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# Integrated BIM-SHM techniques for the assessment of seismic damage

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**Abstract**

Nowadays, there is an increasing massive use of BIM technologies in the field of construction and civil engineering, both in the design phase and in the construction and management of the life cycle of the structure. This work aims to explore the possibility of integrating BIM technologies within the Structural Health Monitoring field. In particular, a framework has been developed to define in probabilistic terms through fragility curves the presence of damage after a seismic event and promptly visualize the damaged elements in a digital twin model and share the information with the various stakeholders. In particular, the effort has been placed in analyzing in detail the flow of data recorded from possible sensors placed on the building, passing through the post-processing and evaluation of the structural health of structural and non-structural elements up to the integration of this information in a BIM environment.



*Keywords:* Building Information Modeling; Structural Health Monitoring; Fragility curves; Seismic damage.

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## 1. Introduction

Researchers and administrative authorities have long recognized the significance of implementing long-term Structural Health Monitoring (SHM) systems for civil structures and infrastructures, in order to secure structural safety and issue warnings regarding the structural damage prior to costly repair or even collapse.

All recent societies are significantly depending on structural systems like bridges, towers, power generation systems, offshore platforms. Some of these structures are near to the end of their design life, although, due to the high replacement costs, damage detection techniques are being developed and implemented with the purpose to extend the service life of these structures. The process of damage detection techniques for civil engineering structures and infrastructures is referred to as Structural Health Monitoring (SHM) (Li et al. 2016). SHM is related with several disciplines (e.g., Civil Engineering, Aerospace Engineering, Mechanical Engineering among others) and it is used for monitoring any structure during his lifetime under direct or indirect loads. SHM allows providing a diagnosis of the health state of a structure at every moment of its residual life, improves the understanding of the structural behavior and detects any change occurring to any component of to the whole structural system through some devices (Sensors), which may be wired or wireless incorporating micro and nano technology in their components. These sensors relate to data collectors which transmit data through a communication system to laptops, computers or cloud for processing. These data help decision makers to plan for the structure maintenance or rebuilt and allow determining the structure residual life. In addition, SHM plays an important role in cost management, as it will decrease the cost of maintenance comparing with periodic maintenance, it decreases downtime and increases the reliability for end users.

Despite years of research in SHM, there are challenges in the design, implementation, and maintenance of monitoring programs. These include (but are not limited to) number, locations, and types of sensors necessary to address the phenomena of interest, reliability of damage detection algorithms, ease of comparison among projects due to variabilities, limitations of signal processing, long term maintenance of the sensors, and data access and efficient utilization of them.

To facilitate the sharing of information among stakeholders, BIM technology offers the necessary storage and visualization capacity necessary for the purpose. To this aim, the present research addresses a possible framework to relate SHM and BIM technology for the damage assessment following a seismic event.

## 2. Framework

The purpose of this study is to efficiently identify and visualize the damage status of the structural and non-structural elements following a seismic event. The input data may come from a simulation of the event, or from direct measurements by sensors installed on the building. The information is then processed therefore it can be inserted into fragility curves (Günay and Mosalam 2012), relating the performance of the element as a function of an engineering demand parameter such as the absolute acceleration or the inter-story drift ratio. This allows to obtain the probability of overcoming a given damage state. This information is then imported into modelling software working on a BIM architecture through a specific code. The procedure provides both a clear and immediate visualization of the building's health status, and its real-time sharing in the cloud.

Fig. 1 schematically shows the framework that can be used for the seismic and environmental monitoring of an existing building. Damage detection techniques could be: Model-based techniques such as Finite Element Model Update (FEMU) (Moaveni et al. 2013) ; FE models with a variable number of parameters to be updated; data-driven based techniques such as processing of damage indices and loss estimation (Bosio et al. 2020, 2022) and seismic monitoring (Lenticchia et al. 2017); implementation and training of AI (Farrar and Worden 2012, Zang et al. 2018, Abdeljaber et al. 2017, HoThu and Mita 2013, Mita and Hagiwara 2003, Gui et al. 2017, Bornn et al. 2009); hybrid techniques, such as Machine Learning techniques that use FE models to generate synthetic damage signals for effectively training a forecasting model to recognize future damage scenarios (Castelli et al. 2021).

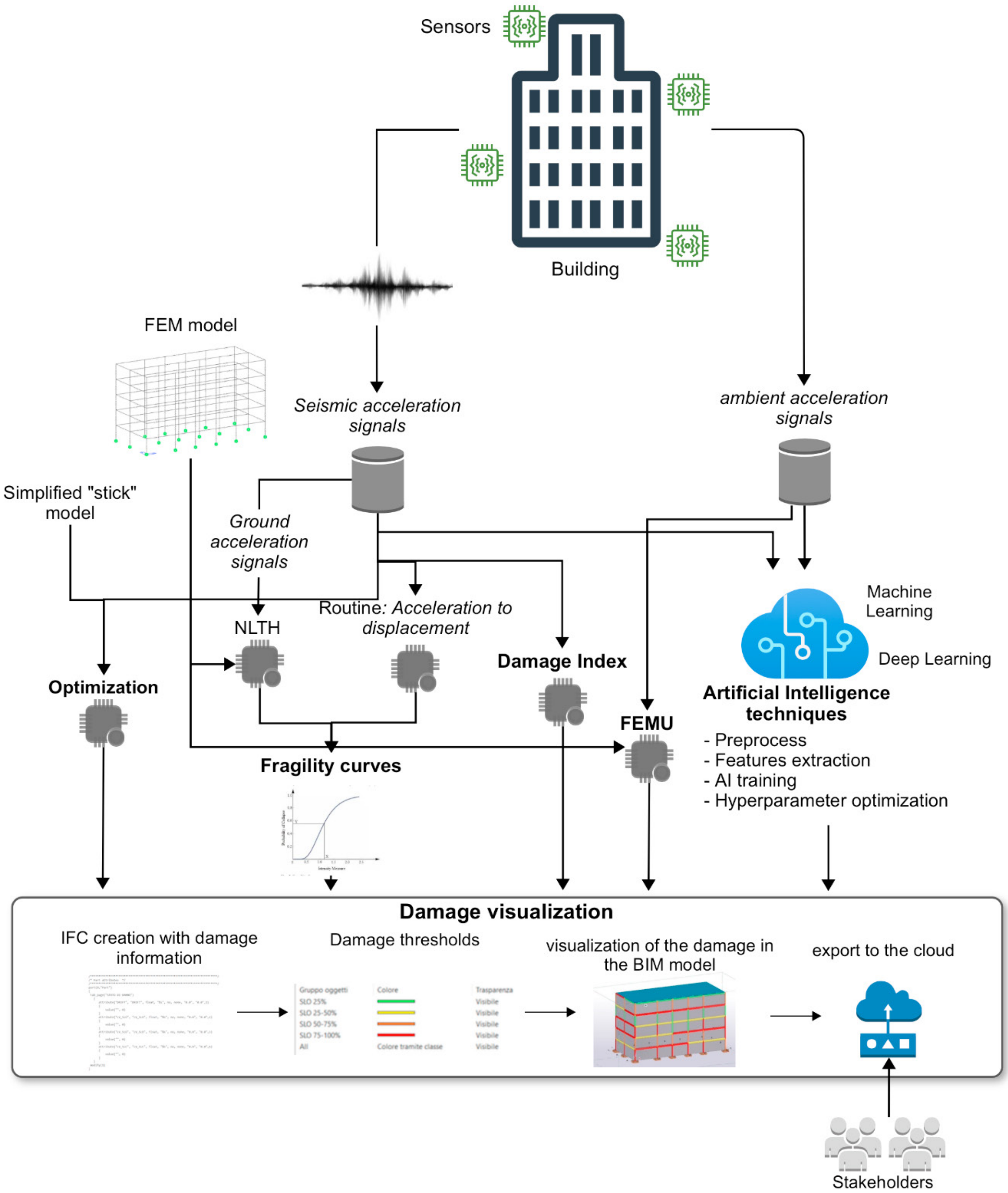


Fig. 1. SHM-BIM connection framework.

## 3. Case study

Herein, the previous concepts are represented through a case study resembling a 5-story reinforced concrete (RC) frame building, with both elevation and plan regularity, designed for gravity loads before the enforcement of modern anti-seismic regulations. In this case, considering that the objective of the research is testing the data sharing algorithm between SHM and BIM, a reference building was defined and a simulated project was carried out. The building, shown in Fig. 2, consists of five bays of 4.5m and 6.5m in the X-direction and two bays of approximately 5-6m in the Y-direction. Non-linear dynamic analyses were carried out, taking sample seismic events, in which the extracted output, in terms of displacements or accelerations, constitute the synthetic signals used for the subsequent damage detection step. Once such data are extracted from the FE software (MidasGen 2019), a specific code was developed in MATLAB (MATLAB 2020) to process the data obtained as to make them suitable for a fragility curve representation. The implemented algorithm provides an estimate of the post-seismic event damage thanks to the use of fragility curves in terms of cumulative probability of the presence of a given damage level. The output was then imported into Tekla Structures where, through customized macros specifically developed, it was possible to associate a user-defined coloring with the rate of exceedance of the damage state. The model with its information was made available in the Cloud through the Trimble Connect application (Trimble).

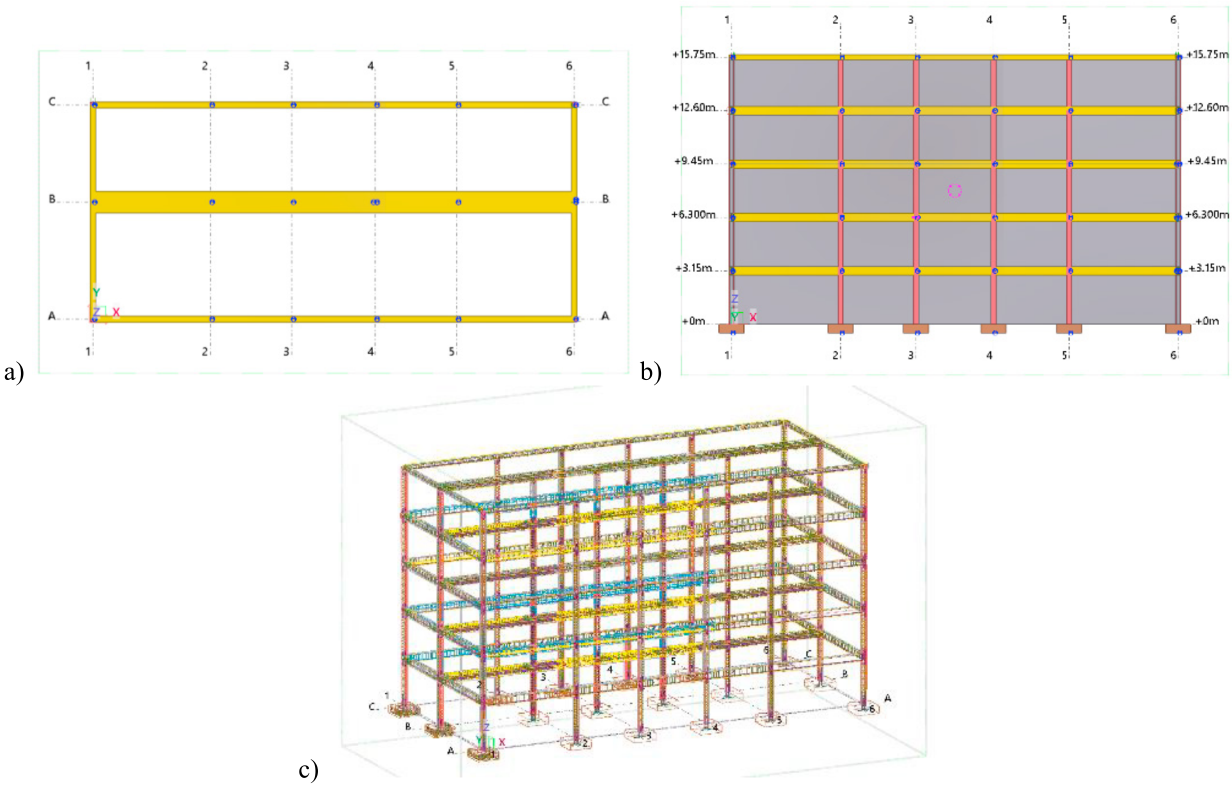


Fig. 2. (a) Plan, (b) side and 3D (c) view of the considered RC frame building.

### *3.1. FEM model*

The implementation of the FE model is briefly addressed: a 3D model was implemented using the FE software MidasGen (2019). Finite elements of the *beam* type were used for both beams and columns in which the non-linearities were inserted by means of non-linear springs placed at the ends of the elements. For the flexural behaviour, a *Takeda tetralinear* model was used with axial-moment interaction for the columns. The materials assumed were C20/25 ($f_c$=20MPa) concrete and FeB44k ($f_y$=440MPa) steel. The gravity loads were applied before the non-linear dynamic analyses and kept constant. Fig. 3 shows the axonometric view of the FE model.

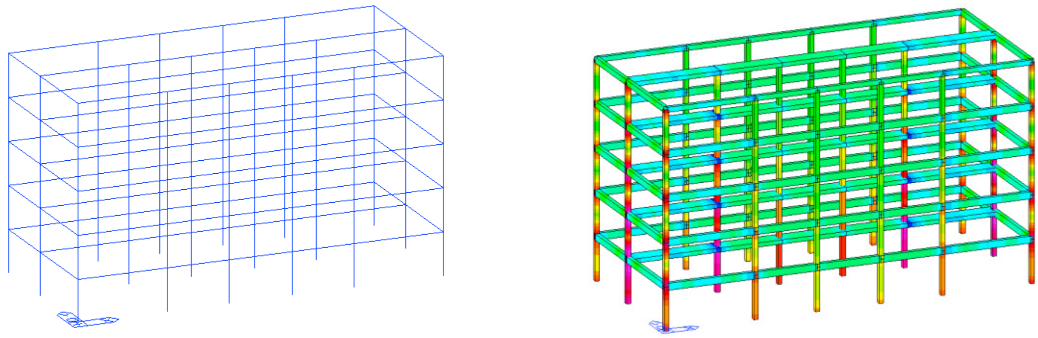

Fig. 3. Scheme of the FE model.

*3.2. Extraction of results and estimation of structural damage*

At this point it is essential that each piece of data is matched to the element to which it belongs, through the use of a Globally Unique IDentifier (GUID). Subsequently, fragility curves are selected (FEMA P-58, 2009) to assess the probability of exceeding selected damage states. Specifically, it was decided to analyze the behavior of selected elements with respect to the operational, damage and collapse limit states. In particular the considered elements are sensitive to inter-story drifts (columns, beams and masonry infills), therefore the associated fragility curves required as input the maximum relative displacement between two consecutive floors. The fragility curves were selected for demonstration purposes from FEMA P-58 (2009) for the beams (fragility id. B1041.101a-b) and the columns (fragility id. B1041.121a-b) and from Del Gaudio et al. (2019) for the infills.

In this research it is possible to extract the signals in terms of displacement directly from the FE model while in a real application, assuming to install accelerometers on the structure, the data recorded in terms of accelerations must be suitably double integrated and filtered to obtain the displacements; once this has been done, it is possible to use the fragility curves as in the previous case.

The second portion of the script associates the source data of the elements with the results from the fragility curves grouping them according to user-defined ranges. This also allows to check the correctness of the information. Now the code can receive data from Tekla Structures (Tekla Structures) reports, the signals from MidasGen and it is able to process the data through fragility curves and return the damage information graphically.

*3.3. BIM model*

The first modelling level is achieved through Tekla Structures using four types of elements: beams, columns, floors and infills. Taking advantage of the features in the BIM architecture, a set of data was associated with each element: starting with geometric information and material categories and ending with an identification system, Fig. 4. Specifically, the interoperability is made possible thanks to the GUID, an alphanumeric code univocally identifying each element and allowing it to be detected any time along the process.

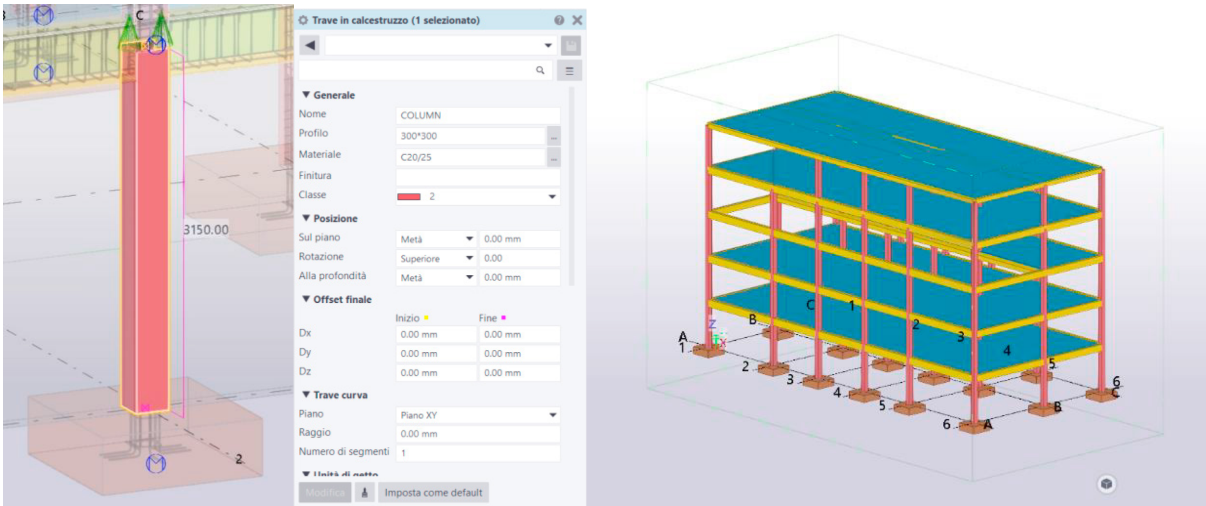


Fig. 4. BIM element with its own characteristics (left); complete BIM model (right).

*3.4. Interoperability and visualization with BIM environment*

Through the second part of the code, by using the traceability thanks to the GUID, the result of the fragility curves is associated with the element. The functions of importing, visualizing according to the damage state and sharing the results are accomplished by exploiting three customized macros.

The first macro allows to reconnect the processed data to the respective objects, reintroducing them into the BIM environment by exploiting the customized attributes introduced through Tekla Structures. The second allows to select the class of damage one wishes to investigate, returning a graphic representation of it through a color graduation that allows clear and immediate visualization of the state of health of the elements. Herein, a coloring was chosen to divide the results of the analysis into four categories, each of them with a percentage of damage in steps of 25%. The third macro allows to export the information in IFC (Industry Foundation Classes) format, an open format that can be managed by many programs as Trimble Connect. The latest function is essential for updating the information received in real time and sharing it in the cloud. The ease of reading the data, processed in this way, allows specialized technicians to extract the results for future analysis and a more immediate and more reliable visualization of the state of health of the building, also at the individual element scale.

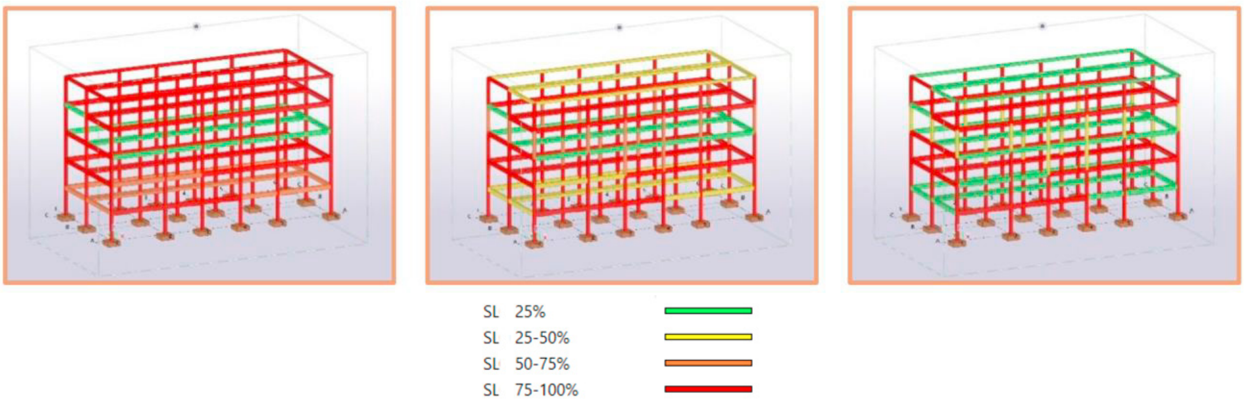


Fig. 5. Color maps for exceeding the thresholds: operational limit state (left), damage limit state (center) and collapse prevention limit state (right).

Fig. 5 shows the results of the analysis conducted on the building under analysis. The percentages of overcoming damage states decrease as the severity of the analyzed state increases. In particular, it was assigned to the color green a percentage in the probability of exceedance interval 0%-25%, yellow in the range 25%-50%, orange in the range 50%-75% and red above 75%. Almost all the structural elements at the operational limit state (OLS) have a high probability of exceeding this state, while for the damage limit state (DLS) the situation is moderate, but still severe, with many elements having a percentage above 50%. The situation changes investigating the collapse prevention limit state (CPLS), where some elements result with a low percentage and others with a high percentage. The latter case allows us to conclude that the considered building after the input earthquake got severely damaged and it is probably prone to collapse. Similar representation can be developed for the nonstructural elements such as the infill walls (Fig. 6).

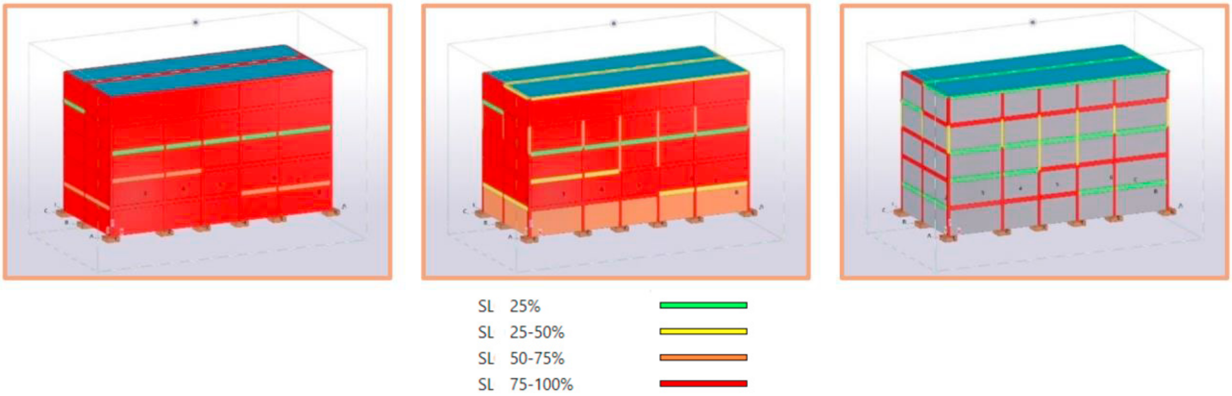


Fig. 6. Color maps for exceeding the thresholds: operational limit state (left), damage limit state (center) and collapse prevention limit state (right).

## 4. Conclusion

The present study investigated the potential of BIM technology in the management and storage of data for the monitoring and maintenance of structures, particularly in the case of earthquakes. The research aimed to develop a framework and subsequently an application to improve the interoperability and visualization of data from the real world with the virtual world represented by the BIM environment. The extension of the BIM model allows, through an automatism, a continuous updating of the model on the transmitted data. Among the various methods of identifying structural damage present in the literature, it was decided to use the output deriving from fragility curves as an indicator of probabilistic damage. A further possibility investigated lies in storing the BIM models in the cloud; this will allow the various stakeholders to query the model to obtain information on the health of the structure from the web and therefore in any place and with any device connected to the network. Future research is reserved for the integration of different damage identification techniques, both for seismic events and environmental vibrations, for the transmission and storage of data recorded in situ directly in the cloud and for the framework integration with multiple types of sensors.

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