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Impacts of varying network parameters on the vulnerability and resilience of interdependent critical infrastructure systems

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ABSTRACT
Critical infrastructure systems are complex and subjected to evolving risks and hazards, which makes anticipating their behavior difficult. To prioritize among actions that increase system resilience, it is critical to understand their impacts on parameters defining a network and on anticipated network performance. In this paper, the authors investigate the impacts of variations in three parameters on network vulnerability: component vulnerabilities, service interdependency redundancies, and system link configuration. The advances of this work compared to prior studies include: 1) The impacts of parameters varied across a range of values at the component level are evaluated considering component functionality and connectivity; 2) quantitative analyses of component performance as parameters vary are investigated based on system redundancies; and 3) probabilistic system interdependencies are analyzed through a Bayesian network that considers component pathways. Results quantify effects of changes in component vulnerabilities and dependencies and are used to discuss impacts on system resilience.

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1. Introduction

Critical infrastructure systems (CIS) are the lifelines of modern society, providing services and resources such as transportation, communication, water, and power to communities for daily functions. Protecting these systems and increasing their resilience are necessary to ensure public health and safety, societal efficiency, and economic growth. As the built and natural environments change, including through continued development and rising threats of natural disasters and climate change, it becomes increasingly important to understand the performance of CIS under a range of network conditions and variations. Exploring the impacts of these conditions on system vulnerability enables the evaluation and prioritization of various actions that owners and operators can take to repair, retrofit, or build out new parts of an infrastructure network to increase performance, and ultimately resilience.

In this work, the authors investigate the effects of varying three network parameters on CIS performance: component vulnerabilities (i.e., conditional probabilities of component failure given hazard occurrence), service interdependency redundancies, and system link configuration. The focus of this work is on quantifying changes in performance across an entire network as changes are made to its component-level parameters, rather than on quantifying baseline risks from a specific hazard. The authors choose these three parameters for evaluation because they correspond to potential actions CIS owners and operators can make to an infrastructure network, accounting for the effects from both hazard events and decisions made to alter the system. For instance, component vulnerability can increase after a hazard event, leading to retrofit decisions, or a network's layout can be altered if decisions are made to build out new parts of the system.

The authors use component marginal probabilities of failure and relative changes in those probabilities across the entire network as parameters change to quantify component performance. These component marginal probabilities of failure are discussed as an indication of overall system performance through network connectivity and supply and path redundancies. Network-level effects are quantified by computing populations impacted by component outages. To obtain each of these probabilistic outcomes, the authors use a network modeling framework that includes dependencies between components within a CIS and interdependencies across multiple CIS. Specifically, a series of inferences is conducted over a Bayesian network model of interdependent CIS (Johansen & Tien, 2018) with changes in each network parameter.

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The water distribution system in Atlanta, Georgia, with its interdependencies between power and transportation networks is used as an example application to draw general conclusions. The results quantify the effects of changes in component vulnerabilities, redundancies, and dependencies and are used to discuss impacts on the overall system's performance and resilience. As the network parameters are varied over a range of possible values, the results and trends observed are applicable to general interdependent CIS. This is confirmed by running a set of inferences over a different example network – the water distribution system in Shelby County, Tennessee – for varied component vulnerabilities.

The novelty of this work is in the quantification of the impacts of variations in different component- and network-level parameters on system vulnerability, including component functionality, network layout and connectivity, and system-level cascading effects. The focus on the parameters of component probabilities of failure, supply redundancies, and system link configuration is relevant in decision-making for a real-world CIS. Outcomes from the analyses are used to compare system states under changing conditions, such as damages occurring during a disaster event or preventive measures taken to increase resilience.

In addition to evaluating components based on their individual vulnerabilities to different hazards such as storms and age, it is important to evaluate them based on their redundancies and dependencies within the system. The holistic views of system behavior and performance provided in this study through component vulnerabilities allow infrastructure owners and municipalities to make decisions with consideration to overall system resilience and the system's impact on the communities and populations it serves. The results in this study also provide perspective on each component's role in the system, which is essential to understand to improve all facets of system resilience, from vulnerability and absorptive capacity to recovery.

Compared to previous works, the Bayesian network-based analyses performed in this study consider the effects of probabilistic dependencies between multiple infrastructure systems and between the multiple paths from supplies to different distribution components within a single network. In addition, performance is evaluated at the individual distribution component level with results used to draw conclusions about impacts across the network, enabling a granular assessment and comparison of parameter variation impacts based on component redundancies and network connectivity.

The remainder of this paper is organized as follows: First, the authors discuss CIS parameters and the need to better understand CIS performance with uncertain parameters and various actions and decisions to increase resilience. Next, the authors describe the Bayesian network modeling approach used to conduct inferences and compute component states in this study. The authors describe the network used for analysis and corresponding model input parameters. The three network parameters varied for this investigation are then defined, as well as the component characteristics used to evaluate the impacts of varying those parameters on network performance. Next, the changes are implemented for each parameter, and results are given of their corresponding impacts on both component and system vulnerabilities. The analysis methodology, findings, and detailed discussion about the resulting comparative impacts of varying parameter changes are provided. The authors then apply the methodology of evaluation to a second network to further support their findings and discuss generalizability and implications of the results for improving CIS resilience. Finally, the authors summarize their findings and contributions in the conclusion section.

2. Background and related work

2.1. Related work in critical infrastructure system resilience assessments

Increasing CIS resilience is a global challenge (Amin, 2002), with infrastructure performance recognized as a critical contributor to overall community resilience (Johansen et al., 2016). There are many facets of CIS resilience, especially when considering interdependencies across systems. These facets include but are not limited to infrastructure component- or system-level vulnerability, adaptive capacity, and ability to recover after a crisis. Increasing overall CIS resilience requires consideration of combinations of these different dimensions of resilience, as well as consideration of existing resilience and decision-making policies (Labaka et al., 2016). In this paper, the authors focus specifically on evaluating CIS vulnerabilities at the component level to draw conclusions about overall system vulnerability and prioritization in decision-making for increasing CIS preparedness and resilience.

Because increasing CIS resilience covers a broad scope, evaluating CIS resilience and the impacts of actions and decisions that affect these systems is equally challenging and complex. There is no universally accepted method for the resilience assessment of infrastructure systems. Instead, a large body of work exists in this area with models for different hazard scenarios, granularities (i.e., component- versus system-levels), types of infrastructure systems, and geographic environments (Liu & Song, 2020). Several of these studies consider interdependencies between CIS in the assessment. For example, Poljansek et al. (2012) investigate the role of system dependencies and interdependencies on infrastructure risk and resilience under a specific hazard type (e.g., seismic risk assessments). Guidotti et al. (2016) also model CIS resilience by including the role of system dependencies but do not provide analysis results that show how resilience is impacted across a range of system inputs. Other studies, such as Attoh-Okine et al. (2009), evaluate resilience for a specific type of infrastructure or a specific system or network. Another type of resilience analysis focuses on a specific subset or aspect of resilience, such as Pant et al. (2014), which evaluates the economic resilience of interdependent infrastructures, and Danziger and Barabási (2022), which provides resilience assessments of recovery coupling between interdependent networks.

Compared to these studies, this work focuses on quantifying and evaluating the impacts of varying network parameters on CIS performance, rather than providing a new methodology or framework for modeling interdependent networks or assessing resilience under specific conditions. To increase CIS resilience, municipalities and policymakers may make decisions and take actions on how and where to rebuild after a disaster event and on how to adapt for future events (Albright & Crow, 2021). These decisions and policies can alter community planning and operations or physical aspects of critical infrastructures, as in retrofits and new construction, and often decisions must be made under uncertainties in infrastructure system parameters and conditions. It is important to understand how the consequences of decisions and policies will be impacted by such uncertainties. Casal-Campus et al. (2018) use a regret-based approach to assess strategies for improving capacities of an urban drainage system, with assessments focused on robustness for sustainability, reliability, and resilience. Zhang and Alipour (2020) analyze the effects of pre- and post-event maintenance actions on a bridge network to find the optimal social-economic outcome for different construction and disruption scenarios, considering costs.

In this paper, the authors consider uncertainties in CIS parameters through a probabilistic Bayesian network modeling framework, described in more detail later in this paper. Compared to prior work, the analysis in this study is not focused on optimizing system performance or comparing specific resilience actions and strategies, but rather on evaluating performance across a range of conditions and parameter values, particularly at the component level with impacts at both component and system levels.

The analysis in this study is also not focused on a specific infrastructure type. There are several models available that do not focus on a specific infrastructure or hazard type, including Sharma and Gardoni (2022), Blagojević et al. (2022), and Liu et al. (2021). As in Applegate and Tien (2019), these models are able to conduct resilience assessments of interdependent CIS by defining component-level parameters and network connectivity. The authors select the Bayesian network model by Applegate and Tien (2019) because it also does not focus on a single infrastructure or hazard, it specifically outputs marginal probabilities of failure, it takes in inputs related to network supply redundancies and conditional probabilities of failure that do not need to be specifically calibrated, and it updates component-level outcomes considering explicit probabilistic relationships among the elements of a CIS.

2.1. Related work in evaluating critical infrastructure network parameters

CIS have a wide range of network topologies and component parameters depending on the types of infrastructure, surrounding environments, and communities they serve. Both system- and component-level network parameters affect CIS behaviors and resulting resilience. System-level parameters including connectivity between components and system redundancies, while component-level parameters include component capacities and probabilities of failure. In this study, both component- and system-level parameters are assessed. Previous studies that investigate the relationship between network parameters and resilience include Zhang et al. (2015), which assesses the effect of system topology measures on the resilience of transportation networks. The results from that study provide insights on the types of topologies that may be more resilient. Genge et al. (2012) focuses on communication and control logic implementation parameters that influence the outcome of attacks on industrial control systems. The study connects communication and control systems to look at the impact of network parameters on the effectiveness of potential cyberattacks. Ouyang et al. (2012) quantify the impacts of improvements at different stages of resilience, investigating the effect of varying the order of resilience actions and strategies. Panteli and Pierluigi (2017) evaluate the resilience of an electrical power system to extreme weather events, including analysis of impacts of varying both component- and system-level parameters, such as by including more robust lines and towers or adding parallel lines (i.e., changing network configuration and component capacities). Other studies that evaluate the importance of component-level parameters including Barker et al. (2013), Espinoza et al. (2020), Xu et al. (2020), and Barker et al. (2013) present component importance measures that describe the adverse and positive impacts of component performance on overall system resilience. Espinoza et al. (2020) and Xu et al. (2020) similarly present component important measures for interdependent networks, ultimately ranking components by criticality in an overall CIS.

In contrast, the work presented in this study evaluates the impact of component-level parameters on overall system performance through component vulnerabilities, network redundancies, and supply to distribution path dependencies. In this study, the authors look at CIS broadly and evaluate the impacts of changes in varying network parameters on the performance of CIS components across a network. The work focuses on CIS performance across a range of parameter values through analyses that are applicable to general infrastructure and hazard types, i.e., not focused on a specific infrastructure type or hazard.

This study also takes a comprehensive approach to CIS analysis, assessing quantified results at the component level and their impacts across all components in the system in order to discuss impacts on resilience. It includes uncertainties and system dependencies and interdependencies in the analysis, rather than presenting new component performance measures. The resulting probabilistic component outcomes in this study are evaluated and compared based on their component characteristics, including functionality, connectivity within the overall network, and the various redundancies available to them. The results enable future performance-based designs and decisions that more effectively prioritize system components for repair, maintenance, construction, and other actions based on anticipated outcomes in increasing infrastructure resilience.

2.2. Bayesian network modeling framework used for analysis

Among the quantified measures assessing network performance outcomes under varying scenarios in this study are marginal probabilities of failure, providing quantitative indicators at the component level, across a CIS. Component marginal probabilities of failure in this study are computed by conducting inferences over a Bayesian network (BN)-based modeling framework for interdependent CIS. The framework was developed by Applegate and Tien (2019) and is used as a tool for analysis for the results and findings presented. Benefits of this framework compared to other Bayesian network models include the ability to model a main network with interdependencies within that network and across other connected networks, the facilitation of many successive and efficient inferences to obtain probabilistic resilience assessments for interdependent CIS and the consideration of supply to non-supply component pathways in the analyses (Sun et al., 2022; Yu & Baroud, 2020). The framework is summarized below and will be referred to as the CIS BN for the remainder of this manuscript.

A BN is an acyclic directed graph in which nodes represent random variables and edges represent the probabilistic dependencies between nodes (Jensen & Nielsen, 2007). The nodes and edges of a BN are defined by conditional probability distributions, which provide node state probabilities conditioned on the states of their parents. The dependencies between discrete state nodes and corresponding conditional probability distributions are represented by conditional probability tables (CPTs). In the CIS BN, nodes are the components of the CIS itself as well as the components characterizing their interdependencies, and edges are probabilistic dependencies between components within and across systems. Each type of node in the CIS BN is described below. Examples of the CPTs used in this study and descriptions of how they are varied for the parameters investigated in this work are provided in the next two sections.

A CIS component in the CIS BN is defined as any part of an infrastructure system or its interdependent systems to be included in the performance analysis of that particular system. For instance, a component can be a pump station in a water network or a pipe used for distribution. In this case, nodes can be in survived or failed states, and the CPT of each component contains the probabilities of failure of the component given the states of its parents or nodes on which it depends. The specific parents of a component in the CIS BN depend on how the network is defined. The authors provide a description of the networks and resulting model structure used in this study in the subsequent sections.

The CIS BN used in this study distinguishes the functionality of two types of components in the main network to model the dependencies within it: supply components (e.g., water treatment facilities) and distribution components (e.g., intermediate pump stations or pipelines). Supplies provide the infrastructure resource to distribution components through minimum link sets (MLSs), which are minimum sets of components that must function in order to link a supply to a distribution component. An MLS will disconnect if any link is removed or not functioning. MLS nodes are defined by paths from a supply to distribution component in the main network.

In addition to dependencies defined within a single network, the CIS BN also includes three types of interdependencies in its probabilistic analyses. These are geographic, service provision, and access for repair interdependencies. Each interdependency type is represented by additional nodes in the CIS BN with user-specified CPTs. Geographic interdependencies occur when components are collocated and subject to the same hazard risks. Inputs to represent these interdependencies are component probabilities of failure conditioned on a hazard node state (e.g., occurred or not occurred) and probabilities of hazard node state within that geographic zone. Geographic interdependency (i.e., hazard) nodes account for potential correlations between component vulnerabilities due to the close proximity of components within a geographic area to each other. Each geographic interdependency node is a parent node for any component impacted at that particular hazard level. Component conditional probabilities of failure should correspond to the hazard represented by its geographic interdependency node parent.

Service provision interdependencies occur when a CIS component depends on the outputs of a component from another system to operate. Inputs are probabilities of failure for each service provision component, e.g., a power supply needed for a component in the main network to function. Service provision components can also have vulnerabilities related to the geographic interdependency nodes for hazard occurrence, which require input probabilities of failure conditioned on their parent geographic interdependency, or hazard, nodes.

Access for repair interdependencies occurs when a damaged component depends on access from another component for repair operations. Access for repair interdependencies tracks component states over time and occurs in post-disaster response and recovery scenarios when component damage or failure has been identified. Because the need to provide access for repair only occurs under component failure scenarios, the states of the components are tracked over time with the access for repair interdependency relationship becoming relevant when the previous state of the component indicates repair is needed. The inclusion of access for repair interdependencies in the CIS BN allows for the analysis of recovery efforts and downtimes (Johansen & Tien, 2018) and is modeled in the CIS BN with access for repair nodes and previous state nodes for the dependent component.

With the node connectivity and dependency relationships in the CIS BN, any changes to one component in the network will propagate through to update the states of all other nodes in the network. This enables the CIS BN to capture cascading effects, where failures in one part of a network cascade to failures in other parts of the network or failure of a component in another system cascades to failures of components in the main network under consideration. Because of the nature of complex and interdependent CIS, it is possible for loops in the CIS BN to occur. A loop in the network can occur when a distribution component is part of multiple MLS nodes, i.e., multiple supply to distribution component paths. These are accounted for in the CIS BN modeling framework with a cyclic dependency removal process as described in Applegate and Tien (2019) to ensure that the final Bayesian network is a directed acyclic graph. Other algorithms for constructing a model using the CIS BN include a network compression algorithm for large networks.

All conditional probability distributions used in this study are assigned values for general infrastructure and hazard types. To compute input conditional probabilities of failure calibrated for a specific infrastructure component and hazard, a probabilistic damage analysis would need to be conducted, which is not within the scope of this study. With the nodes defined, exact inferences can be conducted over the full model using the algorithms as described in Applegate and Tien (2019). Outputs of the model are updated marginal probabilities of all node states. The CIS BN modeling approach is suitable for the analyses conducted in this study to evaluate the impacts of varying network parameters on CIS performance because many successive inferences can be conducted over a range of parameters and parameter values. Furthermore, changes to network parameters can be made efficiently, such as updating probabilistic dependencies between components through the CPTs, adding redundancies as new nodes in the CIS BN, or altering network layout through dependency relationships in the CIS BN. Finally, the ability to obtain component-specific outcomes enables the assessment and discussion of network performance from the constituent component level that this study seeks. To assess the impacts of varying network parameters on CIS outcomes in this study, inferences are run for each value or change in the range of parameter values of interest. The parameter variations are described in more detail in the following sections.

The CIS BN can become very complex as the number of nodes in the main CIS of interest and its interdependencies increase. Figure 1 shows an example of a single branch of an overall network modeled using the CIS BN framework. The schematic shows the connection

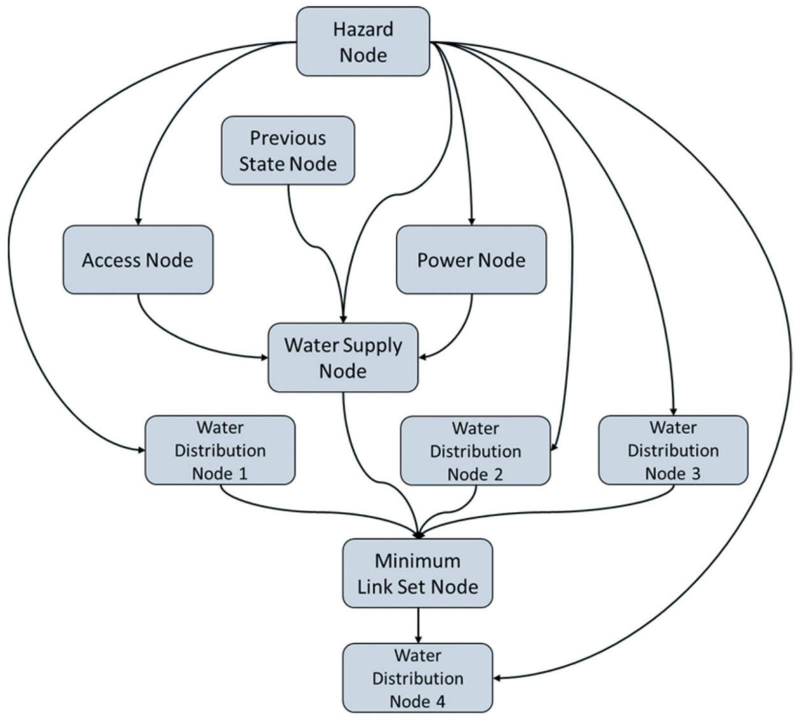

Figure 1. Simplified schematic of a branch of the CIS BN used for analysis.

between a supply in the main network, i.e., Water Supply Node, to a distribution component, i.e., Water Distribution Node 4. Hazard Node represents the geographic interdependency impacting this branch of the main network, and access for repair (via the Access Node and Previous State Node) and service (via the Power Node) interdependencies are shown impacting the Water Supply Node. Other Water Distribution Nodes are parents of the Minimum Link Set Node. It is possible that the same Water Supply Node will be the source for the other water distribution components shown, but this schematic is provided to show potential dependencies from one supply in the main network to one distribution component. Algorithms for inference as well as for network compression and to avoid defining cycles in the CIS BN are implemented as provided in Applegate and Tien (2019).

3. Example Network for analysis – Atlanta water distribution system

To evaluate the impact of network parameter variation on overall system performance and vulnerability, the authors use Atlanta's water distribution network as an example from which to draw general conclusions. The results are generalizable because the CIS BN is consistent in parent–child relationships, regardless of the configuration of the CIS being analyzed. For instance, different system layouts simply have a different number of nodes in the Bayesian network. Additional analysis of a different network to further examine generalizability of findings is provided in a later section.

A simplified graph of Atlanta's water distribution system is presented in Figure 2. Seven major supplies are shown, representing water treatment facilities throughout the metropolitan area. The remaining 105 components are designated as distribution components in the CIS BN. Exact coordinates for component locations are not shown in Figures 2 and 3 to uphold data privacy and security agreements.

Each water supply node (i.e., main network supply) is given one unique service (e.g., power supply) parent node and one unique access for repair (e.g., a roadway) parent node, representing service provision and access for repair interdependencies, respectively. While it is possible to have one service or access component that is a parent to multiple components in a CIS, the authors choose this method of modeling service and access components to reflect typical infrastructure network layouts, uniformly model supplies in the network, and focus results on impacts from the previously defined parameter variations. The authors define all nodes in the network with two states. For instance, a component node state can either be failed or survived and a hazard node can either be occurred or not occurred. Tables 1–3 show the CPTs for sample power supply, access for repair, and water supply nodes in the network, respectively. In this study, the probabilities of

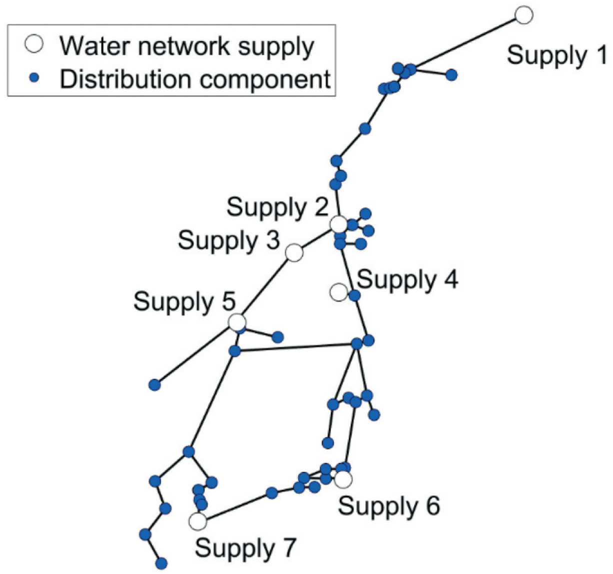

Figure 2. Schematic of Atlanta's water distribution system comprising supply and distribution components.

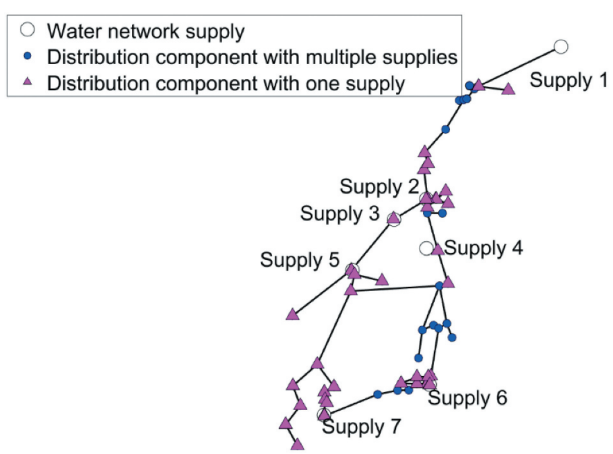

Figure 3. Distribution of one-supply and multi-supply components in the Atlanta water distribution network.

Table 1. Sample conditional probability table for a power supply node.

Power supply state	Hazard occurs	Hazard does not occur
Fails	0.01	0.0001
Survives	0.99	0.9999

failure of power supply and access for repair nodes each vary depending on hazard occurrence. The hazard nodes are defined later in this section. Tables 1–3 show sample values for all conditional probabilities, e.g., 1% conditional probability of failure for a power supply node when a hazard occurs. These values are varied later in this study to investigate the impact of varying component-level vulnerabilities on system performance.

Table 2. Sample conditional probability table for an access for repair node.

Access for repair component state	Hazard occurs	Hazard does not occur
Fails	0.01	0.0001
Survives	0.99	0.9999

Table 3. Sample conditional probability table for a water supply node.

	Hazard occurs		Hazard does not occur	
Water supply state	Power supply fails	Power supply survives	Power supply fails	Power supply Survives
Fails	1.0	0.01	1.0	0.0001
Survives	0	0.99	0	0.9999

Water supply nodes depend on power supply, access for repair, and previous state nodes, as seen in Figure 1, as well as hazard nodes. With more parent nodes, the CPT for a node grows exponentially. For the values of the CPT ordered as in Tables 1–3, the number of columns doubles for each new parent node for binary node states, and thus the CPT for a water node will have 16 columns. Table 3 shows the CPT for a water supply node with only hazard and power supply parents to limit the table size. The authors choose to show a water supply's CPT with these parents because hazard nodes and power supplies are discussed in more detail throughout this paper as part of the analyses.

To identify MLS nodes for the CIS BN, the authors conduct a depth-first search from each supply component to every distribution component in the main network. Each supply-to-distribution path found represents a new MLS node, and components in the path are parents to that MLS node. MLS nodes then become parents of the last distribution component in the MLS path. The number of MLS parents and the number of reachable supplies to each distribution component are recorded for each new network analysis. The authors choose a depth-first search to define MLS nodes as an efficient algorithm to identify supply-to-distribution pathways in the example network. These user-defined inputs to the CIS BN can be changed based on known pathways in a CIS. A simple example MLS node CPT is shown in Table 4. The example MLS has two parents: a water supply node, i.e., the source for the path, and an intermediary distribution component node. The MLS node can only survive if both parents survive.

To define hazard nodes, i.e., geographic interdependencies, the authors use a k-nearest neighbor search to group components into 11 geographic areas. The states of the components within each group are then dependent on each other through dependence on the state of

Table 4. Example conditional probability table for an MLS node.

	Water supply fails		Water supply survives	
MLS node state	Distribution component fails	Distribution component survives	Distribution component fails	Distribution component survives
Fails	1.0	1.0	1.0	0
Survives	0	0	0	1.0

Table 5. Discrete marginal distribution table for a hazard node in the network.

Hazard state	Probability of hazard state
Occurred	0.01
Not occurred	0.99

a common hazard parent node. The k-nearest neighbor approach is selected as an efficient method for grouping nodes into the discrete geographic areas representing varying hazard probabilities.

The authors define general initial component probabilities of failure conditioned on hazard occurrence for the network as 1% for all supply and distribution components and interdependencies, i.e., hazard occurrence probabilities and conditional probabilities of failure for power and access nodes. These are not related to any specific hazard or type of component failure analysis. The purpose of this study is to evaluate the impacts of parameter variation on component vulnerability and overall resilience, including relative comparisons of impacts across components, rather than to evaluate the impacts of a specific hazard or mode of failure. Conditional probabilities of failure calibrated for a specific hazard would generate results more representative of a specific event, but the initial, uniform component probabilities of failure provide a baseline for the analysis and comparison that is applicable to general infrastructure and hazard types. Table 5 shows the discrete marginal distribution table for a hazard node in the CIS BN. Table 6 shows the CPT for a sample distribution component in the network with only one MLS parent. A distribution component survives only if at least one of its MLS parents survives. The makeup of this CPT is varied later in this study to investigate the impact of varying system link configuration on system performance.

Table 6. Sample conditional probability table for a distribution component with one MLS parent.

	Hazard occurs		Hazard does not occur	
Water distribution component state	MLS parent fails	MLS parent survives	MLS parent fails	MLS parent survives
Fails	1.0	0.01	1.0	0.0001
Survives	0	0.99	0	0.9999

4. Network Parameters and Variations

The authors select three parameters to vary across the Atlanta water distribution network and conduct inferences for each variation to obtain resulting component and system impacts. The three parameters are component-level vulnerability (i.e., conditional probabilities of failure given hazard occurrence), service interdependency redundancies (i.e., component backups across infrastructure types), and system link configuration (i.e., possibilities of new builds). Each of these parameter variations corresponds to a different input of the CIS BN, including the defined conditional probability tables (CPTs), and edges in the network model.

Component-level vulnerability is defined in the CIS BN by component conditional probabilities of failure given hazard occurrence and is varied in the CIS BN through the defined CPTs. Component vulnerability is conditioned on a general hazard in this analysis. The probability of hazard occurrence in the CIS BN is set as 1% for a general hazard (see, Table 5) rather than based on a single event or type of hazard and is left constant in the model for consistency in the analysis results. Component conditional probabilities of failure are varied from 0.0001 to 0.75, i.e., 0.01% to 75%. For power supply nodes, this is done by changing the probability of failure conditioned on hazard occurrence as shown in Table 1.The authors choose this range of vulnerabilities to hazards to represent a range of components from those that have been very recently retrofitted and thus have low conditional probabilities of failure, to those that are significantly degraded after an adverse hazard event has occurred and have not been subsequently repaired or upgraded and thus have higher conditional probabilities of failure to the next hazard event.

To vary service interdependency redundancies, the authors introduce additional service nodes to the network at each main water supply. This parameter variation represents, for example, additional power backups at the water supplies. To evaluate the impacts of this action across the full network, the main water supplies have a uniform number of service nodes. That is, each water supply has the same number of unique service or power nodes for each analysis. Lastly, to change system link configuration in the CIS BN, new edges (i.e., dependencies) are introduced into the main network. This variation represents potential new builds in the network and is implemented by adding new parents to the MLS nodes (see, Table 4). The authors identify each new parent–child relationship for the CIS BN by conducting a new depth-first search over the main network with the new system configuration.

To obtain the resulting component-level impacts of these variations, the authors run inferences after each parameter variation and record the new marginal probabilities of failure for all components. An inference over a BN is conducted by providing input evidence (e.g., a known infrastructure component node state of failed or survived or state of occurred or not occurred for hazard nodes) into the model and computing resulting marginal probabilities based on parent–child dependency relationships. Impacts are quantified based on relative changes in component vulnerability, and results are compared based on different network characteristics of system dependencies and system redundancies to obtain a holistic view of system performance. Together, these outcomes are used to quantify the impacts of parameter variations on component performance and evaluate overall system resilience.

Quantified results are the marginal component probabilities of failure over the full CIS BN computed under each parameter variation scenario. Other outcomes include relative changes in results and summary statistics such as the median values of these marginal probabilities of failure over all variations. These outcomes differ from the initial input component conditional probabilities of failure that are varied as they are the resulting probabilities of failure computed from the connections, i.e., dependencies, in the system.

Outcomes are also compared by component attributes to investigate the characteristics of components with greater or lesser impacts on performance based on the network parameter variations to draw conclusions about overall system resilience through network connectivity and redundancies. These attributes include system dependencies and system redundancies. System dependencies are described by the number of parents in an MLS component and define the number of dependencies within and across systems that are required for a component to function, which is directly related to network connectivity in the CIS BN. System redundancies refer to additional supply component nodes (e.g., added service interdependency components), as well as additional pathways from a supply component to any other dependent component in the system, i.e., a distribution component. For instance, by introducing new links into the network, a new MLS component may be added, providing a new redundancy (i.e., path) within the system. The following sections provide the results and findings from running these analyses for the variations of each of the network parameters investigated.

5. Component conditional probabilities of failure

To investigate the impact of component maintenance and retrofit activities, the authors vary the component conditional probabilities of failure for supplies in the water network and service components (e.g., power supply) at each water supply. The authors choose to vary conditional probabilities of failure for these components because distribution components in the network all depend on at least one water supply and each water supply depends on a service component or power supply. In addition, the higher value assets of water and power supplies are more likely to be the focus of improvement for infrastructure owners who have limited funds to invest in retrofit activities for their systems. The inference results of variations in water and power supplies are similar, so the authors only show the results for varying power supply conditional probabilities in this section. For each inference in these analyses, no evidence is input, that is, no components in the network are observed as either failed or survived and no hazard is observed to have occurred or not occurred. Therefore, the resulting marginal probabilities of failure are all low – less than 1%, even as power component conditional probabilities of failure reach 75%.

The authors also conduct analyses varying the probabilities of failure for access components, which model access for repair interdependencies and is related to network recovery. While these nodes impact results because inferences are conducted with the inclusion of all nodes in the CIS BN, the results from these variations were negligible in comparison to the results from varying power supply conditional probabilities of failure. This is because no evidence is input for the inferences in this section; access components are most impactful during analyses when at least one component has failed.

In assessing the results across components of different characteristics, the resulting marginal probabilities of failure across all components show notable differences between components with one reachable supply versus components that have multiple reachable supplies. Components with multiple reachable supplies have almost no change in marginal probabilities across inferences as conditional failure probabilities for those supplies are varied. Figure 3 shows the distribution of one-supply and multi-supply components across the Atlanta network with the number of reachable supplies for a component determined by MLS nodes. The figure shows the same 112 components in the network as in Figure 2, with supplies shown in white and one-supply components (magenta) distinguished from multi-supply components (blue). Components can either be one- or multi-supply components, not both. Some components in the network are very close together at this scale; therefore, several single- and multi-supply components appear to be overlapping.

Showing separate boxplots for the results for one-supply compared to multi-supply components, Figure 4 shows the resulting marginal probabilities of failure distribution components as power supply component conditional probabilities of failure are varied. The authors also compute relative changes in marginal failure probabilities compared to a baseline of results from power supply conditional failure probabilities input at 1%. This reference was chosen to quantify the changes in results for individual components as power supply CPT inputs vary. This analysis allows for an evaluation of how components can be impacted by changes in input parameters over time as supply components degrade or are upgraded. The results are not affected by the baseline chosen to calculate relative changes. To facilitate legibility by scaling and comparisons by relative changes in component vulnerability with the parameter variations, the boxplots in Figures 5 and 6 show the relative changes in marginal probabilities of failure from the marginal probabilities computed when power component conditional probabilities are input as 1% for updated power failure probabilities less than (Figure 5) and greater than (Figure 6) 1%, respectively. Relative changes over 1 indicate a more than 100% increase from the baseline. In Figure 5, the dotted line is at zero. Since the authors have selected a baseline of results of conditional failure probabilities input at 1%, the vertical axis in Figure 5 goes below zero (i.e., as input conditional probabilities of failure decrease from the baseline, so do relative changes in the resulting marginal probabilities of failure). This indicates decreasing input conditional probabilities of failure that correspond with lower initial component vulnerabilities within the system.

Overall, the outcomes in Figures 4–6 show that the multi-supply components have very little change as the power supply components increase in vulnerability, for the entire range of input probabilities given (i.e., 0.01% to 75%), while the one-supply components have increasing marginal probabilities of failure as the power supply components increase in vulnerability. That is, components with only one supply are most sensitive to variations in the input conditional probabilities of failure in the system and that multi-supply components experience almost no changes due to those variations, regardless of number of supplies. This outcome suggests that adding just one path redundancy to a different supply for a one-supply distribution component is enough to significantly decrease that distribution component's vulnerability within the network. The addition of links and therefore paths to reach supplies is discussed in subsequent sections.

In addition, from Figure 6, the variability in outcomes across distribution components as measured by relative changes in marginal failure probabilities with the change in power supply component vulnerability increases as the power supply component conditional probabilities of failure increase. This indicates that not only does system vulnerability increase with increased supply component conditional failure probabilities but so does variability in the anticipated component performance across the entire network.

To better understand the impact of these component-level conditional failure probability variations on the outcomes for one-supply distribution components and specifically the characteristics of components that

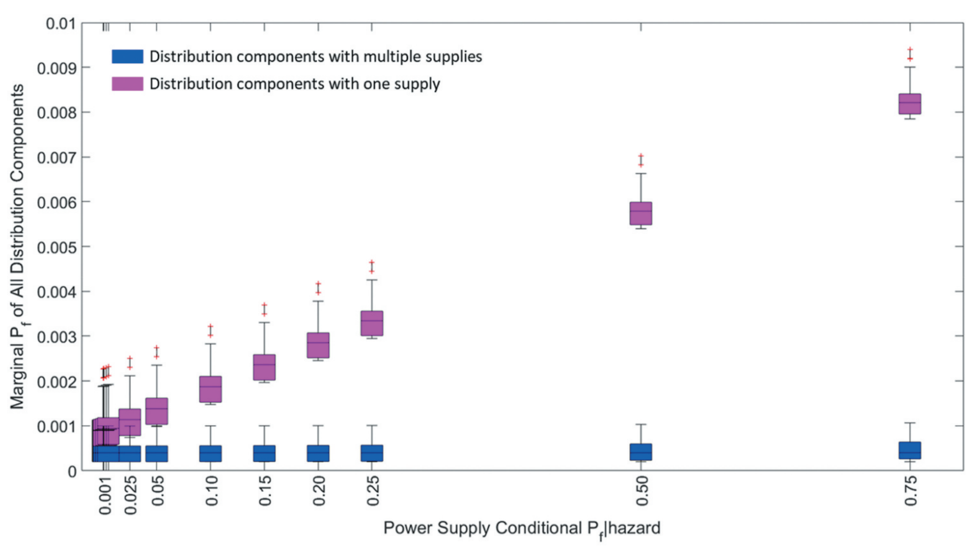

Figure 4. Marginal probabilities of failure for distribution components vs. power supply conditional probabilities of failure.

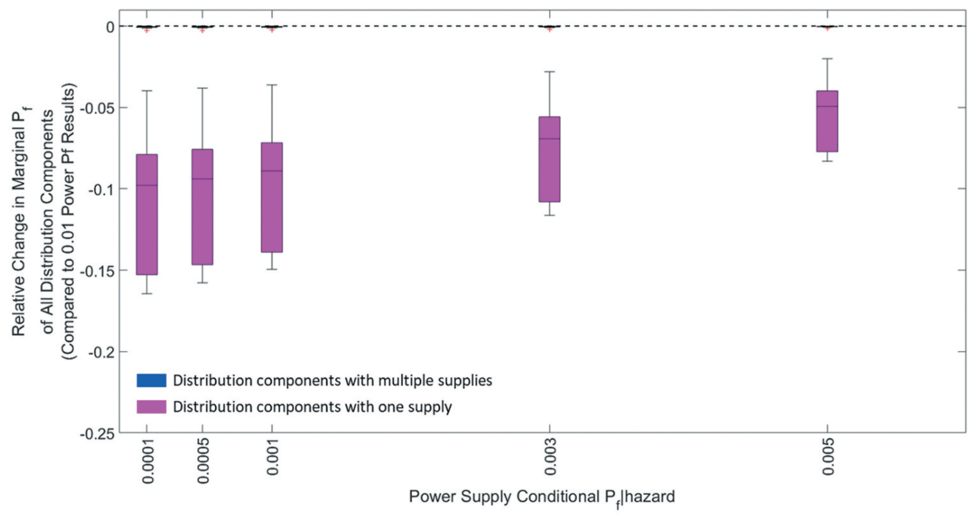

Figure 5. Relative changes in marginal probabilities from baseline results for power Pf values less than 1%.

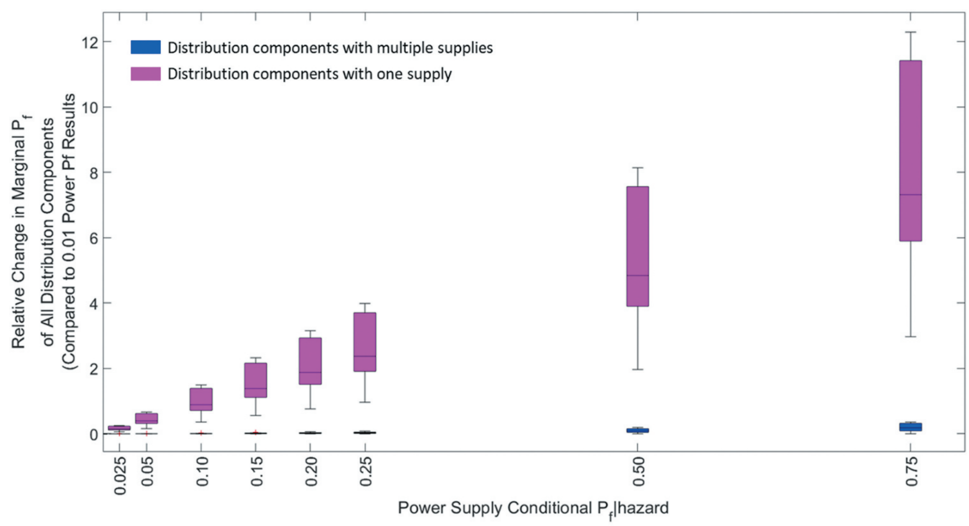

Figure 6. Relative changes in marginal probabilities from baseline results for power Pf values greater than 1%.

are affected differentially across the network under the same network parameter variation, the authors evaluate the inference results comparing distribution component outcomes by two different component characteristics. The characteristics are number of paths to a supply (i.e., number of MLS parent components in the CIS BN) and fewest number of dependencies to the component's supply (i.e., fewest number of constituent parents for an MLS parent).

The number of paths to a supply refers to the number of redundancies for the distribution component. A distribution component can have redundancies in both number of reachable supplies and number of paths to those reachable supplies. The one-supply components have no supply redundancies but can have path redundancies based on the network's link configuration if it has multiple paths to reach its single supply source. Both types of redundancies are described by MLS components, which are defined in this study by a depth-first search.

The fewest number of dependencies to a distribution component's supply indicates the fewest number of other components in the network required to survive in order for the current component to survive on resources from its single supply component source. For instance, a distribution component may rely on the survival of a full set of pipes and pump stations to reach its supply via that path. In the case of Atlanta's water distribution network model in these analyses, one-supply water distribution components with more dependencies to their single supply represent water components that are farther away from any supply in terms of physical distance, with more assets needing to function in between for functionality at the final distribution component. In the CIS BN, this is equal to the number of components in an MLS.

The boxplots in Figures 7 and 8 show the resulting marginal probabilities of failure and the relative changes in results from the baseline previously described, respectively, versus the input conditional probabilities of failure varied for all power supplies in the network. The color bars represent the number of paths to a supply. Figures 9 and 10 show the same results where the color bar represents the discrete fewest number of dependencies to a one-supply distribution component's supply. The boxplots are generated by grouping single-supply components by each characteristic: number of paths and fewest number of dependencies to the supply. Then, a boxplot of output marginal probabilities of failure is generated for each group, i.e., components with one, two, three, etc., paths to a supply to show results at each new input conditional probability of failure from 0.01% to 75%.

In Figures 7–10, inference results from all parameter variations are shown on each figure. At each new input conditional probability of failure (i.e., 0.01% to 75%) for power supply components, distribution components are grouped by number of paths to any supply or fewest

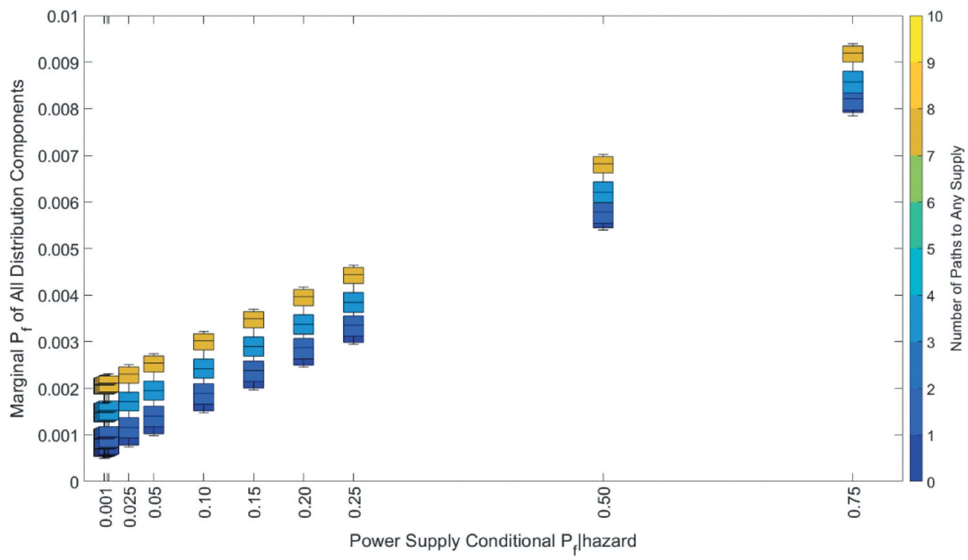

Figure 7. Results for marginal probabilities of failure for one-supply distribution components versus input conditional probabilities of failure for power supply components grouped by number of paths to a supply.

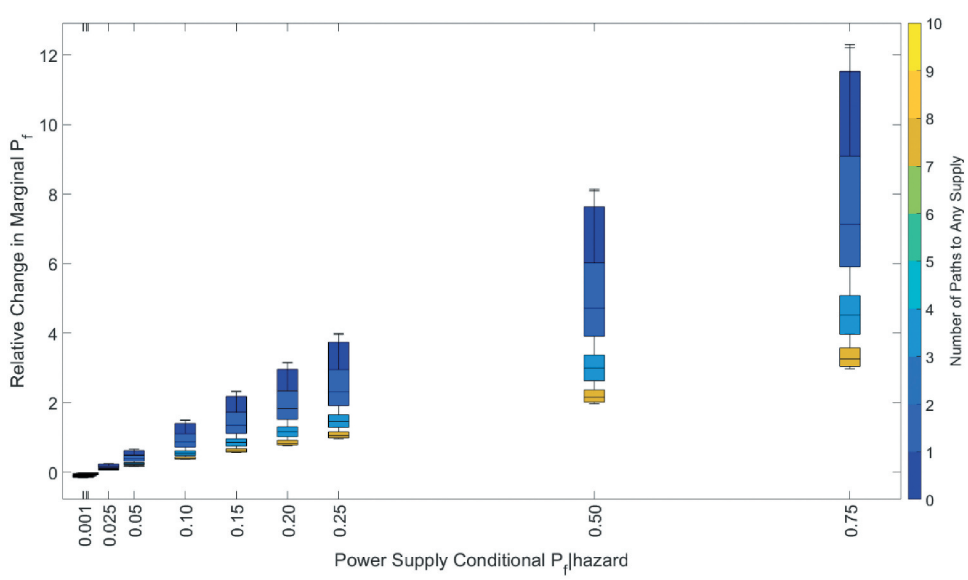

Figure 8. Relative changes in marginal probabilities of failure versus input conditional probabilities of failure for power supply components grouped by number of paths to a supply.

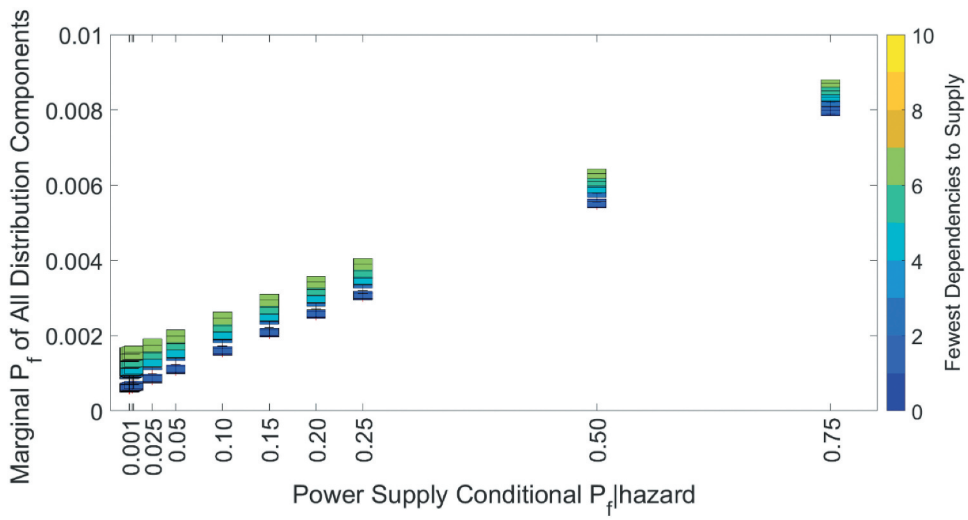

Figure 9. Marginal probabilities of failure for one-supply components versus input conditional probabilities of failure for power supply components grouped by fewest number of dependencies to the supply.

number of dependencies to the supply, which are represented by the discrete values on the color bar in each figure. For instance, the yellow boxplots in Figures 7 and 8 show the variation of results for all distribution components that have eight paths to a supply component as input conditional probabilities of failure increase for power components. The boxplots only include results for one-supply distribution components. Figures 7 and 9 show that as power supply conditional failure probabilities, number of paths to a supply, and fewest number of dependencies to a supply increase, the resulting marginal probabilities of failure for distribution components increase. These figures also show that components with more paths to a supply and more dependencies to a supply have higher marginal probabilities of failure. This is not intuitive for components with more paths (i.e., redundancies) to a supply and is a result of examining the impacts of these component characteristics (i.e., number of paths to a supply versus fewest number of dependencies to a supply and the relationship between the two), which the authors explain later in this section. Figures 8 and 10 conversely show that as the number of paths and fewest number of dependencies to a supply increase, the relative changes in resulting marginal probabilities decrease.

In other words, as the number of paths and fewest number of dependencies to a supply for a component increase, the relative impact from changing component conditional probabilities of failure at the supply decreases. The effect is significant, with a maximum

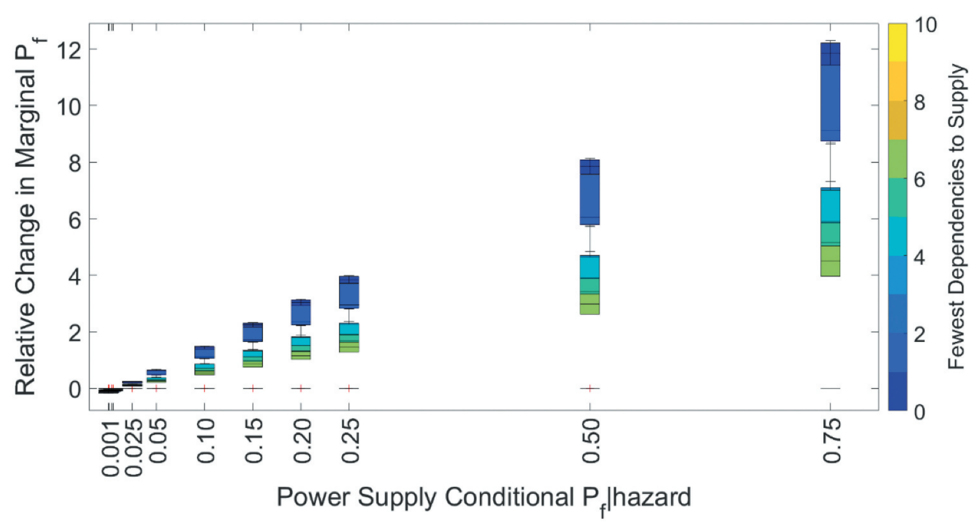

Figure 10. Relative changes in marginal probabilities of failure versus input conditional probabilities of failure for power supply components grouped by fewest number of dependencies to the supply.

relative change in marginal probability of failure of over 800% for components with one or two paths to a supply, compared to an under 300% maximum change for components with eight paths. Similarly, the maximum relative change in marginal probability of failure decreases from over 800% to under 200% for components with one or two compared to ten dependencies to a supply.

Differences in outcome variability are also observed. Figure 8 shows that the variability in results decreases as the number of paths increases. For instance, components with eight paths to a supply have the least variability in relative changes in marginal probabilities compared to the components with fewer number of paths to a supply. This supports the previous conclusion that variability in results decreases as more redundancies are available. Figure 10 shows that the variability in results decreases as the fewest number of dependencies to a supply increases. While dependencies are not the same as redundancies, these results show that components farther away from a supply are less sensitive to changes in network parameters.

To better understand the results from Figures 7–10 and the interaction between the two component characteristics of the number of paths and the fewest number of dependencies to supplies on component outcomes, results are now analyzed for components with a specific number of paths and dependencies. Given the results from Figure 4–6, the focus is on distribution components with one supply. Figure 11 shows the relationship between the number of dependencies versus the number of paths to a supply for all 66 one-supply distribution components.

Inference results are then plotted for a single value for number of paths and dependencies in Figures 12 and 13. In Figure 12, the relative changes in marginal probabilities versus input conditional probabilities of failure for power supplies are shown for components with four dependencies to its supply (i.e., y = 4 in Figure 11). In Figure 13, the relative changes in marginal probabilities versus input conditional probabilities of failure are shown for components with two paths to a supply (i.e., x = 2 in Figure 11). In Figures 12 and 13, the components are again grouped by characteristics, i.e., number of paths and number of dependencies to a supply, respectively, to generate boxplots. The color bar represents these discrete-value characteristics in each figure.

Comparing the results in Figures 12 and 13 shows that the number of paths has a smaller effect on the relative changes than the fewest number of dependencies to a supply. As the fewest number of dependencies to a supply increase, the relative changes in marginal probabilities of failure decrease. In Figure 12, the components with one, two, and three paths to any supply show median relative changes in marginal probabilities of failure that are within 120% of each other (e.g., at a 75% input conditional probability of failure for power supply components, components with one, two, and three paths to a supply have median relative changes of 610%, 697%, and 730%, respectively). In this figure, there is only one component with three paths to a supply and four dependencies to that supply, which is represented as a line across each boxplot. There are seven components with two paths to a supply and four dependencies to that supply, which is shown in dark blue, and seven components with one path and four dependencies to their supply, shown in teal. There is much less variation across the results for components with two paths to a supply compared to components with just one path to a supply, which is consistent with results that show added redundancies (previously, paths to alternative supplies) reduce the relative change in marginal probabilities of failure as input conditional probabilities of failure increase.

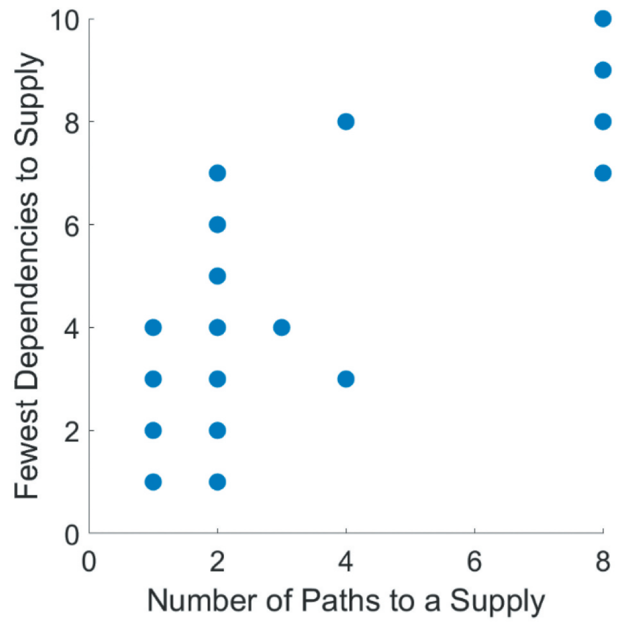

Figure 11. Fewest number of dependencies versus number of paths to a supply for each one-supply distribution component.

In comparison, the results in Figure 13 show larger differences in outcomes based on the fewest number dependencies to a supply. Components with the fewest dependencies to the supply show the largest relative changes in marginal failure probabilities. At a 75% input conditional probability of failure for power supply components, the differences are largest, with median relative changes in marginal probabilities of failure of 1182% for components with one dependency and 515% for components with six dependencies. Therefore,

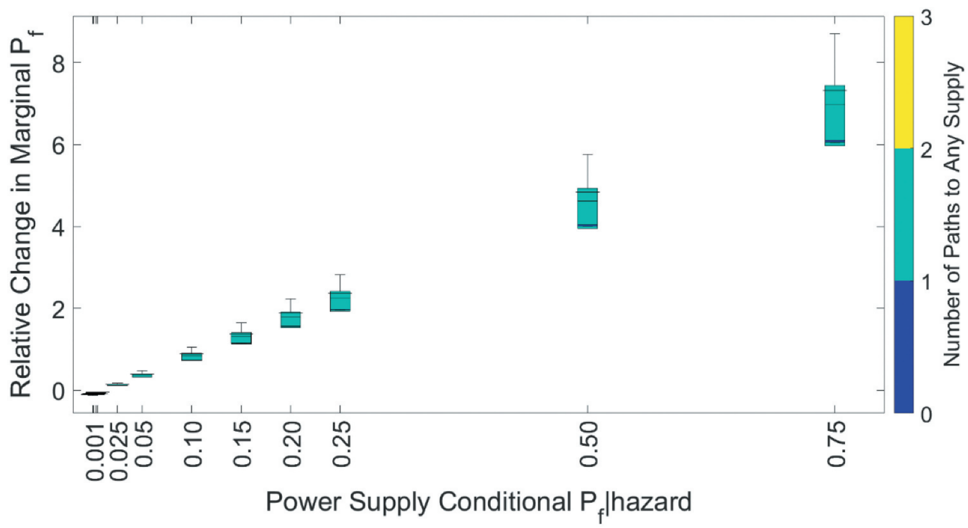

Figure 12. Relative changes in marginal probabilities of failure versus input conditional probabilities of failure for power supply components grouped by number of paths to a supply for one-supply components with four dependencies to the supply.

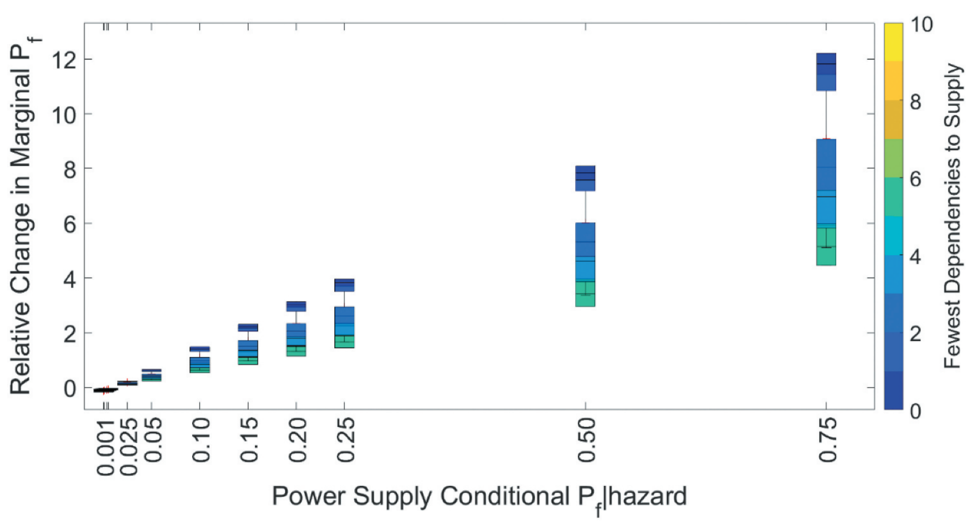

Figure 13. Relative changes in marginal probabilities of failure versus input conditional probabilities of failure for power supply components grouped by number of dependencies to a supply for one-supply components with two paths to a supply.

redundancies to the same supply for these one-supply distribution components (i.e., with varying number of paths) do not decrease their vulnerability as supply vulnerabilities vary, but components with fewer dependencies are more sensitive to these variations.

The marginal probabilities of failure increase as the number of dependencies for a component to reach a supply increases, as seen in Figure 9, while the components have larger relative changes to their marginal probabilities of failure as the number of dependencies decreases (seen in both Figures 10 and 13). This is because more dependencies create more vulnerabilities for a component (Figure 9); however, components with fewer dependencies will have increased sensitivity to changes to the only components they rely on – supply components, both within the same network and across infrastructures as service interdependency components. The results suggest that prioritization of repair, maintenance, and new construction should strongly consider the number of dependencies required for a component to function. While reducing dependencies decreases a component's marginal probability of failure, components that have fewer dependencies are more susceptible to changes at supplies and have larger increases in vulnerability than components with more dependencies as supply vulnerability increases.

6. Service interdependency redundancies

Another parameter of interdependent CIS that may be varied in an effort to reduce system vulnerability and increase system resilience is the number of available service component redundancies. Increasing the number of service component redundancies is an action related to a system's absorptive and adaptive capacities. For instance, a water network component may rely on a power supply to function, which may include redundant power supplies. In this section, the authors change the number of service interdependency redundancies at the water supplies in the Atlanta water distribution network. For each inference, an additional service component, representing an additional power supply, is introduced as a parent for each water supply component. Additional service redundancies in the water network lower marginal probabilities of failure for all distribution components, as expected, and these are not shown. From the inference results, multi-supply components have little to no change even as redundancies are added, which is consistent with the results from varying conditional probabilities of failure as found in the previous section. Moreover, there is little impact on the network by adding more than one redundancy to each water supply.

Instead, including at least one redundancy has the most impact on components that are closest or have fewer dependencies in their shortest path to reach a supply. Figure 14 shows the results from an inference with two power supplies at each water supply component (i.e., adding one redundancy per water supply), focusing on one-supply components. The relative changes in component marginal probabilities of failure between this analysis and the baseline network described in the previous section are plotted against the fewest number of dependencies to their supply. From Figure 14, as the fewest number of dependencies to a supply increases, the relative change in marginal probabilities of failure decreases. These results are consistent with those found in the previous section. Components with fewer dependencies to a supply are more sensitive to changes in the network, and increased vulnerability at supply components (i.e., those without service redundancies) most negatively impacts these components. At the same time, adding service interdependency redundancies such as a power backup at the water supply benefits these components (i.e., those with fewer dependencies to a supply) the most.

7. System link configuration

Finally, the authors vary the Atlanta water distribution network's link configuration by introducing new edges into the CIS BN. In the CIS BN, a new link or edge represents a new element of the network such as a newly constructed pipe or connection in the network between two water network components, whether supply or distribution. To choose new links for the system, the authors identify components that are most at risk for failure along with the next closest, unconnected component to them. The purpose of this analysis is to identify

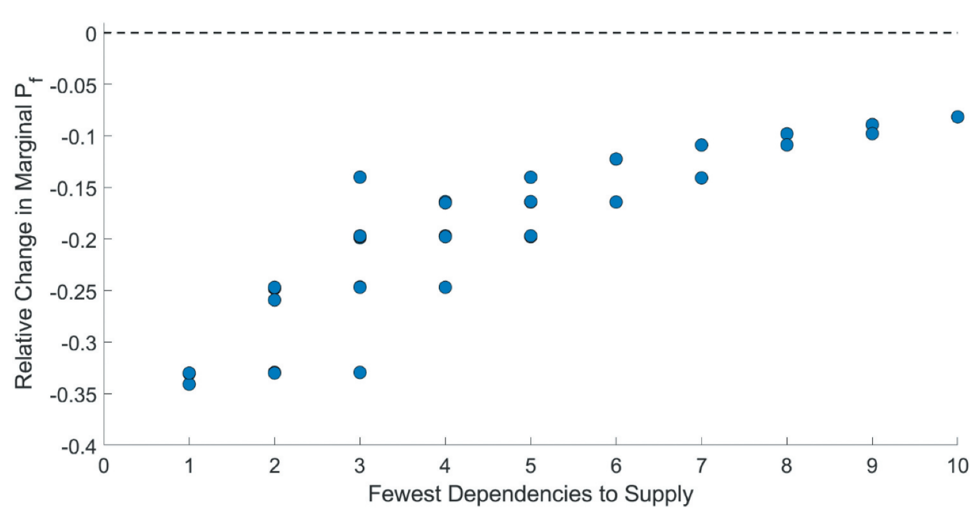

Figure 14. Relative changes in marginal probabilities of failure for one-supply distribution components versus fewest number of dependencies to the supply when adding a service redundancy.

new edges in the network to represent actions to strategically locate and build out new parts of the original network based on anticipated network effects.

To evaluate the efficacy of varying system link configuration options, the authors consider the population impacts of a given asset failure. The authors select population impacts as a metric for quantifying network resilience for this section because for failure scenarios, failed nodes have a 100% probability of failure. This means that all output marginal probabilities of failure for failed components will be equal to 1, whereas population impacts provide a way to quantify and differentiate results for these components.

Population impacts from a failure at different water supply and distribution components are evaluated under the assumption that the population surrounding a component is directly impacted by failure of that component. The population associated with each node in the Atlanta water network is computed using a k-nearest neighbor algorithm to associate United States Census blocks (US Census Bureau, 2010) to individual water supply or distribution components. The population distribution across the water network based on this analysis is shown in Figure 15, where the color bar represents population. The authors next present analysis results from a failure scenario of Supply 4, around which the population density is greatest.

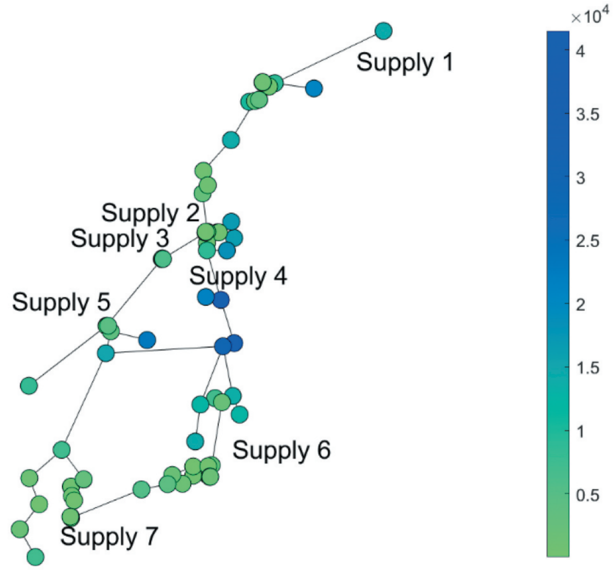

Figure 15. Population distributed across Atlanta water network nodes.

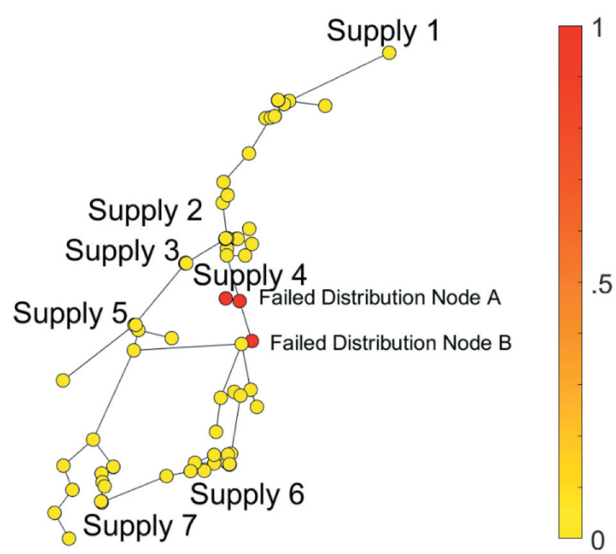

Figure 16. Failure scenario results when Supply 4 fails.

Figure 16 shows the resulting probabilities of failure for components across the network obtained from an inference run over the CIS BN under a failure scenario where Supply 4 has failed. The color bar represents marginal probabilities of failure after inference is conducted with this evidence. This results in two failed distribution nodes, labeled A and B in Figure 16. Distribution components A and B have no other reachable supplies based on the MLS components for this analysis, i.e., they are one-supply components. The remaining distribution components in the network have low marginal probabilities of failure because they are able to reach a different supply, i.e., one(s) other than Supply 4. Figures 17–20 show four options from the link analysis to decrease the vulnerability of the distribution components with a new system link configuration. In these figures, one new link per analysis is added to the network and the inference is rerun to investigate the effects of the new link on system performance under the same failure scenario. The potential new links are identified based on the analysis of the next closest, unconnected components to the failed nodes. Each time a new link is added to the system, a depth-first search is run to identify newly formed supply-to-distribution component paths (MLSs) from the added link. With each additional MLS, a new node is added to the network, creating new dependencies. Table 6 shows the original CPT for Node A as Node A begins with only one reachable supply (Supply 4) and only one path to reach that supply. Table 7 shows a sample CPT for Node A after a new link is added to the system if that link corresponds with the addition of one new MLS (regardless of whether or not the new MLS reaches the same or a different supply).

In Figures 17 and 20, distribution components A and B fail despite a new added link. In Figure 19, Node B survives, while Node A fails, and in Figure 18, both Nodes A and B survive when evidence is input that Supply 4 has failed.

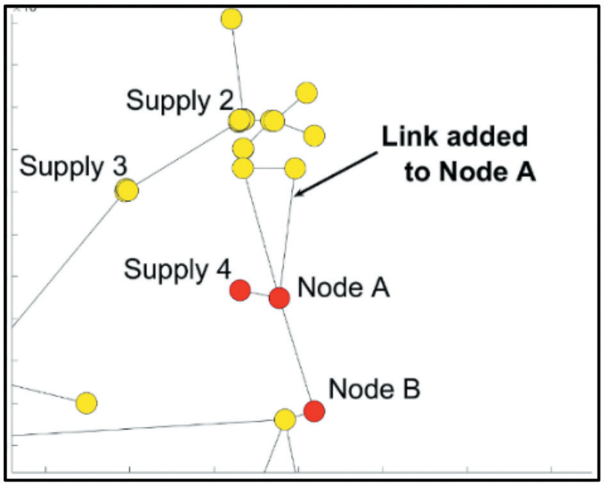

Figure 17. New link added to Node A (1).

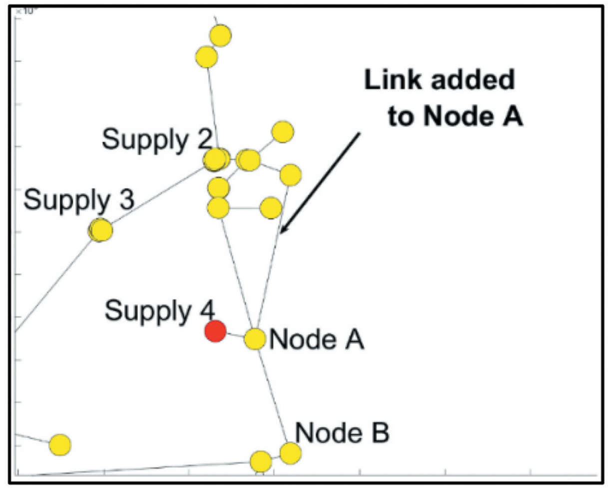

Figure 18. New link added to Node A (2).

Among the new link options, a new edge to the network prevents either Node A or B from failing when they provide new paths to a different supply other than Supply 4. This is the case for the new link added in Figure 18. The paths in this analysis are computed through a depth-first search; MLS components can also be input in the CIS BN by the user, making these results applicable to any distribution component in any network modeled by the CIS BN. In general, a distribution component cannot survive if its only supply or source fails. Given the important relationship between distribution component performance and its connectivity with other nodes in the network, the results underscore the need to better understand the dependencies and redundancies within a CIS before making decisions to build out new parts of the network.

To quantify the variation in outcomes from the four new link options, the authors consider the populations affected by the original failure scenario (Figure 16) and the outcomes from the failure scenario under each new system link configuration (Figures 17–20). This quantification is included in lieu of an analysis of resulting marginal probabilities of failure (i.e., as in the previous section) because the variation in the input parameter, link configuration, does not occur over a range of values. Instead, one failure scenario is selected, and population effects are evaluated for each system link configuration under that failure scenario. As the performance of CIS directly affects the vulnerability and resilience of their surrounding communities, community-based outcomes are selected for evaluation, including population, housing units, and critical facilities affected as shown in Table 8. Population and housing units affected in each scenario are computed using

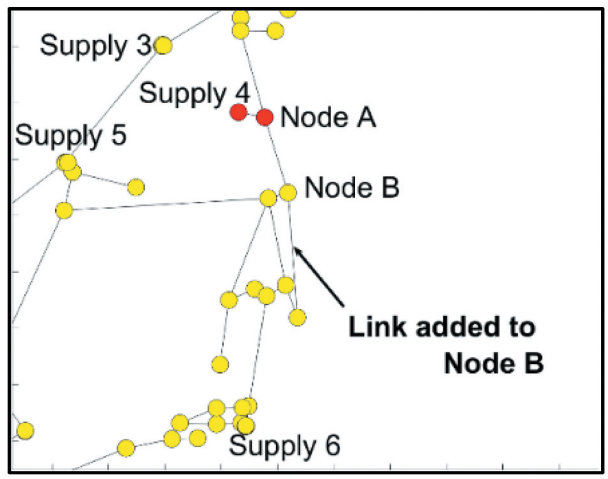

Figure 19. New link added to Node B (1).

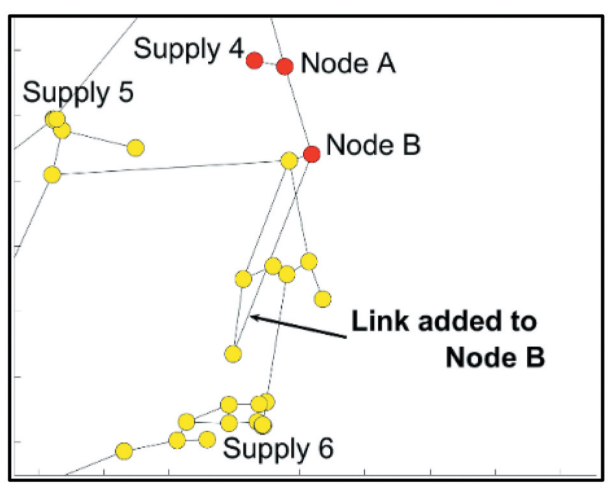

Figure 20. New link added to Node B (2).

Table 7. Sample conditional probability table for Node A after a new link is added connecting it to another node in the network.

	Hazard occurs				Hazard does not occur			
	Original MLS fails		Original MLS survives		Original MLS fails		Original MLS survives	
Node A state	New MLS fails	New MLS survives	New MLS fails	New MLS survives	New MLS fails	New MLS survives	New MLS fails	New MLS survives
Fails	1.0	0.01	0.01	0.01	1.0	0.0001	0.0001	0.0001
Survives	0	0.99	0.99	0.99	0	0.9999	0.9999	0.9999

Table 8. Community impacts from Supply 4 failure and new system link configuration scenarios.

Link Configuration with Supply 4 Failure	Population	Housing Units	Critical Facilities
Figures 17, 18, and 21: Supply 4, Node A, and Node B fail	96,217	57,445	7
Figure 19: Supply 4 fails	21,340	12,203	2
Figure 20: Supply 4 and Node A fail	62,829	37,748	5

census blocks, and critical facilities are counted using OpenStreetMaps data (Open Street Map 2018), including hospitals and other emergency facilities. The data confirm that the highest population impacts from a Supply 4 failure scenario occur when Supply 4, Node A, and Node B all fail. The option considered in Figure 18 leads to the greatest reduction in population vulnerability due to the infrastructure asset failure. Using community- and population-based outcomes as shown in Table 8 is an important analysis to include in the decision-making process to prioritize maintenance, repair, and construction actions to increase CIS resilience.

8. Generalizability of results

The authors draw three general conclusions that are applicable to interdependent CIS from the analyses and results in this study:

(1) Components in a CIS that have only one reachable supply or source are most sensitive to any variations in network parameters, including variations that lead to both increased and decreased vulnerability.
(2) Among components with one reachable supply (i.e., with no supply redundancies), components with fewer path dependencies are more sensitive to network parameter variations. These components are often closest to a supply or source in terms of physical distance with fewer dependencies to that

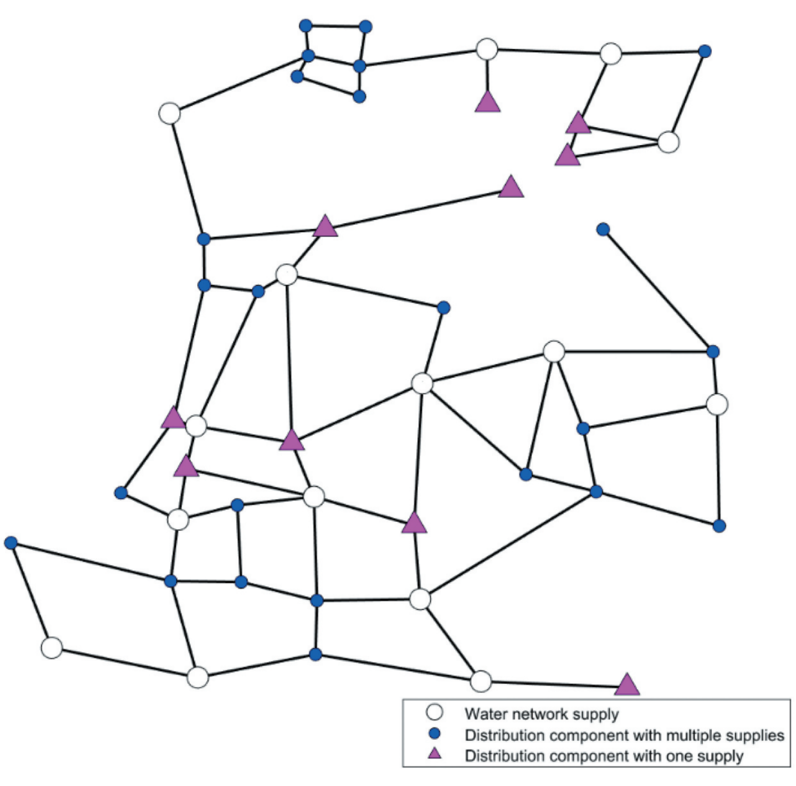

Figure 21. Schematic of the Shelby County, Tennessee, water distribution network with one-supply and multi-supply components shown.

supply. The increased sensitivity to network parameter variations applies to both changes to component conditional probabilities of failure and to the number of service interdependency redundancies.

(3) New edges or links in a system have the most impact on the network when adding new paths to create more supply redundancies. Decisions to build out new system links should consider community and population impacts in potential failure scenarios.

To confirm generalizability of the results from the analysis of the Atlanta water distribution network to other interdependent CIS, the authors conduct a similar, condensed analysis on a different water distribution network in Shelby County, Tennessee. The schematic of the water network is shown in Figure 21. The Shelby County network has 49 components, 15 of which are supply components. Of the remaining 34 distribution components, 10 are identified as one-supply components using a depth-first search analysis to define MLS components for the network. The authors input the same network parameters as for the Atlanta network analysis (i.e., 1% initial conditional probabilities of failure, 1% probabilities of a hazard occurrence, and one service and access component per water supply component).

Figures 22–24 show the results from varying the power (i.e., service) component conditional probabilities of failure. The results from this analysis are consistent with results from analyses of the Atlanta network and are described in more detail below. Variations in other network parameters, such as service redundancies and link configurations, are consistent with conditional probability of failure variation, and results from varying power redundancies and link configurations for the Shelby County network are therefore expected to be consistent with the results from this variation as well.

Figure 22 shows the resulting marginal probabilities of failure for distribution components in the Shelby County network as conditional probabilities of failure at the power supply components are varied. The standard deviations of results across components are smaller than those from the Atlanta network. This is due to the smaller size and compressed layout of the Shelby County network as compared to the Atlanta network. However, the results follow similar trends in both networks: firstly, there is a distinct difference in anticipated outcomes for one-supply compared to multi-supply components; secondly, the marginal probabilities of failure for one-supply distribution components increases as the conditional probabilities of failure at the service components are increased; thirdly, multi-supply components are shown with very little change even as the power supply component parameters (i.e., input conditional probabilities of failure) are varied.

Figures 23 and 24 show the relative changes in marginal probabilities of failure for each new service component parameter variation compared to a baseline of power supply conditional probability of failure equal to 1% for conditional failure probabilities less than (Figure 23) and greater than (Figure 24) 1%,

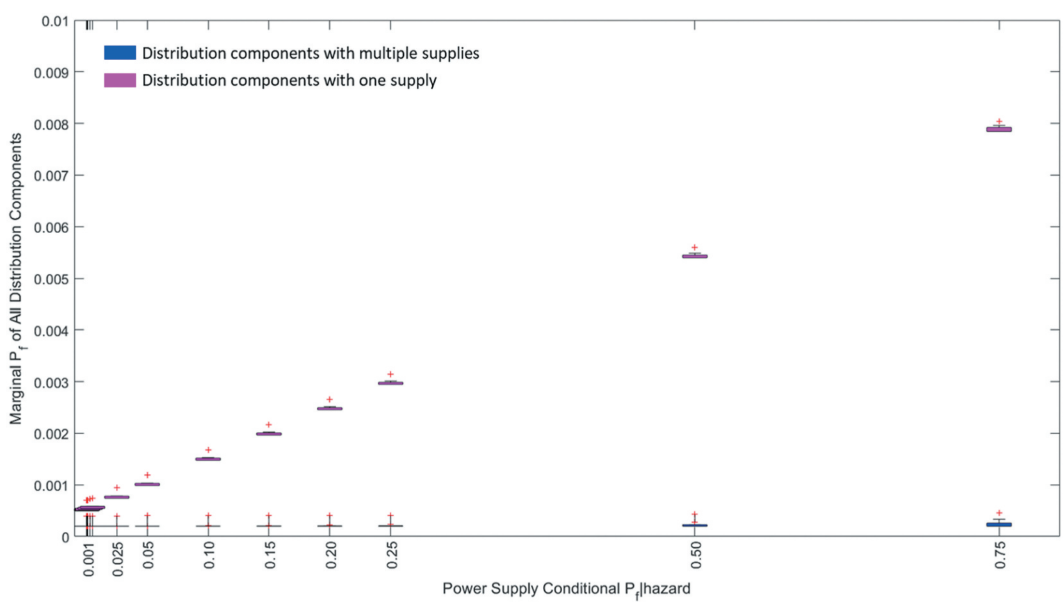

Figure 22. Marginal probabilities of failure results versus power supply conditional probabilities of failure for the Shelby County network.

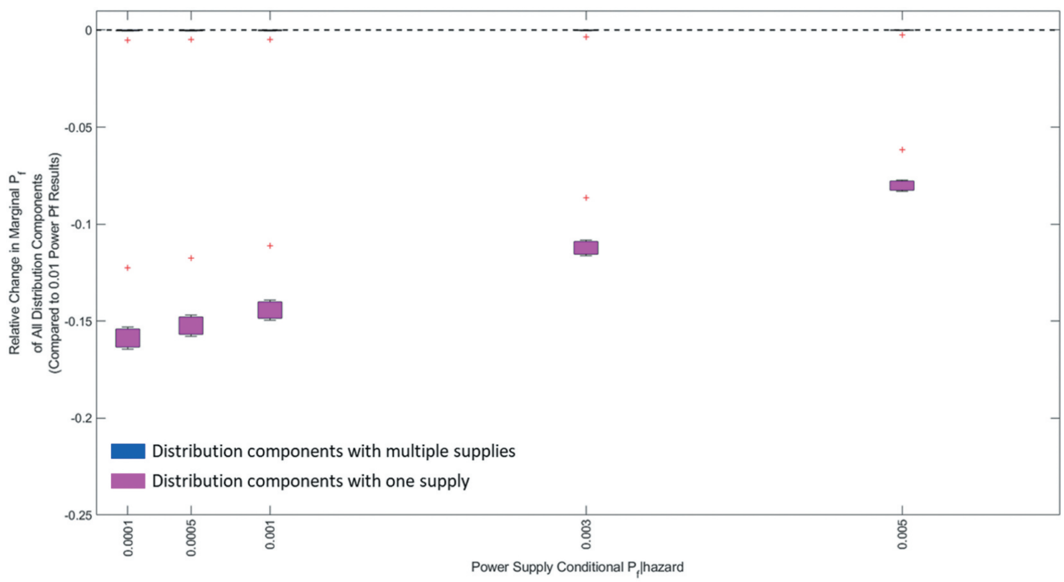

Figure 23. Relative changes in marginal probabilities of failure compared to a baseline inference versus service component conditional probabilities of failure for conditional probabilities less than 1%.

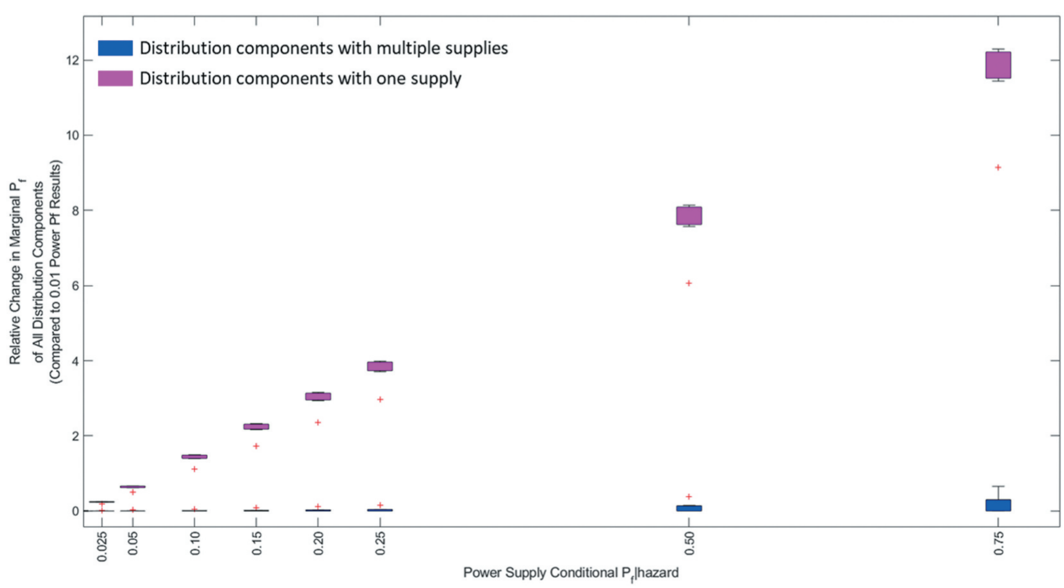

Figure 24. Relative changes in marginal probabilities of failure compared to a baseline inference versus service component conditional probabilities of failure for conditional probabilities greater than 1%.

respectively. As in Figure 5, the vertical axis in Figure 23 goes below zero, representing decreased marginal probabilities of failure with decreased input conditional probabilities of failure for the power supplies. These figures again show that one-supply components are most impacted by changes to this parameter and, more generally, by changes across the entire network, and that the variability in distribution component outcomes increases as power supply vulnerability increases.

9. Conclusion

In this paper, the authors assess the impacts of varying three network parameters on CIS vulnerability and resilience. Impacts are evaluated at the individual distribution component-level with probabilistic analysis results that include interdependencies between multiple types of infrastructure systems. Results are discussed with respect to their implications for making decisions for prioritizing actions for infrastructure resilience. Atlanta's water distribution network is used as an example application for analysis from which general conclusions are drawn. The network is modeled within a Bayesian network framework, with connections to service and access components that represent interdependencies across different infrastructures and with geographic dependencies representing hazard events.

Outcomes from the analyses are used to compare component states under changing conditions captured through variations in network parameters, such as damages occurring during a disaster event (increasing component-level vulnerability) or preventive measures taken to increase resilience (through decreasing component likelihoods of failure). The results are then discussed in the context of actions that can be taken to increase overall system resilience.

The network parameters varied include conditional probabilities of supply-component failure given a hazard event, representing potential retrofit or repair actions to specific infrastructure assets, or degradation of assets due to age or hazard event occurrence; service component redundancies, such as installing redundant or backup power supplies at a node to address vulnerabilities due to service provision interdependencies; and system link configuration, representing new construction in the CIS and modeled through adding new edges to the network. Inferences run over the model result in new marginal probabilities of failure for components across the network. The relative changes in resulting marginal probabilities are also computed between each parameter variation and a baseline inference. Community and population impacts are considered when adding new links to the system to assess CIS impacts under specific failure scenarios.

The results show three main conclusions. First, changes to network parameters have the highest impact on components in a CIS that have only one supply or source. These components have no supply redundancies. This outcome suggests that adding just one path to a different supply for a one-supply distribution component will significantly decrease that component's vulnerability. Second, among one-supply components, those that are most sensitive to changes to network parameters are components with fewer path dependencies to reach a supply. These results suggest that municipalities should not only consider risks to specific CIS components but also the placement of CIS components in a system when seeking to increase overall system performance and when prioritizing resilience strategies and actions. Third, building out new parts of a system has the most impact on the network and the community it is serving when doing so adds new paths to supplies in a system. The results indicate that when considering adding new links to a CIS, infrastructure owners should consider the new path dependencies and redundancies that will subsequently occur to maximize the impact of the new construction. The generalizability of results is confirmed by running a similar set of analyses over the water distribution network in Shelby County, Tennessee.

This work contributes to studies in quantifying CIS performance, and its novelty is in the quantitative evaluation of CIS performance at both the individual distribution component and system levels as multiple network parameters are varied. The findings indicate important considerations in the prioritization of both retrofit and repair actions and for building out new parts of a system to increase CIS resilience. Conclusions are applicable to different types of interdependent infrastructures and hazards that impact them.

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