Towards Quantitative Prioritization Schemes for Bridge Portfolios in Italy

Andres Abarca, Ricardo Monteiro(✉), and Gerard O'Reilly

Scuola Universitaria Superiore IUSS Pavia, Pavia, Italy
{andres.abarca,ricardo.monteiro,gerard.oreilly}@iusspavia.it

Abstract. The Italian government has recently instated guidelines on risk classification, management, safety assessment and monitoring of existing bridges. Such guidelines can also be used as a rapid prioritisation method that, based on the limited information available about assets in the inventory, allows the identification of bridges requiring special attention in the form of inspection, detailed analysis, monitoring and possible retrofitting. However, these guidelines are based on qualitative indicators that can produce overly conservative results. In this paper, the recent Italian guidelines are explored and a quantitative partial modification is proposed, based on average annual loss prioritization results from detailed risk assessment. The proposed modification is evaluated on a case study of 617 reinforced concrete bridges, using seismic hazard to demonstrate its potential large-scale implementation. The results show a notable improvement in the identification of high-risk assets in the portfolio, encouraging the adoption of similar strategies to other hazards and bridge typologies, with a view to multi-hazard and data-driven quantitative prioritization schemes for the Italian territory.

Keywords: bridges · prioritization · transportation infrastructure · regional risk

1 Introduction

The bridge inventory of developed countries can reach thousands of assets that have been built over several decades by different administrations (Calvi, et al. 2019), creating a challenge for the institutions currently managing these large portfolios of bridges for which there is incomplete information about their current structural condition and limited resources available to upgrade or maintain them. In the case of Italy, a great portion of its current infrastructure was built during a construction surge of freeways that happened all over Europe in the 1960s (Calvi, et al. 2019). The longevity of the current inventory, aided by the difficulties of management agencies in providing proper maintenance, has led to a generalized problem of deterioration that increases the vulnerability of these structures, a condition that has become evident by the number of bridge collapses in recent years.

For example, a non-exhaustive list of collapses collected from reports in the media is presented in Table 1, where it can be observed that several months or even years can pass for a bridge to be reopened following its full or partial collapse.

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Considering the situation described above, there is a need for bridge management institutions to determine rapid prioritization methods that, based on limited information available about assets in the inventory, allow the identification of the assets requiring special attention in the form of inspection, detailed analysis, monitoring and possible retrofitting. Such prioritization methodologies have been the source of multiple research efforts worldwide. A summary is available in a recent technical report by the United States Department of Transportation (Chase, Adu-Gyamfi, Aktan, & Minaie 2016). It documents the evolution and application of different bridge health indices used by bridge management agencies interested in preserving the condition of bridge structures or prioritizing the maintenance or replacement projects within their bridge inventory. Recent Italian examples include the simplified index-based methods developed by Pellegrino et al. (2011) and D'Apuzzo et al. (2019), both of which are based on detailed inspection-level information to assess the deterioration status of the bridges and combine it with the importance of each asset to the overall network by incorporating an additional index based on road typology and traffic flows. More recently, the Italian Superior Council of Public Works, within the Ministry of Infrastructure and Transport (MIT), issued a technical report with guidelines on risk classification and management, safety assessment and the monitoring of existing bridges (Consiglio Superiore dei Lavori Publici 2020), which has already become part of the mandatory legislation for bridge management institutions and concessionaries in Italy (Ministero delle Intrastrutture e dei Trasporti 2020). This document, which will be referred to from this point forward as the 2020 MIT Guidelines, intends to standardize the procedure with which existing bridges in Italy are assessed at a large scale by a multi-level and multi-component approach that classifies bridges in risk categories via a combination of qualitative metrics.

Table 1. Recent bridge collapses in Italy

Province	Bridge Name/Location	Length (m)	Collapse Date
Pordenone	Viadotto del Chiavalir	25.0	Dec-04
Genova	Carasco	258.0	Oct-13
Nuoro	Oliena-Dorgali	130.0	Nov-13
Agrigento	Lauricella-Petrulla	476.0	Jul-14
Lecco	Annone	56.0	Oct-16
Ancona	Ancona	45.0	Mar-17
Genova	Viadotto Polcevera	1182.0	Aug-18
Savona	Madonna del Monte	30.0	Nov-19
Massa-Carrara	Albiano Magra	290.0	Apr-20
Novara	Romagnano Sesia	156.0	Oct-20

When looking for an established metric that allows the consideration of the entire scope of the problem in a single value, average annual loss (AAL) is a risk metric that has seen growing use within the structural engineering community (O'Reilly &

Calvi 2019) (Shahnazaryan & O'Reilly 2021), even being proposed as a target metric to be used in new methods for structural design and assessment (Calvi, O'Reilly, & Andreotti 2021). AAL, also referred to in some sources as expected annual loss (EAL), is a product of risk assessment that represents long-term expected economic losses per year, averaged over many years, that are produced by specific hazards of varying intensities and their respective annual exceedance rates, or return periods. In this paper, a seismic risk methodology is applied to a case study of 617 bridges in the Italian province of Salerno to determine prioritization of assets based on AAL, which is then used for two main purposes: as a benchmark to compare with the results obtained using the recent 2020 MIT Guidelines and as a possible guiding parameter to determine the relative importance of each factor affecting the determination of priority, with a view to moving towards a more optimized but still simple prioritization approach.

2 Case Study Bridge Inventory

2.1 Database Description

A bridge database comprising 308 bridges from the National Autonomous Roads Corporation ANAS (*Azienda Nazionale Autonoma delle Strade)* inventory, collected and managed by the Eucentre Foundation, was considered to create the case study for this research. These bridges form a part of the Italian road network, and their actual geographic location is scattered along the primary highway grid of Italy, as shown in Fig. 1.

Fig. 1. Location of the 308 case-study assets in the ANAS bridge inventory.

The information available in the database represents a complete account of geometrical and structural properties of the bridges, allowing detailed structural numerical models of each asset to be created. Each asset in the database is a reinforced concrete (RC) bridge with two or more spans, a predominant configuration in the Italian road network (Zelaschi, Monteiro, & Pinho 2016). In terms of general dimensions, the overall number of spans ranges from 2 to 36, which translates to an overall bridge length range of 50 m to 1250 m. The height of piers ranges between 5 m and 45 m in the overall inventory and it is typical to observe large variation of the pier height within the same asset, leading sometimes to irregular dynamic configurations within straight bridges. In terms of static configuration, most of the case-study assets have spans that are simply supported upon the piers with thin elastomeric pads, and only a small percentage has continuous deck and bearings that can be either elastomeric or isolators.

The construction year was available for all assets, ranging between 1953 and 2000, with most of them built during the 1960 s and 1970 s. As is common for regular Italian bridges of those decades, none of them are expected to have been specifically designed to meet appropriate seismic requirements, especially considering that the first national seismic regulation in Italy that addressed the entire national territory was instated in 2003 (Consiglio dei Ministri 2003). In general, the reinforcement percentages in the piers, both in longitudinal (A_{sl}/A_c) and transverse (A_{st}/A_c) directions, are low in comparison to current design standards and are quite similar across the different pier sections. This is atypical under current design practices, however, both the reinforcement ratios and the properties of the materials used for construction are in line with the age of construction of the inventory. In terms of dynamic properties, a structural model was created for each asset to determine the modal periods in both orthogonal horizonal directions. Since, for the case of bridges, the first mode does not typically account for a significative percentage of the total modal mass, an appropriate number of modes were evaluated for each asset to include 85% of the modal mass in each direction. The distributions for the first modal period (T_1) and the modal period at which 85% of the modal mass is obtained ($T_{85\%}$) as shown in Fig. 2.

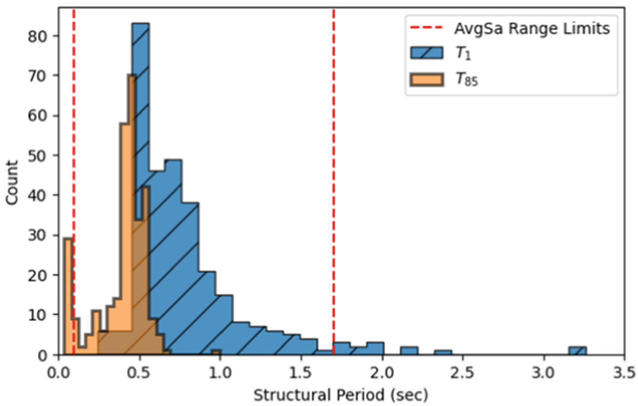

Fig. 2. Results for modal structural periods of the entire inventory and definition of AvgSa range

The intensity measure chosen to perform hazard and fragility calculations was average spectral acceleration (AvgSa), for which the collective results of T_1 and $T_{85\%}$ were used to define the period range. As shown in Fig. 2, the selected range was 0.1 s to 1.7 s, which was defined as per O'Reilly (2021) as 1.5 times the 84th percentile to account for period elongation of the first mode and 0.5 times the 16th percentile to account for higher mode contributions of the T_1 and $T_{85\%}$ periods, respectively, for the entire inventory.

2.2 Case Study Definition

As shown in Fig. 1, the bridges in the ANAS database are scattered geographically all over the Italian territory and not directly connected, therefore, their real location is not ideal to define a case study, since the consideration of the collective and individual role of each asset in the road network would be an unfeasible exercise. Ideally, if a case study of bridges closely connected within the same territory were available, it could be explored and fully analysed to represent a benchmark with which to evaluate the performance of simplified prioritisation frameworks. For this reason, and taking advantage of the fact that even in locations with different seismic hazard demands, bridge design practices did not vary considerably among the Italian territory for the construction period of the bridges in the database (Borzi, et al. 2015), a synthetic case study was created. To do so, the road network of a region for which the location of bridges and road properties was known was taken, with a bridge from the 308-asset database being assigned to each location.

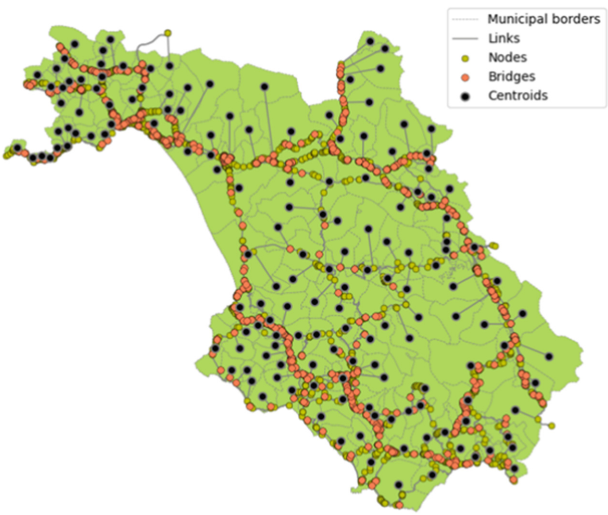

Fig. 3. Road network model for the case study region of Salerno built on AequilibraE (www.aequilibrae.com) based on OpenStreetMap data

The Salerno province was selected for having a transportation network that relies heavily on the vehicular road system, a relatively low number of bridges and a varying seismicity level. Information about the road network of Salerno was taken from the OpenStreetMap database (OpenStreetMap contributors 2020), which comprises all roads within the highway, primary and secondary systems, including 2929 nodes and 3086 links, of which 617 represent bridges. The centroid locations of the 158 municipalities in the Salerno province were used as traffic attraction zones (centroids) from which all trips were assumed to occur to and from. The 308 bridges in the database were therefore randomly assigned to the 617 possible locations of bridges in the Salerno network using a sampling with replacement scheme. Once the final distribution of assets in the case study was defined, a transportation network model was created using the software AequilibraE (www.aequilibrae.com), an open-source Python and QGIS package to perform transportation network analysis, to determine the baseline traffic conditions that are fundamental to assess the importance of each bridge in the network. A graphical representation of the network model is shown in Fig. 3.

A database containing travel pattern information for work and study purposes performed in 2011 was taken from the Italian Institute of Statistics (ISTAT 2014) and used to define origin-destination demands between the different municipalities of Salerno. Furthermore, in order to account for congestion in the network, previous research regarding Italian road characteristics (Maratini 2008) was used to obtain the volume-delay function modelling parameters according to the commonly used BPR model (Bureau of Public Roads 1964) for the different road types in the network. Free flow speed was taken as the speed limit reported for each road in the OpenStreetMap database. A trip distribution based on the minimization of travel time of each user was carried out using a bi-conjugate Frank-Wolfe algorithm (Mitradjieva & Lindberg 2013) to determine the baseline traffic conditions of the fully operational road network, as shown in Fig. 4.

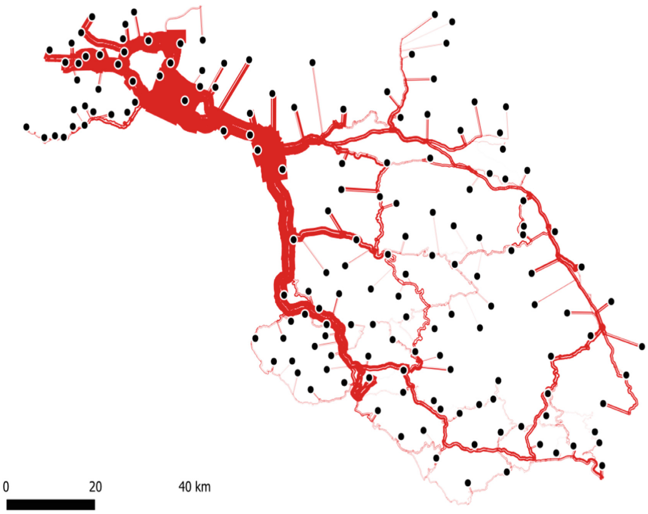

Fig. 4. Baseline traffic flows for case study region (line thickness is proportional to traffic flow)

3 Seismic Risk Analysis

3.1 Seismic Hazar

In terms of hazard curves, the SHARE hazard model (Woessner, et al. 2015), implemented in the OpenQuake Engine (Silva, Crowley, Pagani, Monelli, & Pinho 2014), was used to determine the probability of exceedance of different levels of AvgSa for an investigation period of 50 years at each bridge site. In terms of ground motion record selection, a conditional spectrum scheme (Lin, Haselton, & Baker 2013) was adopted using a modification that allows the conditioning of the spectra for AvgSa (Kohrangi, Bazzurro, Vamvatsikos, & Spillatura 2017). Given the large number of bridge locations, and to minimize the computational burden of performing disaggregation at each location, all assets were assigned to four hazard zones and two soil classes (i.e., soft and stiff soil differentiated by a $V_{s,30}$ threshold of 360 m/s) as illustrated in Fig. 5. Following this, a complete hazard disaggregation analysis was carried out for the eight possible zone-soil combinations. For each combination, sets of 30 bidirectional ground motion records were selected from the NGA West-2 Strong-motion Database (Ancheta et al. 2014) for nine return periods ranging from 98 years to 9975 years and were used for NLTHA.

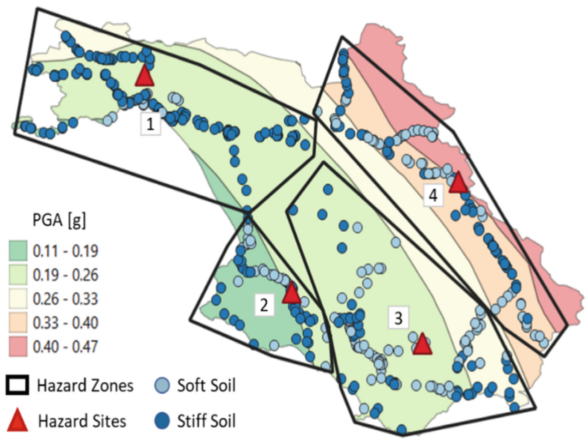

Fig. 5. Hazard zones and soil sites defined for the case study region (PGA values for a return period of 475 years are shown for reference).

3.2 Seismic Risk

3.2.1 Fragility Assessment

In this study, an element-based approach implemented by Borzi et al. (2015) was adopted to evaluate the seismic fragility of each bridge in the case study portfolio. Since the focus of this study was not on the derivation of fragility curves for bridges, the specificities of the numerical models created and the overall analysis procedure is not explained herein. The collapse limit state was focused on since it is the limit state directly related to the complete loss of the bridge connectivity, rendering a straightforward evaluation of indirect losses possible. The results obtained for the fragility curves of each element in the inventory are shown in Fig. 6, where the mean fragility curve is shown for reference.

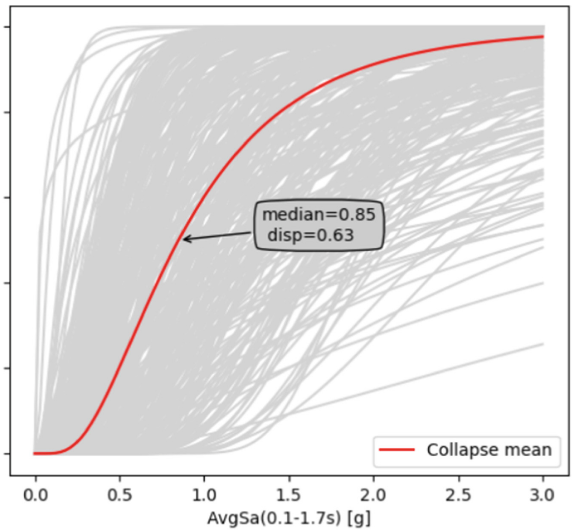

Fig. 6. Fragility curves for collapse limit state obtained for the 308 bridges in the database

3.2.2 Direct Loss Assessment

The calculation of direct losses associated with the collapse limit state was carried out using the basic formulation from the Pacific Earthquake Engineering Research Center's Performance-Based Earthquake Engineering (PEER PBEE) framework (Porter 2003). A straightforward implementation of the formulation is possible by including only the collapse limit state, where the product of the annual probability of exceedance of the limit state and the direct replacement cost will result in the direct collapse-based AAL, as per Eq. 1.

$$\mathrm{AAL} = p(LS_C) \cdot €L|LS_C p(LS_C) \cdot €L|LS_C = APE_C \cdot €RCAPE_C \cdot €RC \tag{1}$$

where:
LS_C: Collapse Limit State.
$p(LS_C)p(LS_C)$: probability of occurrence of LS_C
$€L|LS_C€L|LS_C$: direct economic losses associated to LSC
APE, LS_CAPE, LS_C: annual probability of exceedance of LS_C
€RC: bridge replacement cost

The annual probability of exceedance (APE) for the limit state was obtained by combining the fragility and hazard curves obtained for each bridge in the case study, evaluating the probability of exceedance in terms of the IML and the respective annual probability of exceeding that IML. The integration over the entire IML range results in the APE for each asset. The replacement cost for each bridge was taken as proportional to the deck area, considering a generic cost per square meter of €930, taken from the mean replacement cost per area obtained by Perdomo et al. (Perdomo, Abarca, & Monteiro 2020) for a similar Italian bridge inventory. The results for direct collapse-based AAL are show in Fig. 7, where it can be observed that higher values of loss are concentrated in the areas with higher seismic hazard.

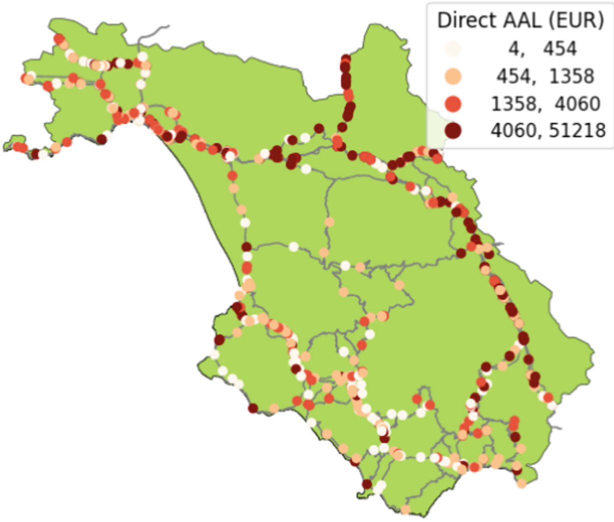

Fig. 7. Direct collapse-based average annual losses in Euros

3.2.3 Indirect Loss Assessment

In general, the same underlying concept and formulation presented previously to calculate direct losses can be used to determine the corresponding indirect ones; however, the difficulty lies in determining the indirect replacement cost associated to the collapse of the bridge. To determine the indirect replacement cost in this study, the previously described road network model, used to determine the baseline conditions of the network when all bridges are operational, was explored. Two main metrics were obtained from the model: the vehicle hours travelled (VHT), and the vehicle distance travelled (VDT), corresponding to the total amount of time and distance, respectively, that all the users in the network experience daily during their respective travels. Both metrics were then combined with median costs for automobile fuel efficiency, fuel prices and hourly salary rates appropriate for the Salerno province (ISTAT 2020). This allowed the calculation of a baseline daily cost (BDC) of operation of the road network in its current configuration.

Subsequently, the road network was modified by assuming the collapse of each bridge in the network, removing the associated link in the model and rerunning the daily operation cost with the modified network configuration to determine a Modified Daily Cost (MDC) associated with the collapse of each bridge. The total indirect cost of each bridge was then calculated as the difference between the BDC and the MDC multiplied by the repair time in days assumed for each bridge. The computation of the repair time to use for each calculation represented another challenge. In this study, the data from the 10 recent collapses in Italy shown in Table 1 was used to fit the lognormal distribution shown in Fig. 8 and the median value of 710 days was found and used as a deterministic value for all elements in the case study.

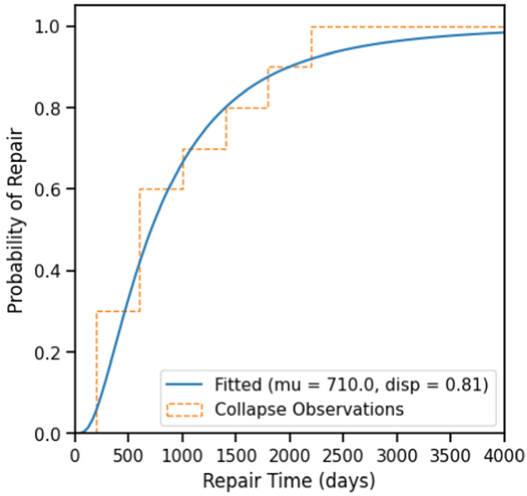

Fig. 8. Cumulative histogram and log-normal fit for repair time observations based on recent collapses in Italy.

The results for indirect AALs are shown in Fig. 9, where it can be seen that the indirect losses were concentrated near the coast of Salerno where the traffic is generally higher, even though the seismic hazard in this area was relatively low. Once both direct and indirect loss components were determined, the total collapse-based AALs were aggregated for each bridge, resulting in the distribution shown in Fig. 10. Analyzing the overall results, it is seen that the indirect losses represent 78% of the total losses and that the overall losses have a very similar spatial distribution to the one found for the indirect losses alone, which is expected given that these are much greater than the direct loss component.

4 Machine Learning Prediction of Aal-Based Ranking

A supervised machine learning model was evaluated using the case-study AAL results to assess the feasibility of predicting losses based on limited data, and to gain insights on the effect and relative importance of simple bridge parameters on the prioritization, defined by sorting bridges based on their individual AAL results. For this case study, the

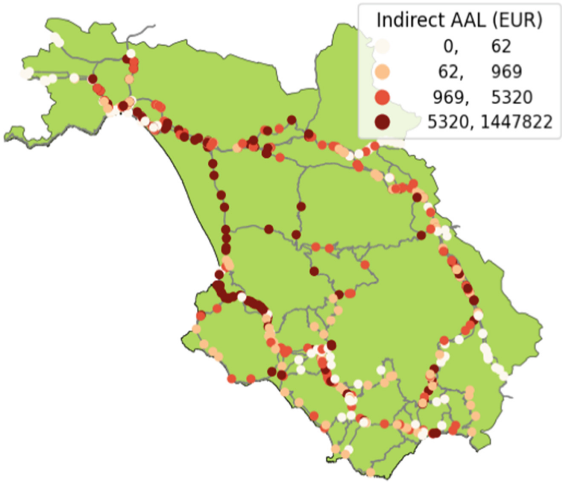

Fig. 9. Indirect average annual losses.

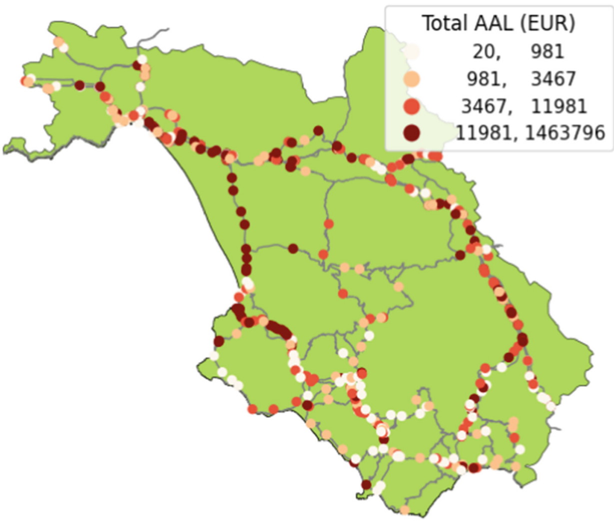

Fig. 10. Total average annual losses.

intention of the machine learning modelling process is not to create a model to be used on bridges outside of the current case study, but to take advantage of the capabilities of this method to infer relationships between independent features (simple bridge parameters and reference hazard values in this case) and their impact on target values of interest (AAL estimates). It is envisaged that these can be later used to guide improvement proposals for the 2020 MIT guidelines.

A random forest regression model was chosen given its recently demonstrated good performance when compared to other machine learning algorithms for similar applications (Mangalathu, Hwang, Choi, & Jeon 2019), and the ability of this algorithm to evaluate the relative importance of each independent variable. A database was assembled using the AAL results for each bridge in the case study to train the random forest model. For this purpose, the AAL representing the dependent variable (target) and a vector of independent variables (or features) was retrieved for each bridge structure. A set of six features were used for each bridge: maximum span length, maximum pier height, daily traffic flow, seismic intensity measure level for a return period of 475 years, number of spans and total replacement cost.

A set of useful regression performance metrics is presented in Table 2, and the relative feature importance is shown in Fig. 11. In general, the model does not have an ideal prediction performance, which is to be expected given the small amount of data points and features used to attempt to predict a complex value such as AAL, which depends on multiple variables that cannot be included in this type of model in a straightforward manner.

Table 2. Performance metrics for the machine learning model on the entire dataset

Parameter	Value
Root-mean-squared error (RMSD)	€ 52,279.8
Mean absolute error (MAE)	€ 10,888.2
Median absolute error (MedAE)	€ 3,398.4
Coefficient of determination (R2)	0.542
Total AAL_{pred} / AAL_{calc}	0.962

Overall, in terms of model performance, daily traffic flow has the highest relative importance over all the evaluated features, which is a consequence of the fact that the indirect losses represent the majority of the losses calculated and are directly related to the daily traffic. Moreover, maximum pier height was found to be the second most relevant feature when trying to predict AAL, which is a parameter that is not currently accounted for in the 2020 MIT Guidelines and has been shown to have a correlation with the dynamic properties of bridges in previous studies (Zelaschi, Monteiro, & Pinho 2016). The maximum span length, which has a great impact in the risk classification of the 2020 MIT Guidelines, as will be shown in the following section, has the lowest relative importance as per the machine learning model exercise implemented.

5 Italian Guidelines for Bridge Portfolio Assessment

The 2020 MIT Guidelines propose a multi-level and multi-component approach that classifies bridges in risk categories through the processing of qualitative metrics, specific to each of the considered hazards: a) structural/foundational, including eventual

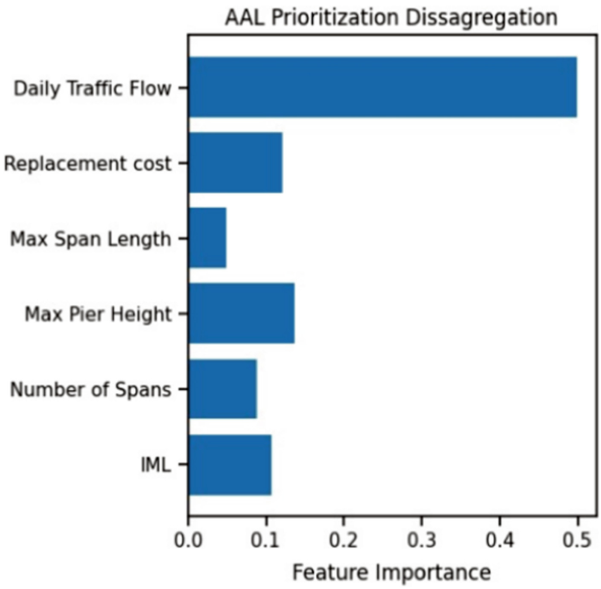

Fig. 11. Feature importance found from machine learning model.

degradation; b) seismic; and c) flood/landslide. These guidelines have been recently analyzed and evaluated by Santarsiero et al. (2021), where a thorough summary of the entire classification methodology is presented. In such study, the simple application of the seismic and degradation components of the guidelines to an inventory of 48 bridges concluded that the obtained classification leads to conservative results. In the study presented herein, the focus will be only on the treatment of the seismic risk classification of bridges, since it is the only component for which the benchmark AAL calculations performed in the previous sections is applicable for comparison. For what concerns seismic risk, as with the other considered risk types, the procedure is divided in the three well-known main components: a) hazard; b) exposure; and c) vulnerability, each of which being assigned one of five possible attention levels that range from low to high. This is done by processing qualitative characteristics of each bridge using a specific set of tabular values, as described in the following paragraphs. After each risk component is processed and a classification is made, all components are convoluted into an overall seismic risk attention class. Once each component has been characterised, they are combined to determine an overall seismic risk class, as per the indications shown graphically in Fig. 12. As noted by Santarsiero et al. (2021), the overall classification is very much affected by the vulnerability component; for example, if this component is high, then the seismic risk class will be assigned the highest category, almost regardless of the other components.

The methodology foreseen by the guidelines was applied to the case study inventory, providing the results shown in Fig. 13. It can be seen that both the hazard and vulnerability components are mostly classified in the highest possible option, leading to an overall seismic risk class with mostly the high category. This is attributed to the fact that the

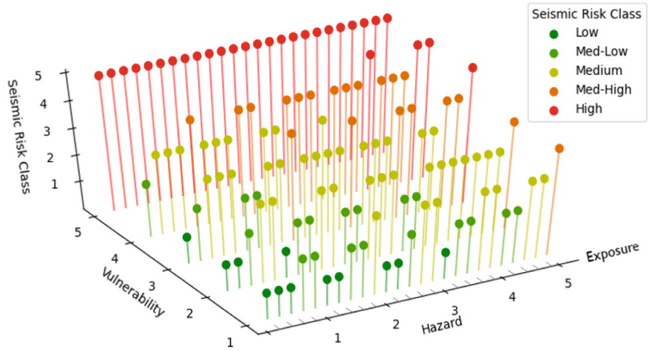

Fig. 12. Determination of seismic risk class based on the partial classification of hazard, exposure and vulnerability, adapted from Santarsiero et al. (2021)

vulnerability component dominates for simply supported bridges with spans longer than 20m that have not been seismically designed, which correspond to the predominant characteristics in the case study and to a large portion of the Italian bridge stock. The fact that there are only two resulting categories and the predominance of the high class creates a problem for the effective implementation of these guidelines as a tool for efficient decision-making and resource prioritization. As per the 2020 MIT Guidelines, 498 bridges from the 531 in the inventory that were classified into the high category would require the immediate development of detailed structural analysis, implementation of periodic inspections and the installation of monitoring systems. This would clearly require a great number of resources to comply with and be, in some respects, not fulfilling the need of being able to prioritize effectively.

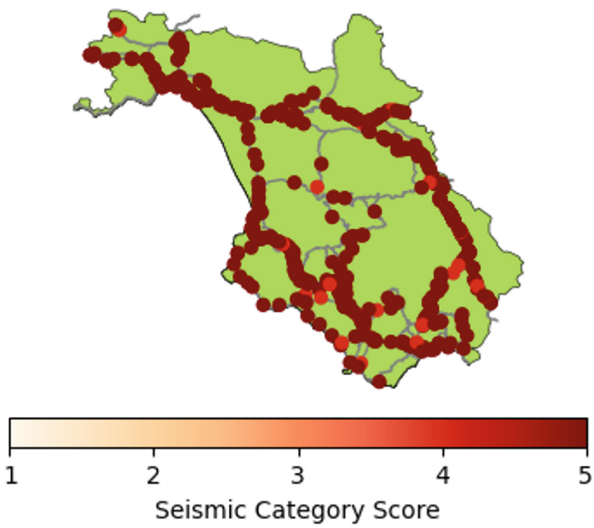

Fig. 13. Results for application of 2020 MIT Guidelines to case study inventory.

6 Directions for Improvement of Prioritization Scheme

Using the insights gained by the application of the seismic risk quantification to the case study, along with the influential features found via machine learning techniques, a possibly improved methodology to perform bridge prioritization, based on the 2020 MIT Guidelines and their observed performance, is outlined and discussed here. In general, the 2020 MIT Guidelines constitute a robust and well-structured methodology for bridge management. The shortcomings that were observed during its implementation are specifically related to the thresholds used to characterize each of its components in a simple and schematic manner, as well as the high relative importance that the vulnerability component has on the overall risk class. While this conservatism in the vulnerability component was likely a conscious decision made to prioritize bridge safety, it has the downside of classifying a large number of bridges, even those with low associated losses, in the categories of highest priority, which is not in agreement with the findings from a complete quantitative exercise based solely on economic losses. Furthermore, the definition of only five risk classes creates an additional limitation since it can be restrictive when a large, thus more diverse, inventory is considered.

To potentially improve the results obtained by the application of the guidelines, the definition of fixed risk classes could be, for instance, changed to an approach based on a point system per component without establishing a limit. The overall seismic risk score would then be composed of the sum of the scores of each component with the available number of points per component being defined as proportional to the findings from the machine learning model, by giving a higher importance to the exposure component and the daily traffic flows, to further stress the importance of the indirect losses. Regarding the exposure component, the thresholds for span lengths could be modified to reduce the impact of this parameter on the overall results. Also, traffic flows would be reduced to increase its sensitivity, given that this parameter was observed during the machine learning exercise to be the most influential in the determination of annual losses. For what concerns the vulnerability component, the threshold values for number of spans and maximum span length were calibrated by iterating on different values and observing their effect in the classification performance with respect to the AAL ranking. Furthermore, the maximum pier height would be included as an additional parameter since it was recognised as a relatively important feature during the machine learning experiment.

Adopting the described modification proposals, the proposed modified methodology was applied to the same case study, leading to the results shown in Fig. 14. It can be observed that there is a higher resolution of results for each of the components (i.e., no saturation with the high limit), which also translates in a wider range of risk scores for the overall inventory. The spatial distribution of the scores is more in agreement with the loss results and the overall prioritization performance appears greatly improved with respect to the outcomes of the original guideline's methodology.

It is important to note that, while the definition of the case study and its properties were designed to be considered as representative of a common typology of the bridge network of Italy, the proposed methodology was made by calibrating values from the available database therefore its applicability would be limited to real case databases that would be created following the same methodology as the one used herein, particularly in terms of road network modelling.

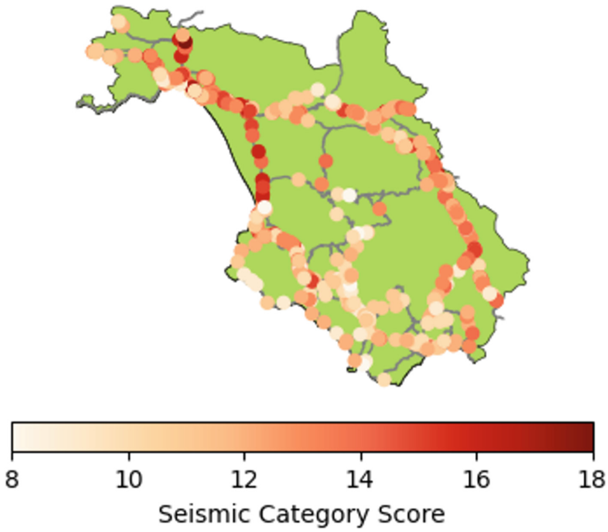

Fig. 14. Proposed modified seismic risk classification's prioritisation.

7 Conclusions

In general, it can be concluded that, when possible, AAL can be considered an alternative or complementary metric by which assets within a bridge portfolio can be prioritized. This also leads to an amplification of the indirect loss component in prioritization (highly correlated to daily traffic flow data), since it has a much higher economic loss contribution than direct losses. Finally, the application of the current version of the 2020 MIT Guidelines leads to large portions of the inventory classified to the highest-risk available category, creating a challenge to use it efficiently to classify bridge priorities and resource allocation. To address this, a proposal for modification was proposed herein, which performed better in comparison to the current guidelines on the case study evaluated.

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