COMPDYN 2015
5th ECCOMAS Thematic Conference on
Computational Methods in Structural Dynamics and Earthquake Engineering
M. Papadrakakis, V. Papadopoulos, V. Plevris (eds.)
Crete Island, Greece, 25–27 May 2015

POST-EARTHQUAKE RECOVERY OF A COMMUNITY AND ITS ELECTRICAL POWER SUPPLY SYSTEM

Max Didier[1], Li Sun[1], Siddhartha Ghosh[2] and Bozidar Stojadinovic[1]

[1] Swiss Federal Institute of Technology (ETH) Zurich
Dept. of Civil, Environmental and Geomatic Engineering, 8093 Zurich, Switzerland
didier@ibk.baug.ethz.ch

[2] Indian Institute of Technology Bombay
Dept. of Civil Engineering, Mumbai 400076, India
sghosh@civil.iitb.ac.in

Keywords: post-earthquake recovery, resilience, infrastructure network, electric power supply system, fragility, sensitivity

Abstract. *Research from the past ten years shows that the seismic fragilities of different infrastructure networks are better understood and estimated than the recovery of a community subjected to these fragilities. Modeling the recovery process for a specific infrastructure system-community-hazard combination is a challenging task due to the lack of data and because the recovery process is subject to a large set of interdependent factors and variables. The primary objective of the present work is to understand how typical modeling assumptions affect the estimated seismic resilience of a community, whose electrical power supply network has been affected by an earthquake. The recovery model relies on component recovery probability functions conditioned on the initial post-disaster damage state of the single components. The loss of resilience (LOR) of a set of systems, composed by an electric power supply system and a community demanding electric power is assessed using a compositional approach to quantify the loss of resilience of the combined system. The modeling assumptions that are considered are: a) the time-varying recovery function, and b) the probabilistic model for recovery. For the recovery function, the adopted probability model of the infrastructure system is found to have a strong influence on the loss of resilience, while it is relatively insensitive to that of the community. LOR is also observed to have a significantly higher sensitivity towards the mean of the used recovery functions than towards their variance.*

1 INTRODUCTION

Seismic resilience assessment of the building stock and of infrastructure systems, like the Electric Power Supply System (EPSS), is essential to estimate the impact of earthquakes to a community and to evaluate pre-disaster mitigation measures or post-disaster emergency plans. The resilience of a system or a community is influenced especially by the robustness of the considered system towards a disastrous event and by its recovery in the aftermath of that event. The fragility of components of the built environment or engineered systems can easily be assessed using, for example, fragility curves, that can be obtained through laboratory tests, finite element analyses of the structure or from diverse databases. However, the computation of recovery is much more challenging. Recovery is a complex, multifaceted and multidimensional process depending on many factors, including especially political decisions and socio-economic considerations which might not be known in advance of the disastrous event and are therefore difficult to model numerically.

The objective of this work is to understand the impact of the modeling assumptions of the component recovery functions to the resilience of a set of systems. The findings should provide guidelines for future modeling of the seismic recovery of infrastructure systems and indicate which parameters need more intricate assessment than others.

2 LITERATURE REVIEW

2.1 Definition of Resilience

The definition of resilience, especially the resilience of a community has been refined during the last decade and the term is often used in different settings (Buffalo). For an engineered infrastructure, the loss of resilience (Figure 1) of a given system can be expressed as the loss of functionality or performance over time [1].

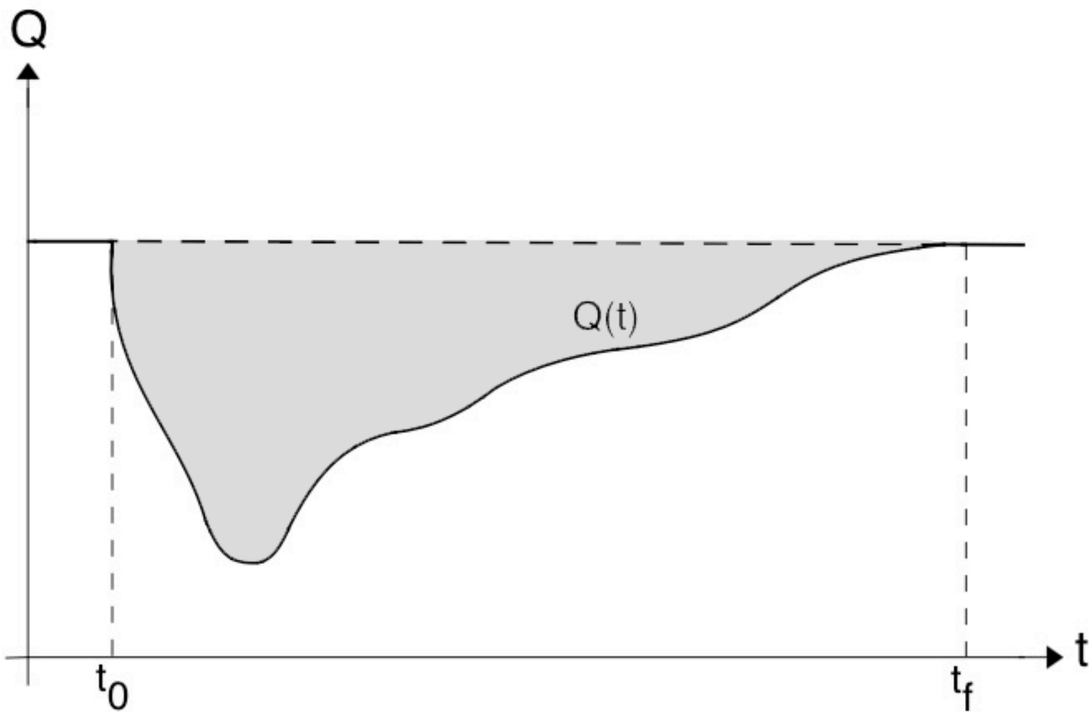

Figure 1: Loss of resilience (shaded area). Adapted from [1]

It can be mathematically defined as

$$R = \int_{t_0}^{t_f} \left[100 - Q(t)\right] dt \tag{1}$$

where, t_0 is the time when the disastrous event (e.g. the earthquake) occurs, t_f the time when the system is fully recovered and Q(t) the performance of the system at a given point in time. The performance function is set at 100% at t_0 [1].

The recovery starts after the absorption phase and ends with the full restoration of the system to its pre-event performance level. Different recovery models have been proposed in the literature. These models can be ordered into five main categories: statistical curve fitting, deterministic resource constraint, Markov processes, network models and discrete event simulations [2].

Statistical curve fitting models usually estimate the parameters of one recovery curve for the whole system using statistical data [3] or a probabilistic parametric approach for a range of parameters [4]. The shape of the system recovery function is predetermined and can take, for example, a trigonometric [4,5], linear or exponential shape [5]. These models do not consider any community or network topology and don't explicitly model the activities that take place during the post-disaster recovery process.

The network approach takes into account the topology of the infrastructure system, which is composed of a number of supply and demand nodes and links between these nodes. It allows the consideration of the temporal and spatial evolution of the systems recovery. This approach has mainly been used in the optimization of the recovery process of the infrastructure system while statistical curve fitting has been used more frequently to model the current recovery process [2].

3 METHODOLOGY

3.1 Estimating the loss of resilience of a set of systems

The definition of the loss of resilience reviewed above only allows to assess the impacts on the performance of a single system - for example, the supply capacity of the electric power supply system over time - and to compare it to its initial performance level. This paper makes use of a compositional approach [6] to calculate the loss of resilience of a set of systems. The compositional approach allows taking into account the changes on the demand side, depending on the performance of a second system, for example a community.

The loss of resilience is therefore the amount of supply that cannot be provided by the damaged supply network in order to cover the demand of a damaged second system or a set of systems (Figure 2). In the example of an EPSS, failure occurs if the post-disaster demand of the community exceeds the available post-disaster power supply capacity of the EPSS. The analytical expression of the loss of resilience (LOR) can be written as

$$LOR = \int_{t_o}^{t_f} \left\langle D(t) - S(t) \right\rangle dt \tag{2}$$

where, D(t) is the demand over time, S(t) is the available supply over time and t_f is the time when both systems have recovered. This quantity is represented by the shaded area in Figure 2.

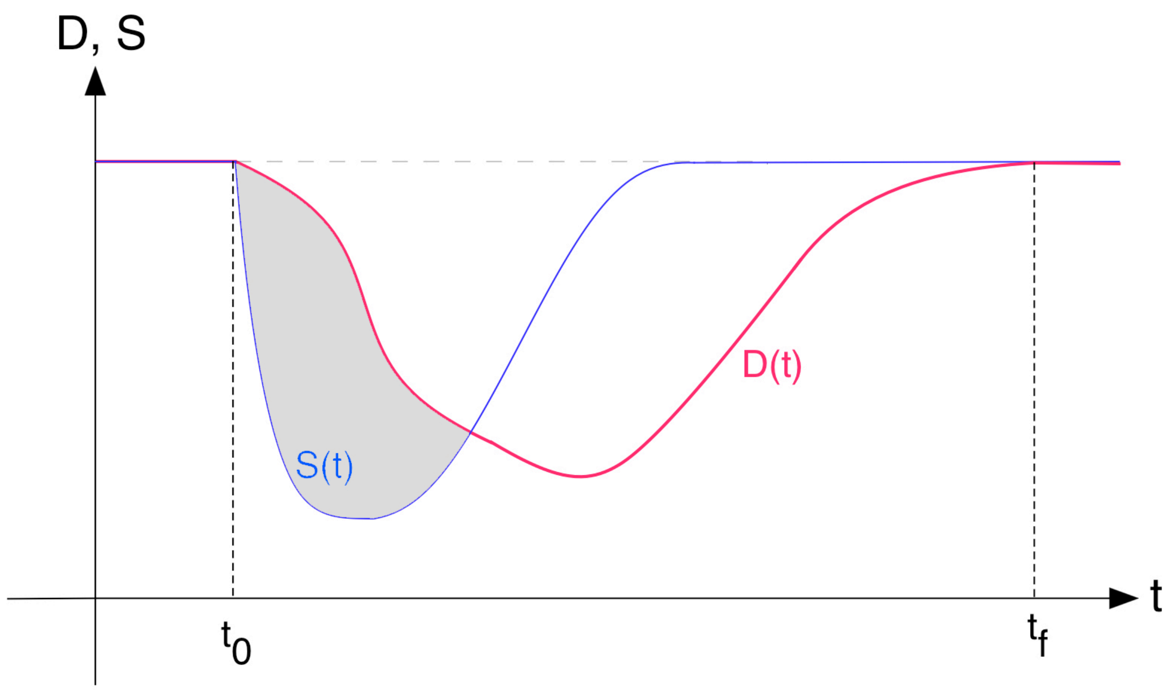

Figure 2: Loss of resilience, compositional approach. Adapted from [6]

3.2 Recovery model

The proposed recovery model combines aspects of the statistical curve fitting and the network approach models. The recovery of every component of the considered systems is expressed by a time-dependent recovery probability distribution conditioned on the damage state of the component. This allows expressing the probability that a certain component of the network has recovered after a certain time after the disastrous event, depending on its initial post-disaster damage state.

It is possible to assign a characteristic recovery distribution to every component in the considered networks and therefore the shape of the system recovery curve is not predetermined. Using the information about the network topology, the available supply and the needed demand at different locations of the considered networks can be calculated and the loss of resilience can be computed using Equation (2).

The advantage of the proposed model is its flexibility and that it only requires few data and no specific knowledge of the detailed recovery process and recovery phases of the considered systems. A specific recovery probability function can be assigned to each component type. The parameters of the used recovery distributions can be estimated using available empirical data, expert opinion or approaches like a discrete event simulation. Different values can be assigned to the parameters depending on the damage state of the components. This allows taking into consideration that heavily damaged components need a longer time to repair than slightly damaged ones [7]. If new information becomes available, all parameters can easily be updated and different recovery speeds can be simulated by simply adapting the parameters of the recovery functions.

4 CASE STUDY

The case study makes use of the introduced concept of loss of resilience (LOR) and the proposed recovery model. In the following, the sensitivity of the LOR of the considered supply-demand system towards the adopted probability distribution type and the probability distribution parameters is analyzed using an example of an EPSS supplying to a virtual community affected by an earthquake.

4.1 Probability distribution for modeling vulnerability and recovery

To model the probability of recovery of a component at a time t after the disastrous event, two distribution types are compared: the lognormal and the Weibull distributions. The investigated distribution types meet the criterion that the support is defined in [0,+∞], which is necessary as the probability of recovery is dependent on the time after the disastrous event and can not take place before the event itself.

The lognormal distribution has been chosen for two reasons: the parameters are easy to estimate from available data or expert opinion and most of the fragility curves for structural seismic demand are based on lognormal distributions. The lognormal recovery functions are therefore orthogonal to the vulnerability functions [6]. Its cumulative distribution function reads:

$$Fx(x) = \Phi\left[\frac{\ln x - \mu}{\sigma}\right] \qquad (3)$$

where, Φ is the cumulative distribution function of the standard normal distribution, and μ and σ are the mean and the standard deviation of the associated normal distribution.

The skewness of the lognormal distribution is always positive, which may not reflect the actual recovery process of many systems. The recovery probability might be better represented using a distribution that allows different negative and positive skewness, for example the Weibull distribution. The disadvantage of the Weibull distribution is that the parameters are more difficult to estimate. The cumulative distribution function for a Weibull model reads:

$$Fx(x) = 1 - e^{-(x/\lambda)^k} \qquad (4)$$

where k (k>0) is the shape parameter and λ is the scale parameter. The skewness of the Weibull distribution is only dependent on k. For k=1 an exponential distribution can be obtained.

4.2 Modeling of the vulnerability of the EPSS and the virtual community

The topology of the EPSS used in the case study corresponds to a part of the IEEE 118 network, which "represents a portion of the American Electric Power System (in the Midwestern US) as of December, 1962" [8]. It is composed of a total of 34 nodes: 15 supply nodes and 19 demand nodes (Figure 3). Two different types of substations are considered in the EPSS, supply substations (220 kV) and distribution substations (35 kV). The substations are modeled using a simplified topology. The supply substation topology includes 3 bus bars (1 reserve) and 7 circuit breakers. Two generators are directly linked to every supply substation [9]. The distribution substations are composed of 3 bus bars (1 reserve), 11 circuit breakers and 3 transformers. Two damage states are considered for bus bars, circuit breakers and transformers: failure and no failure. The corresponding fragility functions are taken from [11]. For generators, three damage states are considered: no damage (DS1), slight / moderate damage (DS2) and extensive damage (DS3), fragility functions are taken from [12].

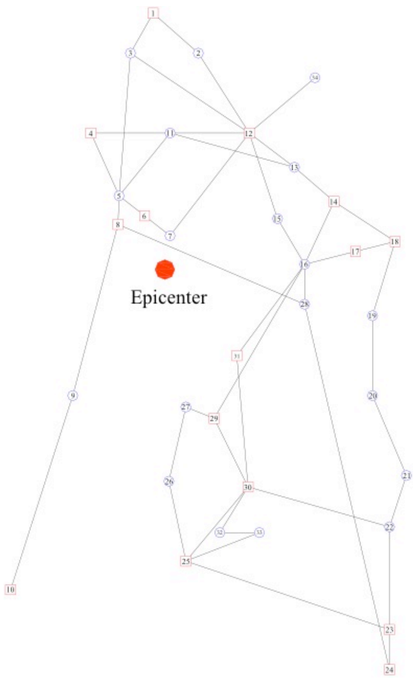

Figure 3: EPSS, virtual community and epicenter. By [6]

The different distribution substations are supplying power to a virtual community, composed of residential buildings, industrial facilities, businesses and critical infrastructure (schools and hospitals), grouped together in several cities, villages and industrial zones situated close to the distribution nodes of the network. 8 different building types are considered and each building type's vulnerability is represented by its own fragility functions [13,14,15,16,17,18]. Three damage states are considered for each building type: no damage (DS1), slight/moderate damage (DS2) and extensive damage/collapse (DS3). The consumption data are obtained from various sources [9]. A power flow balance analysis is run in order to distribute the available supply according to the demand in the network.

The epicenter of the considered seismic event is located close to the geographic center of the considered virtual community environment (Figure 3). The intensity of shaking at the location of each component is measured using peak ground acceleration and peak ground velocity computed using the NGA ground motion model proposed in [19]. The temporal distribution of earthquake recurrence is determined using a Gutenberg-Richter recurrence law, with a=4.4 and b=1 [21].

4.3 Modeling of the recovery

The recovery of the EPSS and the community it supplies to are modeled using different settings (Table 1).

	Setting 1	Setting 2	Setting 3	Setting 4
Components of EPSS	Lognormal	Weibull (k=1)	Weibull (k=1)	Lognormal
Components of community	Lognormal	Lognormal	Weibull (k=5)	Weibull (k=5)

Table 1: Distribution types of the component recovery functions used in the case study.

The mean and standard deviation of the different lognormal component recovery functions of Setting 1 (the ‘reference scenario’) are estimated for each damage state of each component using existing data for recovery rates from natural hazards [3,7,20]. To account for the longer reconstruction time and uncertainties for severely damaged components, it is assumed that the mean and standard deviation for recovery functions from DS3 back to DS1 are considerably higher as those from DS2 back to DS1 [7].

The shape parameter k of the Weibull recovery functions in Settings 2, 3 and 4 is set according to Table 1. Data from past earthquakes show that considerable effort is put in the fast post-disaster reparation of the EPSS. The recovery of the built environment is much more complex and requires often many preliminary processes (financing, building permit) before the actual reconstruction of repairing can start [20]. For the recovery of the EPSS, k is therefore set to 1 and for the recovery of the built community k is set to 5. The mean of the Weibull component recovery functions is set equal to the corresponding mean of the lognormal component recovery functions used in Setting 1.

The comparison of the LOR for the different settings provides an understanding of the sensitivity of the LOR to the different recovery function types. In order to assess the impact of the mean and standard deviation to the loss of resilience, a sensitivity analysis for these parameters are performed, using Setting 1.

5 RESULTS OF THE CASE STUDY

The described case study is run for 2000 MC simulations for moment magnitudes ranging from 4.5 to 7 with an incremental step of 0.1.

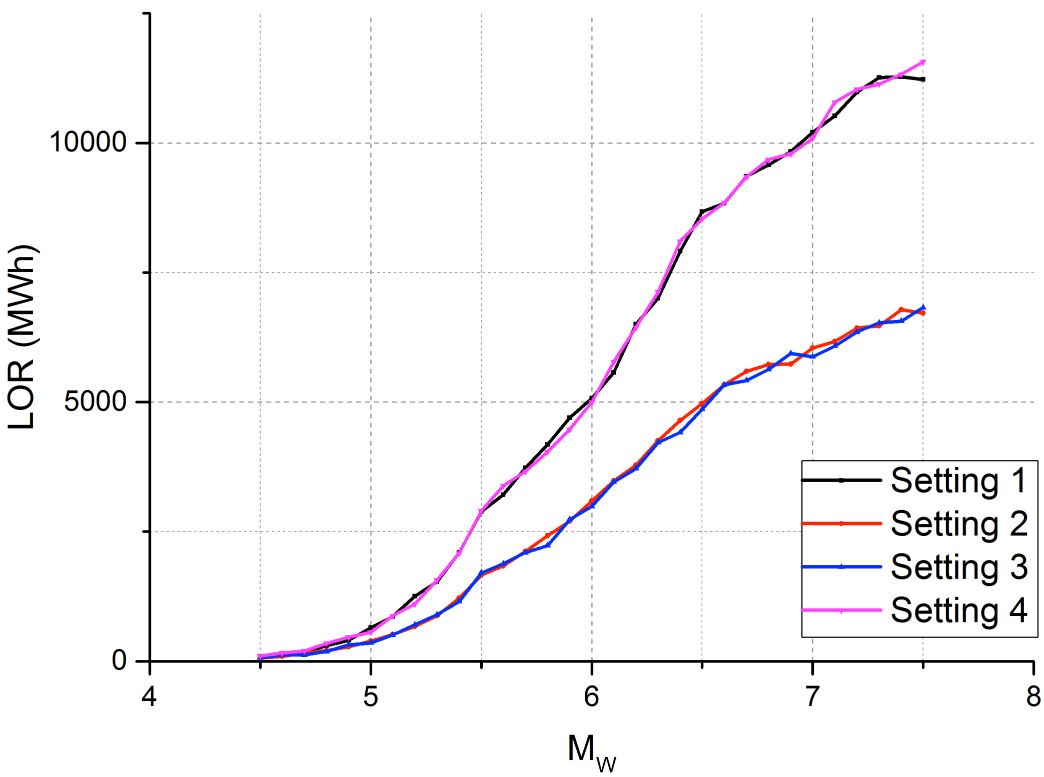

Figure 4: Loss of resilience (LOR) for Settings 1-4 for earthquakes from magnitudes 4.5-7.5.

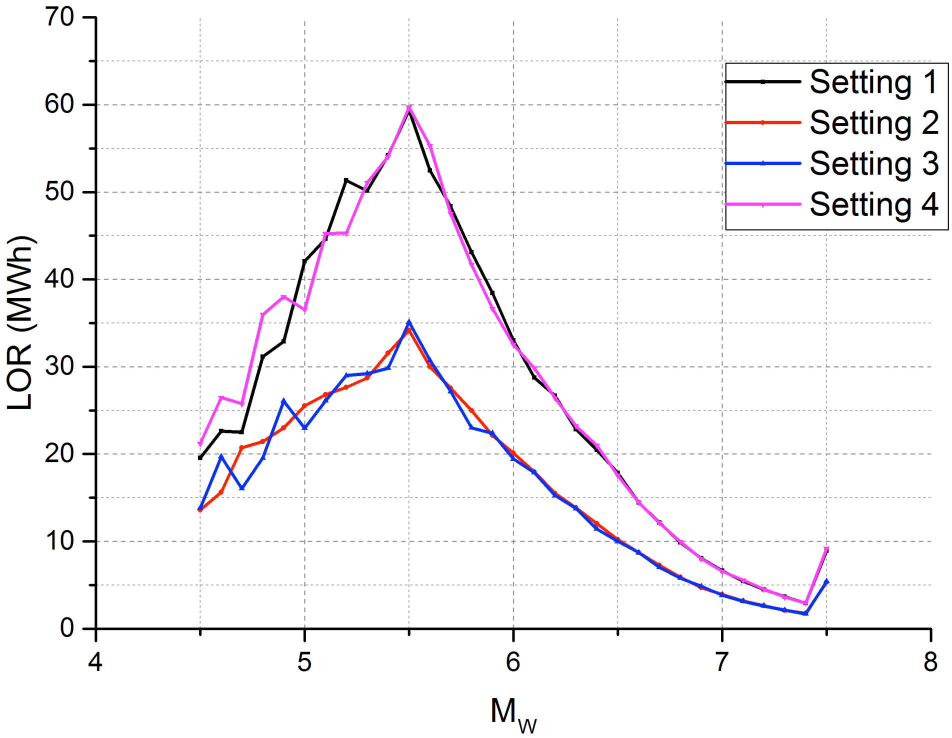

Figure 5: PSHA: Expected loss of resilience (LOR) per year for magnitudes 4.5-7.5.

Figure 4 and Figure 5 illustrate the results for the different recovery settings indicated in Table 1. Figure 4 shows the results of a scenario-based assessment while Figure 5 shows the results of a probabilistic seismic hazard analysis (PSHA). It can be observed that the LOR is higher for the settings, in which the recovery of the EPSS is modeled as lognormal, ie. Setting 1 and Setting 4. This is due to the fact that in Setting 2 and Setting 3, where the recovery of the EPSS is assumed to follow a Weibull distribution, the shape parameter k is set to 1 and the recovery distribution therefore becomes an exponential distribution.

The distribution type of the community recovery function influences the LOR barely. In the modeled set of systems, the recovery of the community is quite slow compared to the one of the EPSS (please note that this may change in other sets of supply-demand systems and the influence of the distribution type of the demand system has to be reassessed for these environments).

Figure 5 indicates that for moment magnitudes ranging from 5 to 6, the difference between Settings 1/4 and Settings 2/3 has the highest impact on the expected LOR per year. If it is assumed that the probability of the recovery of the EPSS following an exponential distribution increases with the preparedness of the community, the elaboration of detailed restoration plans for earthquakes of that range (i.e. M_w 5-6) can considerably reduce the expected LOR.

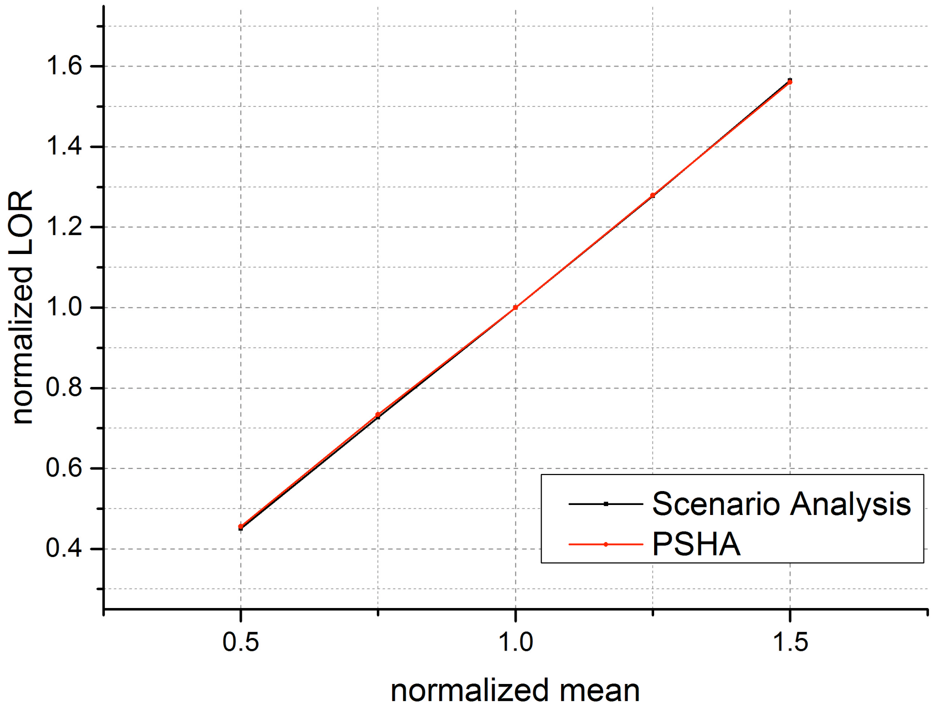

Figure 6: Normalized LOR in function of normalized mean for Scenario Analysis and PSHA.

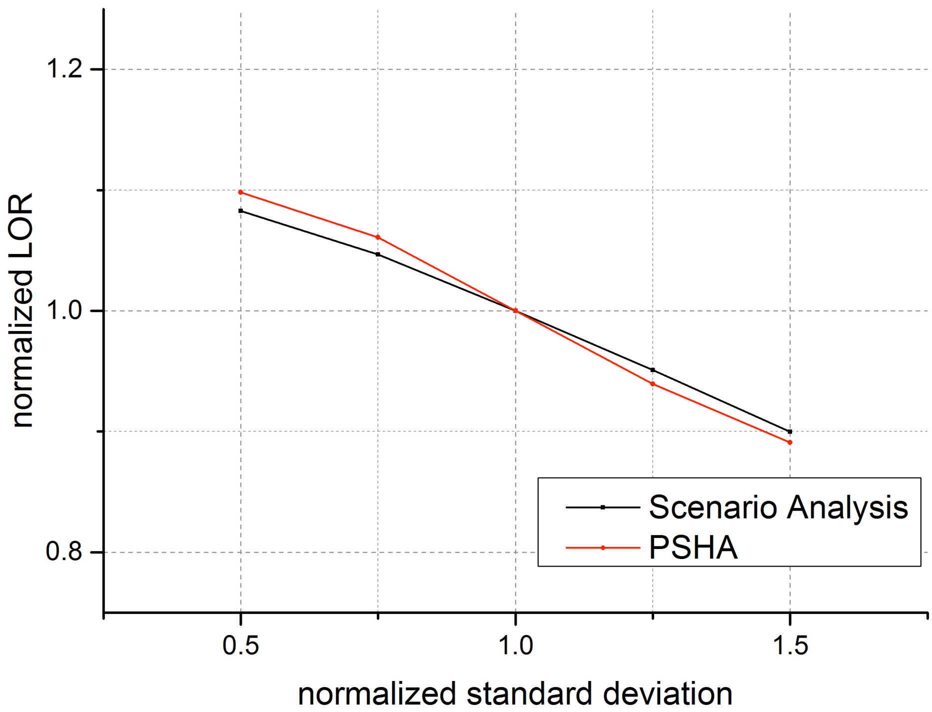

Figure 7: Normalized LOR in function of normalized standard deviation for Scenario Analysis and PSHA.

Figure 6 shows the sensitivity of the LOR towards the variation of the mean of the component recovery functions. It can be seen from the relationship between the normalized LOR and the normalized mean (both normalized to the reference setting) that the LOR is very sensitive to the mean. They change in the same order of magnitude, i.e. a 25% reduction of the mean of the component recovery functions causes a 25% reduction of the LOR of the entire set of systems. The LOR appears to be perfectly correlated to the mean. The sensitivity of the LOR towards the standard deviation of the component recovery functions is relatively smaller (Figure 7). If the standard deviation is reduced for example by 50%, the LOR only changes by 10%. The observations remain the same for the scenario-based simulation and the PSHA.

6 CONCLUSIONS

The loss of resilience of a given set of systems consisting of a supply and a demand system was computed using a compositional approach. It is especially influenced by the recovery of the system. The employed recovery model defines for each component its own time-dependent recovery function conditioned on the component's initial post-disaster damage state. It allows the implementation of the advantages of statistical curve fitting and network approaches. A case study, including a sensitivity analysis, has been carried out in order to determine the influence of the distribution type and the parameters of the recovery functions to the system's total loss of resilience. The distribution type of the recovery of the EPSS has a strong influence on the LOR, while the type of the distribution of the community recovery only causes a slight change in the system's loss of resilience. The results also indicate that the LOR has a higher sensitivity towards the mean of the used recovery functions than towards the standard deviation. These findings should be useful in future modeling of the seismic recovery of infrastructure systems, indicating which parameters need more intricate modeling than others. However, the generality of these outcomes are arguable and should be verified for different network topologies and settings and using different earthquakes sources.

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