damper, story 42 - drift in the X direction was obtained as 0.004424 m. This shows that a 36% reduction in maximum drift is achieved in the damper system.

Table 1. Comparison of Free Vibration Responses for BT with damper and BT without damper structure

Mode	BT Period [sec] Without TMD	BT Period [sec] With TMD	Difference [%]
1	4.3721	5.4946	25.67
2	4.0033	5.4596	36.38
3	1.3844	4.3362	213.22
4	1.1256	3.9878	254.28
5	1.0858	1.3637	25.59
6	1.0088	1.1400	13.01
7	0.9722	1.1123	14.41
8	0.9424	1.1053	17.29
9	0.4486	1.0889	142.73
10	0.3993	1.0725	168.60
11	0.2382	1.0051	321.96
12	0.2088	0.9967	377.35

Table 2. Peak horizontal displacement values.

Peak point displacement [m] X direction		Difference [%]
Without TMD	With TMD	
0.19339	0.18145	-6.174

Table 3. Comparison of Forced Vibration Responses for BT with damper and BT without damper structure under the Kobe Earthquake

	Without TMD	With TMD	Difference [%]
Acc (Top)	1.623e+01	1.247e+01	-23.17
Disp (Top)	9.788e-01	8.778e-01	-10.31

Base Shear	3.204e+08	8.130e+07	-74.63
Base Mom	1.877e+10	1.725e+10	-8.1

Table 4. Comparison of Forced Vibration Responses for BT with damper and BT without damper structure under the Chi Chi Earthquake

	Without TMD	With TMD	Difference [%]
Acc (Top)	8.544e+00	4.692e+00	-45.08
Disp (Top)	5.011e-01	4.699e-01	-6.23
Base Shear	1.996e+08	2.797e+07	-85.99
Base Mom	1.112e+10	8.410e+09	-24.37

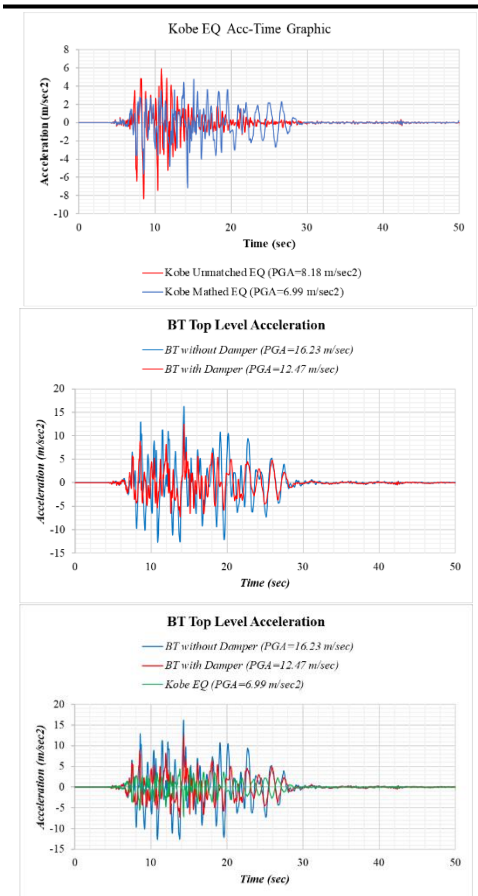


Fig. 8. Kobe EQ Acc-Time Graphic, Comparison of Top-Level Acceleration Responses for BT with damper and BT without damper structure under the Kobe Earthquake

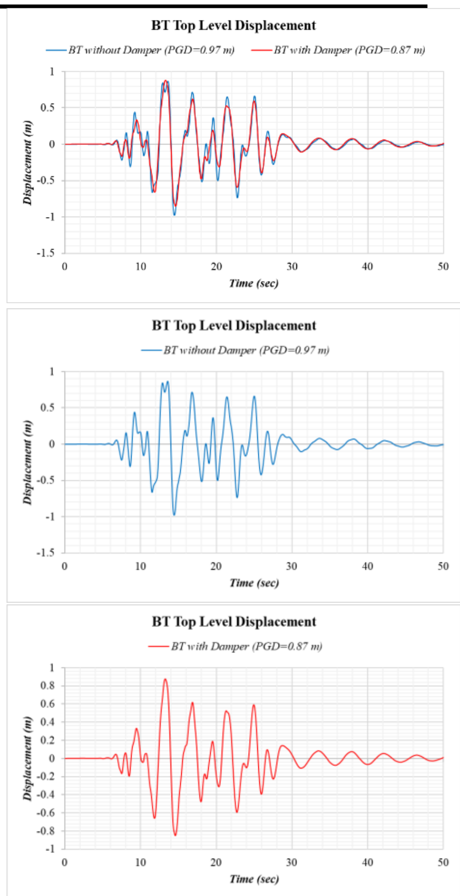


Fig. 9. Comparison of Top-Level Displacement Responses for BT with damper and BT without damper structure under the Kobe Earthquake

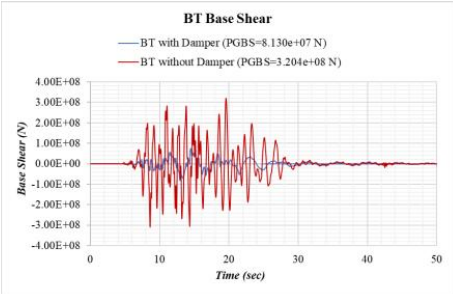


Fig. 10. Comparison of Base Shear Responses for BT with damper and BT without damper structure under the Kobe Earthquake

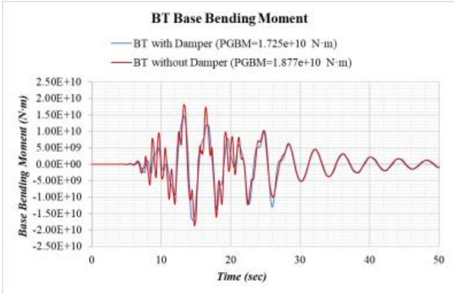


Fig. 11. Comparison of Base Bending Moment Responses for BT with damper and BT without damper structure under the Kobe Earthquake

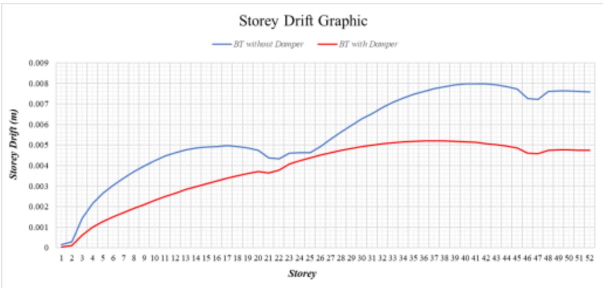
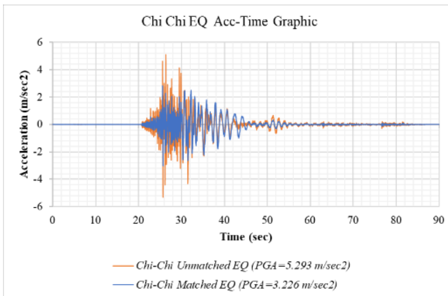
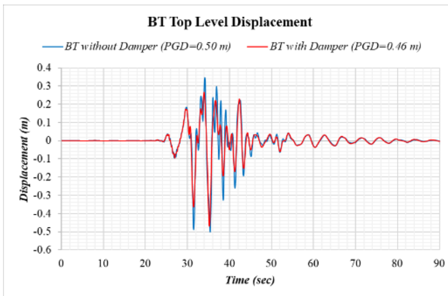


Fig. 12. Comparison of Storey Drift Responses for BT with damper and BT without damper structure under the Kobe Earthquake.





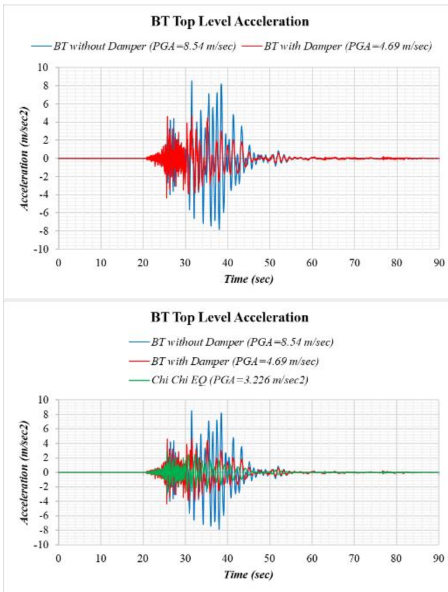


Fig. 13. Chi Chi EQ Acc-Time Graphic, Comparison of Top-Level Acceleration Responses for BT with damper and BT without damper structure under the Chi Chi Earthquake

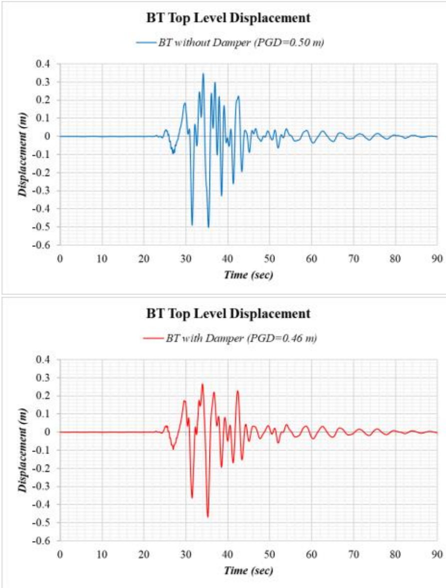


Fig. 14. Comparison of Top-Level Displacement Responses for BT with damper and BT without damper structure under the Chi Chi Earthquake

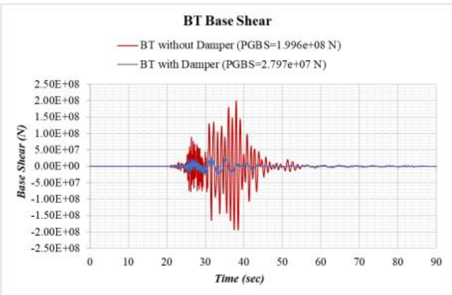


Fig. 15. Comparison of Base Shear Responses for BT with damper and BT without damper structure under the Chi Chi Earthquake

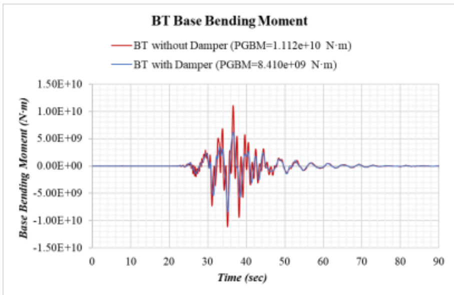


Fig. 16. Comparison of Base Bending Moment Responses for BT with damper and BT without damper structure under the Chi Chi Earthquake

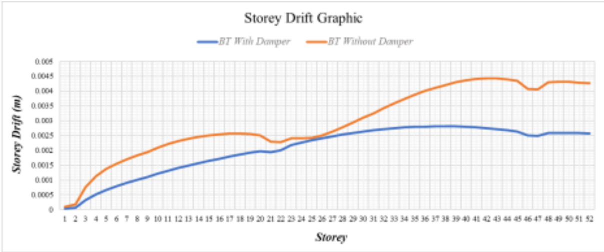


Fig. 17. Comparison of Storey Drift Responses for BT with damper and BT without damper structure under the Chi Chi Earthquake.

6 Comparing with SSIS Approach

The application of a 400-ton Tuned Mass Damper (TMD) system to mitigate wind and seismic effects in the Baku Tower (BT) has significantly improved the dynamic responses of the structure.

Furthermore, by applying the more modern and efficient Structural Seismic Isolation Method (SSIM) for the vibration control of highly reliable structures (HRS), a higher degree of reduction in structural responses can be ensured (Table 5).

By applying the SSIM method, the contact surface between the building base and the foundation is made spherical, and these surfaces are connected to each other with elastomeric devices (LRB, LCRB,). The resulting SSIS system thus gives the structure an inverse pendulum behavior.

Since the building rotates as a single rigid body (inverse pendulum) on the spherical foundation, story drifts are reduced to almost zero. This perfectly protects both the structure itself and the non-structural elements within it (e.g., glass facades, partitions, elevator shafts, etc.)."

Table 5. Comparison of reduction percentages in dynamic parameters provided by TMD (Baku Tower) and SSIS systems

Dynamic Parameter	Reduction Provided by TMD System (BT - Kobe)	Average Reduction Provided by SSIS System for High-Rise Buildings [34]	Average Reduction Provided by SSIS System for Tower Structure [35, 36]
Story Drift	~35 %	Extremely low due to rigid rotation	Extremely low due to rigid rotation
Acc (Top)	23.17 %	46.52 %	82.43 %
Disp (Top)	10.31 %	18.75 %	82.76 %
Base Shear	74.63 %	78.28 %	96.59 %
Base Moment	8.10 %	86.98 %	89.11 %

7 Conclusions

Since the current IT building has dampers, it is possible to use the results obtained from the analyses performed for the damper condition as approximate threshold values. As stated in the findings section, Top Acc. was obtained as 4.69 in the Chi-Chi earthquake and 12.47 in the Kobe earthquake. In this case, when the Top Acc. values obtained from the SHM system are less than 4.69, it is a normal situation; when they are between 4.69 and 12.47, it is a warning situation; and when they are greater than 12.47, it indicates high demand followed by a critical situation. Top Disp. was obtained as 0.469 m in the Chi-Chi earthquake and 0.878 m in the Kobe earthquake. In this case, when the Top Disp. values obtained from the SHM system are less than 0.469 m, it is a normal situation; when they are between 0.469 m and 0.878 m, it indicates a warning situation; and when they are greater than 0.878 m, it indicates high demand followed by a critical situation. In the damper-equipped condition, the maximum drift was determined to be 0.002808 m for the Chi-Chi earthquake and 0.005199 m for the Kobe earthquake. In this case, drift values obtained from the SHM system indicate a normal condition when less than 0.0028, a warning condition when between 0.0028 and 0.0052, and a high demand followed by a critical condition when greater than 0.0052. In warning conditions, structural and system inspections are recommended; in high demand conditions, urgent engineering assessments; and in critical conditions, emergency evacuation and closure of the building are suggested. As stated in the findings section, the damper provides a 35-36% reduction in maximum drift in the structure. If the SHM data shows that the maximum drift values decrease over time from this percentage and approach the drift values of the damper-free condition, it can be understood that the damper performance is starting to decline and the damper system needs to be checked and adjusted.

With the application of the SSIM method, structural responses are reduced by an average of 82%-96%, and story displacements are minimized to the point of being negligible

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