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Identifying Components Important for System Resilience

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ABSTRACT: The resilience of a system is often assessed using models that consist of numerous interdependent system components. To better understand the system's resilience, the performance of each component needs to be evaluated. Such an evaluation requires significant component-level data collection and modeling efforts, which are, in some cases, restricted due to privacy or security concerns. However, the performance of certain system components might be irrelevant for system's resilience. This paper presents a method that can identify such irrelevant components. More specifically, we focus on identifying those components whose vulnerability and recoverability are irrelevant for system's disaster resilience, with minimal information on these two component parameters. The presented method employs a Sobol' sensitivity analysis using uninformed input distributions to initially rank the system's components. An iterative heuristic upper and lower bound search is performed next to identify the subset of highly ranked components whose vulnerability and recoverability significantly affect system's resilience. The efforts aimed at better understanding the performance of system components that are not in the "important components" subset can be avoided without a major impact to system's resilience assessment, simplifying the system model and preventing unnecessary component-level data collection and modeling efforts. The method is illustrated on a virtual community whose disaster resilience is assessed in terms of its ability to meet its community resilience goals.

1. INTRODUCTION

Resilient systems can quickly recover from extreme events, minimizing the negative effects of such events on their users. Analyzing the resilience of complex systems (e.g., infrastructure systems) can be challenging as they consist of numerous interdependent components. Characterizing the post-disaster behavior of such components, as well as their interdependency, can require extensive data collection and modeling efforts, which are in some cases not possible due to privacy concerns. In this paper, we aim to rank components based on their importance for system resilience in cases when minimal component information is available. Such ranking allows us to guide further data collection and component modeling efforts, *apriori* preventing such efforts for components that are not relevant for assessing system resilience. Furthermore, such ranking can inform resilience-improving actions, which should focus on components identified as important for system resilience. The method is illustrated on a virtual community supported by three interdependent civil infrastructure systems.

2. SYSTEM RESILIENCE ASSESSMENT

We use the iRe-CoDeS framework to assess system's disaster resilience (Blagojević et al. (2022b)). A system is discretized into components whose supply and demand for various resources are monitored over the post-disaster recovery period. To simulate the initial post-disaster change in component's supply and demand, each component is assigned an initial damage level that spans from 0 (no damage) to 1 (complete damage). The initial value of a component's damage level is conditioned on component's vulnerability and the expected intensity of the disaster at component's location. To simulate the evolution of component's supply and demand during the post-disaster recovery period, a component recovery model needs to be defined for each component. The purpose of a recovery model in iRe-CoDeS is to simulate the decrease of component's damage level over the recovery period, thus capturing the recovery of component's function and the resulting change in its supply and demand. The recovery model used in this paper is simple and is characterized by a single parameter constant over the recovery period: repair rate. The repair rate spans from 0 to 1. Component's recovery is simulated by reducing the damage level of a component by its repair rate at each time step of the recovery simulation starting immediately following the disaster. Therefore, if the repair rate is 0, the damage level stays at its initial value throughout the recovery simulation, while if the repair rate is 1, the damage level is reduced to 0 in a single time step regardless of the value of the initial damage level (i.e., component is repaired in a single time step). More complex recovery models can also be adopted in iRe-CoDeS (Blagojević et al. (2022)).

A system in iRe-CoDeS is spatially defined by localities: geographically localized units that can contain none, one, or several components. Components can either be in a locality (e.g., a residential building), or between localities (e.g., a pipe). Components between localities are named links and transfer resources between components in localities. The transfer of resources within a locality is assumed to be direct and unconstrained.

Components' interdependencies are captured by simulating the flow of resources among components at each time step of the recovery simulation and constraining components' ability to operate and recover based on components' demand fulfillment. Apart from capturing components' interdependencies, the resource flow simulation is used to calculate components' resource consumption (i.e., how much of the component's resource demand is met by the available supply at a time step of the recovery simulation).

To evaluate system resilience, components' supply, demand, and consumption are aggregated on the system level (Didier et al. (2018)). The percent of system demand (i.e., the sum of the demand of all users in a system) met at each time step of the recovery simulation is used as the system's measure of functionality. The iRe-CoDeS framework can then evaluate the time that a system needs to attain a certain functionality level (i.e., meet a certain percent of users' demand), thus evaluating whether the system fulfills the prescribed resilience goals (Blagojević et al. (2022a); NIST (2016)).

3. METHOD FOR COMPONENT IMPORTANCE QUANTIFICATION

Figure 1 illustrates the proposed method for component importance quantification (Blagojević et al. (2022)). The method starts by defining system's resilience goals, the disaster scenarios for which the goals will be assessed, and the construction of the system model in iRe-CoDeS, as outlined in Blagojević et al. (2022b).

To conduct the initial component ranking, we use the global variance-based sensitivity analysis (i.e., the Sobol' sensitivity analysis) (Sobol (1993)). Such analysis requires that probability distributions are defined for each variable whose importance is investigated. This method quantifies the importance of component's vulnerability and recoverability for system resilience. These component characteristics are represented using variables bounded between 0 and 1: the initial damage level and the repair rate. When no further information on such variables is available, the maximum entropy principle (Kapur (1989)) states that a uniform probability distribution should be adopted to maximize uncertainty with respect to the available information (i.e., the variable bounds). Thus, we adopt a uniform probability distribution bounded between 0 and 1 for the initial damage level and repair rate of all components in the initial Sobol' index-based ranking.

Sobol' sensitivity analysis quantifies how much

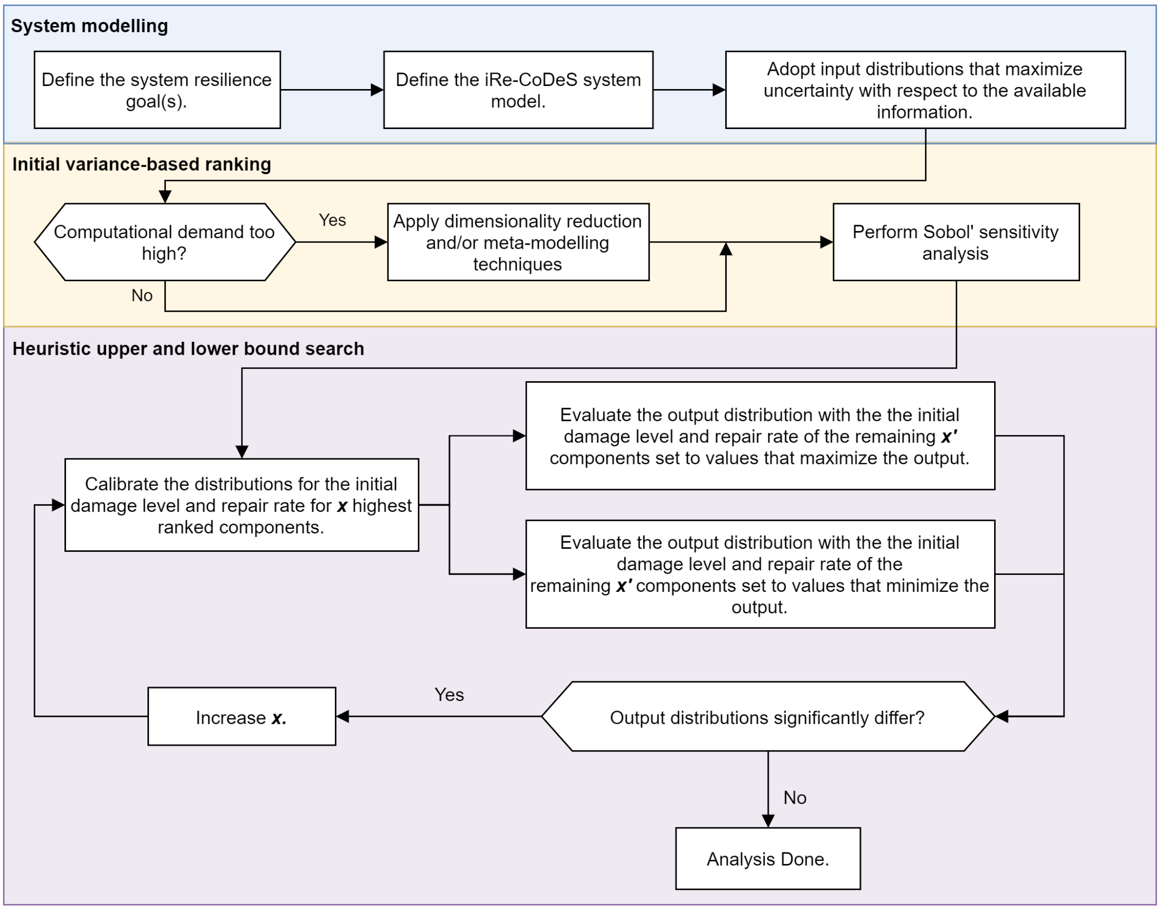

Figure 1: Workflow of the proposed component importance quantification method (Blagojević et al. (2022)).

the variance of a model input contributes to the variance of the model output, attributing a Sobol' index to each considered model input. Such contributions are comparable and can be used to rank components. We assume that components whose vulnerability and recoverability have a higher Sobol' index in the initial, uninformed ranking are more important for assessing system's resilience. As the variance of all inputs is the same (i.e., all inputs are uniform distributions with [0, 1] bounds), the value of their Sobol' indices is not due to the difference in their variance values, but due to other components' characteristics, such as their connectivity, location, redundancy, functionality characteristics and supply and demand values.

Conducting a global variance-based sensitivity analysis can be computationally expensive as it requires numerous runs of the computational model, where the number of runs is conditioned on the number of model inputs (Sobol (2001)). To alleviate the computational burden, inputs can be grouped (Blagojević et al. (2022); Tabandeh et al. (2022)), thus reducing the number of Monte Carlo simulations required. Alternatively, a metamodel can be constructed to decrease the computational effort of Monte Carlo simulations (Liu et al. (2019)) or use the parameters of the metamodel to calculate Sobol' indices (Sudret (2008)). This step can be skipped if the computational effort is not an issue (e.g., high-performance computing clusters are available or the model is cheap to evaluate).

The initial component ranking presents a "best guess" ranking when information on considered components' properties is not available and is qualitative. The next step in the proposed component importance quantification method is to conduct an iterative heuristic upper and lower bound search to identify how many highly ranked components to calibrate through further data collection and modeling efforts, and how many low-ranking components to simplify to obtain a reasonably accurate estimates of system resilience.

The search starts by selecting x highest ranked components and calibrating the probability distributions of their initial damage level and repair rate conditioned on the selected disaster scenarios and component vulnerability and recoverability. The initial damage level and repair rate of the remaining uncalibrated components are then set to two sets of constant values constructed to obtain the upper and lower bound on the probability distribution of the considered resilience metric. The upper bound probability distribution is obtained by running Monte Carlo simulations of the system iRe-CoDeS model where the initial damage level and repair rate of the x calibrated components are sampled from their calibrated probability distributions. The same parameters of the uncalibrated components are set to constant values that result in the ”most pessimistic” resilience metric (e.g., the longest time to recover system functionality). In contrast, the lower bound probability distribution is obtained when the parameters of the uncalibrated components are set to constant values that result in the ”most optimistic” resilience metric (e.g., the shortest time to recover system functionality). The search continues by increasing the number of calibrated components x following the initial component ranking until the difference between the upper and lower bound probability distribution is insignificant.

The components that remain in the uncalibrated set can be considered irrelevant for assessing the considered resilience metric since the most extreme variation in their initial damage level and repair rate does not have an appreciable effect on the probability distribution of the computed community disaster resilience metric. Thus, the properties of x' uncalibrated components do not need to be further calibrated, obviating the data acquisition and modeling efforts. Furthermore, resilience-improving actions aimed at these components are expected not to significantly contribute to system resilience. The computed probability distributions of the considered community disaster resilience metric for the considered disaster scenarios can be adopted for subsequent decision-making.

4. CASE STUDY: VIRTUAL COMMUNITY WITH THREE INTERDEPENDENT CIVIL INFRASTRUCTURE SYSTEMS

The proposed component importance quantification method is illustrated on a virtual community consisting of a building stock and three interdependent infrastructure systems exposed to a seismic hazard (Figure 2). The application of the proposed component importance quantification method on the electric power supply system in the same virtual community is presented in Blagojević et al. (2022). In this paper, we focus on the cellular communication system.

Community resilience goals are defined in terms of the percent of user demand that needs to be met within a certain time following a disaster. The communication system's resilience goal is achieved once 90% of community demand for communication services is met. The demand for communication services is assumed to increase immediately after the disaster due to an increase in emergency calls and return to its pre-disaster level after 10 days (Blagojević et al. (2022b)).

The community iRe-CoDeS model simulates the recovery and interdependency between the building stock and the three supporting interdependent infrastructure systems. The building stock consists of 9 building stock units (BSUs), each housing 400 inhabitants. The electric power supply system consists of electric power plants (EPP) producing electric power and a network of electric power transmission lines (EPTLs) transferring electric power to users. Potable water facilities (PWFs) produce potable water transferred to the BSUs through a network of potable water pipes (PWPs). Cooling water is supplied by the cooling water facilities (CWFs) and transferred using a network of cooling water pipes (CWPs). Finally, the cellular communication system consists of Base Station Controllers (BSCs) that wirelessly control Base Transceiver Stations (BTSs). BTSs wirelessly provide communication services to the people in the virtual community.

These infrastructure systems are interdependent since their components require resources provided

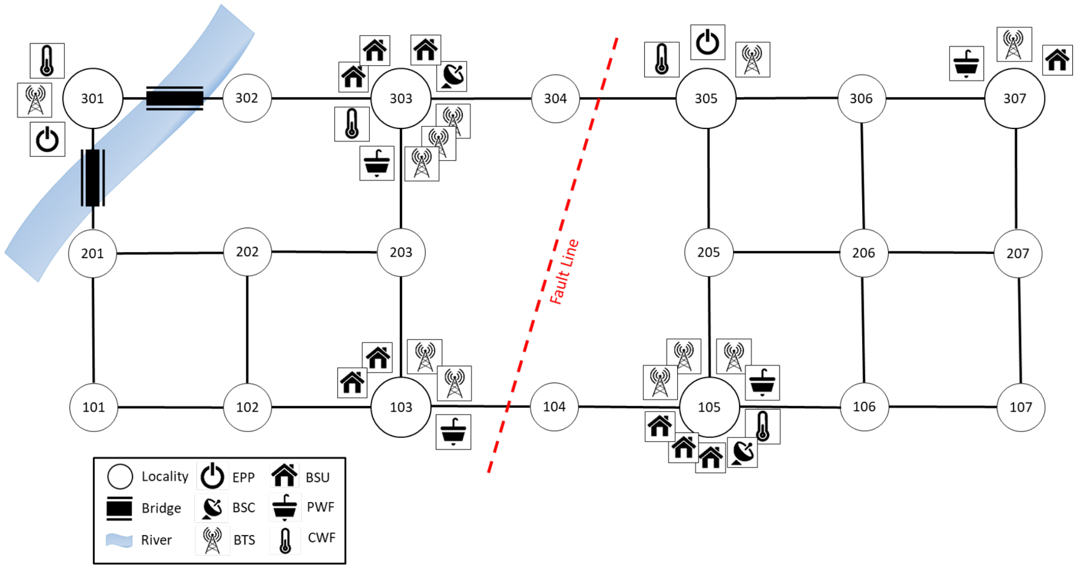

Figure 2: Virtual community set-up. Components in localities are Electric Power Plants (EPPs), Building Stock Units (BSUs), Base Station Controllers (BSCs), Potable Water Facilities (PWFs), Base Transceiver Stations (BTSs) and Cooling Water Facilities (CWFs) (Blagojević et al. (2022)).

by other infrastructure systems to operate: for example, BSCs require cooling water and electric power to operate, BTSs require the BSCs control services (also called high-level communication) and electric power provided by the EPPs and transferred through EPTLs, while EPPs require cooling water and communication services (called low-level communication) provided by the BTSs. Such interdependencies are defined to illustrate the ability of the iRe-CoDeS framework to simulate cascading failures among interdependent components and are described in detail in Blagojević et al. (2022b).

In total, 88 community components located in or between 21 localities are considered in the resilience analysis. Their Sobol' indices are calculated by running 1,780,000 individual Monte Carlo runs of the community iRe-CoDeS model exposed to an M7.0 earthquake. The simulations are ran on the ETH Euler High-Performance Computing cluster, while a minimal repair rate of 0.002 is adopted to prevent excessively long recovery times, resulting in a maximum component recovery time of 500 days. Component importance ranking for the time needed to meet 90% of demand for communication services is shown in Figure 3, presenting mean values and 95% confidence intervals of the community components' total Sobol' index values for 30 (out of 88) components with the highest total Sobol' index values. The component ranking is presented in terms of Sobol' index values for component repair rates. Similar ranking is obtained when initial damage level Sobol' indices are used. The components are labeled on the x-axis. For example, EPP 301 refers to the electric power plant at locality 301, and Bridge (301, 302) refers to the bridge connecting localities 301 to 302.

The direct suppliers of communication services, the BTSs, are not ranked among the most important components: the BTS with the highest Sobol' index is 19th in the initial component ranking. This can be explained by the BTSs redundancy: 11 BTS are operating independently of each other and can meet the user's communication demand. However, the components supporting the operation of BTSs (i.e., the CWFs, BSCs, and EPPs) are not as redundant (e.g., there are only 4 CWFs, 2 BSCs, and 2 EPPs) and are thus identified as more important. The initial Sobol' sensitivity analysis ranked CWFs and BSCs as the most important components, identifying the importance of BTSs' dependence on BSCs, as well as the BSCs' dependence on cooling water provided by the CWFs. The EPPs are important as they provide electric power to CWFs, BSCs, and

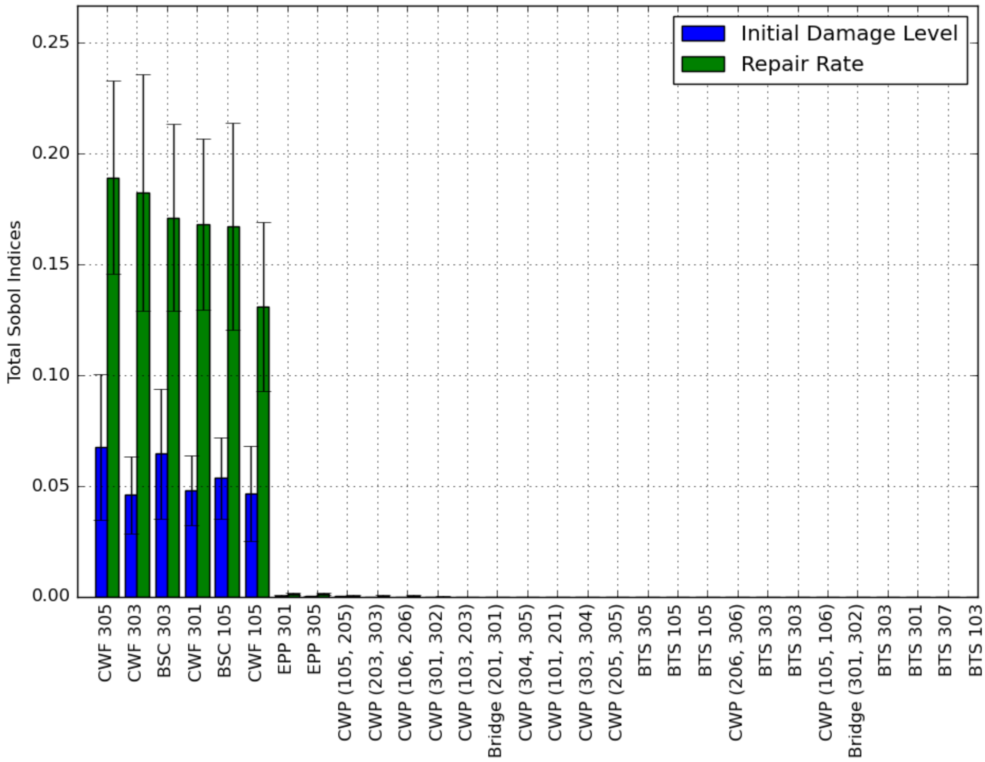

Figure 3: Total Sobol' indices of community components regarding the time to meet 90% of demand for community communication services (Blagojević et al. (2022)).

BTSs. The initial component ranking recognized indirect interdependencies among components, as well as the importance of components transfering resources: CWPs are also recognized as important as they transfer cooling water to EPPs and BSCs. Some CWPs are more important than others due to their location and connectivity. The two bridges are important since they carry the CWPs and EPTLs across the river in the virtual community's top left corner.

The vulnerability and recoverability of highly-ranked components are estimated by combining fragility and restoration curves from HAZUS (FEMA (2012)) with ground motion models. However, EPTLs are assumed not to be damaged by the considered earthquake. Details of component models used to calibrate their probability distributions are given in (Blagojević et al. (2022)).

The final results of the iterative heuristic upper and lower bound search in assessing the communication system's resilience goal are presented in Figure 4. The upper and lower bound probability distribution converged once the probability distribution of the initial damage level and repair rate of 45 highly ranked components were calibrated. All PWFs and almost all PWPs were identified as irrelevant for assessing the resilience of the communication system. This is reasonable since components of the communication system, the BTSs and BSCs, do not require potable water. However, a couple of PWPs did end up in the 45 important components set. The most likely reason for this is the numerical calculation of Sobol' indices using Monte Carlo simulation: a higher number of Monte Carlo simulations would increase the accuracy of Sobol' index values, most likely reducing the rank of PWPs. The BSUs were also irrelevant as their communication demand is assumed to change only in the first 10 days following the disaster. In most scenarios, the communication system's functionality was restored after this time. Thus this change in the communication demand did not significantly affect the time to recover functionality. Parts of the CWP network were also not im-

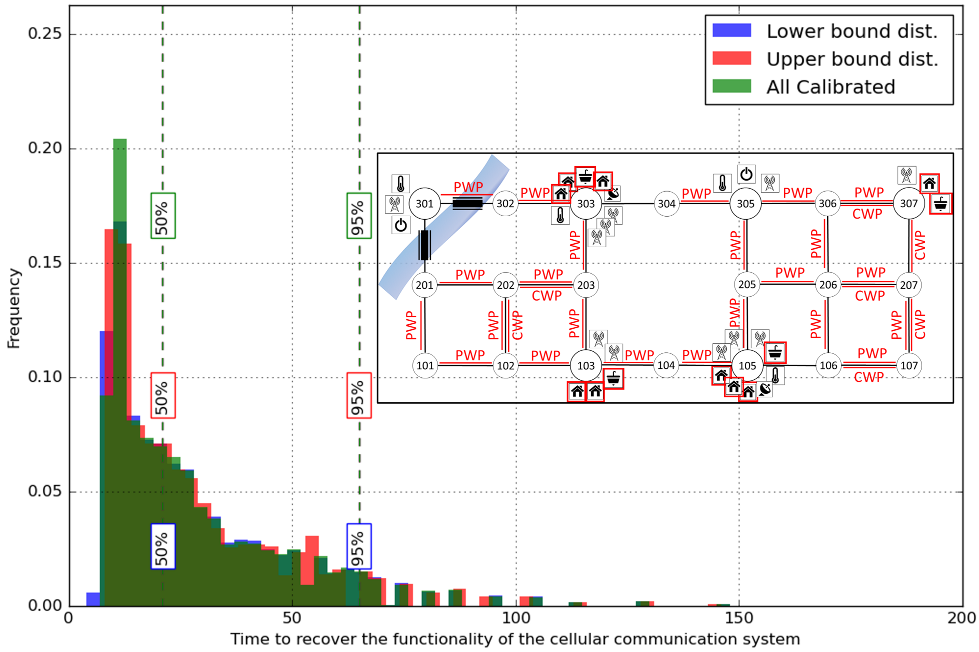

Figure 4: Probability distributions of the time that the cellular communication system needs to meet 90% of community demand when 45 out of the 88 community components are calibrated. The 43 components that are identified as irrelevant are labelled red in the virtual community layout in the upper right corner.

portant since they were not used to transfer cooling water to users whose operations were important for recovering the functionality of the communication system. Thus, the proposed method identified 43 components as irrelevant, preventing unnecessary data collection and modeling efforts related to these components. Furthermore, following the results of initial component ranking, it is expected that resilience-improving actions aimed at CWFs, BSCs and EPPs (e.g., increasing their redundancy or recoverability) would effectively increase communication system's resilience.

The upper and lower bound probability distribution of the resilience metric are compared with the probability distribution obtained once all components are calibrated (i.e., All Calibrated in Figure 4). The three distributions are almost identical, proving that the iterative heuristic search converged correctly. The median time to recover the functionality of the cellular communication system is estimated to be 21 days, while the 95% quantile is 65 days.

5. CONCLUSION

Assessing resilience of complex systems with numerous interacting components requires significant modeling and data collection efforts. This paper presents a method for ranking components based on their importance for system resilience when minimal information on components' vulnerability and recoverability is available. The method then continues with an iterative heuristic upper and lower bound search that identifies components important for assessing system's resilience and prevents unnecessary data collection and modeling efforts for components that are identified as irrelevant. Resilience-improving actions can then be informed using the proposed method by focusing on important components and avoiding investments in components identified as irrelevant. The iRe-CoDeS framework is used to assess system resilience in terms of the time needed to restore system's functionality, where the functionality is measured as the percent of met user demand. The iRe-CoDeS framework captures dynamic component interdependencies by simulating the flow of resources among components and conditioning their operation on their demand fulfillment. The method is illustrated by assessing component importance for the resilience of a cellular communication system of a virtual community. Apart from the communication system, the operations of the virtual community are supported by the electric power and water supply system. The three infrastructure systems are interdependent, as their components require resources from other systems to operate. The initial component ranking based on Sobol' sensitivity analysis assuming minimal information on all components, identified the suppliers of cooling water and electric power, as well as base station controllers, as the components most important for restoring the functionality of the cellular communication system. Thus, component interdependencies were recognized by the proposed method. The iterative heuristic upper and lower bound search then showed that around half of community components considered in the resilience analysis are not important for assessing the resilience of the cellular communication system, thus preventing significant data collection and modeling efforts. Additionally, it is expected that resilience-improving actions that focus on the components identified as important will effectively increase system's resilience. Apart from identifying irrelevant components and guiding resilience-improving actions, the proposed method can also be used to estimate the bounds of probabilistic resilience metrics in cases when the data on certain components is unavailable due to security or privacy concerns.

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