Optimal Location of Strong Ground Motion Sensors for Seismic Emergency Management

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Abstract. In the aftermath of an emergency, the state of the transportation network should be evaluated, and necessary emergency actions should be taken immediately by the manager/owner of the structure. This study is dedicated to the development of a methodology for the identification of the optimal ground motion sensors' layout for seismic emergency management purposes. The information acquired through the strong ground motion network installed in the proximity of the infrastructure can greatly improve the decision-making process by allowing for improved estimation of the demand posed by the earthquake and thereby of the structural reliability after the seismic event. In this paper, we assess the optimum layout of the strong ground motion network based on the maximization of the value of information acquired through the recorded ground motions. A procedure is proposed to reduce the computational burden related to the modeling of the ground motion required for the computation of the Value of Information.

Keywords: Value of Information · Seismic Emergency Management · Strong Ground Motion.

1 Introduction

The management of infrastructures is one of the most complex fields in structural engineering since it is associated with large epistemic and aleatory uncertainties, and requires a robust optimization process, in which all possible candidate actions are assessed carefully considering the available knowledge and the financial constraints [1]. In the case of seismic emergency management, the expected demand of an earthquake should be modeled considering an – in principle – infinite set of scenario earthquakes consistent with the seismic hazard of the region. In general practice, Monte Carlo Simulation (MCS) and its variants are employed to model the seismic hazard. The Ground Motion Prediction Equations (GMPEs) are employed to predict the Intensity Measure (IM) that is assumed to be a metric of ground shaking level. Besides the uncertainty associated with the location and magnitude of the seismic event, the GMPEs also model the epistemic uncertainty in the IM. The need for considering a large set of possible earthquake scenarios makes these analyses computationally expensive. Therefore, several methodologies directed toward reducing computational effort have been developed. Examples are importance sampling [2] or mixed-integer linear optimization [3, 4]. They are based on selecting the set of scenarios that can model the seismic hazard/risk accurately enough to solve the problem at hand at the same time reducing the computational effort. The information acquired through the Strong Ground Motion (SGM) network can greatly improve the ground motion models and consequently, the decision-making process associated with seismic management. SGM information allows for an improved estimation of the demand posed by the earthquake and thereby of the structural reliability after the seismic event. Although the optimal layout for strong ground motion networks is studied from the perspectives of early earthquake warning [5] and rapid detection and characterization of earthquakes [6] by many researchers, there is still a literature gap in the investigation of the effect of the location of strong ground motion sensors on the benefit they provide to post-earthquake decision-making. The optimal layout for sensing devices based on the Gaussian Random field models is discussed in detail by Krause [7]. Malings [8] investigates the optimal sensor layout for the management of infrastructures system under the effect of different kinds of hazards (e.g., seismic, urban heat) considering different network topologies (connectivity) and different evaluation metrics such as Value of Information (VoI) and entropy. Giordano et al. [9] presented a methodology to optimize the location of sensors for a network of bridges that are subjected to degradation. In this paper, the optimum sensor layout for the seismic stations that can be used in the seismic emergency management of a network of bridges is identified based on the maximization of the Value of Information (VoI) from the Bayesian decision theory [10]. Compared to the previous studies: i) a more detailed ground motion modeling technique is adopted to consider the interdependency of intensity measures at adjacent locations; ii) a technique to select a subset of the seismic scenario is employed to reduce the computational effort; and ii) the decision problem is formulated assuming that only sensors for measuring the ground motion intensity measures are installed whereas no sensors are installed on the structure.

2 Methodology

The proposed methodology has three steps concerning (i) modeling the seismic demand, (ii) selecting the subset of scenarios that best represent the seismic hazard associated with the considered region, (iii) value of information analysis. The three steps are described in this section.

2.1 Modeling the Seismic Demand

In this step, the seismic demand IM_{es} posed by an earthquake e at a given site s is predicted using the GMPE. The observed IM_{es} is modeled in terms of median value of the GMPE, $I\bar{M}$, and of two residuals δB_e and δW_{es} that account for the variability of the observed intensity measure IM with respect to its median value $I\bar{M}$ [11]:

$$\log\left(IM_{es}\right) = \log\left(I\bar{M}\right) + \delta B_e + \delta W_{es} \tag{1}$$

The term δB_e, is defined between-event residual and represents the average shift of the ground motion with respect to its median value, observed during an earthquake. For a given earthquake e, this term is the same at all sites over the considered region [12]. The term δW_{es} represents the site-to-site variability of the ground motion. It is the residual between the observed intensity measure IM_{es} at a specific site s for an earthquake e, and the earthquake specific median prediction of the observed intensity measure for the considered earthquake (modeled as the sum of $I\bar{M}$ and δB_e) [11]. The within-event residual δW_{es} can be modeled using a spatial correlation model. The model of the median value $I\bar{M}$ depends on several parameters specific of the earthquake and of the site. The distribution of the magnitudes must be extracted from a suitable recurrence law (e.g., Gutenberg-Richter [13]), which provides the annual number of earthquakes in a region equal to and greater than a given magnitude. In other words, the mean annual rate of an earthquake magnitude, λ_m, is derived based on the recurrence law, which in turn, controls the exceedance rate of a given IM. The location of the earthquakes can be considered uniformly distributed over the seismic sources to simulate its aleatory variability. Using the parameters required by the GMPE, the distribution of $I\bar{M}$ can be modeled. The residual δB_e, and δW_{es} can be sampled using the distribution given by the GMPE.

2.2 Selection of Scenario Earthquakes

The VoI analysis requires the estimation of the seismic demand that would be measured at the bridge locations by the deployed sensors. To this aim, the distribution of the demand, e.g., in terms of IM, must be estimated for all the possible earthquake scenarios that are likely to occur in the region during the reference period. The GMPE can be used to this scope, but this task may require a large computational effort. In this paper a procedure to estimate the seismic demand based on a limited number of earthquake scenarios (magnitude and epicenter couple) is employed. For this purpose, the procedure provided in [4] for the selection of an optimized set of scenarios is adapted to the problem at hand. A minor modification is made to account for the different goal of the optimization that, in this study, is to optimally estimate the marginal distributions of the IMs at all the bridge locations. The objective function to minimize is defined over N_s bridge sites as: $\sum_{i=1}^{N_s} \left|\left| diag\left(\lambda\right)^{-1}\left(\lambda - \mathbf{\Theta_i w}\right)\right|\right|_1$ subject to $\mathbf{Card}(\mathbf{w}) \leq N_q$ and $\mathbf{0} \leq \mathbf{w}$. The last two conditions respectively limit the number of selected earthquake scenarios to N_q, and prevent the annual occurrence rate $\mathbf{w}$ of the earthquakes to be negative. The term $||.||_1$ is the L1-norm of the matrix, λ is the annual rate of exceedance of the IMs that are sampled from the scenario earthquake, $\mathbf{\Theta_i}$ is the matrix of constants corresponding to site I and $\mathbf{Card}(\mathbf{w})$ is the cardinality of vector $\mathbf{w}$. In section 3 a comparison between the annual exceedance rate of IM based on the subset and on the extensively sampled set is shown.

2.3 Value of Information Analysis

The value of information from ground motion sensors is used in this paper as a metric to quantify the benefit of diverse layouts of the seismic stations to support seismic emergency management of a network of bridges. The problem is formulated assuming that several ground motion sensors are installed at the locations of selected bridges in the network, whereas no sensors are installed on the bridges. The alternative sensing schemes correspond to different numbers and combinations of deployed sensors. The value of information associated with each sensing scheme is calculated as the difference between the prior and pre-posterior costs. Detailed expressions on the components of value of information analysis have been developed and are reported in reference [9] for a similar decision problem.

Actions, Damage states and Expected costs For a network of N bridges, given E alternative emergency actions that can be performed on each bridge in the aftermath of an earthquake (e.g. close, limit the traffic, etc.) the total number of combinations of actions is $C = E^N$. Each of these combinations will be denoted as one action on the bridge network and denoted as $\mathbf{A^c}$. After an earthquake, each component of the bridge network can be in one of several different damage states. Assuming that each bridge can be in one of L damage states, for a network of N bridges, $K = L^N$ combinations of damage states must be considered. Each of the K combinations will be indicated as $\mathbf{DS}_k$ and denoted as k-th damage state of the bridge network. The probability of each of these network damage states is calculated as the product of the probabilities of the damage states of the n-th bridge in the k-th network damage state, $DS_{k,n}$: $P(\mathbf{DS}_k) = \prod_{n=1}^{N} P(DS_{k,n})$. The expected cost of the action $\mathbf{A^c}$ in damage state $\mathbf{DS}_k$ is the sum of the expected indirect costs, $E[Cost_I(\mathbf{A^c})|\mathbf{DS}_k] = f(\Delta\bar{\eta}(\mathbf{A}^c))$, due the loss of connectivity $\Delta\bar{\eta}$ in the network [9] and of direct costs:

$$E[Cost_D(\mathbf{A}^c)|\mathbf{DS}_k] = \sum_{n=1}^{N} P(F_n|\mathbf{A}^c, DS_{k,n})\, c_{Fn}(\mathbf{A}^c) + P(S_n|\mathbf{A}^c, DS_{k,n})\, c_{Sn}(\mathbf{A}^c) \tag{2}$$

where, $c_{Fn}(\mathbf{A}^c)$ and $c_{Sn}(\mathbf{A}^c)$ are the costs associated with the failure and survival of the n-th component of the bridge network. $P(F_n|\mathbf{A}^c, DS_{k,n})$ and $P(S_n|\mathbf{A}^c, DS_{k,n})$ are respectively the failure and survival probabilities of the n-th component, conditional on the action $\mathbf{A^c}$ on this component in combination c and on the damage state $\mathbf{DS}_k$.

Prior Analysis In the prior analysis, the probability of experiencing any of the given damage states ($\mathbf{DS}_k$) under the effect of an earthquake e, characterized by an IM are assigned using outputs of associated hazard analysis and the capacity associated with the damage state of each bridge, based on the reliability analysis methods as it is presented in [9]. The demand posed by the earthquake at N_s locations is described through a vector $\mathbf{D}(e)$ collecting the intensity measures $IM_1,\ IM_2,\ \ldots IM_{N_s}$ at those locations. $\mathbf{D}(e)$ can be modeled as a Gaussian multivariate distribution $\mathbf{D}(e) \sim N(\mu_{\mathbf{D}}(e), \Sigma_{\mathbf{D}}(e))$ whose parameters depend on the earthquake, e. For simplicity of notation, this dependency will not be explicitly reported in the rest of the section, but it will be addressed and considered in section Value of Information quantification. The capacity $\mathbf{C}_{\mathbf{DS}_k}$ of the N bridges in damage state $\mathbf{DS}_k$ and the limit state function are modeled as Gaussian multivariate distribution [9], [14]: $\mathbf{C}_{\mathbf{DS}_k} \sim N(\mu_{\mathbf{C}_{\mathbf{DS}^k}}, \mathbf{\Sigma}_{\mathbf{C}_{\mathbf{DS}^k}})$, $\mathbf{G}_{\mathbf{DS}_k} \sim N(\mu_{\mathbf{G}_{\mathbf{DS}^k}}, \mathbf{\Sigma}_{\mathbf{G}_{\mathbf{DS}^k}})$ where $\mu_{\mathbf{G}_{\mathbf{DS}_k}} = \mu_{\mathbf{C}_{\mathbf{DS}_k}} - \mu_{\mathbf{D}}$ and $\mathbf{\Sigma}_{\mathbf{G}_{\mathbf{DS}^k}} = \mathbf{\Sigma}_{\mathbf{C}_{\mathbf{DS}_k}} + \mathbf{\Sigma}_{\mathbf{D}}$. To each limit state is associated to a value of the reliability index $\beta_{\mathbf{DS}_k} = \mu_{\mathbf{G}_{\mathbf{DS}_k}} / \sqrt{diag(\mathbf{\Sigma}_{\mathbf{G}_{\mathbf{DS}_k}})}$. The total expected cost of the actions $\mathbf{A}^{\mathbf{c}}$ is calculated as follows.

$$E\left[Cost\left(\mathbf{A}^c\right)\right] = \sum_{k=1}^{K} E\left[Cost\left(\mathbf{A}^c\right)|\mathbf{DS}_k\right] P(\mathbf{DS}_k) \tag{3}$$

where the prior probability of the k-th network damage state $P(\mathbf{DS}_k)$ is defined using the formulation in [9]. The network action resulting in the minimum expected cost is selected as optimal prior action:

$$\mathbf{A}^{Prior} = \arg min_{\mathbf{A}^{\mathbf{c}}} E\left[Cost\left(\mathbf{A}^{\mathbf{c}}\right)\right] \tag{4}$$

This expected cost is estimated based on the demand $\mathbf{D}(e)$ defined for a given earthquake, e, e.g, for a given set of realizations of $IM_1,\ IM_2,\ \ldots IM_{N_s}$ at the bridge locations. As described in section 2.2, these realizations are simulated herein using the GMPE and considering both the extensively sampled set and a subset of earthquake scenarios. For each of the two sets, the prior cost associated with a given earthquake scenario, Q, is calculated as the mean of the cost associated to N_e realizations of that scenario.

Pre-Posterior Decision Analysis In the posterior analysis, the demand associated with each earthquake is updated based on the multivariate normal distribution theorem given the ground motion measurements. The measurements $\mathbf{D_m}$ of the intensity measures at the sensors locations can be modeled as follows:

$$\mathbf{D_m}\left(e\right) = \mathbf{\Omega_m}\mathbf{D}\left(e\right) + \varepsilon \tag{5}$$

where $\mathbf{\Omega_m}$ is the measurement matrix indicating the location of the M measurements. ε is the error associated with the difference between the measurements and their estimation at the measured locations $\mathbf{\Omega_m}\mathbf{D}$. The error term can be modeled as Gaussian multivariate distribution $\varepsilon \sim N(\mu_\varepsilon, \Sigma_\varepsilon)$. The functional dependence on the earthquake e is again dropped in the following for simplicity of notation. Measurements can be modeled as Gaussian multivariate distribution $\mathbf{D_m} \sim N(\mu_{\mathbf{D_m}}, \mathbf{\Sigma}_{\mathbf{D_m}})$ where: $\mu_{\mathbf{D_m}} = \mathbf{\Omega_m}\mu_{\mathbf{D}} + \mu_\varepsilon$ and $\mathbf{\Sigma}_{\mathbf{D_m}} = \mathbf{\Omega_m}\mathbf{\Sigma_D}\mathbf{\Omega_m^T} + \mathbf{\Sigma}_\varepsilon$. The posterior distribution of the demand parameters for earthquakes can be updated conditional on the measurements using multivariate normal distribution, $\mathbf{D}|\mathbf{D_m} \sim N\left(\mu_{\mathbf{D}}\left|\mathbf{D_m}, \boldsymbol{\Sigma}_{\mathbf{D}}\right| \mathbf{D_m}\right)$ where: $\mu_{\mathbf{D}}|\mathbf{D_m} = \mu_{\mathbf{D}} + \boldsymbol{\Sigma}_{\mathbf{D}}\boldsymbol{\Omega}_{\mathbf{m}}^{\mathbf{T}}\boldsymbol{\Sigma}_{\mathbf{D}}^{-1}\left(\mathbf{D_m} - \mu_{\mathbf{D_m}}\right)$ and $\boldsymbol{\Sigma}_{\mathbf{D}}|\mathbf{D_m} = \boldsymbol{\Sigma}_{\mathbf{D}} - \boldsymbol{\Sigma}_{\mathbf{D}}\boldsymbol{\Omega}_{\mathbf{m}}^{\mathbf{T}}\boldsymbol{\Sigma}_{\mathbf{D_m}}^{-1}\boldsymbol{\Sigma}_{\mathbf{D}}^{\mathbf{T}}\boldsymbol{\Omega}_{m}$. The limit state functions are updated by replacing the prior with the posterior distribution parameters: $\mu_{\mathbf{G}_{\mathbf{DS}_k}}\left|\mathbf{D_m} = \mu_{\mathbf{C}_{\mathbf{DS}_k}} - \mu_{\mathbf{D}}\right| \mathbf{D_m}$ and $\boldsymbol{\Sigma}_{\mathbf{G}_{\mathbf{DS}_k}}\left|\mathbf{D_m} = \boldsymbol{\Sigma}_{\mathbf{C}_{\mathbf{DS}_k}} + \boldsymbol{\Sigma}_{\mathbf{D}}\right| \mathbf{D_m}$. The updated reliability is: $\beta_{\mathbf{DS}_k}|\mathbf{D_m} = \mu_{\mathbf{G}_{\mathbf{DS}_k}}|\mathbf{D_m}/\sqrt{diag\left(\boldsymbol{\Sigma}_{\mathbf{G}_{\mathbf{DS}_k}}\middle|\mathbf{D_m}\right)}$. Finally updated damage states given the measurements can be derived using the updated reliability index as it is done in the prior analysis. The expected cost of each network action $\mathbf{A}^c$ given the measurements is calculated as follows.

$$E\left[Cost\left(\mathbf{A^c}\right)|\mathbf{D_m}\right] = \sum_{k=1}^{K} E\left[Cost\left(\mathbf{A^c}\right)|\mathbf{DS}_k\right] P(\mathbf{DS}_k|\mathbf{D_m}) \tag{6}$$

The pre-posterior expected cost is obtained considering all the possible outcomes of the monitoring system and their probability of occurrence. As previously mentioned, this expected cost is relevant to a realization of an earthquake e. The measurements $\mathbf{D_m}$ relevant to this realization are obtained from equation (5), where $\mathbf{D}\left(e\right)$ contains IMs sampled from the GMPE in equation (1).

$$E\left[Cost\left(\mathbf{A}^{PrePost}|Q\right)\right] = \sum_{m=1}^{M} E\left[Cost(\mathbf{A}^{PrePost}|Q, \mathbf{D_m})\right] P(\mathbf{D_m}) \tag{7}$$

where $\mathbf{A}^{PrePost} = \arg min_{\mathbf{A^c}} E\left[Cost\left(\mathbf{A^c}\right)|\,\mathbf{D_m}\right]$. The expected cost of the optimal preposterior action, associated with each earthquake scenario, Q, is calculated in a similar way as it is done in the prior analysis, as the average of the expected costs relevant to the single realizations.

Value of Information Quantification For each earthquake scenario Q (e.g. for each magnitude and epicenter couple), the VoI for a given sensing scheme:

$$VoI\left(\mathbf{D_m}|Q\right) = E\left[Cost\left(A^{Prior}\right)\middle|Q\right] - E[Cost\left(A^{PrePost}\right)|Q] \tag{8}$$

Considering all the possible scenario earthquake $Q\left(m,p\right)$, each defined by a magnitude m and an epicentral location p, the total VoI is:

$$VoI(\mathbf{D_m}) = \int_m \int_p VoI\left(\mathbf{D_m}|Q\left(m,p\right)\right) f_m\ f_p dm\ dp \tag{9}$$

where f_m and f_p are the probability densities of the magnitude and epicentral location: f_p is considered uniform whereas f_m is modelled based on the truncated Gutenberg-Richter recurrence law. As described in [8], assuming independency between seismic events, a Poisson process with annual rate λ_{annual} can be used to describe their occurrence. The annual rate describes the expected number of earthquakes per year and can be used to estimate the expected annual VoI and γ_{annual} is the annual discounting factor:

$$VoI_{annual}(\mathbf{D_m}) = \frac{\lambda_{annual}}{\gamma_{annual}}\ VoI(\mathbf{D_m}) \tag{10}$$

When the VoI is calculated using the optimized subset, the density of the VoI is calculated using the same formulation but considering only the selected earthquake scenarios. Then the total VoI is calculated by multiplying the term given in Eq. (10) by a constant which is derived as the ratio between the sum of the original rate of occurrences of earthquake scenarios and the sum of the adjusted annual rate of occurrence (obtained from the optimization procedure) of selected scenario earthquakes.

3 Application

The proposed methodology is applied to select the optimum sensor layout for the seismic stations that can be used in the seismic emergency management of a bridge network composed of 3 identical bridges with natural period T= 1 s and located on rock site. The bridges connect 3 cities. The seismic zone ZS935, Sicily, Italy is selected for this study and the seismic characteristics of the considered region are retrieved from Barani et al. [15]. The Vs30 values are retrieved from the global Vs30 model provided by USGS [16]. The rate of occurrence of earthquakes is derived using the well-known truncated Gutenberg-Richter recurrence law [13] and the epicenter of the earthquakes is assumed to be uniformly distributed over the seismic source. Figure 1 shows the boundary of the seismic zone (red polygon), 3 bridge locations (B1 to B3), and 3 city locations (C1 to C3). The magnitudes of the earthquake vary between 4.3 and 7.6, the annual rate of earthquake occurrence above a minimum threshold magnitude 0.09 and the strike-slip faulting mechanism is selected following [15]. The GMPE provided by Lanzano et al. [17] is selected to generate intensity measures. For each earthquake scenario 10 individual earthquakes (with varying δB_e and δW_{es}) and corresponding IMs are sampled to account for the variability in the ground motions. Using the optimization procedure described in section 2.2 a subset of 287 scenario earthquakes is selected from the original extensively sampled set of 6384 earthquake scenarios. The right panel of Figure 1 illustrates the annual exceedance rates of IM at the bridge locations calculated based on the extensively sampled set and on the optimal subset. The error between the subset and the extensive sampled set is about 7%, which is calculated using the Mean Hazard Curve Error (MHCE) [3]. The possible actions considered in the analysis are keeping the bridge open to the traffic or closing the bridge. Therefore, for the 3 bridges, 8 sets of possible combinations of actions must be considered. For each bridge 3 damage states, namely, light, medium and severe, are considered which correspond to 27 combinations of damage states of the bridge network. The direct costs associated with the failure of each component are assumed to be 10,000,000 and 0 € for actions open and close, respectively. The direct costs associated with the survival of a bridge are assumed to be 0 €. The indirect costs are calculated as a function of loss of connectivity ($1000000\Delta\bar{\eta}\mathbf{A^c}$) and the cost of each measurement is assumed equal to 5000 €. The distances between the cities are considered equal to: 11.5, 12.1 and 8.5 km between cities 1-2, 1-3, and 2-3 respectively and used while calculating the loss of connectivity. The measurement error is modelled as

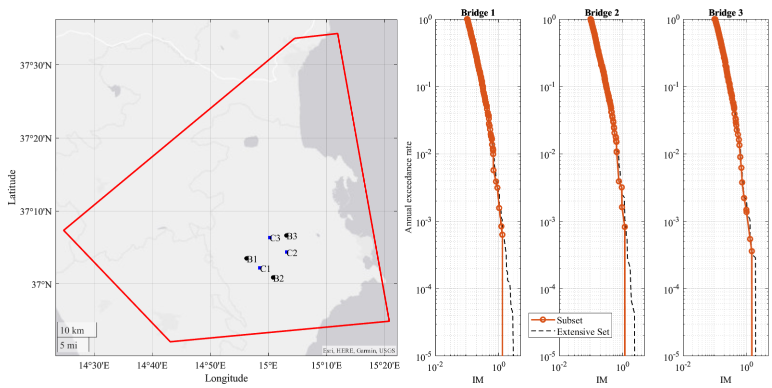

Fig. 1. Study region and comparison between the annual exceedance rate of IMs at the bridge locations based on the subset and extensively sampled set.

a Gaussian random variable with median value 1 and coefficient of variation 0.2. Figure 2 shows the comparison between net value of information for different sensing schemes obtained from the extensively sampled and the optimal subset of earthquake scenarios (top left panel). The highest net VoI corresponds to two sensors deployed at the locations of bridges 1 and 3. When the measurements are acquired at bridge locations 1 and 3 or 2 and 3, approximately the same level of net VoI is achieved. The net VoI corresponding to measurements at all bridges is lower than those two measurement schemes due to the cost of the sensors. The net VoI corresponding to one measurement at each bridge locations and two measurements at bridges 1 and 2 results in lower net VoI compared to the other measurement schemes. Figure 2 also shows the net VoI corresponding to each magnitude conditional on the selected measurement scheme. The net VoI is low for both low- and high-magnitude events. In the case of low-magnitude events the probability of failure is low while in the case of high magnitude events the probability of failure is higher. Therefore, the decision action is more straightforward. In the moderate magnitude events (approximately magnitude 5.5 to 6.5) the net VoI reaches its highest value since the making a decision is more complicated compared to the low- and high-magnitude events. When the measurements are obtained from a single bridge the net VoI corresponding to moderate magnitude decreases as the median value of the demand conditional on measurements ($\mu_{\mathbf{D}}|\mathbf{D_m}$) is overestimated. The overestimated $\mu_{\mathbf{D}}|\mathbf{D_m}$ leads to higher probability of failure, hence higher cost of actions. The situation is the same for the case of two measurements acquired at bridges 1 and 2. The maximum discrepancy in the net VoI calculated from optimal subset is equal to 10% (1700 €) of the VoI calculated from the extensive set. The maximum discrepancy is observed in the case when a single measurement is acquired at the location of bridge 3. The subset is mostly populated by earthquake scenarios with moderate magnitudes. Depending on the selected scenarios the net VoI obtained from the subset can be

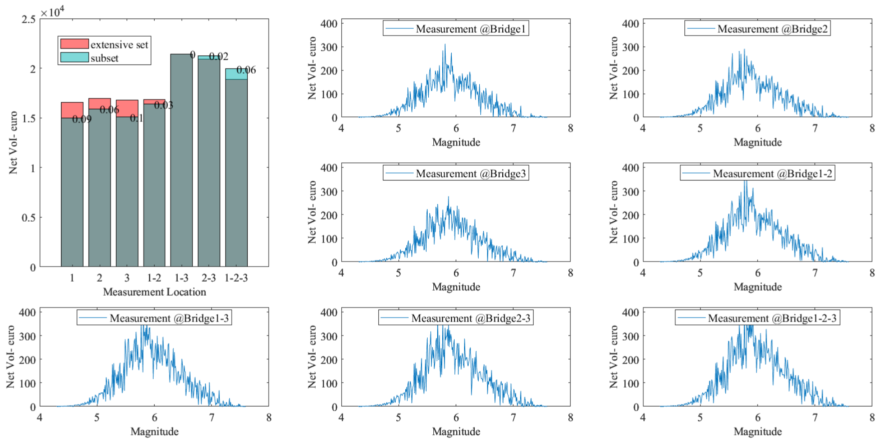

Fig. 2. Comparison between net VoI correspondıng to extensive and the optimal sets and the net VoI for each magnitude for each sensing scheme.

either greater than the net VoI obtained from the extensively sampled set and in the case of the single measurement this effect combined with overestimated $\mu_{\mathbf{D}}|\mathbf{D_m}$ leads to lower values of the net VoI.

4 Conclusion

In this paper, a methodology to select the optimum layout of seismic stations deployed to support the seismic emergency management of a network of bridges is presented. The methodology uses the Value of Information (VoI) from ground motion sensors as a metric to select their optimal number and location. The quantification of the VoI requires the modeling of the ground motion for the generation of earthquake scenarios. In this study a detailed model able to account for the spatial correlation through the within-event residuals is employed. To reduce the computational burden associated with the generation of earthquake scenarios using the ground motion model, an optimization procedure is employed to select a subset of the earthquake scenarios. The procedure has been applied to the exemplary case of a network of 3 bridges connecting 3 cities, For this case, the optimization enables a significant reduction of approximately 95% in the number of scenarios, with a quite small variation of 10% of the corresponding VoI computed with a extensive set of scenarios. Although these results cannot be generalized, it provides an encouraging starting point toward the implementation of the proposed methodology for the optimization of a sensor layout using VoI analysis associated with optimized ground motion modelling.

Acknowledgement Maria Pina Limongelli was partially funded by the Italian Civil Protection Department within the project Accordo CSLLPP e ReLUIS "WP3: Analisi, revisione e aggiornamento delle Linee Guida".

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