Quantifying Component Importance for Disaster Resilience of Communities with Interdependent Civil Infrastructure Systems

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Abstract

Communities and their supporting civil infrastructure systems can be viewed as an assembly of, often numerous, interacting components. Tools that can identify components relevant for community disaster resilience can help to efficiently allocate limited resources to reach community resilience goals. We use Sobol' indices to measure the importance of vulnerability and recoverability of components for disaster resilience of communities with interdependent civil infrastructure systems. The initial component importance analysis requires no prior knowledge regarding component's vulnerability and recoverability. We first rank components based on their importance, using their Sobol' indices. Secondly, we illustrate how the results of the component importance analysis can be used to improve community disaster resilience. Finally, we use component importance to show how model complexity can be reduced by abstracting less important components.

Keywords: interdependent civil infrastructure systems; Sobol' indices; disaster resilience; sensitivity analysis; component importance

1. Introduction

Developing strategies to improve disaster resilience of communities presents a new frontier in our efforts to face and survive natural and man-made disasters

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(EERI (2016); OECD (2019); RRMC (2019); NIBS & BSSC (2020)). Identifying components relevant for disaster resilience of a community can aid our efforts to reach community resilience goals in several ways: i) component importance can guide resilience-improvement measures; ii) high-fidelity simulations can be performed for components that significantly affect community resilience, while simplified, computationally less expensive, models can be used for less important components; iii) data acquisition can be prioritized based on component importance; and iv) communities can be designed so that component importance is evenly distributed, and, hence, no component is too big to fail (Taleb (2012)).

Barker et al. (Barker et al. (2013)) proposed some of the first component importance measures (CIMs) for system disaster resilience. They quantify resilience as a time-dependent ratio of the recovered system performance at the considered time step over the initial loss of performance following a disruption, and, propose two resilience-based CIMs. The first CIM measures the weighted contribution of a disrupted component to the time until full system performance is restored. The weighing factor is the ratio between the loss of performance due to the disruption of the considered component over the maximum loss of performance among all components. The second CIM measures how the invulnerability (i.e., robustness) of a component affects the system recovery time. Since both proposed CIMs are stochastic, the authors used a modified Copeland score, based on comparing quantiles of CIM distributions, to rank components. Baroud et al. (Baroud et al. (2014)), then, used these CIMs to quantify component importance for the resilience of inland waterway networks.

Fang et al. (Fang et al. (2016)) pointed out that the resilience-based CIMs proposed by Barker et al. (Barker et al. (2013)) do not capture how improving components' recoverability could affect system resilience. Furthermore, the way in which system resilience is quantified is "memoryless" since it only includes the system performance at the considered time step. Hence, the system behaviour before the considered time step is not included in the proposed system resilience metric. Fang et al. (Fang et al. (2016)) quantify resilience using cumulative system functionality that considers the entire time period starting with initial recovery actions and spanning until the time step at which the resilience is measured. Based on this resilience metric, they propose two CIMs: *resilience reduction worth* and *optimal repair time*. Resilience reduction worth quantifies the loss in system resilience if the recovery of a component is delayed. Optimal repair time recognizes components whose recovery should be prioritized to maximize system resilience.

Xu et al. (Xu et al. (2020)) assume that after a disruption there are multiple states that a network can reach to satisfy the minimum flow demand of the network users, following different recovery paths. For each recovery path, authors quantify component importance in two ways: i) by assessing the contribution of a recovered component to the flow capacity of the network and ii) by calculating the ratio of the recovery time of the link to the total recovery time of the network. These two CIMs are, then, unified over all possible recovery paths and all considered disruptions to form a single stochastic resilience based CIM. CIMs are, then, ranked using Copeland score, similarly to (Barker et al. (2013)).

Espinoza et al. (Espinoza et al. (2020)) performed a probabilistic assessment of seismic resilience of the Northern Chilean electric power supply system. They quantified component importance as the change in system performance, if a component is assumed to be invulnerable. The system performance measure is the expected interruption cost defined for a certain disaster return period.

A community is a system of systems, where each system consists of numerous components that interact both within and between systems (e.g., inoperability of an electric power plant can lead to the inoperability of components belonging to other systems, such as communication system or water supply system). These interdependencies additionally increase the vulnerability of civil infrastructure systems (CISs), when exposed to man-made or natural disasters (Rinaldi et al. (2001); Kröger (2008)). Hence, CIMs should account for these effects.

Almoghathawi and Barker (Almoghathawi & Barker (2019)) defined two CIMs that consider both the vulnerability and the recovery of physically interdependent civil infrastructure systems. The authors simulate interdependency as a link between components from different networks, where the functionality of the dependent node depends on the functionality of the parent node. They define *optimal recovery time* CIM as the optimal time to recover a component to maximize the resilience of interdependent networks. The *resilience reduction worth* CIM considers the extent to which the inoperability of a component affects the functionality of interdependent networks in a certain time step.

Yu and Baroud (Yu & Baroud (2020)) consider network interdependencies to be uncertain and dynamic, where the probability of two nodes being interdependent is characterized using stochastic block models. Resilience is measured using the same method as in (Barker et al. (2013)). Authors define component importance as the relative improvement in the resilience of interdependent networks at a certain time step, if the considered component is recovered. Components with higher importance are recovered first. Component importance can be static, if component ranking is performed once before starting the recovery process, or dynamic, if component importance is repeatedly calculated at each time step, thus, constantly updating the recovery strategy.

The aforementioned system resilience related CIMs originate from reliability analysis or network theory. Formal global sensitivity analysis methods (Iooss & Lemaître (2015)) offer another way to assess the importance of components in system. In this paper, we use Sobol' indices (Sobol (1993)), to quantify component importance for disaster resilience of communities with interdependent civil infrastructure systems. Sobol' indices belong to the class of variance-based methods – a subclass of global sensitivity analysis methods. Sobol' indices quantify input importance by decomposing the output variance into contributions from each input and/or input group. Hence, the importance of an input or an input group is measured by how much its variance contributes to the output variance.

Different component characteristics are often ranked using different CIMs: they are, therefore, not directly comparable. We quantify the importance of both vulnerability and recoverability of components using the same tool – Sobol' indices. Therefore, the importance of different component characteristics is directly comparable.

Since variance-based methods require inputs defined as probability distributions, the sensitivity analysis presented here is implicitly probabilistic. As opposed to quantifying component importance on a scenario-by-scenario basis, Sobol' indices quantify component importance over all possible scenarios considered by the input probability distribution.

We use the iRe-CoDeS extension (Blagojević et al. (2021b)) of the Re-CoDeS framework (Didier et al. (2018a)) to quantify disaster resilience of communities with interdependent systems. The iRe-CoDeS resilience quantification model treats interdependencies among components in a dynamic manner: the flow of resources and services in the community determines how community components and systems interact at each instant of the post-disaster recovery process.

2. Disaster Resilience Quantification for Communities with Interdependent Civil Infrastructure Systems

Most disaster resilience quantification methods are based on the framework proposed by the Multidisciplinary Centre for Earthquake Engineering Research (MCEER), in which the disaster resilience of a system is quantified based on its post-disaster functionality (Bruneau et al. (2003)). Didier et al. (Didier et al. (2018a,b)) extended the MCEER framework by presenting the Re-CoDeS framework that uses three measures of system functionality over time: the supply, the demand and the consumption of a resource or a service a system is producing or making available. The Re-CoDeS framework accounts for the impact of the disaster on both the demand and the supply side of a system. Lack of resilience (LoR) of a system regarding a resource or a service is defined as the unmet demand of the system for the considered resource or service over the considered time frame. Disregarding the demand side of a system reduces the Re-CoDeS system LoR metric to the MCEER system functionality metric.

2.1. Re-CoDeS framework for disaster resilience quantification

The Re-CoDeS framework consists of three main elements: the demand layer, the supply layer and the system resource and service distribution model. A system is defined as a set of components that exchange resources and services, according to the system resource and service distribution model. A component of the system can belong to the supply layer (i.e., be a supplier), to the demand layer (i.e., be a user), or to both the demand and supply layers (i.e., be a supplier and a user). A resource or a service produced and consumed in the system and considered in the resilience analysis is labelled in the following as R/S, for convenience.

The system's demand for a R/S over time, $D_{sys,R/S}(t)$, represents the sum of the demands of all components $i \in \{1, ..., I\}$, where I is the total number of components of the considered system and $D_{i,R/S}(t)$ is the demand of a component i for a R/S at time t:

$$D_{sys,R/S}(t) = \sum_{i \in \{1,...,I\}} D_{i,R/S}(t) \tag{1}$$

The supply capacity of a component i for a R/S at time t is labelled as $S^C_{i,R/S}(t)$. System supply capacity, $S^C_{sys,R/S}(t)$, is similarly obtained by summing the supply capacities of individual components:

$$S^C_{sys,R/S}(t) = \sum_{i \in \{1,...,I\}} S^C_{i,R/S}(t) \tag{2}$$

The system R/S distribution model describes the flow of R/Ss from suppliers to users. It considers the system's topology, the technical and physical laws governing the distribution of R/Ss (e.g., hydraulic flow laws), and possible dispatch/allocation strategies (e.g., prioritization of some users, restrictions for others). The interaction between the demand and the supply layer, defined by the system R/S distribution model, determines the R/S consumption of each component, $C_{i,R/S}(t)$. It represents the amount of R/S that is consumed by the user i at time t. The system's consumption, $C_{sys,R/S}(t)$, is then the sum of the R/S consumptions of all components:

$$C_{sys,R/S}(t) = \sum_{i \in \{1,\ldots,I\}} C_{i,R/S}(t) \tag{3}$$

The Re-CoDeS disaster resilience metric, Lack of Resilience of a system regarding a R/S, $LoR_{sys,R/S}$, is amount of the unmet demand for the R/S the considered system is producing over the resilience assessment period, calculated as:

$$LoR_{sys,R/S} = \int_{t_0}^{t_f} (D_{sys,R/S}(t) - C_{sys,R/S}(t))dt = \int_{t_0}^{t_f} LoR_{sys,R/S}(t)dt \tag{4}$$

where t_0 and t_f are the start and end times of system resilience assessment, respectively.

2.2. Extending the Re-CoDeS framework to consider system interdependencies

Blagojević et al. (Blagojević et al. (2021b)) proposed an extension of the Re-CoDeS framework to enable disaster resilience quantification for systems-of-interdependent-systems, the iRe-CoDeS framework. As in Re-CoDeS, a component is the lowest level of system discretization considered in the iRe-CoDeS framework. Each component is characterized by instantaneous R/S supply and demand values. The supply values represent the supply capacities of a component at a given time in the resilience assessment interval. The demand values represent the amounts of R/Ss the component needs to operate and, consequently, supply the system with its supply capacities. The iRe-CoDeS framework simulates interdependency effects among components, by decreasing the supply capacity of those components whose demand cannot be met. At every time step of the resilience assessment interval any supplier of an R/S can meet the demand of any user for that R/S, and, hence, a component is dependent on a R/S, not on a pre-determined component that produces that R/S. Therefore, interdependency relations between components are dynamic, not static.

Component properties that affect the instantaneous R/S demand $D_{i,R/S}(t)$, supply capacity $S^C_{i,R/S}(t)$ and consumption $C_{i,R/S}(t)$, as well as the system LoR metric (Eq. 4) are *damage level*, *repair rate* and *functionality level*. In addition to these component properties, component locations, system topology and system operation also affect the LoR metric. In the iRe-CoDeS framework and the subsequent sensitivity analysis, these component and system properties are considered to be independent of each other.

2.2.1. Damage, recovery and functionality of components

A continuous variable, labelled *damage level* represents the state of components' physical damage at each time step in the resilience analysis. Immediately after a disaster, an initial damage level is assigned to each component using that component's disaster vulnerability function, a conditional probability that a component will be at a certain (or larger) damage level if it experiences a disaster of a given intensity (Blagojević et al. (2020a,b)). In iRe-CoDeS, the damage level of a component is a real number that varies from 0 – no damage, to 1 - complete damage.

The recovery of a component from disaster-induced damage is simulated in iRe-CoDeS by decreasing its damage level at each time step (e.g., one day) of the resilience analysis using component's *repair rate*, which characterizes the recoverability of the component. The repair rate of a component can span from 0 – the component never recovers, to 1 – component recovers in one time step, regardless of the initial damage level. The component is considered fully recovered once its damage level reaches 0. In iRe-CoDeS resilience analysis used herein, the repair rate of a component is assumed to be constant over the entire recovery period and its damage level is decreased by the repair rate at each time step until the component is fully recovered. These assumptions are sufficient to illustrate the Sobol' index component sensitivity analysis, but can be replaced by more realistic ones if such information is available (Blagojević et al. (2021a)).

The *functionality level* of a component describes how much of component's function has been lost due to damage and recovered due to repairs after a disaster. iRe-CoDeS accommodates different relations between component damage and functionality levels. In this study, binary and linear damage-functionality component functions (Blagojević et al. (2021b)) are used, together with an assumption that the supply capacities of a component are reduced in proportion to its current post-disaster functionality level. Therefore, as opposed to CIMs that assume components functionality is binary (e.g., the component is either operational or not), the iRe-CoDeS framework allows for partial component functionality.

2.2.2. Localities and links

The spatial distribution of components is defined using geographically localized units, *localities*. An example of a locality is a district, if the considered system is a city, or a city, if the considered system is composed of several cities. Components can either be in a locality (e.g., a facility) or between localities. Such components are named links (e.g., roads or pipes) that connect localities, enabling the transfer of R/Ss from one locality to the other. The transfer of R/S within a locality (e.g., between two facilities at the same locality) is assumed to be direct, without any links, and unconstrained.

The functionality of a link can be pre-conditioned on the functionality of another component, the link carrier (e.g., a bridge) carrying the link. The functional dependency between a link and a link carrier is also modelled using the supply/demand approach. The links that need to be carried have a demand for *carrier* R/S, which the link carrier provides.

2.2.3. R/S distribution and interdependency modelling

Two groups of R/Ss are considered in iRe-CoDeS: utilities (e.g., electric power supplied by the electric power plants); and transfer services (e.g., electric power transfer service supplied by electric power transmission lines). To obtain the utility R/S consumption of community components, the utility R/Ss are distributed among components at each time step following the utility R/S distribution model. To account for the state of the distribution networks, the transfer service supply capacity of links is used to form optimal paths among localities, as explained in (Blagojević et al. (2021b)). Before a utility R/S is transferred between components from different localities, the transfer service supply capacity of the optimal path connecting considered localities is compared to the transfer service demand of such a utility transfer. If the supply is higher than the demand, the utility R/S is transferred, otherwise, the supply available to the component is set to zero and the component ceases to operate, simulating interdependency effects. Additionally, the same interdependency effect occurs if the amount of utility R/S transferred to the component is not enough to meet its demand in full. The R/S distributions are repeated several times in a time step to simulate the interdependency feedback loops and thus-induced cascading component shutdowns. A component cascading shutdown sequence is assumed to unfold completely within one resilience analysis time step. Hence, the interdependency effects do not propagate to the next time step.

Once the recovery target is met (e.g., all components are fully recovered), an iRe-CoDeS resilience analysis is ended. Then, the LoR values for each of the considered R/Ss in the community are computed following equations 1-4 to quantify the disaster resilience of the community and its interdependent systems.

3. Quantification of Community Component Importance for Disaster Resilience

Component importance for community disaster resilience is quantified using a Sobol' index variance-based global sensitivity analysis of community disaster resilience, evaluated using the iRe-CoDeS framework and the LoR metric, with respect to component vulnerability and recoverability properties. Recall that component vulnerability defines its initial disaster-induced damage level, while the component recoverability defines the rate of component repair and recovery of its function in the community. These component properties directly affect the LoR metric (Eq. 4), since they directly affect component demand, supply and consumption. Additionally, intervening to change component vulnerability and recoverability is localized (component-scale) and involves conventional planning, means and resources typically readily available to community system operators. Therefore, the majority of studies on component importance for system resilience focus on components' vulnerability and/or recoverability (e.g. Almoghathawi & Barker (2019); Espinoza et al. (2020)). However, other component properties, such as their locations, and community properties, such as the topology and the operation of community systems, are important as well. Interventions to change these system-level properties are often global (community-scale) and involve extraordinary planning, means and resources. Based on the previous studies done on this topic and the aforementioned assumptions regarding the ability of system operators to intervene in systems, the sensitivity analysis performed in this study involves only component vulnerability and recoverability properties.

Variance-based sensitivity analysis requires that the component parameters to which the system sensitivity is investigated are defined as probability distributions (Iooss & Lemaître (2015)). Probability distributions characterizing the vulnerability and recoverability of components depend on numerous factors, such as the considered hazard, the pre-disaster preparedness of the community, the type, age and level of maintenance of components, etc.. A variety of unbounded or bounded, discrete or continuous probability distributions could be assumed based on the available data about the components and the community, as well as considering the investigated disaster scenarios. This sensitivity study is constructed assuming a minimal amount of data regarding component's vulnerability or recoverability is available at the outset: these are the bounds of component property values. In the iRe-CoDeS framework, both the initial damage level and the repair rate are bounded between 0 and 1. When only the bounds of a component property probability distribution are known, the appropriate decision for a sensitivity study is to assign a uniform probability distribution to both component properties to maximize the entropy with respect to the available information (Kapur (1989)). Therefore, it is assumed that the initial damage level and repair rate of all components are uniformly distributed.

The importance of community components with respect to its disaster resilience is quantified using Sobol' indices (Sobol (1993)), also described briefly in the following section. Sobol' indices quantify component property (input) importance by decomposing the variance of the community LoR metric (output) into contributions from each input and input group. Hence, the importance of a component is measured y how much the variance of its properties contributes to the variance of the community LoR metric. Such variance contributions are comparable to each other, enabling the ranking of community components in terms of their importance to community disaster resilience, from those with highest variance contributions (most important) to those with lowest variance contributions (least important)

Sobol suggested several ways in which Sobol' indices can be used (Sobol (2001)). Sobol' index community component importance ranking is in itself an important decision-making basis. One way to use component importance ranking is to focus on the most important components and improve their vulnerability and recoverability properties. For example, if the sensitivity analysis shows that the initial damage level and the repair rate of a bridge are important for disaster resilience of a community, engineering resources can be invested to more precisely determine the current state of the bridge and obtain a more accurate bridge vulnerability function. Alternatively, better recovery plans for that bridge can be developed prior to the disaster, thus shortening the time needed for bridge repair and return to function. Due to such actions, the probability distributions representing the bridge vulnerability and recoverability properties would be changed from a uniform to one that has a smaller variance, thus reducing the contribution of the bridge to the community disaster LoR metric variance and reducing its importance for community disaster resilience.

Another way to use component importance ranking is to focus on the least important components. If the variance of these component properties does not significantly affect the variance of community disaster resilience, the value of information about these components is low. It follows that community model complexity can be reduced by assuming the properties of these less important components are deterministic (and have pre-assigned constant values). It follows further that resilience-improvement measures aimed at these component would have little or no effect on the community disaster resilience.

Sobol' indices are usually obtained using Monte Carlo sampling (Sobol (2001)). However, the dimensionality and complexity of community disaster resilience models can grow quickly with the size of the community and detail of the analysis. Thus, an important limitation of the Sobol' sensitivity analysis, the high computational cost, must be kept in mind. This issue is usually solved using meta-modelling techniques (Sudret (2008); Abbiati et al. (2021)). However, thanks to the streamlined implementation of the iRe-CoDeS framework on high-performance computers and the relatively low computational time of the case study, the computational cost of computing Sobol' indices using Monte Carlo sampling was relatively low (i.e., a few seconds per one iRe-CoDeS resilience quantification). Thus, meta-models were not used in the case study.

4. Sobol' indices

The Sobol' index sensitivity analysis can be applied to any deterministic model with multiple independent inputs and a finite-variance output. The main idea behind Sobol' indices is to define an expansion of the model output comprising summands, which are functions of the input variables of increasing dimensions (Sobol (1993)). Then, the contribution of the variance of each summand to the total variance of the model output is quantified.

Given an integrable function (i.e., a computational model) $y = f(x)$, where y is a scalar output and $\mathbf{x} = x_1, \ldots, x_n$ is an input vector of n dimensions, $f(x)$ can be decomposed into:

$$f(\mathbf{x}) = f_0 + \sum_{i=1}^{n} f_i(x_i) + \sum_{i=1}^{n}\sum_{j>i}^{n} f_{ij}(x_i x_j) + ... + f_{1,2,...,n}(x_1, x_2, ..., x_n) \quad (5)$$

Or using a shortened notation:

$$f(\mathbf{x}) = f_0 + \sum_{s=1}^{n} \sum_{i_1<...<i_s}^{n} f_{i_1,...,i_s}(x_{i_1}, ..., x_{i_s}) \tag{6}$$

where total number of summands is $2^n - 1$. The expansion is unique if the integrals of the summands with respect to their own variables are equal to zero:

$$\int f_{i_1,...,i_s}(x_1, ..., x_s)dx_k = 0 \quad for \quad 1 \leq k \leq s \tag{7}$$

Therefore, summands can be calculated by integrating f(x):

$$\int f(\mathbf{x})d\mathbf{x} = f_0 \tag{8}$$

$$\int f(\mathbf{x})d\mathbf{x}_{\sim\ \mathbf{i}} = f_0 + f_i(x_i) \tag{9}$$

$$\int f(\mathbf{x})d\mathbf{x}_{\sim\ \mathbf{i},\mathbf{j}} = f_0 + f_i(x_i) + f_j(x_j) + f_{ij}(x_i x_j) \tag{10}$$

where $\mathbf{x}_{\sim\ i}$ stands for vector $\mathbf{x}$ that excludes its i-th element. The higher order summands are calculated in the same manner.

If $f(\mathbf{x})$ is square-integrable, it follows that all the summands are also square-integrable. Squaring the expansion and integrating over the input domain we get:

$$\int f^2(\mathbf{x})d\mathbf{x} - f_0^2 = \sum_{s=1}^{n} \sum_{i_1<...<i_s}^{n} \int f^2_{i_1,...,i_s}(x_{i_1}, ..., x_{i_s})dx_1, ...dx_s \tag{11}$$

The total variance of the function is given by the equation:

$$D = \int f^2(\mathbf{x})d\mathbf{x} - f_0^2 \tag{12}$$

It is, then, decomposed into contributions from each group of inputs:

$$D = \sum_{s=1}^{n} \sum_{i_1<...<i_s}^{n} \int f^2_{i_1,...,i_s}(x_{i_1}, ..., x_{i_s})dx_1, ...dx_s = \sum_{s=1}^{n} \sum_{i_1<...<i_s}^{n} D_{i_1,...,i_s} \tag{13}$$

In the expanded form:

$$D = \sum_{i=1}^{n} D_i + \sum_{i=1}^{n} \sum_{j>i}^{n} D_{ij} + ... + D_{1,2,...,n} \tag{14}$$

Now, Sobol' indices can be defined as variances of inputs and/or input groups normalized by the total variance:

$$S_{i_1,...,i_s} = \frac{D_{i_1,...,i_s}}{D} \tag{15}$$

All indices are non-negative and sum up to 1. The integer s defines the order of the Sobol' index. For example, S_1 is the first order Sobol' index that shows how much the variance of input 1 alone contributes to the variance of the output. Setting an input with a high first-order index to a constant value will significantly reduce output variance. Hence, this input is considered important. However, a low first-order index does not necessarily mean that the input is not important: it may be important when interacting with other inputs. This is captured in higher order Sobol' indices containing the considered input. Total Sobol' indices (Homma & Saltelli (1996)) are used to account for the total effect of an input, including the first-order effects and the interactions with other inputs. The total Sobol' index of an input i represents the sum of Sobol' indices of all orders that contain input i:

$$S_i^T = \sum_{i \in [i_1,...,i_s]} S_{i_1,...,i_s} \tag{16}$$

Saltelli et al. (Saltelli et al. (2010)) presented efficient methods to calculate Sobol' indices using Monte-Carlo (MC) sampling. In this study, the Python library SALib is used to calculate the MC-based Sobol' indices (Herman & Usher (2017)). The total number of samples that needs to be generated to calculate first-order and total Sobol' indices is:

$$N_{Tot} = N_{InputDim} \cdot (n + 2) \tag{17}$$

where N_{Tot} is the total number of samples, $N_{InputDim}$ is the chosen number of samples per input and n is the number of model inputs.

5. Case Study

The subject of the case study is a virtual community (Figure 1) with 3600 inhabitants, located in 9 Building Stock Units (BSUs), supported by three interdependent CISs. The considered CISs are: the Electric Power Supply System (EPSS), the Water Supply System (WSS), and the Cellular Communication System (CCS). Modelling how these CISs function is simplified for this case study, as shown in Figure 2. The EPSS consists of Electric Power Plants (EPPs) producing the electric power (EP) R/S and Electric Power Transmission Lines (EPTL), transferring the EP to the users. The CCS consists of Base Station Controllers (BSCs) that manage the cellular communication traffic between Base Transceiver Stations (BTSs), through the High Level Communication (HLC) R/S. BTSs then supply the community inhabitants with communication services, labelled as Low Level Communication (LLC) R/S. Both communication R/Ss are measured in Erlang [E] (Erlang (1925)) and are transferred wirelessly. The WSS provides Potable Water (PW) and Cooling Water (CW) R/Ss to the virtual community. Potable Water Pipes (PWPs) transfer the PW from Potable Water Facilities (PWFs) to the BSUs and community inhabitants who occupy them. Cooling Water Pipes (CWPs) are used to transfer CW from the Cooling Water Facilities (CWFs) to the end users, which are components in other CISs. PWPs, CWPs and EPTLs share the same links shown in Figure 1, where the community localities are represented by circles and the links between localities are shown using black lines. Further details on this virtual community can be found in (Blagojević et al. (2021b)).

The virtual community experiences a disaster and recovers from it. The effects of a disaster are represented by an initial damage level of each community component. The recovery of each component is assumed to proceed independently and simultaneously, at a component repair rate. Since the damage level

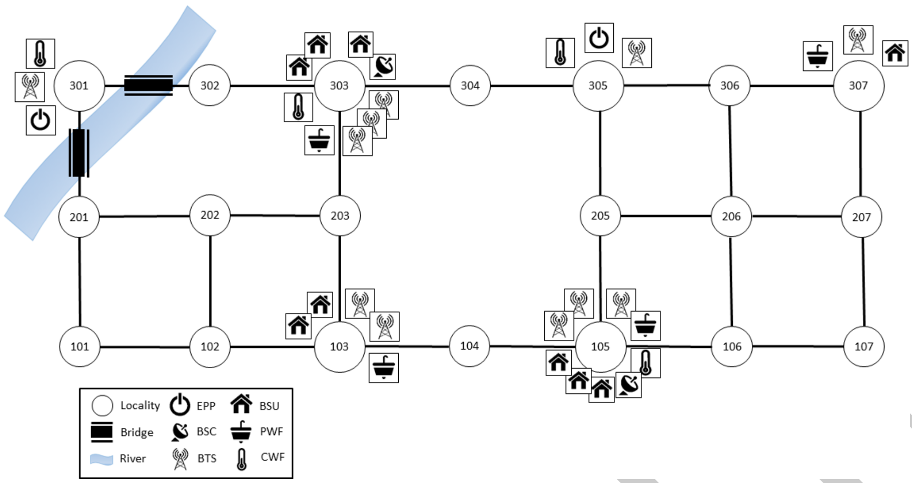

Figure 1: Virtual Community set-up. Components in localities are Electric Power Plants (EPPs), Building Stock Units (BSUs), Base Station Controllers (BSCs), Potable Water Facilities (PWFs), Base Transceiver Stations (BTSs) and Cooling Water Facilities (CWFs)

of a component is reduced by its repair rate at each time step following the disaster, the recovery time of a component depends on its initial damage level and its repair rate. In this study, impeding factors are not considered, and recovery of all components starts immediately after the disaster. The assumption that recovery is linear and uninterrupted is a simplification of the actual recovery process occurring in a community after a disaster. More sophisticated recovery modelling methods can also be implemented (Blagojević et al. (2021a)).

From a sensitivity study standpoint, each virtual community component is characterized by two inputs, its initial damage level and its repair rate. These two inputs describe the vulnerability and the recoverability of that component, respectively. The virtual community is composed of 32 facilities, 2 bridges, 27 PWPs, CWPs and EPTLs, summing up to in total 115 components. Each disaster scenario is then characterized by a total of 230 inputs representing the specific initial damage and repair rate of each community component in that disaster scenario. The iRe-CoDeS framework is used to quantify the disaster re-

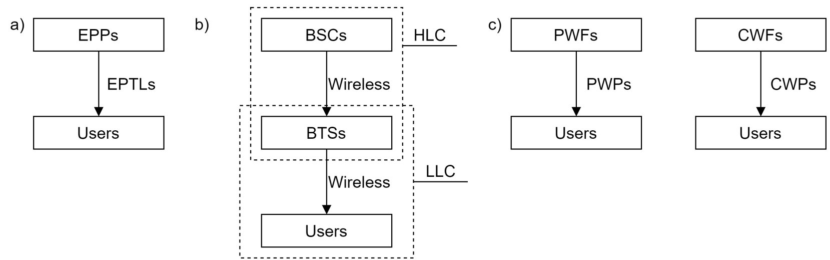

Figure 2: Simplified CIS functionality, a) electric power supply system, b) high level and low level communication systems, c) potable water supply system, d) cooling water supply system

silience of the virtual community in each scenario by computing five LoR values (Eq. 4), one for each of the five considered utility R/Ss. The virtual community disaster resilience sensitivity is assessed separately for each utility R/S using Sobol' indices, setting up five sensitivity analyses each with a 230-dimensional input and one-dimensional output space. The MC-based Sobol' indices are computed using 10,000 samples per input, creating 2,320,000 (Eq. 17) distinct disaster scenarios, each assessed in a separate iRe-CoDeS run. To prevent long recovery times, and to decrease computational time, the lower bound of the uniform distribution for the repair rate was set to 0.01 instead of 0, leading to a maximal recovery time of 100 time steps. The required computations were performed on the Euler HPC cluster, part of the ETH parallel computing facilities. The computation involved running 5000 jobs in parallel, where each job ran 464 disaster scenarios. One job was performed using 4 processing threads, required on average 6 (mostly from 4 to 10) minutes of computational time and around 7.5GB of memory.

6. Results and Discussion

First, we use the computed total Sobol' indices to assess the disaster resilience of the virtual community regarding each considered R/S and discuss the findings to identify and quantify CIS interdependencies. Then, we examine two ways to use the computed Sobol' indices to improve community disaster resilience. On one hand, we focus on the most important community components (those that have high total Sobol' index values) with respect to community disaster resilience and examine how changing the parameters of the probability distributions that describe the relevant characteristics of these components changes the disaster resilience of the entire community. On the other hand, we focus on the least important community components and show how to use this information to reduce the complexity of the community model without sacrificing the quality of its disaster resilience assessment.

6.1. Evaluation of component importance using total Sobol' indices

Figure 3 to Figure 7 present mean values and 95% confidence intervals of the community component total Sobol' index values obtained from disaster resilience sensitivity analyses for the five considered R/Ss (i.e., EP, LLC, HLC, PW and CW). For clarity, only 30 (out of 115) components with the highest total Sobol' index values are shown in each figure. Components are labelled on the x-axis. For example, EPP 301 refers to the electric power plant at locality 301 and Bridge (201, 301) refers to the bridge connecting localities 201 to 301 in Figure 1.

6.1.1. EP LoR

Figure 3 presents the sensitivity analysis outcome for electric power disaster resilience of the virtual community: it depends primarily on the suppliers of EP R/S, the two EPPs in localities 301 and 305. The total Sobol' indices show that the repair rate is more important than the initial damage level of these suppliers. Bridges connecting localities 301 and 302, and 201 and 301 are also recognized as important. This is a consequence of the virtual community layout, namely, locality 301 is connected to the rest of the network only by the two bridges that carry EPTLs and CWPs to the EPP (Figure 1). Further, several EPTLs are important, out of which the EPTL connecting localities 105 and 205 stands out. This is also a consequence of the topology of the virtual community. Several paths between different localities include the link connecting localities 105 to 205. Hence, when optimal EP paths are calculated in iRe-CoDeS, this link is oftentimes included, and hence affects the EPTL transfer supply capacity.

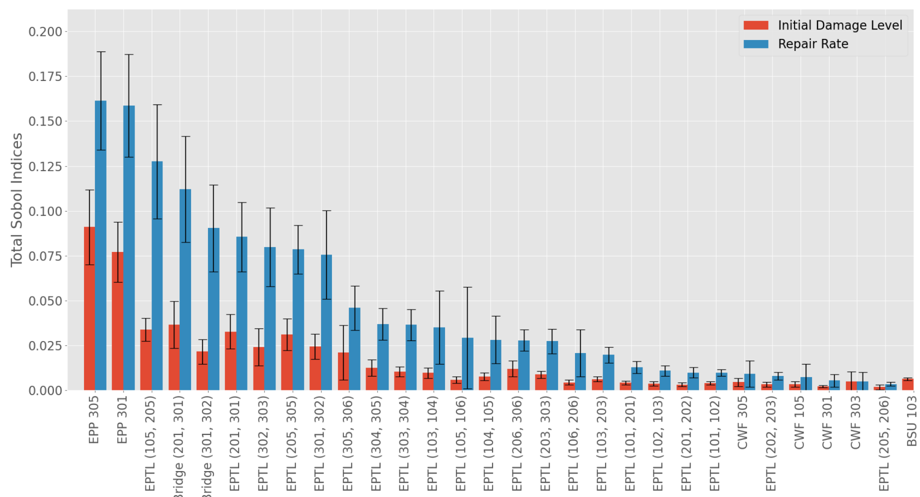

Figure 3: Total Sobol' indices for EP LoR

6.1.2. HLC LoR

Figure 4 presents the component total Sobol' indices for high-level communication community disaster resilience. The sensitivity analysis indicates that the suppliers of HLC, the BSCs, are most important. As in the case of EP disaster resilience sensitivity, the recoverability had higher importance than the vulnerability of the components. Once again, several EPTLs emerged as important for HLC disaster resilience, recognizing that supply of EP is crucial for the BSCs. Additionally, CWFs have notable Sobol' index values. This is due to the assumed BSC demand for CW (Blagojević et al. (2021b)). Importantly, these findings show that the virtual community CISs are interdependent, and that the iRe-CoDeS framework is capable of identifying and quantifying such interdependencies.

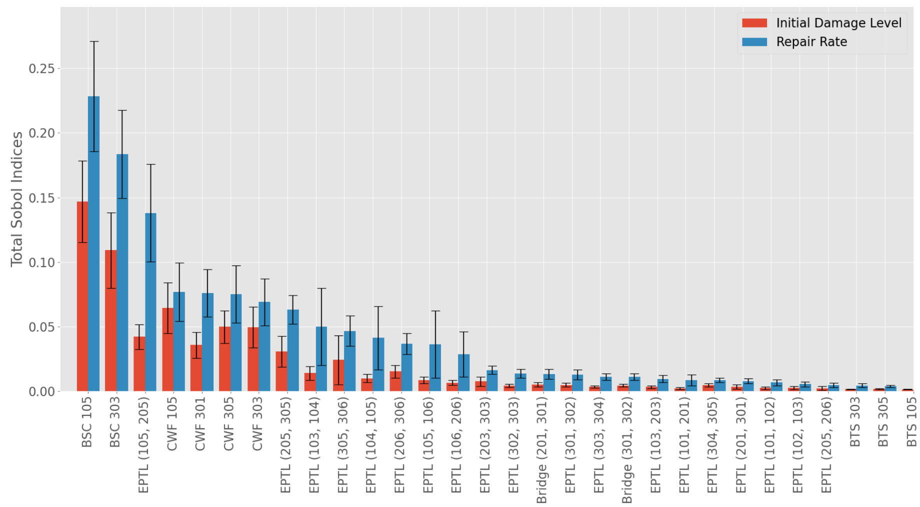

Figure 4: Total Sobol' indices for HLC LoR

6.1.3. LLC LoR

The component importance ranking for community disaster resilience regarding the low-level communication R/S is presented in Figure 5. The inputs with the highest importance are the initial damage level and the repair rate of several EPTLs, BSCs and CWFs. These EPTLs have a high Sobol' index because they transfer the EP needed to operate the BTSs (for LLC), as well as BSCs and CWFs. Note that BTSs need HLC supplied by the BSCs to operate, while the BSCs, in turn, need CW supplied by CWFs to operate. Therefore, the iRe-CoDeS framework was able to represent, and the Sobol' index sensitivity analysis was able to recognize such multi-level interdependencies among components of different CISs. The larger number of LLC suppliers, the BTSs, compared to the number of suppliers of CW and HLC in the virtual community can explain why the vulnerability and the recoverability of the BTSs is less important than the vulnerability and recoverability of the components that the BTSs depend on. In fact, there are only two BSCs and 4 CWFs, while there are 11 BTSs. Therefore, there is more redundancy in the production of LLC due to a larger number of suppliers.

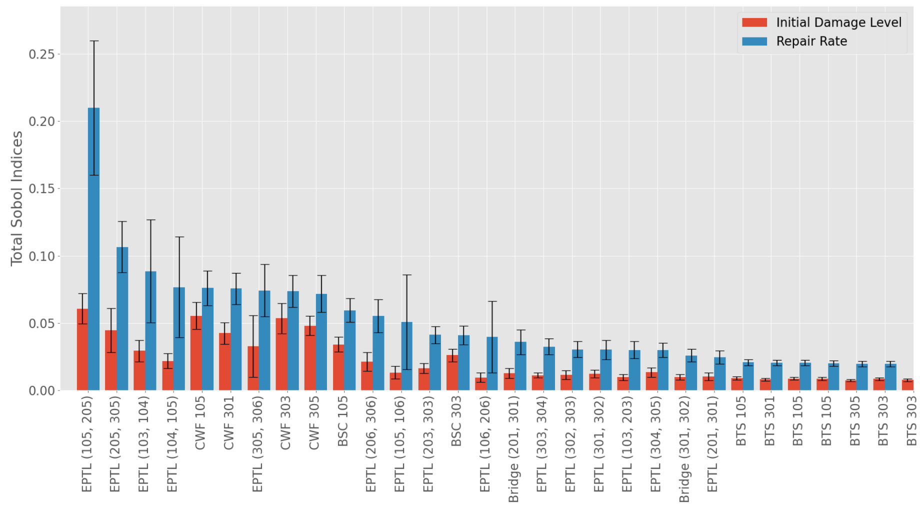

Figure 5: Total Sobol' indices for LLC LoR

6.1.4. PW LoR

Figure 6 presents the component importance for community disaster resilience regarding the potable water R/S. Evidently, it depends almost exclusively on the vulnerability and recoverability of PW suppliers, the PWFs. This means that the supply of PW is independent of other community CISs. Notably, PWPs that connect the PWFs to the BSUs (and the inhabitants) are not identified as important. This is a consequence of the highly redundant water pipe network of the virtual community (Figure 1).

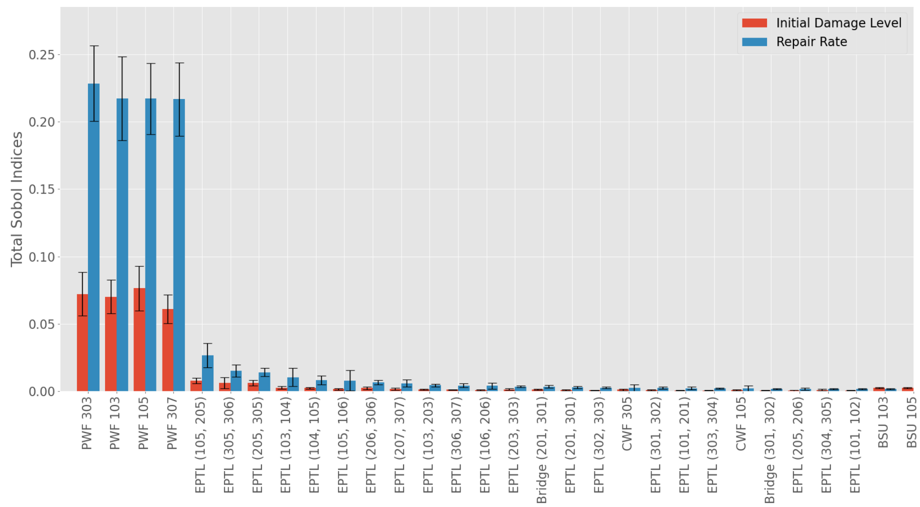

Figure 6: Total Sobol' indices for the PW LoR

6.1.5. *CW LoR*

Component importance for community disaster resilience regarding the cooling water R/S is shown in Figure 7. The total Sobol' indices are high for the repair rate and the initial damage levels of CWFs, the supplier of CW. Notably, several EPTLs and the two bridges also have high Sobol' index values. These EPTLs connect the CWFs with the EPPs and the bridges carry the EPTLs, enabling the flow of EP from EPPs to the CWFs. This indicates the dependence of the community WSS on its EPSS. The CWPs, connecting CWFs and the components of the EPSS and CCS that need CW to operate, are not as important because the redundancy of the virtual community cooling water pipe network diminishes the reverse dependence of community EPSS and CCS on the WSS's distribution network (Figures 3, 4).

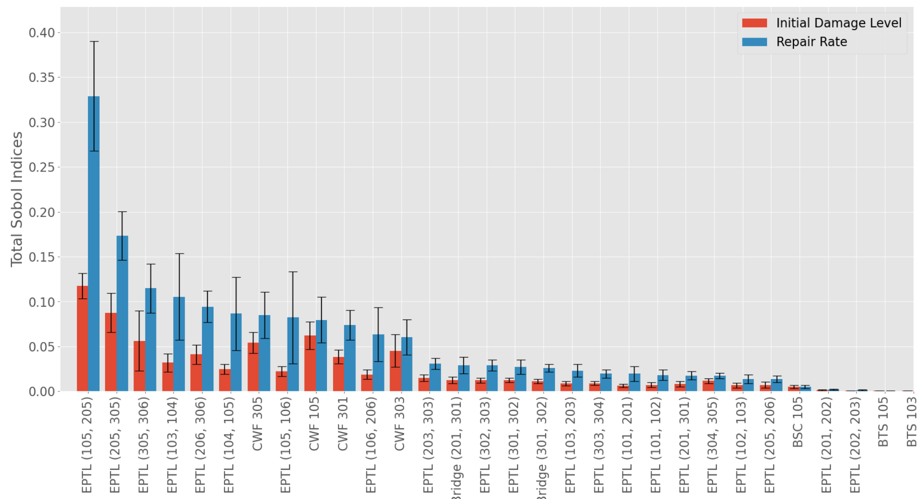

Figure 7: Total Sobol' indices for CW LoR

6.2. Making decision to increase community disaster resilience using total Sobol' indices

The information about community component importance for its disaster resilience can be used to select the components whose improvement may improve community disaster resilience the most. In this case study, let us assume that a decision maker wants to increase the virtual community disaster resilience regarding the EP R/S. Figure 3 shows that the recoverability characteristics of the four components (the two EPPs, the EPTLs from 105 to 205 and the Bridge from 201 to 301) have the highest importance. Let us imagine that the uninformed priors of these four input variables – the uniform distributions, are now updated to a Beta distribution with parameters $a = 9$ and $b = 3$, an informed posterior. This may be based on component inspections, newly developed recovery plans, and/or better vulnerability and recoverability models of these four important components. The posterior distribution of the inputs has a higher mean and a lower variance than the uninformed prior (Figure 8), and, hence, the mean and the variance of the output, (i.e., the EP LoR), as well as the value of the total Sobol' indices, also change. To illustrate this, the sensitivity analysis is run, first, with all inputs being uniformly distributed. Then, the simulations are run with the repair rate of two EPPs, the EPTL from 105 to 205 and the Bridge from 201 to 301, sampled according to the Beta distribution. The difference in the LoR_{EP} and the total Sobol' indices are shown in Figure 8 and Figure 9, respectively. From Figure 8, it can be seen that the mean LoR is reduced by 24%, from $\mu_{LoR_{EP}} = 174.34MWh$ to $\mu_{LoR_{EP}} = 132.53MWh$ and its standard deviation is reduced by 34%, from 131.66MWh to 87MWh. Furthermore, the 95% quantile of the LoR_{EP} distribution is reduced by 30%, from 387MWh to 273.4MWh. This is a result of changing the distribution of only 4 component properties, out of a total of 230 considered component properties. Additionally, due to the change in variance of the 4 component properties probability distributions, their total Sobol' indices, and, hence, their importance for community disaster resilience, is now reduced (Figure 9). The EPTLs from localities 205 to 305, 201 to 301, 301 to 302 and 302 to 303, are now the 4 most important components. Compared to the sensitivity analysis results presented in section 6.1.1, their importance increased from being 6th to 10th most important components to 1st to 4th ranking. Interestingly, the bridge from locality 301 to 302 remained the 5th most important component in both sensitivity analyses.

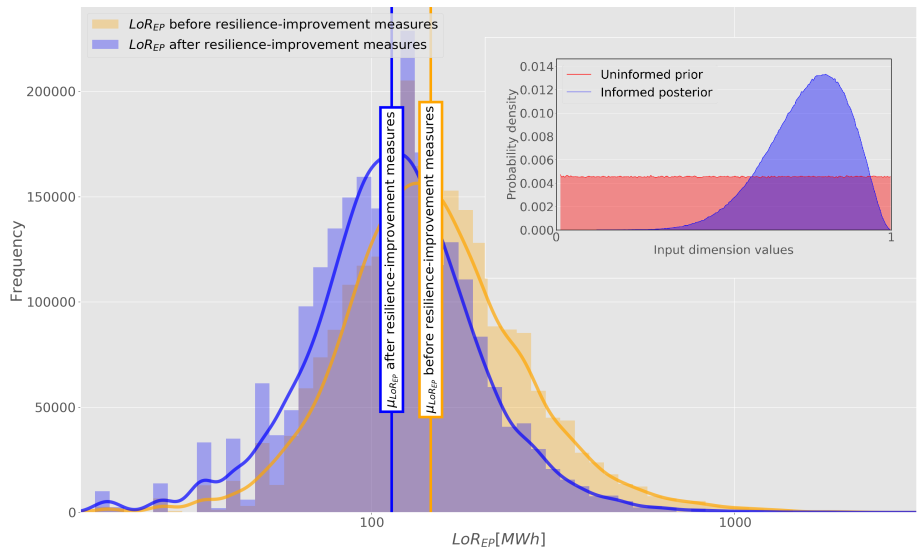

Figure 8: Comparison between the LoR_{EP} with uninformed priors and with informed posterior distributions for important components.

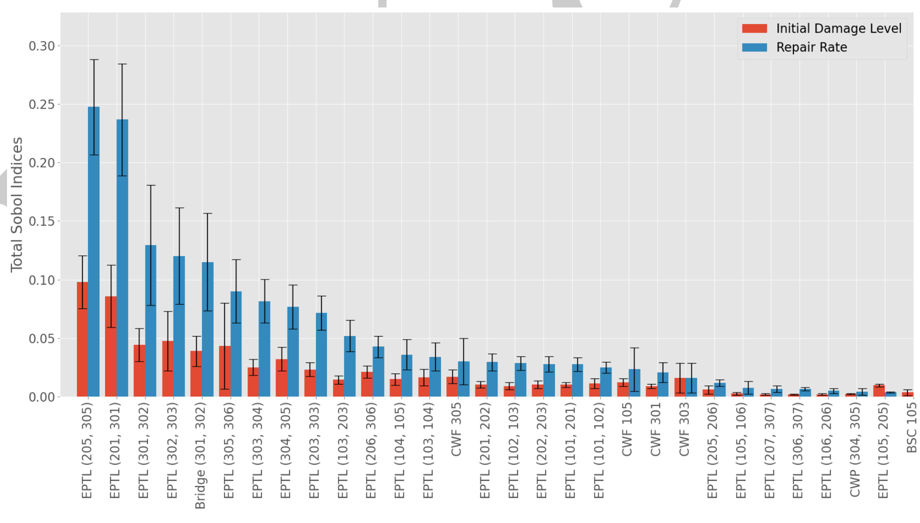

Figure 9: Total Sobol' indices after modifying the probability distributions of important components

6.3. *Reducing model complexity using total Sobol' indices*

The information about community component importance for its disaster resilience can also be used to significantly reduce the complexity of the virtual community model. Low-ranked component properties have small total Sobol' index values, indicating that the variance of their properties (vulnerability and recoverability) has a very small effect on the variance of the community LoR metric. Recall that Figures 3-7 show only 30 components with the highest-ranked total Sobol indices. For EP LoR (Figure 3), 62 of the 115 iRe-CoDeS virtual community components have a total Sobol index value for both their damage level and repair rate smaller than 0.001. These components may be considered unimportant for the community EP LoR metric. Further, the complexity of the virtual community model can be reduced by not considering the damage and recovery of these components for EP resilience assessment. To demonstrate this, twi sets if 10,000 simulations were run: first, by setting the damage level and repair rate of the 62 unimportant components to 0 (no damage, no repairs needed) across all scenarios, while the damage levels and repair rates of the remaining 53 components followed a uniform distribution (i.e., the simplified model); and second, sampling the damage level and repair rate of all component properties from a uniform distribution (i.e., the original full model). The histograms of LoR_{EP} for the full and the simplified model are compared in Figure 10. The curves fitted to the histograms vary only in the peak LoR_{EP} values, with the simplified model undershooting the full model by less than 2%. The shapes of the fitted distributions are quite similar.

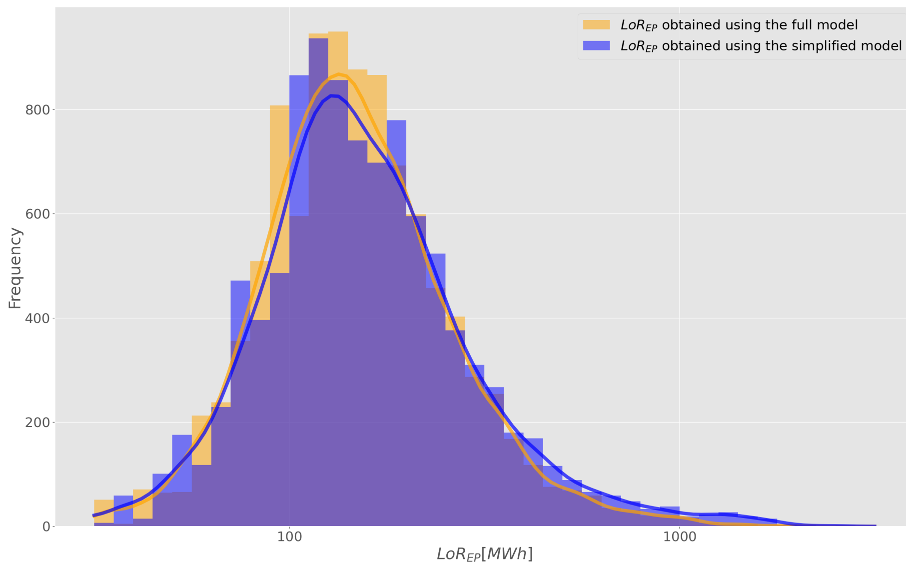

Figure 10: Comparison between the LoR_{EP} distribution obtained using the full virtual community model and the simplified model, that does not consider the damage and recovery of 62 unimportant community components.

7. Conclusion

Intervening to increase disaster resilience of communities with complex and interdependent systems and numerous hard-to-inspect components is difficult. Decision-makers are likely to undertake the least costly and most beneficial interventions, preferably localized at a small number of components whose resilience-related characteristics can be improved using already available means and resources. In this paper, we presented a sensitivity analysis approach aimed at identifying the community components whose importance for community disaster resilience is the highest, and whose resilience improvement is likely to improve the resilience of the entire community the most. The presented approach is based on a compositional, bottom up, approach to quantifying the disaster resilience of communities with interdependent systems, facilitated by the iRe-CoDeS framework (Blagojević et al. (2021b)), and a Sobol' index based component sensitivity quantification and ranking. This combination makes it possible to investigate the sensitivity of the community disaster resilience with respect to disaster-relevant properties of each of the community components. An important feature of the presented approach is that it works with minimal initial knowledge about the resilience-relevant component vulnerability and recoverability properties.

The presented approach to quantify component importance for community disaster resilience was illustrated using a case study on a moderately complex virtual community. The case study confirmed that the iRe-CoDeS framework and the Sobol' indices are capable of modelling the interdependencies among community components and systems, and reflecting such interdependencies when quantifying component importance for community disaster resilience. Additionally, the case study demonstrated two important benefits of using the Sobol' index based sensitivity analysis to rank community components by their importance. One is the ability to select a few most important (highest-ranked) components for resilience-improving interventions and to demonstrate the effect of these interventions in a before-after comparison. The other is the ability to significantly reduce the complexity of the community resilience model by treating the (often numerous) less important (low-rank) components deterministically.

The principal drawback of the proposed approach is the complexity and dimensionality of the community resilience model and the computational effort needed to compute Sobol' indices. However, use of meta-models for Sobol' index computation offers a computationally efficient way to handle significantly more complex problems that the one analysed in the presented case study.

Even though the presented approach can be used to identify components relevant for community disaster resilience, investing into improving the resilience-related properties of high-ranked component may not be the option with the best cost-benefit ratio. It is possible that improving mid-ranked components, for which resilience-improvement measures are more affordable than those for high-ranked components, represents a more rational investment strategy for increasing community disaster resilience. This issue needs further investigation.

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