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A compositional demand/supply framework to quantify the resilience of civil infrastructure systems (Re-CoDeS)

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ABSTRACT

Disaster resilience of civil infrastructure systems is essential to security and economic stability of communities. The novel compositional demand/supply resilience framework named Re-CoDeS (Resilience-Compositional Demand/Supply) generalizes the concept of disaster resilience across the spectrum of civil infrastructure systems by accounting not only for the ability of the civil infrastructure system to supply its service to the community, but also for the community demand for such service in the aftermath of a disaster. A Lack of Resilience is consequently observed when the demand for service cannot be fully supplied. Normalized resilience measures are proposed to allow for direct comparisons between different civil infrastructure systems at component and system levels. A scheme is introduced to classify component and system configurations with respect to their resilience. In addition to quantify the resilience of civil infrastructure systems, Re-CoDeS can be used to evaluate or design community risk mitigation strategies and to optimize post-disaster recovery.

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Resilience; civil infrastructure system; recovery; vulnerability

1. Introduction

Civil infrastructure systems (CISs), such as electric power supply, telecommunication, gas, and water distribution systems are the backbones of contemporary societies. Their services, meeting certain quality standards, are indispensable in daily life of modern communities. It follows that the CISs vulnerability to and their performance after disasters is of paramount importance to minimize the adverse effects of such events. Systemic disaster risk evaluation of CISs has attracted continuous attention in the scientific literature in recent decades (e.g. Adachi & Ellingwood, 2008; Cavalieri, Franchin, Buritica Cortes, & Tesfamariam, 2014; Dueñas-Osorio & Rojo, 2011; Esposito et al., 2014; Jayaram & Baker, 2010; Mieler, Stojadinovic, Budnitz, Comerio, & Mahin, 2015; Pitilakis, Alexoudi, Argyroudis, Monge, & Martin, 2006; Reed, Powell, & Westerman, 2010; Song, Der Kiureghian, & Sackman, 2007; Wang, Au, & Fu, 2010).

Based on the National Infrastructure Advisory council (NIAC, 2009) and on the US Presidential Policy Directive 21 (2013), the disaster resilience of a CIS can be defined as the CIS's ability to anticipate, absorb and adapt to events potentially disruptive to its function, and to recover either back to its original state or to an adjusted state based on new post-event conditions. In fact, after past disasters, it

has been observed that the post-event performance and recovery of CISs has a remarkable impact on the resilience of communities. CIS performance influences the coordination and the execution of emergency actions in the direct aftermath of a disaster, e.g. an earthquake, as well as the long-lasting post-disaster recovery process of a community. In particular, inability to meet the post-event service demand induces indirect costs, such as those related to business interruptions (e.g. due to persisting power blackouts), that may exceed direct losses due to physical damage to the components of the CISs.

There is, thus, a growing need to quantify disaster resilience. An extensive review and a categorization of a variety of proposed resilience quantification measures are presented by Francis and Bekera (2014) and Hosseini, Barker and Ramirez-Marquez (Hosseini, Barker, & Ramirez-Marquez, 2016). A functionality-based model that captures the fundamental features of disaster resilience, e.g. the losses (consequences of an event) and the recovery process after a disaster, is introduced by Bruneau et al. (2003). A CIS functionality or performance measure, e.g. the amount of service that an electric power supply system or a water distribution system can supply to a community, is tracked as it varies during the post-disaster recovery process. The loss of resilience is defined as the cumulative

CIS performance deficiency after a disaster with respect to a pre-disaster level until full recovery of the tracked metric. An example of the implementation of the model is given by Cimellaro, Reinhorn and Bruneau (2010) for hospitals. The concept is further extended in the PEOPLES framework for evaluating resilience (Cimellaro, Renschler, Reinhorn, & Arendt, 2016).

An approach to merge engineering and ecosystem resilience is suggested by Cavallaro, Asprone, Latora, Manfredi and Nicosia (2014). The spatial network layers of CISs are extended with further nodes and links, representing the interactions of the CISs with the community inhabitants, to form Hybrid Socio-Physical Networks (HSPNs). Then, a resilience metric is formulated as the area under the curve that tracks the evolution of HSPN communication efficiency after a disaster. This approach allows assessing the capability of a system to recover, even in a different configuration compared to the initial one. A case study of the city of Acerra (Italy), considering the road network and the building stock with its inhabitants in case of earthquakes, is presented by Cavallaro, Asprone, Latora, Manfredi, and Nicosia (2014). An application of quantifying seismic resilience using HSPNs in a synthetic city, composed of the building stock and different CISs, is given by Franchin and Cavalieri (2014). A multi-stage framework to measure the expected annualized resilience of a CIS is proposed by Ouyang, Dueñas-Osorio and Min (2012). Given the occurrence rate and the interdependence of multiple hazards, the annual resilience of a given system can be calculated for different hazard types, or a combination of them. The framework is tested on the power transmission grid in Harris County (USA). The concept is extended by Ouyang and Dueñas-Osorio (2012) towards a time-dependent resilience metric defined over a given time period. This resilience measure is given by the ratio of the real and the target performance curves. The approach allows to account for future system evolution, e.g. the integration of new technologies, which have a direct impact on a system's future characteristics and, thus, on its resilience. The suggested resilience metric quantifies different dimensions of resilience (technical, organizational, social or economic), depending on the chosen performance indicators. Cavalieri, Franchin, Gehl and Kazai (2012) and Franchin (2014) develop a model allowing to assess the interactions between the physical damage state of buildings and the post-disaster serviceability of CISs to compute, for example, the displaced population. Cutler, Shields, Tavani and Zahran (2016), Ellingwood et al. (2016) and Guidotti et al. (2016) investigate and develop algorithms and metrics for community resilience assessment using the Centerville Virtual Community Testbed, which is composed by several CISs whose failures have a direct impact on community resilience.

Many resilience quantification frameworks proposed in literature impose the idealistic point of view that an infrastructure owner's or operator's goal is to fully recover the CISs back to their initial (or an improved) state as fast as possible, and to quickly repair all (physical) damage after a disaster. The evolution of the community demand is not considered or is considered implicitly (e.g. by tracking the water pressure in a water supply pipeline, or the waiting time at a hospital). In the case of major disasters, these approaches might have only limited validity. The CISs do not exist in a vacuum: they are built to deliver a service to a community. For this reason, the focus of a CIS resilience assessment should be not only on the impact of a disaster in terms of the loss of service or performance of the CIS over time, but also on the ability of a CIS to supply the time-varying community demand for its services and to recover the supply/demand balance as fast as possible for parts of or for the entire community. A CIS resilience quantification framework needs, thus, to explicitly account for both the evolution of the supply (i.e. the service supply capacity of the system) and the evolution of the demand of the community and other CISs for its services in the aftermath of a disaster.

In this study, a novel compositional demand/supply disaster resilience quantification framework named Re-CoDeS (Resilience – Compositional Demand/Supply) is presented. Re-CoDeS is based on demand and supply layers, defined locally for CIS components and extended to the system level by a system service model. Component variables, i.e. demand, supply and consumption at a component, are defined first. A Lack of Resilience occurs when the service demand at a component cannot be fully supplied. In a second step, the demand, supply and consumption variables are defined at a system level. Lack of Resilience at the system level is computed using a compositional, bottom-up, approach, i.e. by integrating the component states using a system service model. Normalized resilience metrics, designed to directly compare the resilience of different CISs, are presented. The supply reserve margin is proposed as metric to assess the redundancy and robustness of a CIS, while the notion of resilience time is proposed as a measure of the resourcefulness and the rapidity of the recovery process. A scheme is introduced to classify different component and system resilience configurations with respect to their post-disaster behavior. An application case study is used to demonstrate the proposed framework and to indicate that changes in the post-disaster demand due to recovery efforts and population movements can also be considered using the Re-CoDeS framework. Finally, the potential for using the Re-CoDeS framework for post-event supply and demand scenario analysis, as well as for optimization of post-disaster recovery strategies is discussed. Specifically,

the Re-CoDeS framework may serve infrastructure owners and operators as well as community administrators in their efforts to plan post-disaster community recovery with the goal to minimize the impact of CIS service unavailability on the community.

2. Compositional demand/supply resilience quantification framework (Re-CoDeS)

CISs are built to deliver a service to a community (composed of its residential building stock, industries, businesses and critical facilities) and to other CISs. Thus, a CIS disaster resilience assessment needs to be demand-oriented, based on the ability of a CIS to supply the time-varying community demand for its services. The compositional demand/supply resilience quantification framework (Re-CoDeS) enables such CIS disaster resilience assessment. The framework accounts for the impact of a disaster on both the demand and the supply side of the CIS-community system, and tracks the post-disaster evolution of demand and supply at the component and the system levels. The elements of the Re-CoDeS framework are:

- (1) The demand layer, used to model the evolution of the CIS demand. The evolution of the demand for CIS service depends mainly on the vulnerability, the recovery and the individual demand of the components of the demand layer (noted by index i).
- (2) The supply layer, used to model the evolution of the CIS supply. The evolution of the supply of CIS service depends mainly on the vulnerability, the recovery and the individual service supply of the components of the supply layer (noted by index j).
- (3) The system service model, regulating the allocation (or dispatch) of the CIS service supply in order to satisfy the demand of the consumers. This model accounts, for example, for the capacity limitations and interactions of different CIS elements: the service supply system, the distribution system and the transmission links between the demand and the supply layers, the technical functioning limits and control mechanisms of the system, and the system or network effects. It considers, thus, the topology of the system, the operator service allocation policies, and the possible supply distribution strategies.

2.1. Resilience at a component level

At a component (element, node or location) i of the demand layer, the component Lack of Resilience, LoR_i ,

represents the amount of supply that cannot be provided by the (damaged) CIS to cover the demand at component i over a given period of time. This is the amount of unsupplied demand or the supply deficit. The following variables are defined:

- The component demand, $D_i(t)$, is the total demand of all consumers using the CIS service at component i at time t . For example, in the case of a local water well supplying water to a community, $D_i(t)$ is the water demand of the consumers at time t ; in the case of an electric substation, $D_i(t)$ is the electric power demand of the buildings and other facilities connected to that substation at time t .
- The component available supply, $S_i^{av}(t)$, is the available service supply at component i at time t . For example, $S_i^{av}(t)$ is the water supply of a well or the electric power available at a distribution substation at time t .
- The component consumption, $C_i(t)$, is the effective consumption, i.e. the effectively consumed amount of service by the consumers at component i at time t . For example, $C_i(t)$ is the consumed amount of water at a well or the consumption of electric power at a distribution substation at time t .

The consumption $C_i(t)$ can match either $D_i(t)$ or $S_i^{av}(t)$. If it is not possible to cover all of the demand at component i at time t , the consumption is equal to the available supply. However, if the available supply is sufficient, the consumption is equal to the demand. Thus:

$$C_i(t) = \min(S_i^{av}(t), D_i(t)) \quad (1)$$

Given the above definitions, LoR_i is defined as

$$LoR_i = \int_{t_0}^{t_f} \langle D_i(t) - S_i^{av}(t) \rangle dt = \int_{t_0}^{t_f} (D_i(t) - C_i(t)) dt \quad (2)$$

where $\langle \cdot \rangle$ is the singularity function that returns 0 for negative arguments, or the argument otherwise. The start and the end time of the resilience assessment are denoted as t_0 and t_f , respectively. Equation (2) is valid as long as the available supply at element i at time t is known and can be strictly delimited, i.e. effects of other system elements are accounted for, negligible, or the available supply is independent of and not influenced by other parts of the system. The demand/supply concept at the component level is qualitatively shown in Figure 1. $SR_i(t)$ is the supply reserve margin at component i at time t , defined as the difference between the available supply and the demand at element i at time t (i.e. $SR_i(t) = S_i^{av}(t) - D_i(t)$). $SR_i(t)$ can be integrated over a given time period to obtain SR_i , as shown in Figure 1. T_i^R is the component resilience time, defined as the duration of time during which a supply deficit is observed.

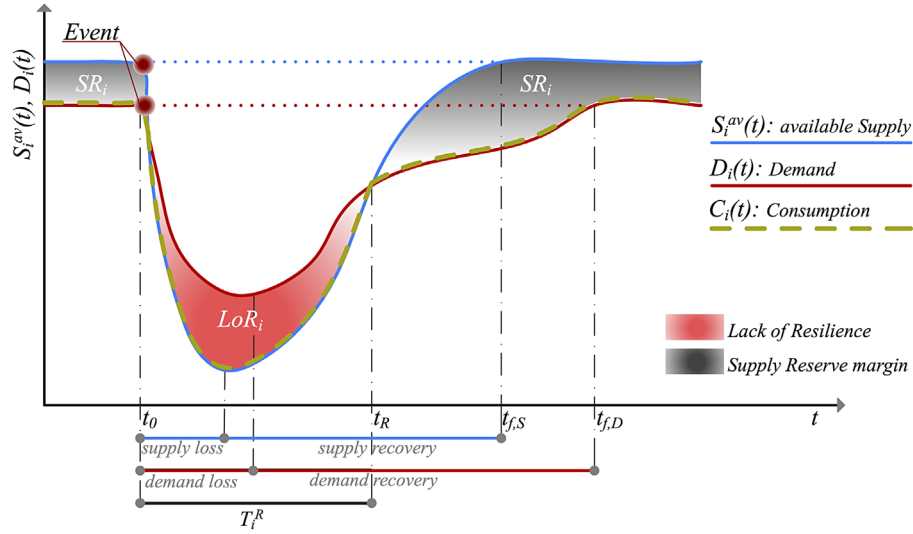


Figure 1. Lack of Resilience at the component level.

Depending on the scope and the duration of the CIS disaster resilience assessment, different values for t_0 and t_f can be chosen. The start of the resilience assessment, t_0 , is often set to the moment of occurrence of a disaster. The end of the resilience assessment, t_f , can theoretically be set to infinity. For practical reasons, e.g. for strategic planning of the system operator, financial, or insurance aspects, t_f might be set to the moment when the demand or the supply attain again their pre-disaster levels, $t_{f,D}$ and $t_{f,S}$, respectively (see Figure 1), or the moment when the supply again meets the demand, t_R , or to the lifespan or the lifecycle of the system.

To obtain a dimensionless Lack of Resilience metric in the $[0,1]$ range that makes it possible to compare the resilience of different components of the same or different CISs, the obtained LoR_i is divided by the cumulative service demand over the resilience assessment period, $\int_{t_0}^{t_f} D_i(t)dt$. Such normalization is used because the proposed definition of resilience is demand-oriented: namely, if all of the demand can be supplied all of the time, no Lack of Resilience is observed, if no demand is satisfied at any time, the normalized value of the Lack of Resilience is 1. The normalized metric for the Lack of Resilience at node i , \widehat{LoR}_i , over the resilience assessment period $t_0 \leq t \leq t_f$ is, therefore, given by:

$$\widehat{LoR}_i = \frac{\int_{t_0}^{t_f} \langle D_i(t) - S_i^{av}(t) \rangle dt}{\int_{t_0}^{t_f} D_i(t) dt} = \frac{\int_{t_0}^{t_f} (D_i(t) - C_i(t)) dt}{\int_{t_0}^{t_f} D_i(t) dt} \quad (3)$$

The resilience R_i of the component i , over a time period $t_0 \leq t \leq t_f$ is, finally:

$$R_i = 1 - \widehat{LoR}_i \quad (4)$$

Note that $0 \leq R_i \leq 1$. In particular, $R_i = 1$ corresponds to a fully resilient component whose demand $D_i(t)$ can always be completely covered after the event, and $R_i = 0$ corresponds to full lack of resilience of a component for which none of the demand $D_i(t)$ can be covered at any time after the event.

2.2. Resilience at a system level

At a system level, a Lack of Resilience, LoR_{sys} , occurs when the demand exceeds the available supply of service at any component of the system over a given period of time. The following variables are defined:

- The system demand, $D_{sys}(t)$, is the total demand for the services of a CIS at time t . It is defined as the aggregate sum of all component demands, $D_i(t)$:

$$D_{sys}(t) = \sum_{i=1}^I D_i(t), \quad (5)$$

where I is the total number of components of the demand layer of the system.

- The system consumption, $C_{sys}(t)$, is the total service consumption in the CIS. It is defined as the aggregate sum of all component consumptions, $C_i(t)$:

$$C_{sys}(t) = \sum_{i=1}^I C_i(t). \quad (6)$$

Note that, regardless of the chosen discretization of the demand layer, the consumption can in no case exceed the demand. For example, a hospital that is connected to the electric power supply system, but that has also an emergency power generator, still poses a well-defined

demand to a node because its consumption is limited by the demand of its equipment. Consequently, if the entire hospital demand is supplied by the electric power supply system, it does not present any demand to the emergency power system and vice versa.

- The system supply capacity, $S_{sys}^c(t)$, is the total service supply capacity of the entire CIS at time t . It can be defined as the aggregate sum of all component supply capacities, $S_j^c(t)$:

$$S_{sys}^c(t) = \sum_{j=1}^J S_j^c(t), \quad (7)$$

where J is the total number of components of the supply layer of the CIS, and $S_j^c(t)$ is the supply capacity of supply node j at time t . Specifically, $S_j^c(t)$ corresponds to the actual maximum supply capacity of that component, reduced by the supply layer component losses, such as losses due to disaster-caused damage, losses due to long term environmental stressors (e.g. aging, corrosion) or losses due to maintenance interventions at the supply component.

The distribution of the system supply capacity $S_{sys}^c(t)$ to the (often) geographically disjoint demand components depends on the nature and on the topology of the CIS and on the system service model. This distribution process is qualitatively shown in Figure 2. In the first step, the service of a CIS (e.g. electric power in an electric power supply

system) is produced or made available at the different supply components, $j \in \{1, J\}$. The second step is the distribution of service to the individual demand components, $i \in \{1, I\}$ according to the system service model. The relationship between component available service supply at a component i of the demand layer, $S_i^{av}(t)$, and the system supply capacity, $S_{sys}^c(t)$, is not trivial. The available service supply at a component of the demand layer can be represented as:

$$S_i^{av}(t) = \varphi(S_1^c(t) \dots S_J^c(t), C_1(t) \dots C_I(t), D_1(t) \dots D_I(t), S_1^{loss}(t) \dots S_I^{loss}(t)) \quad (8)$$

where φ is the system service model. Demand layer component loss at a demand component i at time t , $S_i^{loss}(t)$, is the loss of service occurring in the distribution of service to that component of the demand layer due to the characteristics of the system service model and losses due to disaster-caused or environmental stressor damage to the demand component. For example, service losses can be incurred due to the technical functioning of the system (e.g. capacity limitations, transmission losses) or due to the system dynamics imposed by the allocation/dispatch strategy of the system service model (e.g. grid stability measures in an electric power supply system to prevent cascading failures or an overload of parts of the system). Similarly, losses due to damage to the distribution systems caused by the disaster or because of aging, corrosion or wear and tear of a demand layer component can be quantified using $S_i^{loss}(t)$.

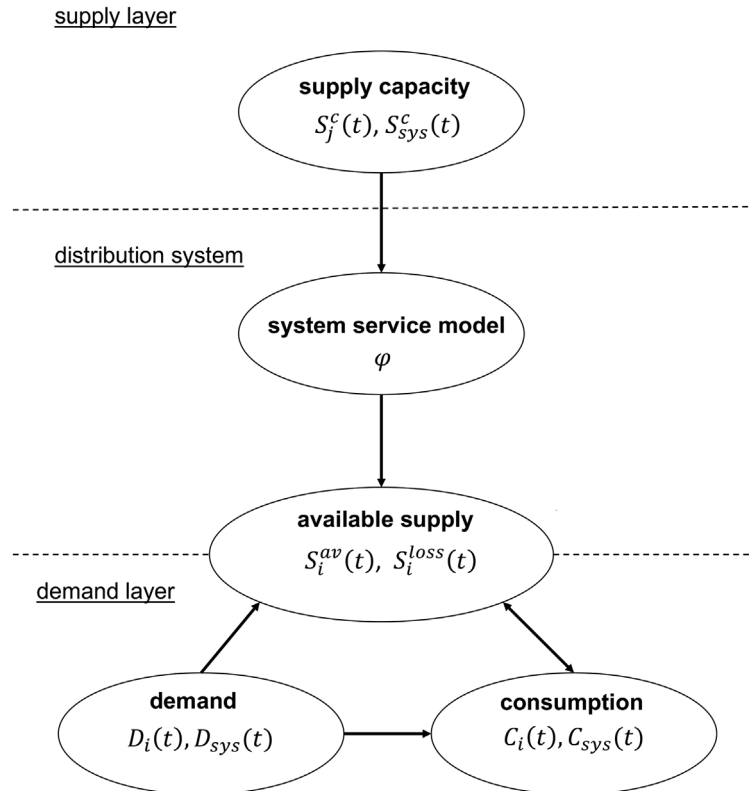


Figure 2. Scheme to determine the supply, demand and consumption quantities.

The system service model φ depends on three main elements: the technical functioning of the CIS, the topology of the CIS, and on the dispatch/allocation strategy of the CIS operator. The technical functioning represents the physics laws that govern the generation and distribution of the CIS service. For example, flow balance equations govern the service flow in utility networks such as electric power, water supply and gas networks. The dispatch strategy of the operator includes both the technical decisions aimed at minimizing the damage to the distribution network (e.g. due to overpressure or high currents) and prevention of cascading failures, and the strategic decisions for supply allocation to different components of the community (e.g. hierarchical dispatch of services based on a set of critical consumers, especially during phases of service deficit or system breakdowns). The complexity of the system service model φ is influenced by the scale of the resilience analysis and the modeling and the discretization of the demand and supply layers. A finer granularity from the functional component level down to the sub-components (e.g. the sub-components of an electric substation or the individual consumers connected to a substation) increases the complexity of the analysis. The art of modeling is in finding the right balance between the complexity of φ and the scale of the problem. The selection of the scale depends mainly on the accuracy of the available data and the scope of the analysis. For example, in case of a lack of high resolution spatial data of a pipeline system, the geometry of the network needs to be simplified. On the other hand, to model the service delivered, for example, by a gas distribution network to the buildings, not only the serviceability of the stations and the pipes of the medium- and low-pressure network needs to be considered, but service delivery also depends on small diameter pipes that connect the low-pressure pipes to individual buildings. These pipes should, thus, be considered in the model. Examples of Re-CoDeS employed at different scales (national and city level) are provided by Didier, Grauvogl, Steentoft, Ghosh, and Stojadinovic (2017) and Didier, Baumberger, Tobler, Esposito, Ghosh and Stojadinovic (2017).

Therefore, the component available service supply, $S_i^{av}(t)$, depends on the demand at the component itself, the losses in the distribution of service and in the demand layer, the consumption at other connected components, the supply capacity of the supply components and the system service model. It is defined on the component level: $S_i^{av}(t)$ of different components are, generally, not additive on the system level, i.e. the system supply capacity $S_{sys}^c(t)$ is not the simple sum of the component available service supply quantities,

i.e. $S_{sys}^c(t) \neq \sum_{i=1}^I S_i^{av}(t)$. Instead, the system supply capacity is defined by Equation (7), considering the supply layer.

Given the above definitions and constraints, the system Lack of Resilience for the investigated CIS, LoR_{sys} , is defined as the sum of the Lack of Resilience of the components of the demand layer over a time period $t_0 \leq t \leq t_p$ i.e.

$$LoR_{sys} = \sum_{i=1}^I LoR_i, \quad (9)$$

which can be written as follows:

$$\begin{aligned} LoR_{sys} &= \sum_{i=1}^I \int_{t_0}^{t_f} \langle D_i(t) - S_i^{av}(t) \rangle dt \\ &= \sum_{i=1}^I \int_{t_0}^{t_f} (D_i(t) - C_i(t)) dt \\ &= \int_{t_0}^{t_f} (D_{sys}(t) - C_{sys}(t)) dt. \end{aligned} \quad (10)$$

The normalized Lack of Resilience on a system level, \widehat{LoR}_{sys} , over a time period $t_0 \leq t \leq t_p$ is obtained by dividing Equation (10) by the aggregate CIS demand over the same time period:

$$\begin{aligned} \widehat{LoR}_{sys} &= \frac{\sum_{i=1}^I LoR_i}{\sum_{i=1}^I \int_{t_0}^{t_f} D_i(t) dt} \\ &= \frac{\sum_{i=1}^I \int_{t_0}^{t_f} \langle D_i(t) - S_i^{av}(t) \rangle dt}{\sum_{i=1}^I \int_{t_0}^{t_f} D_i(t) dt} \\ &= \frac{\int_{t_0}^{t_f} (D_{sys}(t) - C_{sys}(t)) dt}{\int_{t_0}^{t_f} D_{sys}(t) dt} \end{aligned} \quad (11)$$

The resilience R_{sys} of a CIS, over a time period $t_0 \leq t \leq t_p$ is therefore:

$$R_{sys} = 1 - \widehat{LoR}_{sys} \quad (12)$$

Note that $0 \leq R_{sys} \leq 1$. The compositional demand/supply concept on the system level is shown in Figure 3. $SR_{sys}(t)$ is the system supply reserve margin, defined as the difference between supply capacity and demand on a system level (i.e. $SR_{sys}(t) = S_{sys}^c(t) - D_{sys}(t)$). $SR_{sys}(t)$ can be integrated over a given time period to obtain SR_{sys}^R , as shown in Figure 3. T_{sys}^R is the system resilience time. The proposed Lack of Resilience measure follows conceptually the original resilience measure proposed by Bruneau et al. (2003) in that it represents the (normalized) area between supply and demand evolution curves.

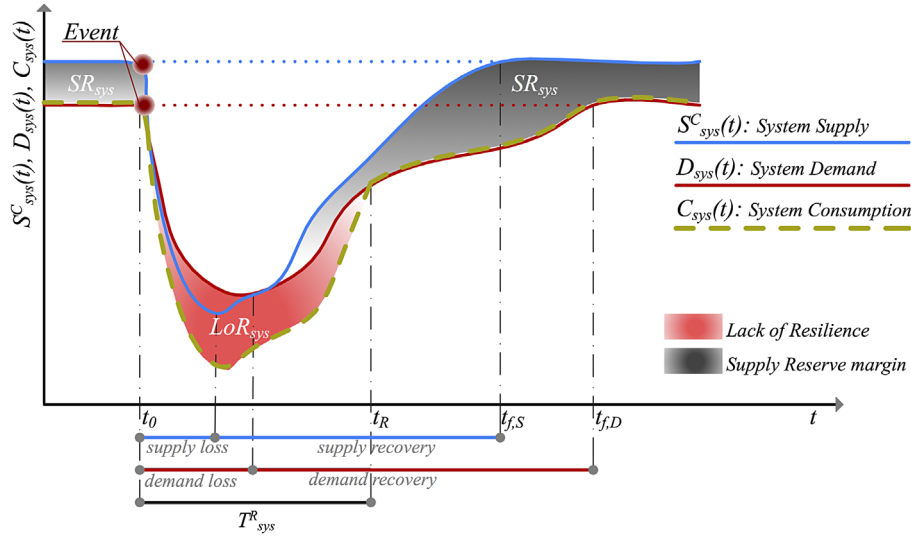


Figure 3. Lack of Resilience at the system level.

Observe that:

$$\begin{aligned} LoR_{sys}(t) &= \sum_{i=1}^I LoR_i \\ &= \int_{t_0}^{t_f} (D_{sys}(t) - C_{sys}(t)) dt \geq \int_{t_0}^{t_f} (D_{sys}(t) - S_{sys}^c(t)) dt. \end{aligned} \quad (13)$$

The definition of the system resilience is, thus, not a naïve extension of the component resilience definition. Instead, using Equations 8, 9 and 10, it accounts consistently for system dynamics, interdependencies and losses. These may not be identified if the system-level supply $S_{sys}^c(t)$ and demand $D_{sys}(t)$ are used in a simple extension of Equation 2, giving the last element of Equation 13. In fact, such an approach results in an underestimation of the actual Lack of Resilience of the CIS.

2.3. Other resilience metrics

2.3.1. Supply reserve margin and robustness

The supply reserve margin, as defined in Section 2.1 at the component level, and in Section 2.2 at the system level, can be used as a measure of the redundancy of the CIS (the extent to which components or systems are substitutable) and of the robustness of the CIS (the strength of its components or systems). These two properties of a resilient system were defined by Bruneau et al. (2003). For example, a supply reserve could be used to substitute (completely or in part) for the loss of supply due to disaster-induced damage to some supply layer components of the CIS. However, the actual supply to the demand layer components also depends on the transmission system and the system service model. Therefore, it is possible to observe a Lack of Resilience at a system level while having a supply reserve

at the same time. The supply reserve margin can also be normalized by the demand to assure comparability across different components or systems.

On the component level, the normalized supply reserve margin of a component i at time t , $\widehat{SR}_i(t)$, is defined as:

$$\widehat{SR}_i(t) = \frac{S_i^{av}(t) - D_i(t)}{D_i(t)} = \frac{S_i^{av}(t)}{D_i(t)} - 1 \quad (14)$$

On the system level, the normalized supply reserve margin at time t , $\widehat{SR}_{sys}(t)$, is defined as:

$$\widehat{SR}_{sys}(t) = \frac{S_{sys}^c(t) - D_{sys}(t)}{D_{sys}(t)} = \frac{S_{sys}^c(t)}{D_{sys}(t)} - 1 \quad (15)$$

If $\widehat{SR}_{sys}(t) \geq 0$, or $\widehat{SR}_i(t) \geq 0$, the system or the demand component i have a supply reserve. If a service is not available at all at the system level or at the demand component level, then $\widehat{SR}_{sys}(t) = -1$, or $\widehat{SR}_i(t) = -1$.

Using the supply reserve margin, the robustness of a CIS is defined as:

$$r_{sys} = \min_t \left(\frac{SR_{sys}(t)}{SR_{sys}(t_0)} \right) \quad (16)$$

where t_0 is the start of the resilience assessment defined above. These normalized resilience measures can be used to compare the redundancy and robustness of different CIS components or to compare different CISs.

2.3.2. Resilience time

The system resilience time, T_{sys}^R , is defined as the total duration of the aggregate service deficit, i.e. when $C_{sys}(t) < D_{sys}(t)$ (Figure 3). Equivalently, the component

resilience time, T_i^R , is defined by the total duration of the local service deficit, i.e. $C_i(t) < D_i(t)$ at a given component i (Figure 1). When a sequence of disaster events is of concern (e.g. a series of aftershocks following the main seismic event), the resilience time is defined as the sum of the partial resilience times, i.e. $T_{sys}^R = \sum_k T_{sys,k}^R$ and $T_i^R = \sum_k T_{i,k}^R$ where k is the number of partial resilience times and $T_{i,k}^R$ and $T_{sys,k}^R$ are the k -th partial component and system resilience time, respectively (Figure 4). The addition of partial resilience times can be applied if demand drops repeatedly below the consumption, for example, due to a varying recovery speed of demand and supply. $T_{i,k}^R$ are only additive for the given component i and should not be added across different components. Instead, the system resilience time, T_{sys}^R , should be used to characterize the system behavior.

The resilience time can be used as measure of the resourcefulness (the capacity to mobilize resources to achieve goals) and the rapidity (the capacity to achieve goals in a timely manner) of recovery of the CIS, as defined by Bruneau et al. (2003). The component and system resilience time can be normalized, for example, by the duration of the resilience assessment, $(t_f - t_0)$:

$$\hat{T}_i^R = \frac{T_i^R}{t_f - t_0} \quad (17)$$

$$\hat{T}_{sys}^R = \frac{T_{sys}^R}{t_f - t_0} \quad (18)$$

where \hat{T}_i^R is the normalized component resilience time of component i , and \hat{T}_{sys}^R is the normalized system resilience time. If $(t_f - t_0)$ is set to the lifetime of the component

or the system, \hat{T}_i^R and \hat{T}_{sys}^R correspond to the unavailability of the component or the system over its lifetime. These normalized resilience measures can be used to compare the resourcefulness and the rapidity of different CIS components or different CISs.

2.4. Component and system resilience-related configurations

Changes in both the community service demand and the CIS service supply are expected after a disaster. The ability of a CIS to supply its services often decreases, depending on the vulnerability of its components. However, the CIS can be designed, or extraordinary measures may be taken, to increase the supply of its service after a disaster. On the other hand, the community component and system demand for services may drop, remain constant or increase and vary significantly during the post-disaster recovery period depending on the recovery efforts and movements of the population. The proposed Re-CoDeS framework is designed to account directly for the changes in component and system supply and demand, and to consistently quantify the arising Lack of Resilience. Such quantification depends on magnitudes and rates of change of the demand, supply and consumption, and, thus, on a myriad of factors.

The Re-CoDeS framework makes it possible to classify CIS-community component and system configurations based on the states of the component variables $D_i(t)$ and $S_i^{av}(t)$, and the system variables $D_{sys}(t)$, $S_{sys}^C(t)$ and $C_{sys}(t)$, defined above. Note that every configuration can lead to good or bad performance, i.e. a smaller or larger Lack of Resilience. However, some configurations, like the anti-fragile configuration (i.e. an increase in post-disaster demand and supply), are less prone to a large Lack

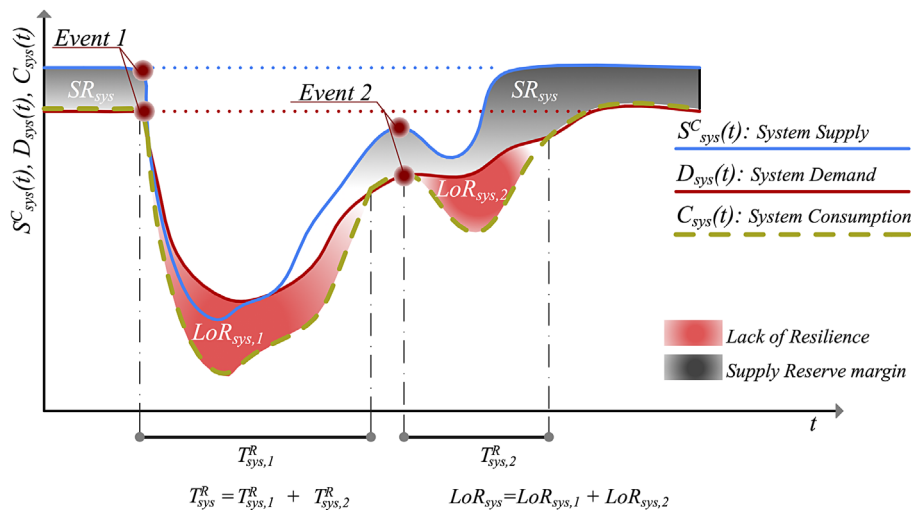


Figure 4. System resilience time T_{sys}^R in the case of two consecutive disastrous events.

of Resilience, while others, like the fragile configuration (i.e. an increase in post-disaster demand and a decrease in post-disaster supply), are more likely to result in a large Lack of Resilience. Analysis of the CIS-community component and system configurations is, therefore, an important step in a resilience evaluation and optimization procedure.

2.4.1. Component resilience-related configurations

Four possible relations between demand and supply at the component level, shown in Figure 5, define four types of component resilience-related configurations:

- Classical configuration: $D_i(t) \leq D_i(t_0) \wedge S_i^{av}(t) \leq S_i^{av}(t_0)$, $t > t_0$. In the classical component configuration, the components of the supply and the demand layers are vulnerable to the disaster (e.g. components of an electric power supply system and buildings of the community building stock are simultaneously damaged during a disaster). Consequently, component demand and supply both decrease after the disaster, and a Lack of Resilience may occur, depending on the magnitude and the rate of the demand and supply decrease. A majority of CIS-community system components is expected to belong to this performance category.
- Inefficient configuration: $D_i(t) \leq D_i(t_0) \wedge S_i^{av}(t) > S_i^{av}(t_0)$, $t > t_0$. In some cases, component demand decreases (e.g. due to fatalities or temporary reallocation of
- population), whereas the supply available at the component increases. While a Lack of Resilience is not likely to occur, such configuration leads to an (often unnecessary and inefficient) increase in the supply reserve margin, $SR_i(t)$. For example, due to large donations, large reserves of food and clothing were generated and wasted after the 2010 Haiti earthquake and the 2012 hurricane Sandy (Fessler, 2012).
- Fragile configuration: $D_i(t) > D_i(t_0) \wedge S_i^{av}(t) \leq S_i^{av}(t_0)$, $t > t_0$. A simultaneous increase in service demand and decrease in service supply is likely to result in a Lack of Resilience. Components of the telecommunication system or elements of the transportation systems are likely to exhibit such fragile configuration during the post-disaster emergency phase. For example, in the aftermath of the 2011 Tohoku earthquake, local telecommunication demand is indicated to have increased up to 8 or 10 times the normal demand (ASCE, 2011). Even if the telecommunication system remains fully functional (i.e. no loss of resilience is observed in a resilience framework evaluating only the functionality of the CIS), it may have difficulties to meet the post-disaster demand at all demand layer components.
- Anti-Fragile configuration: $D_i(t) > D_i(t_0) \wedge S_i^{av}(t) > S_i^{av}(t_0)$, $t > t_0$. An increase of both the demand and the supply compared to their pre-disaster levels may still

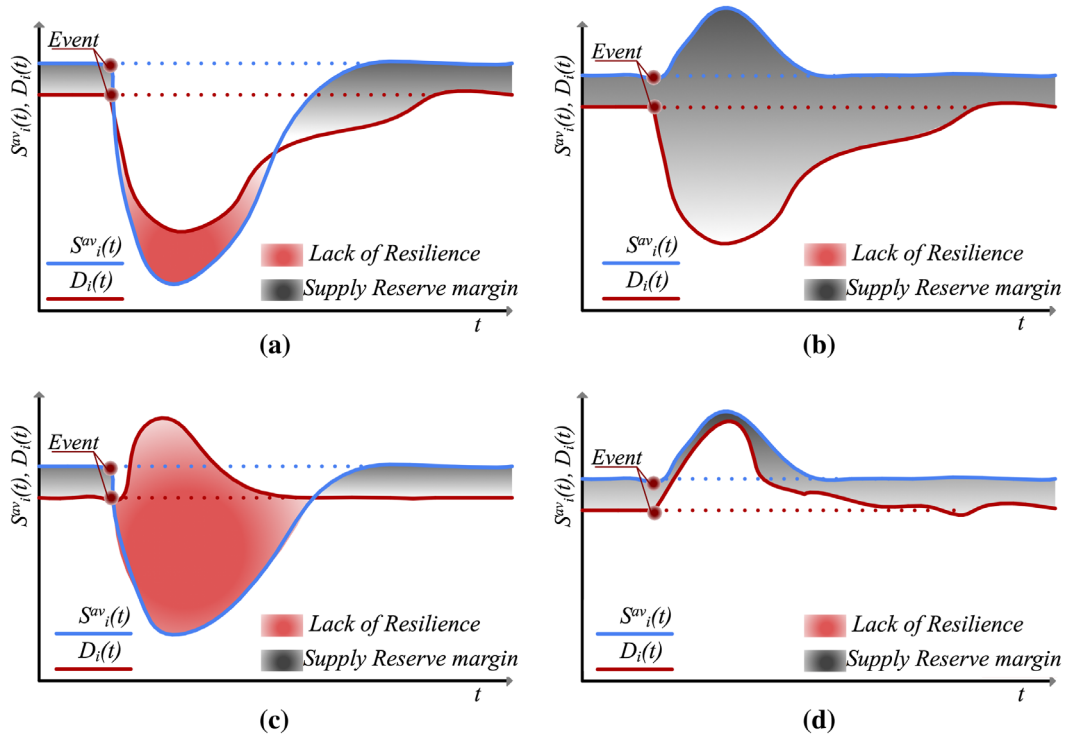


Figure 5. Component resilience-related configurations: (a) Classical; (b) Inefficient; (c) Fragile and (d) Anti-Fragile.

result in a Lack of Resilience, depending on the size of the pre-disaster component supply reserve margin and on the magnitude and rate of demand and supply increase. However, if the increase in supply matches or exceeds the increase in demand, no Lack of Resilience is observed. An example of such configuration are health care facilities that set up temporary beds and improvised emergency rooms, and, thus, increase the supply of their service to meet an increased post-disaster demand. Such performance is classified as anti-fragile, adopting a concept introduced by Taleb (2012). Here, this concept is used to identify components that (resource-fully) adapt after a disaster to minimize the Lack of Resilience. Anti-fragility should be a target design objective for the critical components of disaster-resilient CISs.

2.4.2. System resilience-related configurations

Resilience-related performance categorization of components is based solely on the comparison between component demand $D_i(t)$ and available supply $S_i^{av}(t)$, since component consumption cannot exceed its demand (Equation (1)). However, at the system level, demand $D_{sys}(t)$ and supply capacity $S_{sys}^C(t)$ are not sufficient to categorize the post-disaster performance of a CIS-community system. As was observed when LoR_{sys} was defined above, it is necessary to account for the changes in the system consumption, $C_{sys}(t)$ (Equation (6)), as complexity can arise e.g. due to the topology or the nature of the system service model of the CIS. Eight possible CIS-community system resilience-related configurations are listed in Table 1 and shown in Figure 6.

The system resilience-related configurations are grouped into two sets. The first set includes the four CIS-community system configurations equivalent to the four resilience-related component configurations. Again, a Lack of Resilience may occur in any configuration, independently of their supply reserve margin. However, some systems, for example, those with an anti-fragile resilience-related configuration, have desirable defense-in-depth features. They are usually more capable of efficiently redistributing the service supply and are less prone

to experience a Lack of Resilience due to a disaster than, for example, fragile configurations with similar pre-disaster supply reserve margins.

The second set of system resilience-related configurations includes four special configurations (Table 1), as follows:

- Reserve-Margin configuration (Figure 6(e)): These systems usually have a supply reserve margin designed to absorb increases in the system demand and can avoid or minimize the Lack of Resilience. This ability depends, for example, on the size of the supply reserve margin, possible redundancies in their transmission system, and efficient service dispatch strategies. Such a configuration can be found, for example, in nuclear energy facilities where the high-consequence low-probability events justify a substantial (but costly) system reserve margin.
- Cliff-Edge configuration (Figure 6(f)): A cliff-edge configuration is usually observed in systems where either critical components (especially of the transmission system) are vulnerable and difficult to repair, or where damage may cascade to otherwise undamaged components exacerbating a possible system Lack of Resilience. Such systems experience cliff-edge failures because of non-redundant designs, inefficient system service models, or poor recovery strategies. A simple example of such a system is a two nodes system, consisting of a supply node (source) and a demand node (sink) connected via a single highly vulnerable link. The supply node, for example a health care facility, is designed in a way to increase its supply capacity in case of a hazardous event, since an increase in the service demand due to injuries is expected. However, the facility can only be reached by a highly vulnerable link, in this case a bridge that was damaged by the earthquake. It is, thus, not possible to access the services of the hospital anymore.
- Inadequate configuration (Figure 6(g)): These CISs do not satisfy the demand of the community before the disaster, even despite possibly large supply reserve margins. A likely cause of such system performance is poor system design and maintenance,

Table 1. System resilience-related configurations.

		$S_{sys}^C(t)$	$D_{sys}(t)$	$C_{sys}(t)$	Configuration
Set 1	(a)	$S_{sys}^C(t) \leq S_{sys}^C(t_0)$	$D_{sys}(t) \leq D_{sys}(t_0)$	$C_{sys}(t) \leq C_{sys}(t_0)$	Classical
	(b)	$S_{sys}^C(t) > S_{sys}^C(t_0)$	$D_{sys}(t) \leq D_{sys}(t_0)$	$C_{sys}(t) \leq C_{sys}(t_0)$	Inefficient
	(c)	$S_{sys}^C(t) \leq S_{sys}^C(t_0)$	$D_{sys}(t) > D_{sys}(t_0)$	$C_{sys}(t) \leq C_{sys}(t_0)$	Fragile
	(d)	$S_{sys}^C(t) > S_{sys}^C(t_0)$	$D_{sys}(t) > D_{sys}(t_0)$	$C_{sys}(t) > C_{sys}(t_0)$	Anti-Fragile
Set 2	(e)	$S_{sys}^C(t) \leq S_{sys}^C(t_0)$	$D_{sys}(t) > D_{sys}(t_0)$	$C_{sys}(t) > C_{sys}(t_0)$	Reserve-Margin
	(f)	$S_{sys}^C(t) > S_{sys}^C(t_0)$	$D_{sys}(t) > D_{sys}(t_0)$	$C_{sys}(t) \leq C_{sys}(t_0)$	Cliff-Edge
	(g)	$S_{sys}^C(t) > S_{sys}^C(t_0)$	$D_{sys}(t) \leq D_{sys}(t_0)$	$C_{sys}(t) > C_{sys}(t_0)$	Inadequate
	(h)	$S_{sys}^C(t) \leq S_{sys}^C(t_0)$	$D_{sys}(t) \leq D_{sys}(t_0)$	$C_{sys}(t) > C_{sys}(t_0)$	Under-Designed

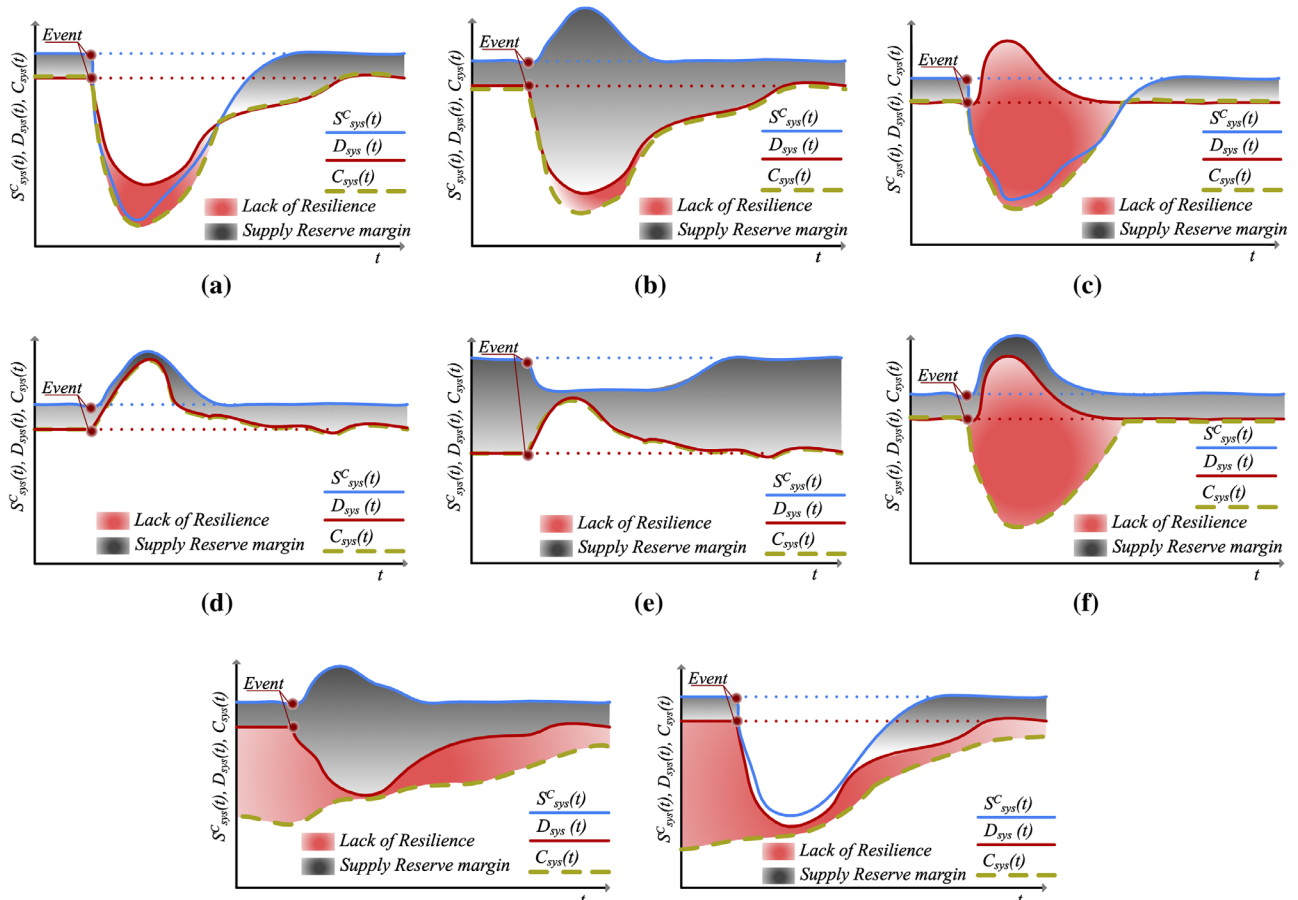


Figure 6. System resilience-related configurations: (a) Classical; (b) Inefficient; (c) Fragile; (d) Anti-Fragile; (e) Reserve-Margin; (f) Cliff-Edge; (g) Inadequate; and (h) Under-Designed.

with the distribution components of the system unable to execute the CIS service dispatch. Another cause may be high transmission losses, resulting in a pre-disaster supply deficit. Examples for such a configuration are systems with some supply facilities that may only be available during emergencies and at a high cost (e.g. emergency power generators). While they remain unused in normal situations, system operators might decide to use these supply facilities in the case of a disaster in order to increase the supply and limit the Lack of Resilience after an event.

- Under-Designed configuration (Figure 6(h)): Such CISs are not adequately designed, have an inefficient or costly supply distribution or have, for example, been damaged in recent disasters such that they are not able to execute pre-disaster CIS service dispatch without failure (e.g. black- or brown-outs in the electric power supply system). An example for this configuration is the electric power supply system in Nepal, which was under-designed before the 2015 Gorkha earthquake, with its supply performance deteriorating further despite a temporary

reactivation of two idled hydrocarbon fuel electric power generation plants and the use of local emergency power generators to increase the service supply (Didier, Grauvogl et al., 2017).

2.5. Illustrative example

The proposed Re-CoDeS framework is demonstrated on the task of quantifying the resilience of an electric power supply system of a virtual community. The aim of the example is to demonstrate the application of the Re-CoDeS framework in an academic setting. A more elaborated application of the Re-CoDeS framework using a virtual CIS-community system is illustrated in Didier, Esposito, & Stojadinovic (2017). In addition, the Re-CoDeS framework was used to analyze the resilience of the electric power supply system in Nepal (Didier, Grauvogl et al., 2017) and of the water distribution system and the cellular communication system of the Kathmandu Valley (Didier, Baumberger et al., 2017) after the 2015 Gorkha earthquake. Resilience evaluation of more complex, but still virtual systems is presented in Didier, Sun, Ghosh, & Stojadinovic (2015). Systems with agent-based recovery models, still employing

the Re-CoDeS framework for resilience evaluation, are presented in Sun, Didier, Delé, & Stojadinovic (2015).

The virtual CIS (Figure 7(a)) comprises 2 supply layer nodes (e.g. hydropower plants, $j \in \{1, 2\}$) and 4 demand layer nodes (e.g. small cities, $i \in \{1, 2, 3, 4\}$) connected by links. The system service model is based on a simple dispatch strategy: demand node $i = 1$ is served first, until its local demand is satisfied, demand node $i = 2$ is served second, and so on, until either all the demand at all the demand nodes is satisfied, or the system supply capacity is entirely distributed. Losses due to capacity limitations of the transmission lines, and the electricity flow restrictions are not considered, but can be included using models proposed by Pires, Ang, & Villaverde (1996) and (Modaressi, Desramaut, & Gehl (2014)). Thus, the available supply at a demand node is:

$$S_i^{av}(t) = \begin{cases} S_{sys}^c(t), & \text{for } i = 1 \\ S_{sys}^c(t) - \sum_{i=1}^{i-1} C_i(t), & \text{for } i > 1 \end{cases} \quad (19)$$

This dispatch strategy (system service model) is used to distribute the electric power supply both pre- and post-disaster. Possible occurrence of network disconnects and formations of network islands are considered by applying the adopted dispatch model to the different formed network components.

At time t_0 , the system is shocked by an earthquake. In this scenario, one supply layer node becomes partly damaged, the demand at several demand layer nodes decreases

(due to damage to the building stock and displacement of the population), and three links are broken (Figure 7(a)). Seismic fragility functions can be used to determine the expected damage to the components (e.g. Didier, Esposito & Stojadinovic, 2017 or Didier, Grauvogl et al., 2017). The disaster-induced damage is absorbed during the first 6 days. At $t = 6$ days, the connection between nodes $j = 1$ and $i = 4$ is repaired. The demand at node $i = 1$ recovers during this period (some people are, for example, allowed to return to their homes after a safety evaluation) and the demand at node $i = 4$ increases, compared to the pre-event level due, for example, to relocation of the population from other damaged locations. At $t = 9$ days, the connection between nodes $j = 1$ and $i = 1$ is repaired and a part of the supply capacity lost at supply node $j = 1$ is recovered (repairs of the generator are finished). Finally, at $t = 12$ days, the supply system recovers back to its pre-disaster capacity. Simultaneously, the demand at the different nodes continues to gradually recover. This process is tracked for 60 days. The evolution of the metrics at the system level and at the demand and supply layer components is shown in Figure 7(b–f). The values of the different resilience metrics over time can be found in Table A1.

While the demand layer nodes $i = 2$ and $i = 3$ do not experience any Lack of Resilience, despite the drop in the available supply at both nodes, a Lack of Resilience is observed for the demand layer nodes $i = 1$ and $i = 4$. The resilience-related post-disaster behavior of these nodes is classified into the classical configuration. At node $i = 1$, which is completely disconnected from the network, there is no supply available at all during the first 9 days after the

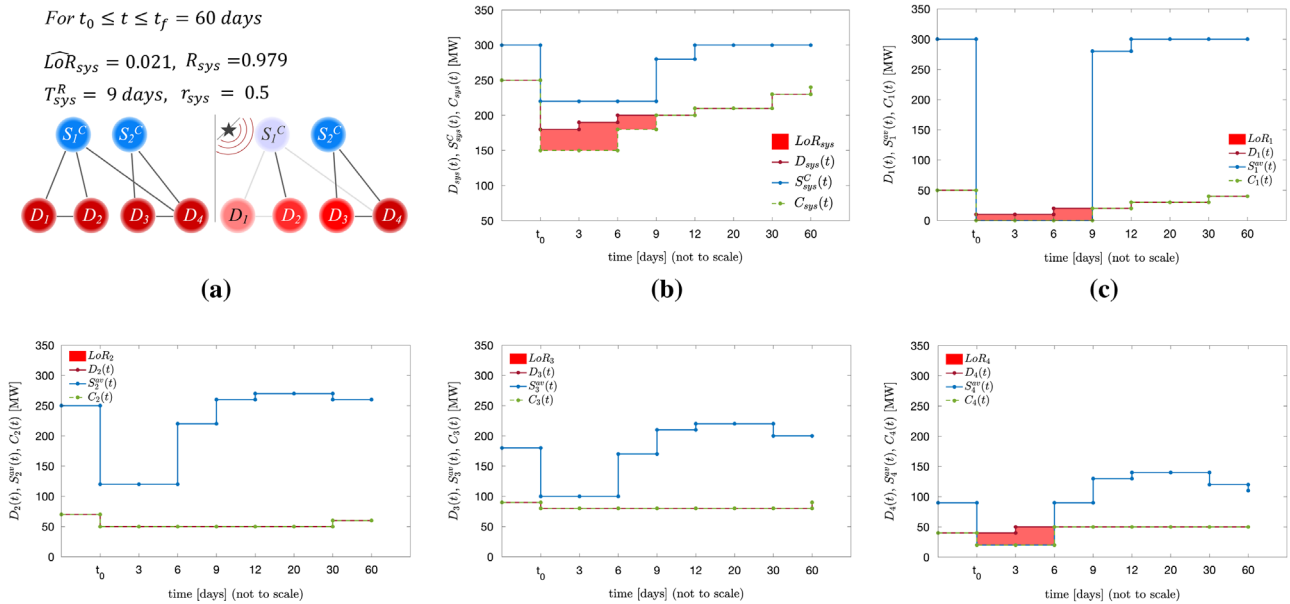


Figure 7. Virtual CIS-community (a) system topology before and after a disaster, results; Lack of Resilience evaluation for (b) the system and (c–f) the demand nodes 1 through 4.

disaster. The available supply at node $i = 4$ is not sufficient to cover the increased demand during the first 6 days. Note that although there is a system supply reserve before and after the disaster, a system Lack of Resilience is observed at the same time. This is due to the topology of the damaged system, the prioritization of the recovery actions, and the dynamics of demand caused by population movement. The example shows that although the supply is higher than the demand on a system level at every moment, i.e. $\int_{t_0}^{t_f} \langle D_{sys}(t) - S_{sys}^c(t) \rangle dt = 0$, different nodes have a supply deficit and there is a Lack of Resilience at the system level, $LoR_{sys} = \sum_{i=1}^I LoR_i > 0$. Therefore, Equation (13) holds. It is interesting to note that a recovery strategy prioritizing the recovery of the links, as opposed to the recovery of the supply nodes, would minimize the Lack of Resilience for this virtual CIS-community system in this scenario. In fact, the system supply capacity is, at each time step of the analysis sufficient to cover the demand in the system. However, the service supply cannot be distributed to all the demand nodes.

3. Discussion and applications

The proposed Re-CoDeS disaster resilience quantification framework accounts for a dynamic adaption of the post-disaster demand and supply to indicate that a Lack of Resilience of the CIS-community system occurs only when the desired demand of the community cannot be fully supplied by the CIS. This is in contrast to other disaster resilience quantification frameworks that focus mostly on CIS supply and often suppose that it will recover back to the pre-disaster state to affect a full recovery of the CIS-community system.

The Re-CoDeS framework can be used to model the CIS resilience in disaster scenarios where entire regions might be destroyed or become uninhabitable, leading to displacements of population and relocation of economic activities to other geographic locations. In such a context, the focus on the full recovery of CIS service to the pre-event level is misplaced because the community using the services does not exist anymore. A prominent and extreme case of such decreasing and/or disappearing demand is Pompeii (Italy) after the 62 AD Pompeii earthquake and the volcano eruption in 72 AD. Instead, the CISs in the newly populated areas need to be upgraded to meet the increased demand levels. Such CISs may also exhibit a Lack of Resilience, but at post-disaster supply and demand situations that are very different from the pre-disaster situations. Another illustration of the effect of permanently changed demand is the Port of Kobe after the 1995 Kobe earthquake. Many resources have been allocated to rebuild

the port. However, while the port was rebuilt to its full pre-disaster capacity, container transshipments cargo traffic gradually decreased to about 10% of pre-disaster levels as it was switched to other ports (Chang, 2010). Another example of changes in both demand and supply occurred in the regional gas supply network after the 2009 L'Aquila earthquake. The gas pipe network was modified in response to a new set of needs: inaccessible zones were bypassed, the gas network in L'Aquila downtown was completely replaced, missing links added, and temporary or new urbanized areas connected (Esposito, Giovinazzi, Elefante, & Iervolino, 2013). The topology and the operation of the L'Aquila gas network changed so significantly in the aftermath of the 2009 earthquake that a comparison to the pre-disaster state was rendered meaningless. These examples illustrate the need to take the evolution of both the post-disaster demand and supply explicitly into account. However, the mere balance of supply and demand at a low level does not necessarily mean that the CIS-community system recovery process is satisfactory or over.

The Re-CoDeS framework is also able to account for different recovery priorities and rates of recovery of various CIS-community system configurations (e.g. the electric power supply system may recover in a few days, while the built inventory may require significantly more time to recover its functions). This makes it possible to use the Re-CoDeS framework to optimize post-disaster recovery by minimizing the Lack of Resilience under resource and time constraints, while simultaneously accounting for the pre-disaster planning and preparedness, disaster mitigation and recovery management actions, and possible new post-disaster supply and demand patterns. The ability to account for the future evolution of the demand, as well as for the evolution of the supply, makes it possible to extend the Re-CoDeS framework beyond the recovery phase to plan optimal allocation of sparse resources and financial means to better prepare for the next disaster.

Major challenges include the development of improved models of the evolution of post-disaster service demand and the consideration of effects of interconnectivity and interdependence of the investigated CIS with other CISs. For example, models to estimate the evolution of the post-disaster service demand have been proposed for the electric power supply system (Didier, Grauvogl, Steentoft, Broccardo et al., 2017) and the cellular communication system and the water distribution system (Didier, Baumberger et al., 2017). Further research may also address possible implications of population movement related to a (temporary) inability to occupy otherwise undamaged buildings due to the lack of CISs services (Franchin, 2014). Such population movement leads to an interdependency of the evolution of the demand at different demand components.

This process may be dynamic and the demand/supply configuration may change in the hours, days and weeks following a disaster, driving recovery strategies and vice versa.

4. Conclusion

This study presented a novel compositional demand/supply disaster resilience quantification framework named Re-CoDeS. Re-CoDeS is based on demand and supply layers, defined locally for CIS and community components and linked by a system service model. In particular, the demand layer determines the evolution of the demand, the supply layer determines the evolution of the supply, and, finally, the system service model regulates the allocation of the service supply in order to satisfy the demand of the consumers considering the constraints to service distribution and service dispatch priorities. Re-CoDeS enables explicit and comprehensive tracking of the evolution of the CIS-community system demand and supply during the post-disaster recovery period.

Lack of Resilience is the main resilience measure used in the Re-CoDeS framework. Two dimensions of Lack of Resilience are proposed: a component Lack of Resilience and a system Lack of Resilience. The component Lack of Resilience is based on the component demand and the component available supply. The system Lack of Resilience is based on the aggregation of the Lack of Resilience of the components. It was shown that the system Lack of Resilience can be defined using two system variables: the aggregate demand and the aggregate consumption. In addition, a measure of the supply reserve margin and a notion of resilience time have been introduced. Normalized versions of these resilience measures have been proposed at the component and the system levels to enable a direct comparison across different CISs. A resilience-based component and system classification scheme was proposed. This classification enables to hotspot potential fragile components and system features, and encourages the design of anti-fragile components and systems to improve disaster resilience of modern communities.

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Appendix

Table A1. Resilience metrics tracked in the illustrative example.

	$t < t_0$	$t = t_0$	$t = 3 \text{ days}$	$t = 6 \text{ days}$	$t = 9 \text{ days}$	$t = 12 \text{ days}$	$t = 20 \text{ days}$	$t = 30 \text{ days}$	$t = 60 \text{ days}$
<i>Components</i>									
$D_1(t)$	50	10	10	20	20	30	30	40	40
$D_2(t)$	70	50	50	50	50	50	50	60	60
$D_3(t)$	90	80	80	80	80	80	80	80	90
$D_4(t)$	40	40	50	50	50	50	50	50	50
$S_1^c(t)$	200	120	120	120	180	200	200	200	200
$S_2^c(t)$	100	100	100	100	100	100	100	100	100
$S_1^{av}(t)$	300	0	0	0	280	300	300	300	300
$S_2^{av}(t)$	250	120	120	220	260	270	270	260	260
$S_3^{av}(t)$	180	100	100	170	210	220	220	200	200
$S_4^{av}(t)$	90	20	20	90	130	140	140	120	110
$C_1(t)$	50	0	0	0	20	30	30	40	40
$C_2(t)$	70	50	50	50	50	50	50	60	60
$C_3(t)$	90	80	80	80	80	80	80	80	90
$C_4(t)$	40	20	20	50	50	50	50	50	50
$LoR_1(t_0, t)$		0	30	60	120	120	120	120	120
$LoR_2(t_0, t)$		0	0	0	0	0	0	0	0
$LoR_3(t_0, t)$		0	0	0	0	0	0	0	0
$LoR_4(t_0, t)$		0	60	150	150	150	150	150	150
$\widehat{LoR}_1(t_0, t)$		0	1	1	1	0.67	0.29	0.17	0.06
$\widehat{LoR}_2(t_0, t)$		0	0	0	0	0	0	0	0
$\widehat{LoR}_3(t_0, t)$		0	0	0	0	0	0	0	0
$\widehat{LoR}_4(t_0, t)$		0	0.50	0.56	0.36	0.26	0.15	0.10	0.05
$R_1(t_0, t)$		1	0	0	0	0.33	0.71	0.83	0.94
$R_2(t_0, t)$		1	1	1	1	1	1	1	1
$R_3(t_0, t)$		1	1	1	1	1	1	1	1
$R_4(t_0, t)$		1	0.5	0.44	0.64	0.74	0.85	0.90	0.95
<i>System</i>									
$D_{sys}(t)$	250	180	190	200	200	210	210	230	240
$S_{sys}^c(t)$	300	220	220	220	280	300	300	300	300
$C_{sys}(t)$	250	150	150	180	200	210	210	230	240
$LoR_{sys}(t_0, t)$		0	90	210	270	270	270	270	270
$\widehat{LoR}_{sys}(t_0, t)$		0	0.17	0.19	0.16	0.12	0.07	0.04	0.02
$R_{sys}(t_0, t)$		1	0.83	0.81	0.84	0.88	0.93	0.96	0.98

$LoR_1(t_0, t)$ stands for $\int_{t_0}^t \langle D_1(t) - S_1^{av}(t) \rangle dt$; $C(t)$, $D(t)$, $S^c(t)$, $S^{av}(t)$ in [MW]; $LoR(t_0, t)$ in [MWd]; $R[-]$, $\widehat{LoR}_1(t_0, t)$ [-].