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A Bayesian Framework for Seismic Resilience Analysis of Intermodal Freight Networks

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ABSTRACT

This study introduces a Bayesian framework for seismic resilience analysis of intermodal freight networks. A damaging earthquake event can impact bridges, roads and railway tracks, resulting in traffic closures, disrupted freight movement and consequent economic losses that recover with time gradually after the hazard. Exisiting studies on intermodal network resilience to extreme events do not account for actual damage and functionality models, and do not provide a holistic framework connecting the various input models of the resilience analysis framework. The proposed Bayesian framework addresses this gap by providing an approach to evaluate the joint probability distribution of hazard parameters, structural damage parameters and resilience indicators at both bridge and network level, for applications to a post-earthquake decision framework. Resilience quantification leverages a Bayesian network, with a series of directed edges representing conditional dependence between successive variables. The proposed framework connects the various predictive models constituting the resilience framework, such as ground motion prediction equations, fragility models, restoration models and network analysis models. The Bayesian framework not only provides the baseline for updating the inference on some variables based on observed values of other variables, but also helps in propagating uncertainty through the various constituent models. Bayesian inferencing and learning of unknown parameters using new evidence in demonstrated using Markov Chain Monte Carlo (MCMC) simulations and Gibbs sampling. The conceptual Bayesian framework to derive a network-level performance index is demonstrated using a hypothetical 10-node transportation network and adapting a network resilience metric suitable for application to intermodal freight transport.

Keywords: Bayesian, networks, freight, intermodal, resilience.

INTRODUCTION

Earthquakes are one of the leading natural hazards in terms of the potential for damage and consequent losses inflicted upon the community. The transportation network forms the backbone of a functional community, allowing efficient and expedient movement of people, goods and emergency relief materials. Railway and highway infrastructure constitute two of the leading carriers of freight in the United States of America (USA), with a 2017 study by the Bureau of Transportation Statistics [1] suggesting that about 89% by ton-miles of freight in the USA move either by truck, rail or a combination thereof. Intermodal networks, formed when two or more transportation modes are linked end-to-end for the purpose of freight movement, offer more fuel and cost efficient alternatives to single mode transport, leading to their growing popularity among freight shippers. Estimating and enhancing resilience of intermodal networks is important to ensure recovery of the regional as well as nationwide economy following extreme events. Resilience of an infrastructure system quantifies not only the inherent robustness of its constituent components to an external shock, but also its inherent ability to cope with and recover from the consequences of the shock [2]. Existing studies on intermodal network resilience [3,4,5] focus on developing the mathematical framework for estimating resilience of damaged networks for targeted link failures; however realistic simulation of post extreme event failure and recovery have not been performed. Moreover, resilience-informed post extreme event decision making requires a holistic framework that connects the various input models that constitute the resilience framework, encoding their interdependencies. In this study, a Bayesian network is proposed as a possible solution to the above problem, to describe the entire seismic resilience analysis framework, adapted specifically for application to intermodal freight networks.

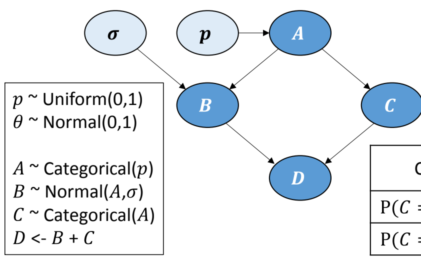
A Bayesian network is a probabilistic model expressed in the form a directed acyclic graph, where the variables are represented by nodes and probabilistic dependencies between these variables are represented by directed links [6]. The directionality of these links represents the causality in these networks. Several recent studies have explored the application of Bayesian networks for evaluating performance of infrastructure systems consisting of components with mutual interdependencies, such as natural gas pipeline networks [7, 8], electrical power networks [9] and transportation networks [10, 11]. The primary reasons for the popularity of this framework are the ability to perform backward inferencing as well as parameter updating based on newly acquired evidences, thereby aiding post-hazard decision support tools [11]. Bensi et al. [10] used Bayesian networks to model transportation infrastructure system-level performance for aiding in real-time decision support, using connectivity to critical facilities as an indicator of network or system level performance. Gehl and D' Ayala [12] used a Bayesian network to formulate the multi-hazard fragility framework for bridge systems, considering earthquake and flood hazards. The study by Gehl and D'Ayala considers a single bridge as a system, with individual components such as abutments, bearings and columns contributing to system performance. However, large infrastructure systems consisting of many components pose a challenge for tractable modeling via a Bayesian network, as the complexity of the problem increases exponentially with number of components. As a result, several studies [11, 13, 14] have explored efficient and approximate Bayesian network modeling strategies by identifying critical components and reducing the number of variables.

In the present study, a Bayesian network framework is proposed that sequentially maps site-specific hazard intensity measures to bridge component damage states, bridge system level functionality, and finally integrates the functionality status of all bridges in the network to evaluate a network level performance index. The proposed framework is demonstrated for a small-scale hypothetical freight transportation network intended to perform specific performance objectives, adapting a resilience metric suitable for application to intermodal freight networks. However, the general framework can be adapted to other hazards and alternate network performance objectives. Building on past research in this area, this study incorporates the following additions: (i) mapping component level performance to system level performance both at an individual bridge level as well as at a network level (ii) using data on bridge closures for various component damages, this framework presents a more realistic representation of post extreme event decision making by bridge inspectors and (iii) using a time evolving network resilience framework suitable for application to both unimodal and intermodal freight transportation networks. The advantages of using the proposed Bayesian network framework demonstrated in this paper include: (i) using Bayesian inferencing to learn previously unknown parameters (ii) updating prior beliefs on some variables using new evidence on other variables.

STRUCTURE OF THE PROPOSED BAYESIAN NETWORK

Bayesian Network Terminology

A Bayesian Network is a directed acyclic graph that represents a system, a process, or a sequence of phenomena, where each node represents a variable and each link represents the conditional stochastic dependency between two variables. An example Bayesian Network U represented by the variables σ, p, A, B, C, D is shown in Figure 1.



CPT	$P(C\|A = 0)$	$P(C\|A = 1)$
$P(C = 1\|A)$	0.8	0.2
$P(C = 2\|A)$	0.6	0.4

Figure 1. Example Bayesian Network

The joint probability distribution of the Bayesian network shown in Figure 1 can be represented as follows.

$$f(U) = f(p)f(A|p)f(\sigma)f(B|A,\sigma)f(C|A)f(D|B,C) \tag{1}$$

Thus, a Bayesian network helps to represent the joint distribution as a multiple of several conditional distributions which are assumed to be conditionally independent of each other [6]. A Bayesian network needs to be fully specified in terms of the conditional probabilities of each of its constituent nodes. Depending on whether the variable in question and its parents are discrete or continuous, this conditional probability may be expressed either in the form of a discrete conditional probability table (CPT) or as a continuous conditional probability distribution (CPD). For example in Figure 1, the node A has a discrete prior distribution (the '~' sign is used to denote a probabilistic function), which can take values of 0 and 1 with probabilities p and $1-p$ respectively. Node B follows a Gaussian distribution with a mean equal to the value at node A and a standard deviation of σ. Node C is also a categorical variable conditioned upon node A, which can take values 1 or 2 conditioned upon the value of node C as defined by its CPT. Node D is a deterministic node (the '<-' sign is used to denote a deterministic function) that is a function of the values at nodes B and C. Nodes p and σ, which have no parents, require some prior distribution, as described in Figure 1.

Proposed Bayesian network structure for seismic resilience of intermodal networks

The Bayesian network structure shown herein is constructed based on our knowledge of interdependencies between components and systems on a bridge as well network level, following from the resilience analysis framework commonly used. Figure 2 illustrates the complete Bayesian network structure for seismic resilience analysis of transportation networks in general. In Stage 1, a scenario seismic hazard is generated using a suitable ground motion attenuation model, to evaluate the seismic hazard intensity measure $\mathbf{IM}[i]$ at the location ($\mathbf{Location}[i]$) of each of n bridges (where $i \in [1, n]$). In this problem, it is assumed that structural damage is restricted to bridges only; so the ground motion intensity measure is required at each bridge location. In Stage 2, a network-wide physical damage scenario is generated for each individual bridge component using the bridge component fragility curves that provide the probability of exceeding various levels of damage conditioned upon ground motion intensity measure. Damages to three primary bridge components, namely abutments ($\mathbf{Ab}[\mathrm{i}]$), the bearings ($\mathbf{Brg}[i]$) and the columns ($\mathbf{Col}[i]$) are considered. In the Stage 3, the closure status of each bridge ($\mathbf{Closure}[\mathrm{i}]$) is estimated using bridge restoration models that provide the probability of closure conditioned upon the bridge component damage levels. Every instance of a closed bridge is realized at the network level as a failure of the corresponding network link. Finally, in Stage 4, the closure status of each bridge at any given instant of time t after the earthquake informs the network resilience index $\alpha(t)$, which evolves in time with gradual network recovery.

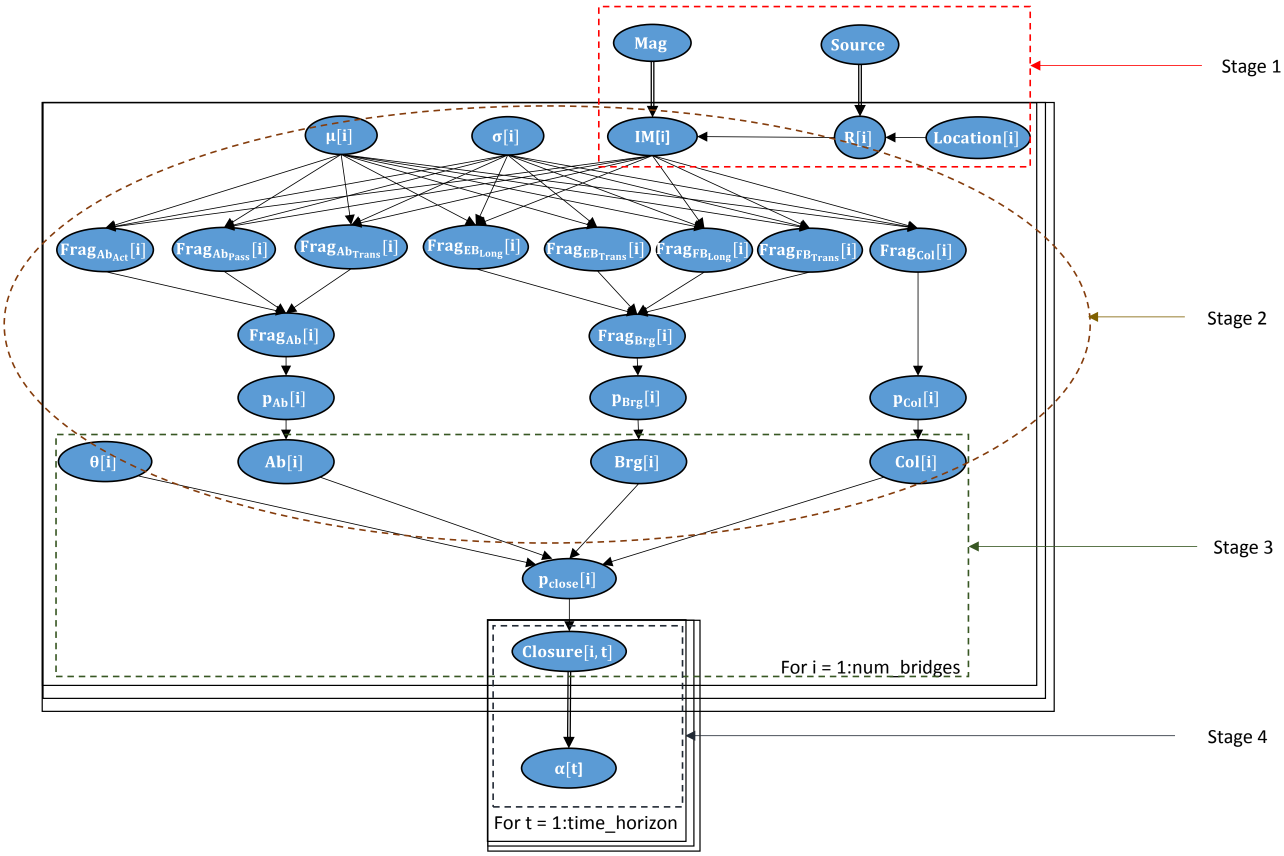


Figure 2. Simplified Bayesian Network structure for post-earthquake network performance

It should be noted here that, while some of the CPDs in the Bayesian network structure of Figure 2 are known from previous literature, others need to be inferred from data. More specifically, bridge fragility models, that provide the probability of exceeding various damage limits states for bridge components conditioned upon the ground motion intensity measure, provide the framework to evaluate the CPDs informing component damage states. The bridge closure probabilities conditioned upon component damage require is a more subjective process and involves human decision making, so the corresponding CPDs must be inferred from relevant data. Also, the network resilience index $\alpha(t)$ conditioned upon bridge closure states is specific to the network topology and pre-defined performance objectives. In order to illustrate the construction of the Bayesian network in detail and encoding all the dependencies within the framework, the detailed structure in Figure 2 is discussed in multiple stages throughout the following sections.

BAYESIAN NETWORK PARAMETER ESTIMATION AT THE BRIDGE LEVEL

In this section, the parameters of the Bayesian network required for evaluating bridge level performance in terms of the closure state from the ground motion intensity measure are illustrated.

Bayesian network parameters inferred from past studies

The CPDs connecting ground motion prediction parameters such as magnitude (Mag) and source location ($Source$) to the intensity measure ($\mathbf{IM}[i]$) at the bridge locations, as well as those connecting the intensity measure to bridge component damage states ($\mathbf{Ab}[i]$, $\mathbf{Brg}[i]$ and $\mathbf{Co}l[i]$) are derived from relevant existing studies. The intensity measure at each bridge location is a deterministic node, which is a function of the ground motion magnitude, the source location, and the location of the bridge, as illustrated by Stage 1 of Figure 2. For this example, the attenuation model proposed by Atkinson and Boore [15] is used to evaluate the ground motion intensity bridge at the bridge site. Similarly, other ground motion prediction equations can be used for this purpose, for which the relevant parameter priors need to be defined. In this example, the magnitude is assigned a uniform prior distribution between 6 and 7.5, while a fixed point source location ($35.3°$ N, $90.3°$ W) is assumed.

The component damage state probabilities can be derived from relevant bridge component fragility models. In this study, highway bridge fragilities proposed by Nielson and DesRoches [16] are used. In Nielson and DesRoches' study, lognormal fragility curve parameters were estimated for eight bridge components for each of six different bridge classes. Following this, system level fragility curve parameters are evaluated with the assumption that the components are connected in series. It may be noted that the eight components described in Nielson's study can be distilled into three primary components, namely abutments, bearings and columns, using the series system assumption. The nodes representing component damage are categorical variables that can exist in one of five states, ranging from "No Damage" to "Complete Damage". Each of these damage states is associated with a probability, which is calculated with the help of the component fragility curve parameters, the lognormal median μ and the lognormal standard deviation σ and the ground motion intensity measure IM.

The steps involved in computing the component damage states from the ground motion intensity measure and the fragility parameters are shown in detail for the abutment (Ab) node, in Equations 2 through 4. A similar sequence of steps are used for arriving at the damage states of the two other primary components, namely bearing (Brg) and column (Col). The Bayesian network for this stage is illustrated as Stage 2 in Figure 2. For the k^{th} damage state (where $k \in [1,4]$ with 1 corresponding to "Slight Damage" and 4 corresponding to "Complete Damage"), the vector containing the probability of exceeding that level of damage for the bridge abutment is evaluated as:

$$\mathbf{Frag}_{\mathbf{Ab}}[k] = \max(\mathbf{Frag}_{\mathbf{Ab}_{\mathbf{Act}}}[k], \mathbf{Frag}_{\mathbf{Ab}_{\mathbf{Pass}}}[k], \mathbf{Frag}_{\mathbf{Ab}_{\mathbf{Trans}}}[k]) \tag{2}$$

The quantities within the parentheses are evaluated from the fragility curve parameters specific to that component, as demonstrated for $\mathbf{Ab}_{\mathbf{Act}}$ in Equation 3.

$$\mathbf{Frag}_{\mathbf{Ab}_{\mathbf{Act}}}[k] = \left|\Phi\left(\frac{\ln(IM)-\ln(\mu_k)}{\sigma_k}\right)\right|_{\mathrm{Ab}_{\mathrm{Act}}} \tag{3}$$

Using the probabilities of exceeding damage state k for each k ∈ [1,4] computed using Equations 2 through 6, a (5×1) vector containing probabilities of being in "No Damage", "Slight Damage", "Moderate Damage", "Extensive Damage" and "Complete Damage" respectively is computed. This results in a (5×1) vector $\mathbf{p}_{\mathbf{Ab}}$, containing the probability of being in each of the damage states. Using this, the actual damage state of the abutment ($\mathbf{Ab}$) is expressed as a five-state categorical variable informed $\mathbf{p}_{\mathbf{Ab}}$, as shown in Equation 4.

$$\mathbf{Ab} \sim \mathrm{Categorical}(\mathbf{p}_{\mathbf{Ab}}) \tag{4}$$

The component damage states evaluated as described above are then mapped to bridge closure, for every bridge in the network. The closure status of every bridge at any given instant of time is an indicator of the bridge level performance index at that instant of time. Estimation of Bayesian network parameters for estimating bridge closure state is discussed in the following section.

Bayesian network parameters learned from data

The damage states of the three primary components of the i^{th} bridge informs the bridge closure state ($\mathbf{Closure}[i]$), a binary variable that states whether the bridge is completely closed to traffic or not. In order to model the probabilistic relationship between bridge component damage and closure, a logistic link function is assumed parameterized upon the damage state of each component, as shown in Equations 5 and 6.

$$\mathbf{p}_{\mathbf{close}} = \mathrm{logit}^{-1}(\theta_0 + \theta_1 \times \mathbf{Ab} + \theta_2 \times \mathbf{Brg} + \theta_3 \times \mathbf{Col}) = \frac{\mathbf{e}^{\theta_0+\theta_1\times\mathbf{Ab}+\theta_2\times\mathbf{Brg}+\theta_3\times\mathbf{Col}}}{\mathbf{1}+\mathbf{e}^{\theta_0+\theta_1\times\mathbf{Ab}+\theta_2\times\mathbf{Brg}+\theta_3\times\mathbf{Col}}} \tag{5}$$

$$\mathbf{Closure} \sim \mathrm{Categorical}(\mathbf{p}_{\mathbf{close}}) \tag{6}$$

Unlike the fragility models that provide the probability of bridge component damage given earthquake intensity measure, the bridge closure probability is not informed by physics-based models, but instead is a result of post event decision making by bridge inspectors accounting for the observed damage to bridge components. Moreover, the joint probability distribution represented by the entire Bayesian network cannot be evaluated in closed form; hence approximate techniques of estimating the parameters are sought herein. The unknown parameters $\theta = [\theta_0, \theta_1, \theta_2, \theta_3]$ are estimated using Markov Chain Monte Carlo (MCMC) simulation with Gibbs sampling [17]. Using this technique, variables are sequentially sampled from their respective marginal probability distributions in a Markov chain approach instead to attempting to compute the joint probability distribution. The technique can be applied for any arbitrarily complex marginal CPD, and results in Monte Carlo estimates of the unknown parameters. The quality of the estimates can be assessed by the Monte Carlo (MC) error, an estimate of the computational accuracy of the unknown parameter mean. The Bayesian network model is built and the MCMC simulations performed in the open source software OpenBugs [18].

One of the major advantages of using the Bayesian network framework is the ease it affords in incorporating new evidence in some variables to update prior beliefs about certain parameters. The unknown parameters $\theta = [\theta_0, \theta_1, \theta_2, \theta_3]$ are estimated from data relating bridge component damage states to closure decisions. The source of this data is a combination of empirical evidence [19] and an online survey of experts in post hazard roadway and bridge repair and restoration [20]. The Bayesian network structure represented by Equations 5 and 6 is illustrated by Stage 3 in Figure 2.

In order to specify the Bayesian network completely, initial estimates of all parameter priors need to be provided. The initial prior CPDs assigned to θ may be either non-informative or informative. A non-informative prior CPD is usually assigned to parameters for which there is no a priori evidence on the distribution. Table 1 shows examples of the logistic regression parameters calculated using Bayesian updating for various assumed prior distributions for θ. In the last case, we use informative prior distributions for θ, learned from the empirical dataset [19] and update them using new data derived from survey [20].

Table 1. Comparison of logistic regression parameters through MCMC simulation using different priors.

Parameter	**Case-I (Non-informative priors)**		**Case-II (Informative priors)**	
	Mean	**Standard Deviation**	**Mean**	**Standard Deviation**
θ_0	-9.594	1.892	-9.427	2.229
θ_1	2.143	1.056	2.149	1.084
θ_2	2.675	0.620	2.543	0.750
θ_3	-0.320	0.389	-0.251	0.418

It is evident from Table 1 that, even with non-informative prior estimates, a decent approximation of the parameters can be obtained. The dataset, obtained by combining the empirical data with the survey data is now used to perform MCMC simulations with non-informative priors. The results, reported in Table 2, provide estimates of the parameters $\theta = [\theta_0, \theta_1, \theta_2, \theta_3]$ that are eventually used to determine the probability of closure given damage state using Bayesian logistic regression.

Table 2. Logistic regression parameters for bridge closure.

Parameter	**Mean**	**Standard Deviation**	**M.C. Error**	**Median**
θ_0	-5.066	0.884	0.047	-5.036
θ_1	1.061	0.342	0.015	1.054
θ_2	0.739	0.157	0.007	0.442
θ_3	0.641	0.153	0.006	0.353

The parameters obtained in Table 2 using Bayesian logistic regression were best fit by Gaussian distributions. The low MC errors suggest that the mean parameter estimates obtained through Monte Carlo simulations are indeed reliable. The parameter statistics presented in Tables 1 and 2 are computed over 50,000 iterations, after eliminating the first 1,000 burn-in samples. Converge of the MCMC simulations is ensured by running two simultaneous chains with different initial values and tracing the parameter history plots for both chains to check how many iterations are required for convergence.

BAYESIAN NETWORK PARAMETER ESTIMATION AT THE NETWORK LEVEL

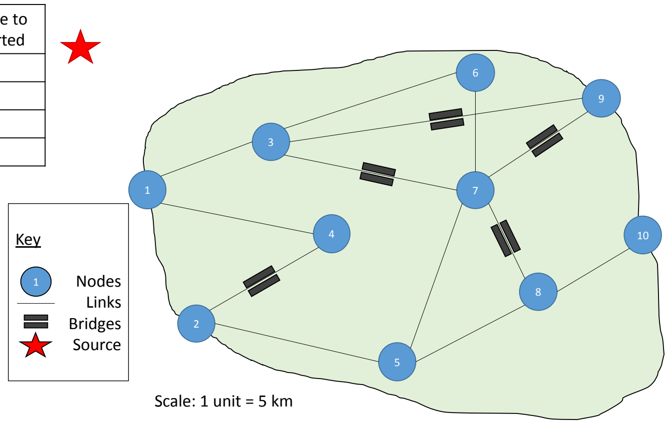
In this section, an assumed simple transportation network with five bridges is shown, and the network performance index is estimated using the proposed Bayesian network framework.

Hypothetical bridge network

The network performance index immediately after an earthquake is assessed for a hypothetical bridge network. This network is assumed to have 10 nodes and 13 links, with five bridges that are each assigned to one of the links. For the sake of simplicity, all five bridges are assumed to be MSSS Concrete Highway bridges [16], although diverse bridge types can be easily incorporated into the framework as long as their corresponding fragility functions are available. The network performance objective is to transport freight of specified value between certain Origin-Destination (O-D) pairs, incurring the least possible cost. Costs associated with freight transportation include the travel distance cost, given by the length of each link and the terminal delay cost, given as pre-specified node costs. The layout of this assumed network along with the node costs and specified performance objectives are shown in Figure 3.

Performance Objectives

O-D pair	Freight value to be transported
1-9	100
1-10	200
2-9	150
2-10	100



Node	X	Y	Terminal Cost
1	0	1	0
2	1	1	0
3	2	5	1,000
4	3	3	250
5	4	0	150
6	5	7	125
7	5	4	300
8	6	2	200
9	7	6	0
10	8	3	0

Figure 3. Hypothetical bridge network with specified performance objectives

The network performance index used in this study is adapted from the resilience metric proposed by Miller-Hooks et al. [17], where resilience is defined as the fraction of pre-event demand that can be satisfied in a post-event scenario, as shown in Equation 7.

$$\alpha = \frac{1}{\sum_{w\in W} D_w} E\left(\sum_{w\in W} d_w\right) \tag{7}$$

where d_w is the post-earthquake performance index of the network for a specific O-D pair $w \in W$, D_w is the same performance index for O-D pair $w \in W$ calculated pre-event and W denotes the set of all O-D pairs of interest. The network performance index is calculated as

$$d_w = V_w \frac{1}{R_w} \tag{8}$$

where R_w is a measure of minimum resistance along the path connecting the O-D pair w for the network after the hazard, and V_w is the value of freight that needs to be transported between the O-D pair. The value of resistance along a given path, in this context, is taken as a sum of the link costs and the node costs incurred along the path. The network performance index thus computed yields a value between 0 and 1, with 0 indicating disconnection of all O-D pairs and 1 indicating complete restoration of pre-event conditions.

Conceptual Bayesian network for bridge network resilience analysis

The network performance index α is a function of the damaged network topology, link costs, node costs and network performance objectives. The closure status of every individual bridge, each of which is associated with a network link, along with the original network adjacency matrix (Adj), inform the adjacency matrix in the damaged network (Adj_{dam}). The network performance index α is conditioned on this damaged network adjacency matrix, along with the network performance objectives (Obj) and associated travel costs ($Costs$). This conceptual Bayesian network, illustrated in Figure 4, helps estimate the network performance index $\alpha[t]$ at any time t. Since each bridge can be in either of two states, i.e. open or closed, there can be 2^n different combinations of individual bridge states for a network with n bridges. For the hypothetical network example in Figure 4, there can be only 32 such combinations. However, for a realistic network with even 50 bridges, the number of combinations increases to 1.12×10^{15}, making it computationally prohibitive to define α uniquely in terms of individual bridge conditions. In case of realistic networks, a dataset of multiple damage realizations can be created using Monte Carlo simulations, and a parameterized machine learning model can be trained to predict $\alpha[t]$ calculated for each such scenario. In the present example, a simplified form of this conceptual framework is used, wherein the network performance index α immediately after the earthquake is expressed as a function of individual bridge closure states only ($\mathbf{Closure}[i]$). Future work will explore the more general framework of Figure 4 that will be parameterized upon network specific properties, apart from accounting for the temporal evolution of $\alpha[t]$ with evolving network state. The best regression model to predict α from the closure status of each bridge, having the lowest root mean squared error, is a stepwise linear regression model with $R^2 = 0.997$. It must also be noted that these coefficients are specific to the particular network in Figure 4, for the specific performance objectives described in this problem.

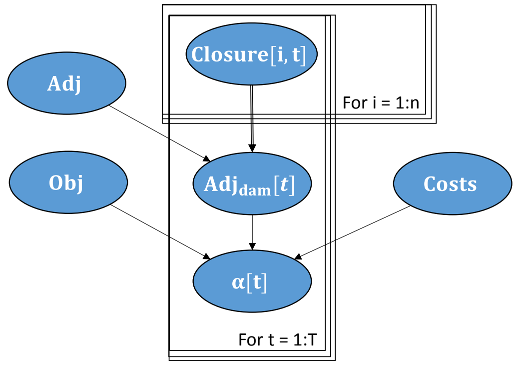


Figure 4. Conceptual Bayesian network for predicting network performance index given bridge closure states

The Bayesian network with fully specified parameters can, as stated previously, also be used for backward inferencing. For example, given that the bridge between nodes 7 and 9 is closed, the likely bridge component damage states causing this observed closure status can be evaluated using MCMC simulations, as shown in Figure 5.

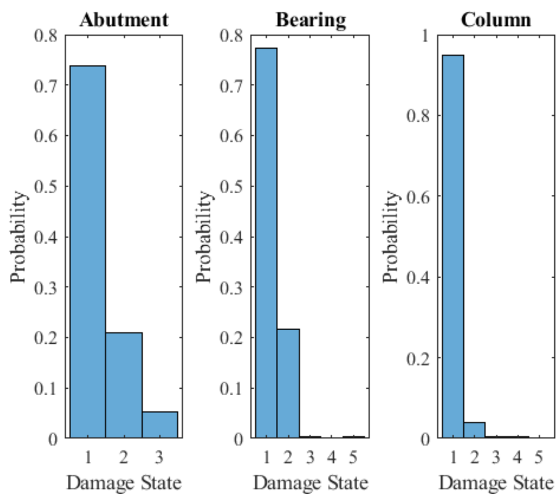


Figure 5. Probability of component damage states given observed closure state at bridge 5

Figure 5 shows the probability of component damage states independently for each component based on 10,000 MCMC simulations. The three histograms express the prior damage probabilities of the three primary bridge components independently. In reality, a joint probability distribution is obtained, which suggests that there is a 45.8 % probability of at least one of the components of this bridge having some level of damage, given that it is closed. Thus, the Bayesian network framework can be used to draw inferences about prior system states given the posterior state. This is ideal in a post-earthquake decision making framework, wherein using observed bridge condition the most likely components to be inspected for damage can be identified. Thus, the Bayesian framework can be a valuable tool for post-earthquake decision making.

CONCLUSIONS AND FUTURE WORK

This study proposed a framework for resilience analysis of transportation networks subjected to extreme events using a Bayesian network, with an example application focusing on seismic resilience of intermodal freight networks. The proposed Bayesian network structure maps component level performance to system level performance both on an individual bridge level as well as on a network level, in addition to leveraging available data to inform bridge closure probabilities from component damage states. Although the network resilience metrics used in the example application are tailored to freight transportation networks that can involve highway, railway or intermodal transport, the framework can be suitably adapted for application to other infrastructure networks and performance objectives. Bayesian network offers a powerful tool for post-event decision support. Examples provided in this study show that Bayesian networks can be used to learn unknown parameters, even with no prior knowledge of their distributions using Markov Chain Monte Carlo (MCMC) Simulations with Gibbs sampling. The same technique is also used for drawing backward inference on component damage states given the observed bridge closure status, thus laying the foundation for improved post-earthquake decision making.

Future work will leverage the proposed framework to build on the example shown herein, to include a time evolving network performance metric that covers the entire recovery timeline. In addition to this, the framework for evaluating network resilience will be generalized further, by using machine learning techniques to infer network performance index from bridge closure states, network topological characteristics and specific performance objectives.

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