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Comparing decision models for disaster restoration of interdependent infrastructures under uncertainty

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ABSTRACT:

As infrastructure systems are highly interdependent, one needs to analyze their disaster resilience and develop restoration plans with the consideration of infrastructure interdependencies. This study presents two probabilistic models for infrastructure decision-makers to simulate the recovery of interdependent systems in a post-disaster scenario. The models consider interdependencies related to damage, functionality, and restoration. To incorporate uncertainty in restoration, this study assumes that the actual duration of each restoration activity follows a random distribution. To simulate the decision-making process in the recovery, this study uses the PRAISys platform to implement two schemes with different restoration criteria. The first scheme uses the priority ranking of the damaged structure (based on its importance, criticality, etc.) as the criterion and the platform simulates the restoration plan under resource and dependency constraints. In contrast, the second uses the criterion of minimizing the restoration completion time by framing all restoration activities within a constrained optimization formulation, and the platform implements the optimal schedule as the restoration plan. To exemplify the applicability of the two schemes, this study simulates the recovery of interdependent systems after a hypothetical earthquake in the Lehigh Valley, a multi-county community in eastern Pennsylvania, USA.

1. INTRODUCTION

Critical infrastructures serve as the backbone of the economy, security, and welfare of a nation. There are complex interdependencies among critical infrastructures, and the clear trend is that these interdependencies are growing (Sun et al., 2018b). Historical disasters, such as the 2011 Great Tohuku Earthquake-Tsunami and Hurricane Irma in 2017, have demonstrated the catastrophic cascading failures and escalating impacts due to interdependencies (Koshimura et al., 2014; Cross, 2017). In this respect, the following questions arise from decision-makers of local governments and utility companies. If a severe event like Tohuku Earthquake happens in our administrative region, how should we develop efficient strategies to protect our community and rapidly restore infrastructure functionality in future hazards?

To answer this question, computational frameworks and simulation tools have been developed worldwide to assess the disaster resilience of interdependent infrastructures. In Europe, SysRes (Lundberg and Woltjer, 2015) and GRRASP (Galbusera and Giannopoulos, 2016) are under development to assess the risk and resilience of critical infrastructures. In the United States, MCEER (Multidisciplinary Center for Earthquake Engineering Research) has developed the PEOPLES resilience framework (Renschler et al., 2010; Cimellaro, 2016). Miles and Chang (2011) developed ResilUS to assess the community resilience, with spatial and temporal predictions of infrastructure service losses and recoveries in a probabilistic manner. The Center for Risk-Based Community Resilience Planning is developing IN-CORE to evaluate the community resilience under different types of hazards (Ellingwood et al., 2016). As part of an NSF project, the PRAISys (Probabilistic Resilience Assessment of Interdependent Systems) platform is being developed to assess the community resilience by simulating stochastic infrastructure interdependencies under a deterministic scenario (The PRAISys Team, 2018).

A critical component of all these frameworks should be a model to capture the decision-making process. This study compares two potential models: one very simple and strictly following a predefined priority ranking list, and one much more sophisticated, based on the formulation and solution of a constrained optimization problem. The PRAISys platform is adopted to assess the disaster resilience of two infrastructure systems after a hypothetical earthquake scenario in a testbed, using both decision models. Simulation results from different schemes are compared, to discuss the features of the two models. This comparison is useful for modelers, who can see the implications of different modeling assumptions, and for decision makers, who can see how different criteria can lead to variations in practical outcomes.

2. THE PRAISYS PLATFORM

2.1. Description of the PRAISys platform

The PRAISys platform is a comprehensive regional disaster simulator for modeling critical infrastructures and their stochastic interdependencies. Given a hazard scenario, the PRAISys platform can predict possible consequences and recovery for infrastructure systems, considering resource and dependency constraints. PRAISys focuses especially on two features. On the one hand, it considers *uncertainties* in damage assessment, restorations, and functionality dependencies. On the other hand, it rigorously classifies nine types of *interdependencies* related with hazard, damage, restoration, and functionality, and provides proper interfaces for the implementation. The following content describes the ten types of interdependencies.

A *first type* of interdependency can be considered as the spatial correlation of the intensity in a hazard scenario. This is addressed system-wide through correlated hazard maps, which give the event intensities over the entire region. The platform could also handle multiple correlated intensity measures, such as a hurricane that brings both high winds and heavy rainfalls, or snow storms.

Three additional types of interdependencies are damage-related. *The second type* corresponds to correlated sub-component damages. For example, damaged columns are often associated with damaged bridge decks in an earthquake. This type of interdependency can be addressed by a co-variance matrix for interdependent sub-components, which has not yet been implemented in the current version of PRAISys. *The third type* represents mechanical cascading failures, representing the fact that a falling transmission tower breaks down adjacent power lines, which is modeled through the failure library. *The fourth type* indicates cascading failures due to flow redistribution, which is common in the power sector and can be captured with power flow analysis, but they are not included in the current version of PRAISys.

Restoration-related interdependencies fall into four additional types. *The fifth type* represents the delaying effect due to escalating failures, such as a severely damaged transportation system delaying the transportation of repair crews and equipment. This type of interdependency is modeled by a delaying factor when the system functionality loss reaches a threshold level. *The sixth type* represents functionality requirements while conducting restoration tasks, such as repair of a supporting bridge before installing utility lines. This type of interdependency is modeled by functionality requirements in the restoration task library. *The seventh type* represents resource-sharing interdependencies, which is represented by resource constraints in the simulations. *The eighth type* refers to the sequence among different restoration activities, which is represented by precedence constraints of restoration tasks.

Finally, there are the functionality-related interdependencies. *The ninth type* corresponds to functionality dependencies across or within systems, which are modeled by mechanistic functionality assessment for every component and every system over time. *The tenth type*, called "compositional functionality dependencies", represents the fact that a system's functionality depends on the functionality its components and is assessed with system-level analyses or system functionality function (e.g., traffic flow analysis, power flow analysis, connectivity analysis).

2.2. *Five analysis steps*

As shown in Figure 1, the PRAISys platform consists of five analysis steps. *The first step* reads all input describing the hazard scenario and infrastructure systems, as well as the analyst's simulation choices. In the input, PRAISys allows the analyst to set up different levels of interdependencies. For instance, there are two levels of resource-sharing interdependencies (*the seventh type*) in PRAISys: high – across systems, or low – only within an individual system. Currently, local governments and utility companies usually do not share resources across systems even though they might coordinate restorations of different systems. Therefore, this study chooses resource-sharing within every individual system and keeps all other types of interdependencies at high levels.

The second step conducts a fragility analysis for every structural component and samples the damage state, followed by the assessment of cascading failures. The fragility library stores fragility models of all types of components, including electric substation (Zareei et al., 2017; FEMA, 2017), transmission tower (Xie et al., 2012), central office (FEMA, 2017), and communication tower (Giovinazzi et al., 2017). After that, PRAISys determines the required restoration tasks associated with the damage state for every structural component, according to the restoration task library, which is compiled on the basis of reports and papers, such as Cagnan (2005), and consulting with professional engineers and construction managers.

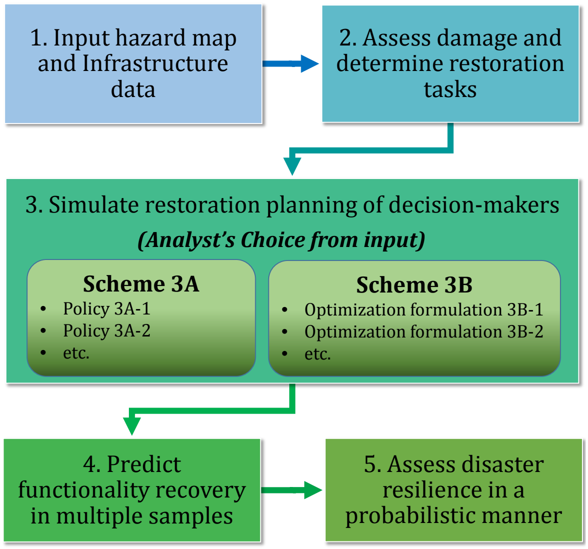

Figure 1: The PRAISys computational procedure.

In *the third step*, the selected decision model simulates the human planning of restoration activities. There are two categories of simulation models in PRAISys to determine the restoration sequence: policy-based (3A) and optimization-based (3B), described in detail in Section 3. This study compares simulation results from the two restoration schemes to assess how different decision modes impact functionality recovery and system resilience.

According to the restoration sequence, *the fourth step* predicts possible functionality recovery for every system under resource and dependency constraints. Uncertainties in restoration are captured by sampling task durations from appropriate probability distributions. The entire procedure is repeated for various samples of damage, restoration durations, random dependencies, etc., in a Monte Carlo approach. Finally, PRAISys computes statistics of system resilience and other metrics in *the fifth step*.

2.3. *Functionality and resilience metrics*

PRAISys provides multiple functionality and resilience metrics for various components, systems, and systems-of-systems, from which the analyst can choose. This study chooses the following functionality metric for both systems:

$$Q(t) = \frac{\sum_{k=1}^{N} w_k \cdot q_k(t)}{\sum_{l=1}^{N} w_k} \quad (1)$$

where $Q(t)$ is the functionality at time t for a system consisting of N components; w_k is the weight of component k; $q_k(t)$ is the functionality of component k at time t. This study considers only functional substation components contributing to the system functionality for the power system, using the substation voltage as the weight. It considers functional components of both central offices and communication towers contributing to the functionality for the communication system, with each component having the weight of 1.

For every functionality recovery sample $Q_i(t)$, system resilience is measured by the resilience index (Reed et al., 2009; Bocchini et al., 2014), following Equation 2 and also presented in Figure 2:

$$RI_i = \frac{\int_{t_0}^{t_h} Q_i(t)\mathrm{d}t}{t_h - t_0} \quad (i = 1, ..., S) \quad (2)$$

where RI_i is the resilience index of the functionality recovery sample $Q_i(t)$; t_0 is the time instant when the event strikes; t_h is the time horizon of the analysis; S is the number of random samples.

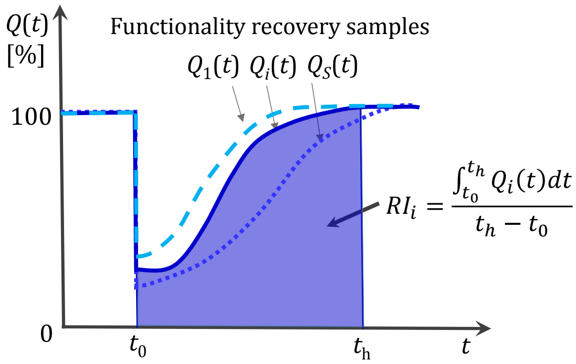

Figure 2: Functionality recovery samples and illustration of resilience index.

3. RESTORATION PLANNING MODELS

3.1. *The policy-based model*

Table 4 presents an example of the policy-based model, called "Scheme 3A", for structural components in every system. This study neglects the damage potential for power plants because of their very low vulnerability. Restorations of other components in the power system follows the policy-based priority ranking, starting from electric substations to power lines, and then transmission towers. Similarly, restoration of damaged components in the communication system follow the ranking from central offices to communication lines, and then communication towers. Damaged components of the same type have the restoration priority rank based on their capacity; damaged components of the same capacity are randomly restored in sequence. For example, electric substations at a high voltage level are restored ahead of those at a low voltage; electric substations at the same voltage level are randomly restored. These priority policies and the ranks themselves are assumed to be defined pre-event by appropriate decision makers, and then followed blindly in the post-event restoration.

3.2. *The optimization-based model*

"Scheme 3B" is an example of a decision model rigorously following the outcome of an optimization, with specific objective(s) and constraints. In this study, the criterion of minimal restoration completion time (Karamlou et al., 2017; Sun et al., 2018a) has been chosen, along with resource and dependency constraints. This formulation is a resource-constrained project scheduling problem.

Find binary decision variables

$$x_{jt} = \begin{cases} 1, \text{ if task } j \text{ finishes at the period } t, \\ 0, \text{ otherwise} \end{cases} \quad (3)$$
$$\forall j \in J \text{ and } t \in [EF_j, LF_j]$$

that will reach the objective of finishing all restoration tasks as soon as possible

$$minimize(\sum_{EF_n}^{LF_n} t \cdot x_{nt}) \quad (4)$$

and also satisfy the following constraints:

$$\sum_{t=EF_j}^{LF_j} x_{jt} = 1 \quad (5)$$

$$\sum_{t=EF_j}^{LF_j} (t-d_j)\cdot x_{jt} - \sum_{t=EF_i}^{LF_i} t\cdot x_{it} \geq 0, \qquad \forall j \in J \text{ and } i \in P_j \tag{6}$$

$$\sum_j u_{jr} \cdot \sum_{q=max(t,EF_j)}^{min(t+d_j-1,LF_j)} x_{jq} \leq a_r, \qquad \forall r \in R \text{ and } t=[1,2,...,t_h] \tag{7}$$

where x_{jt} is a binary decision variable, $x_{jt}=1$ when task j $(j=1,2,...,n)$ is finished at end of period t, $x_{jt}=0$ otherwise; d_j is the duration of task j; EF_j and LF_j are the earliest possible finishing time and the latest possible finishing time of task j; t_h is the time horizon that the analyst is interested in; u_{jr} is the required amount of the r^{th} type of renewable resource when conducting task j; $[a_r]$ is the available amount of the r^{th} type of renewable resource in R; P_j is the set of predecessor tasks for task j; J is the entire set of restoration tasks, including a dummy end task n. In particular, Equation 4 is the objective of minimizing the finishing time of the dummy end task, which is to minimize the completion time of all restoration tasks. Equation 5 requires that every task is executed once. Equation 6 enforces the precedence requirement for every task. Equation 7 enforces that the amount used for every type of resource does not violate the resource availability.

4. APPLICATION EXAMPLE

4.1. *The Lehigh Valley testbed*

The Lehigh Valley testbed covers a region of Lehigh and Northampton Counties in eastern Pennsylvania, United States. This study focuses on the post-earthquake performance of two infrastructure systems: power and communication. Figure 3(a) presents a hypothetical earthquake scenario, in term of peak ground acceleration (PGA), in the unit of g, with an approximate return period of 80,000 years. This rare earthquake scenario is used in this study, simply for demonstrating how PRAISys can predict possible consequences and infrastructure recovery in case of an extreme hazard. The power system consists of 6 power plants and 67 electric substations, shown in Figure 3(b). The communication system consists of 40 central offices and 89 communication towers in Figure 3(c). Table 1 presents the amount of electric substations at different voltage levels. Tables 2 and 3 show central offices and communication towers of different companies.

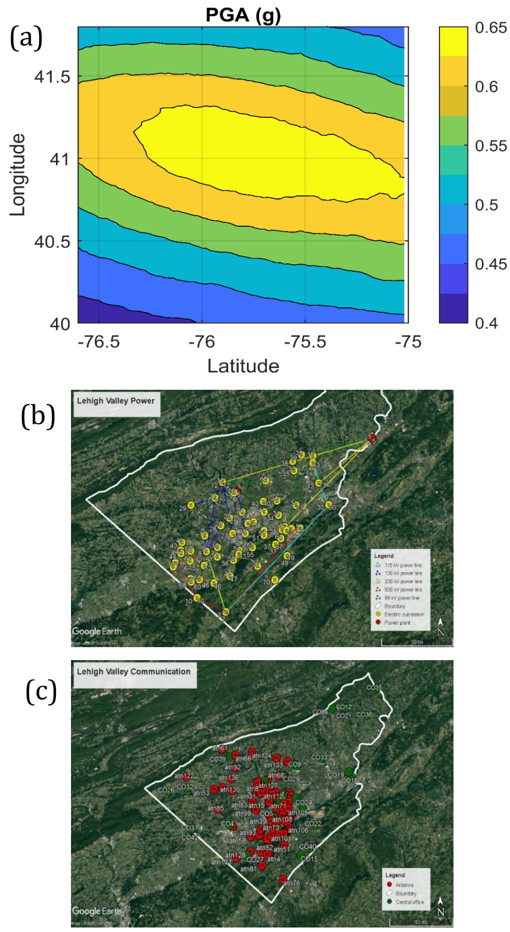

Figure 3: The Lehigh Valley testbed: (a) Earthquake scenario in terms of peak ground acceleration (PGA), (b) Power system, and (c) Communication system.

Substation type	Transmission-level		Distribution-level		
Voltage (kV)	500	230	138	115	69
Amount	5	4	14	1	43

Table 1: Electric substations at different voltage levels

PRAISys simulates system functionality recovery under resource constraints and dependency constraints, using the two restoration schemes described in Section 3. The time horizon is set as $t_h=90$ days. Under each scheme, a total of 1,000 samples are computed for this example. The

Company	Verizon	SET	CTC	Sprint	RCN	Others
Count	17	11	6	1	1	4

Note: SET = Service Electric Telephone, CTC = Commonwealth Telephone Company, RCN = RCN Corp., formerly Residential Communications Network Corporation.

Table 2: Central offices of different companies

Company	Amount
AT&T	16
Verizon	5
T-mobile	7
Sprint	2
RCN	4
Capstar	9
American Towers	12
Others	35

Table 3: Communication towers of different companies

platform considers that there are four types of renewable resources, representing crew, equipment, truck, and tool in each of the two systems. Resource constraints are set as $[a_r]_P = [15, 25, 20, 20]$ for the power system and $[a_r]_C = [15, 25, 20, 20]$ for the communication system. The following section presents simulation results using the two schemes.

4.2. Results

Figure 4 presents the functionality recovery samples of the two systems using Schemes 3A and 3B, respectively. Based on every functionality recovery sample, the restoration completion time is computed. Figure 5 shows the distributions of the restoration completion time for the two systems. The power system shows a slightly stretched distribution under priority planing (3A), with similar mean completion times under both schemes. Conversely, the communication system recovers 3 days faster on average if planning the restoration through optimization (3B), rather than policy (3A).

Figure 6 shows the probability of the two systems having achieved or exceeded a certain functionality threshold over time. The power system is most likely to have the functionality over 80% after 7 days and being fully functional after 12 days when using Scheme 3A. Conversely, the power system is fully functional after 7 days while optimizing the completion time. For the communication system, it is most likely to having the functionality over 80% after 6 days and being fully functional after 31 days while using the policy-based decision making. However, it only takes 29 days

Scheme 3A	Ranking	Power	Communication
Policy based	1	Substation	Central office
	2	Power line	Co. line
	3	Tr. tower	Co. tower

Note: Tr. tower = transmission tower; Co. line = communication line; Co. tower = communication tower.

Table 4: Priority ranking in Scheme 3A

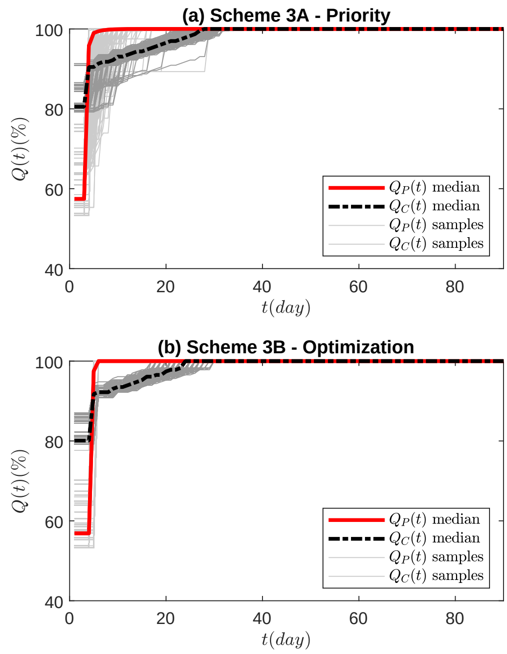

Figure 4: The functionality recovery samples of two systems: (a) Scheme 3A, and (b) Scheme 3B.

to fully recover under Scheme 3B. This is probably because Scheme 3B simulates restoration decisions that make full use of available resources at all time steps to complete restorations as soon as possible. Instead, Scheme 3A may sometimes lead to idling resources that are not used for tasks of low priority components.

For every functionality recovery sample, the resilience index is computed using Equation 2 at $t_h = 90$ days. Figure 7 presents mean values and standard deviations of the resilience index for the two systems. The power system has the mean resilience index of 0.9799 under Scheme 3A, lower than 0.9851 under Scheme 3B. A similar increasing trend from 0.9801 in Scheme 3A to 0.9806 in Schme 3B is found for the communication system.

5. CONCLUSIONS

Using PRAISys, this study investigates how two restoration planning models yield different func-

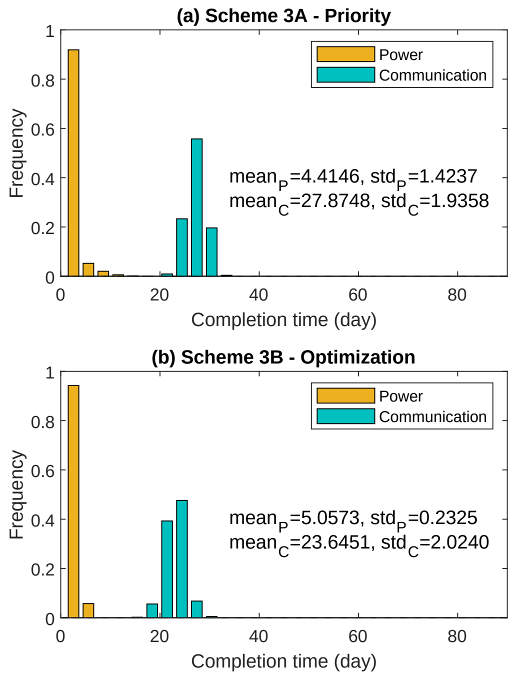

Figure 5: Distributions of completion time for the two systems: (a) Scheme 3A, and (b) Scheme 3B.

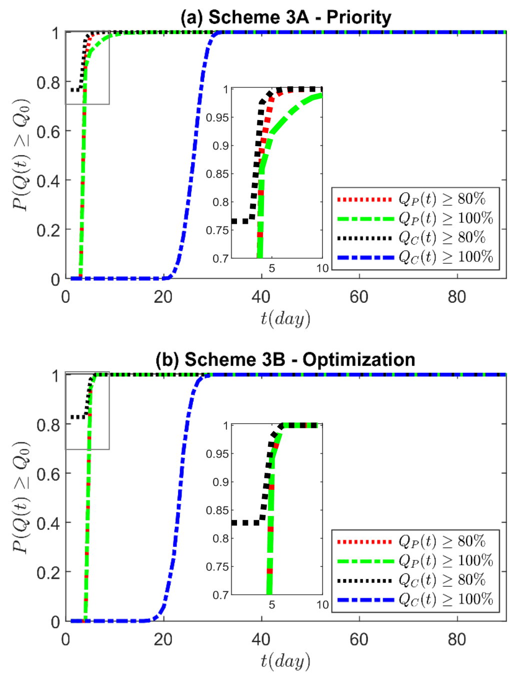

Figure 6: Probabilistic restoration function of the two systems: (a) Scheme 3A, and (b) Scheme 3B.

tionality and resilience predictions for interdependent systems, with the following major findings.

(1) Functionality recovery samples from the two schemes show quite different trends, under the same resource and dependency constraints. The power system shows similar means of completion time, but the communication system takes 3 days longer using Scheme 3A than using Scheme 3B to fully recover on average. In addition, both systems show smaller mean values of resilience when using the policy-based decision model than when optimizing for the restoration completion time.

(2) The PRAISys platform can predict probabilistic restoration functions and system resilience for interdependent infrastructures. It is a generalized simulator, applicable to different infrastructure systems and different types of hazards. Uncertainties in damage assessment, restoration, and functionality dependencies are considered through fragility analyses, random distributions of restoration duration, and probabilistic dependency relations. To simulate human decision making in developing restoration plans under resource and dependency constraints, the platform provides two categories of restoration models, allowing the analyst to choose at the initial input. It can compare disaster restoration plans with different decision criteria to support informed decision-making.

6. ACKNOWLEDGMENT

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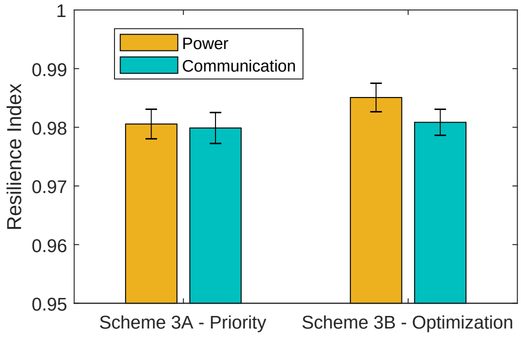

Figure 7: Mean values and standard deviations of resilience index for two systems.

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