SEISMIC PERFORMANCE ASSESSMENT

OF

INTERDEPENDENT LIFELINE SYSTEMS

September, 2007

YoungSuk Kim
Graduate Research Assistant
Department of Civil and Environmental Engineering
University of Illinois at Urbana-Champaign

B. F. Spencer, Jr.
Nathan M. and Anne M. Newmark Endowed Chair
Department of Civil and Environmental Engineering
University of Illinois at Urbana-Champaign

Junho Song
Assistant Professor
Department of Civil and Environmental Engineering
University of Illinois at Urbana-Champaign

Amr S. Elnashai
William J. and Elaine F. Hall Endowed Professor
Department of Civil and Environmental Engineering
University of Illinois at Urbana-Champaign

Ty Stokes
Graduate Research Assistant
Department of Civil and Environmental Engineering
University of Illinois at Urbana-Champaign

ABSTRACT

Lifeline systems such as transportation and utility networks consist of numerous structural components which are spatially distributed and mutually interdependent. The damage to a particular system caused by natural or man-made hazards is propagated to other systems and results in additional losses due to cascading failures. Therefore, understanding the influence of hazards on these interdependent systems is critical to mitigate damage and to perform effective response and recovery efforts. This report focuses on modeling the interdependency between lifeline systems and investigates the effect of such interdependency on the seismic performance of these systems. A probabilistic model is developed to characterize the interdependencies and integrated into a simulation model for estimating the seismic performance of the system. Example analyses show the effect of various levels of interdependency on the performance and demonstrate the importance of considering such interdependencies.

TABLE OF CONTENTS

1. INTRODUCTION

Lifeline systems such as transportation and utility systems (e.g., water delivery, power, and oil systems) are critical civil infrastructures. These systems are essential elements for the functioning of all economic and social activity of an industrialized nation. The functional loss of these systems due to an external perturbation can cause severe impact on a community in numerous ways. This loss has the potential to cut water supplies, reduce or eliminate electrical system capacity, and sever gas links. Specifically, seismic hazards cause significant damage to these systems. The 1994 Northridge earthquake (Mw = 6.8) caused extensive damage to lifeline systems. Portions of major highways and freeways in California were closed due to the extensive damage or failure of bridges, inducing widespread disruption after the event [1]. The entire city of Los Angeles suffered a blackout, and approximately 15% of the population (about 100,000 customers) served by Los Angeles Department of Water and Power (LADWP) lost water services immediately following the earthquake [2-4]. Therefore, understanding the influence of hazards on these systems is critical to mitigate damage and to perform effective response efforts.

Recent research has assessed the response of a complex urban lifeline system under seismic conditions. Some approaches rely on simulation models to estimate seismic performance of a lifeline system [5-7], while others adopt system reliability frameworks to estimate the probabilities of complex system events [8-10]. These approaches generally incorporate the vulnerability of components represented by fragility curves in a system level analysis.

Although these approaches are important advances in the understanding of the seismic response of a lifeline system, consideration of interdependencies (i.e., the influence from the failures of other networks) in modeling and analyzing lifeline systems accordingly is still a significant challenge. The need of accounting for this *interdependency effect* is seen by looking at the importance of a functioning power grid to the water and gas distribution systems. Water and gas distribution systems must have power for proper operation. When a power station is damaged by significant seismic forces, the likelihood that water and gas systems dependent on that power station can continue to function properly is reduced. Therefore, there has been an emerging need of modeling complex and interdependent critical infrastructure to better understand their susceptibility against potential hazards.

A new approach to assess the seismic performance of interdependent lifeline systems is presented herein. A probabilistic model is developed to characterize network interdependency. This probabilistic model is then incorporated into network flow algorithms to assess the seismic performance of the interdependent lifeline systems. Example analyses validate the proposed approach and show the effect of various interdependency levels on the performance of these systems under seismic conditions. The results provide important information to mitigate seismic damage on lifeline systems.

This report is divided into 6 sections. Section 2 provides a brief review of previous efforts in modeling interdependent critical infrastructures. Section 3 describes the new approach to model the interdependent systems. Section 4 presents system performance measures and associated network flow algorithms. In Section 5, the new approach is compared to an existing model through a series of sample examples. Finally, Section 6 summarizes this study.

2. Review of Previous Studies

Efforts to model interdependent civil infrastructure systems and to evaluate the effect of external perturbations have included the use of complex-adaptive systems (CASs) and economic-input output frameworks. In the CAS-based approaches [11-13], complex systems are modeled as a collection of individual intelligent agents which represent their components. These agents respond to disturbances acting competitively and cooperatively for the good of the entire system. Rinaldi et al. [12] showed the potential application of CAS-based approaches to interdependent lifelines including electric, oil, transportation, gas, telecommunication, and water systems. Haimes and Jiang [14] applied an economic input-output model to understand the economic effect of the functional loss of a system on interconnected infrastructure. The model was applied to simple power and transportation systems for demonstration. While system interdependency was addressed in these approaches, the application to the network seismic performance problems was not considered.

Dueňas-Osorio et al. [15, 16] proposed an alternative model for interdependent lifeline systems in which the interdependency was determined by geographical immediacy. The seismic performance of interdependent infrastructure systems under various interconnectedness levels was considered in the study. Although this approach sheds light on the issue of modeling interdependent networks in the context of earthquake engineering, certain issues require further refinement before this approach can be used to assess the seismic performance of the system. These issues are summarized in this section.

a) Probabilistic Model for Interdependency.

The work in references [15, 16] focuses on the dependence of a water system on the power grid. In this work, the dependence of the failure of the j^{th} node in the water network, designated W_j, on the failure of the i^{th} node in the power grid, designated E_i, is given by:

$$P(W_j \mid E_i) = p_{W_j|E_i}, \text{ for all } j \sim i \qquad (1)$$

where $p_{W_j|E_i}$ is the value of the conditional probability of W_j given E_i, which represents the strength of dependency; and ~ indicates node adjacency between the W_j node and the E_i node. $p_{W_j|E_i}$ is considered constant and is bounded as follows:

$$P(W_j) \le p_{W_j|E_i} \le 1 \qquad (2)$$

Because the failure of the j^{th} water node due to seismic forces and due to a power outage are not considered separately, the challenge in using this model is to understand how the event W_j in Eqs. (1) and (2) should be interpreted.

To clarify this situation, consider the Venn-Diagram shown in Figure 1, where for simplicity, attention is restricted to the case where the j^{th} node in the water network draws power only from a single node in the power grid (i.e., the i^{th} node). Here, the sample space is conditioned on the occurrence of a particular level of the ground motion. The associated events in Fig. 1 are defined as follows:

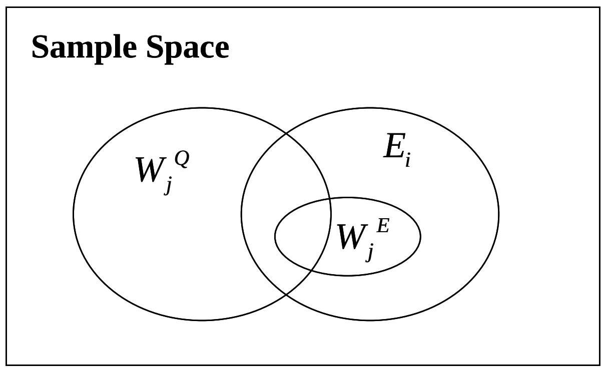

Figure 1. Venn-Diagram.

E_i = failure of the i^{th} node in the power grid

W_j^Q = failure of the j^{th} node in the water network due to earthquake

W_j^E = nonfunctionality of the j^{th} node in the water network due to a power outage.

The event W_j can then be defined as the union of the events W_j^Q and W_j^E, i.e.,

$$W_j = W_j^Q \cup W_j^E \tag{3}$$

With these events, the dependency in Eq. (1) can be defined in more precise terms as follows:

$$P(W_j^E \mid E_i) = p_{W_j^E|E_i}, \quad \text{for all } j \sim i \tag{4}$$

Eq. (4) allows the parameter $p_{W_j^E|E_i}$ to be interpreted as probability of failure of the backup power generation for the j^{th} node in the water network. Additionally, the bound given in Eq. (2) is seen to no longer be valid.

b) Evaluation of Link Failure

The vulnerability of a complex network usually considers the failure of the links and the nodes separately. In this approach, the failure probability is specified for each link and node, and the network is analyzed without further aggregation.

An alternative approach to model the water network, lumping the probabilities of failure of the links onto the node to which these links are attached, was adopted in [15, 16]. This approach assumes that all the links that feed into a node must fail before the node itself has failed. Therefore, the failure of a specific water distribution node is treated as a parallel system event, where the failure of the individual links is considered statistically independent (s.i.). This simplification may result in a more efficient analysis, but it is at the expense of the seismic reliability of the network being overestimated.

c) Directivity of Links

In critical infrastructure, a link can carry bidirectional or unidirectional flow. Most links of lifeline systems, however, generally carry unidirectional flow. In [15, 16], the lifeline system is modeled as an undirected network, which assumes that all links can carry bidirectional flow. This assumption may yield misleading simulation results because power generators may send electricity to power substations but not vice versa in normal operational condition. Therefore, modeling the utility networks with the mixture of bidirectional and unidirectional links are more realistic (refer to 5.2.5 for more detail). In addition, the failure of a link can disrupt the flow in both directions when a link is assumed to be carry bi-directional flow while, in reality, two directional links must fail to stop flow, which is a less probable event. Therefore, results based on the assumption in [15, 16] will typically underestimates the seismic reliability of a system.

d) Network Representation

To represent a network, the topology of a network and its associated data need to be stored. The performance of a network flow algorithm depends not only on the algorithm, but also the way the network is represented and how it is managed during the associated analysis.

An adjacency matrix [17] is one of the popular ways to represent the network. This matrix has a row and a column that correspond to each node in the network. If a link exists between the i^{th} and j^{th} node, the $(i, j)^{th}$ entry of the matrix equals 1. Otherwise, the entry equals 0. This matrix has n^2 elements (where n is the number of nodes), while only m (the number of links) entries are nonzero. Link data (i.e., length, time, capacity, etc) as well as network topology can be stored in additional adjacency matrices. Although the simplicity of the adjacency matrix is an advantage (especially for undirected networks), this sparse matrix requires a significant amount of memory, especially for nondense networks. Furthermore, this sparseness is a bottleneck in identifying all of the outgoing/incoming links from/to nodes, which is a key task in network flow algorithms. When dealing with large networks that will need to be analyzed in seismic loss assessment programs such as MAEviz [18], this problem may be acute. The adjacency matrix representation is used in the model developed in [15, 16]. A more efficient way of storing the network topology and the associated data is the forward star representation, which will be described in Section 4 of this report.

3. PROBLEM FORMULATION

Lifeline systems are modeled as directed networks in this study. The network, which consists of nodes and links, represents a system of power generation stations, power distribution stations, power lines, pumping stations, water pipelines, pipeline junctions, etc. By considering the systems in this way, network flow algorithms can be employed to ascertain network behavior that is of interest to end users and emergency responders.

This section develops a new probabilistic model for interdependent utility networks. The issues described in the previous section with regard to the model in [15, 16] are addressed by the proposed model.

Problem Description

Consider an example of power grid and water system shown in Fig. 2, where the electrical needs of a node in the water distribution network can be supplied by one or more nodes in the power grid.

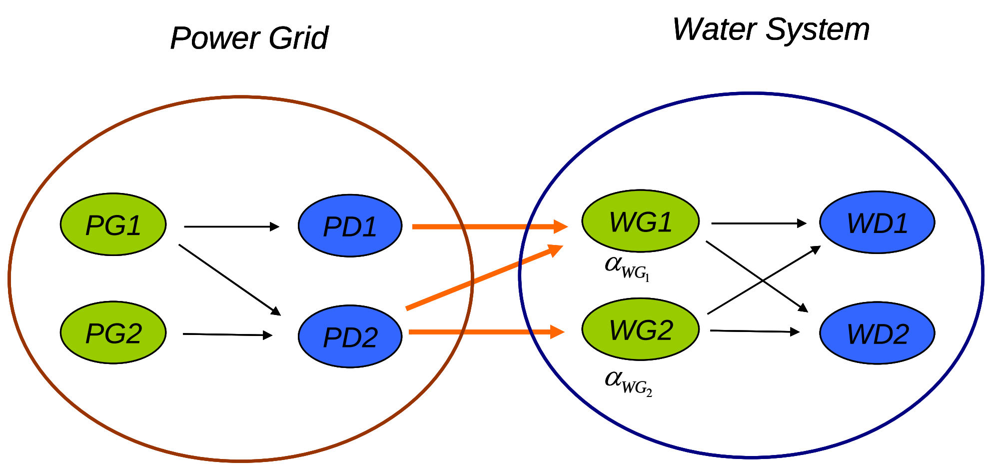

Figure 2. Interdependent Systems.

To account for network *interdependency*, a relationship must be developed to describe how the failure of a node in one network is affected by failures in another network. This relationship can be determined as a function of the geospatial location of the network components and the associated connections. For example in Fig. 2, water generation node 1 (WG1) is dependent on power distribution node 1 (PD1) and 2 (PD2), and WG2 is dependent on PD2. WG1 and WG2 have backup power generation units for which their failure probabilities are α_{WG_1} and α_{WG_2}, respectively.

The dependent nodes in the water system (e.g., WG1 and WG2 in Fig. 2) must have power for proper functionality. Consider the failure of these nodes in the water system due to a power outage. Each dependent node has a backup power generation unit; therefore, both the nodes on the power grid which it is dependent on and its backup power generator must fail so that the dependent node in the water system is rendered nonfunctional. This means that we need to consider the reliability of the backup supply unit in determining the strength of interdependency and in evaluating interdependency effects.

The following section describes the proposed model to characterize the dependency of a node in the water system on the nodes in the power grid.

Interdependency Model

Let $\underset{\sim}{E}_{S_j}$ denote the failure of the set of power nodes (S_j) on which the water node j is dependent. More specifically, the event $\underset{\sim}{E}_{S_j}$ is defined as

$$
\begin{aligned}
\underset{\sim}{E}_{S_j} &= \bigcap_{k \in S_j} E_k \\
&= \bigcap_{k \in S_j} \{E_k{}^Q \cup E_k{}^N\}
\end{aligned}
\tag{5}
$$

where

$E_k{}^Q$ = failure of the k^{th} node in the power grid due to earthquake

$E_k{}^N$ = nonfunctionality of the k^{th} node in the power grid because of failure due to earthquake of the nodes or links that feed electricity to the k^{th} node

and

$$E_k = E_k{}^Q \cup E_k{}^N \tag{6}$$

As in the previous section, the failure of a node in the water distribution network due to earthquake and due to power failure are considered separately, and the sample space is conditioned on the occurrence of an earthquake of a specified magnitude. An updated Venn diagram of this problem's sample space is shown in Fig. 3.

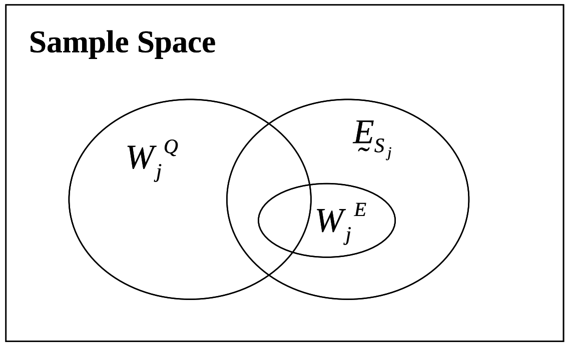

Figure 3. Venn-Diagram for interdependent events.

Assuming that the events E_k^Q and W_j^Q are conditionally s.i. events given the magnitude of the ground motion, then the probability of the joint failure is $P(E_k^Q) \cdot P(W_j^Q)$ where $P(E_k^Q)$ and $P(W_j^Q)$ are determined respectively by fragility curves [19]. The probability of the event E_k^N is difficult to compute analytically because it is associated with the probability of failure of other components in a network. Therefore, $P(E_k^N)$ is generally determined by system reliability framework [9] for a relatively small size network or by Monte-Carlo simulations for a complex network [20].

The interdependency can be described by the following conditional probability:

$$P(W_j^E \mid \underset{\sim}{E}_{S_j}) = \alpha_j \quad \text{for all } j \tag{7}$$

where α_j represents the strength of the dependency which is determined by the failure probability of the backup supply unit at node *j*. This physically represents the probability that a water node will be nonfunctional given the failure of all the power nodes that supply power to the water node.

By simulating network flow, the interdependent system response can be evaluated. The next section presents the system performance measures for quantifying the functional loss of this system and network flow algorithms corresponding to the system performance measures employed in this study.

4. SIMULATION MODEL

The proposed probabilistic model presented in Section 3 is integrated into two network flow algorithms to evaluate the seismic response of interdependent systems. This section describes the system performance measures and network flow algorithms employed in this study.

4.1 System Performance Measure

To quantify the functional loss of a lifeline system, two system performance measures are adopted: Connectivity Loss (*CL*) and Service Flow Reduction (*SFR*).

Connectivity Loss is a measure of the ability of every distribution node to receive flow from the generation nodes. Connectivity loss is defined as:

$$CL = 1 - \sum_{i=1}^{N} \frac{nG^{i}_{post}}{nG^{i}_{pre}} \quad (8)$$

where N is the number of distribution nodes, nG^{i}_{pre} denotes the number of generation nodes able to feed flow to the i^{th} distribution node under intact conditions, and nG^{i}_{post} denotes the number of generation nodes able to supply power to the i^{th} distribution node under seismic conditions. The performance measure in Eq. (8) is an extension of the one proposed in [15, 16] for undirected networks.

Service Flow Reduction (*SFR*) determines the amount of flow that the system can provide compared to what it provided before the disturbance. Service Flow Reduction is defined as:

$$SFR = 1 - \sum_{i=1}^{N} \frac{S^{i}}{D^{i}} \quad (9)$$

where S^i denotes the actual flow at the i^{th} distribution node under seismic conditions, and D^i represents the demand of the i^{th} distribution node. This SFR was proposed in [15].

The SFR provides a better measure of the consequences of a seismic event on lifeline systems in that supply/demand at each node, capacity of a link, and actual flow are considered, while CL is only concerned with the existence of a path that can deliver flow from generation nodes to distribution nodes.

4.2 Network Flow Algorithm

To estimate Connectivity Loss (CL) and Service Flow Reduction (SFR), two different network flow algorithms are employed for simulations.

The forward star representation [17] is used in this study to store the topology of the network and its associated data in a single matrix. Each row corresponds to each link and has 2 (tail and head node) + k (the number of link properties such as length and capacity) elements. The rows are sorted in the ascending order of their tail node and numbered sequentially. A pointer for each node i, indicating the smallest numbered link of which tail node is node i, is maintained to determine the set of outgoing links of node i efficiently. This representation not only saves computing memory, but also enables network flow algorithms to identify links emanating from a node faster than when using the adjacency matrix [17]. The network flow algorithms used in this study are tailored to accept this network representation. A summary of the network flow algorithms are given subsequently.

Search Algorithm (For Connectivity Loss):

Connectivity loss is concerned with whether available paths exist between generation and distribution nodes. This connectivity may be evaluated using a search algorithm. The search algorithm determines if there exists a path between nodes. Therefore, the breadth-first search algorithm is employed to estimate CL. The mathematical formulation of breadth-first search is given in Ahuja et al. [17].

As in [15, 16], a shortest path algorithm is employed for the problem of the connectivity loss analysis. The shortest path algorithm repeatedly compares the cost of the paths that connect a (source) node to the other nodes to find the shortest path. Because the search algorithm does not include the process of comparing path travel cost, the shortest path algorithm is less efficient in terms of simulation speed. This advantage increases as the size of a network increases.

Min-Cost/Max-Flow Algorithm (For Service Flow Reduction):

SFR is evaluated by considering link capacities and supply/demand of nodes. Successive Shortest Path (SSP) algorithm [17] was modified to solve the min-cost/max-flow problem and implemented to simulate flow in this study. If a network is disturbed by an earthquake (i.e., failures of generation nodes and links), this algorithm routes the flow from generation (supply) nodes to distribution (demand) nodes considering the capacity of links in the network.

In [15], the SFR is determined by solving min-cost and max-flow problems separately and sequentially. Although the algorithm used in the reference [15] can consider convex (nonlinear) cost flow, sequentially solving the optimization problem is computationally inefficient.

5. MODEL COMPARISON

To illustrate the advantages of the proposed model, several simple examples are considered for comparison with the model developed in [15, 16]. Section 5.1 describes the fragility information used by the analyses in this report. Section 5.2 shows the sample networks and the simulation results.

5.1 Fragility Information for Network Components

Lifeline systems comprise numerous structural components which are spatially distributed. Typically, the vulnerability of these components is represented by fragility curves which show the conditional probability of being in a specific damage state given the ground motion intensity. These fragility curves are used for power system components such as electric substations, gate stations, and power generation plants, as well as for water system components which include pumping stations, storage tanks, and pipelines.

The fragility information used in this report was obtained from the open literature. The fragility data for power generation, power distribution, and water generation components are obtained from the HAZUS 99 manual [19]. For buried pipelines, a study conducted by O'Rouke and Ayala [21] was used to estimate the vulnerability of pipelines. This data was also used by the analyses in [15, 16].

For power generation, power distribution, and water generation components, it is assumed that a component that experiences at least "extensive" damage is not able to function. The fragility parameters used for the evaluation of component functionality are shown in Table 1, and the probability of reaching or exceeding extensive damage can be calculated using Eq. (10).

Table 1. Fragility information for network components [19].

Classification	Damage State	Median	β
Power Generation component			
High-Voltage ESS5	Extensive	0.2	0.35
Power Distribution component			
Low-Voltage ESS1	Extensive	0.45	0.45
Water Generation component			
Plants with Unanchored Subcomponents-PPP4	Extensive	0.77	0.65

$$\mathrm{P[Extensive\ Damage|PGA = a]} = \Phi\left(\frac{\ln(a) - \ln(\mathrm{median})}{\beta}\right) \tag{10}$$

A break in a pipe is assumed to result in the failure of buried pipelines. To ascertain if a pipe has a break, the repair rate is calculated using the following equation [21]:

$$\text{Repair Rate (repairs/km)} \cong 0.0001 \times \mathrm{PGV}^{2.25} \tag{11}$$

where PGV is *Peak Ground Velocity* in cm/s. A repair rate of 20% is assumed to be the rate of breaks in the pipeline. Using the break rate and assuming that the breaks constitute a Poisson process, the probability that a segment of pipe experiences at least one break can be determined. In the proposed approach, as well as the model by Dueňas-Osorio et al. [15, 16], the occurrence of at least one break is assumed to impair the functionality of a pipeline segment. Therefore, the probability of pipeline break occurrence is calculated as:

$$P(B_r > 0) = 1 - P(B_r = 0) = 1 - e^{-\mathit{Break\ Rate} \times \mathit{Length}} \tag{12}$$

where B_r is the number of breaks.

5.2 Example Analyses

Five example networks, including a simplified Memphis network, were selected to demonstrate the differences between the proposed approach and the one in references [15, 16]. The Matlab code developed by Dueňas-Osorio et al. [15, 16] was provided and used for these comparisons and the proposed model is also coded in MATLAB.

The first example shows the difference between the node-based and link-based approaches in considering failure of links. The second example is for a power network with transmission nodes. The third and fourth examples demonstrate the discrepancy in results for cases in which a water node depends on multiple power nodes and multiple water nodes that depend on a single power node. The last example is for a simplified Memphis water and power network.

A water generation node is assumed to be dependent on power distribution nodes, and a water distribution node is modeled as a junction of pipes which is not dependent on the power nodes. Hence, a water generation node may be rendered nonfunctional from seismic effects and the nonfunctionality of all power distribution nodes that supply power to the water generation node. Failure of two directional links that carry bi-directional flow between two components is assumed to be perfectly correlated events.

For both the proposed approach and the approach in [15, 16], Monte-Carlo simulation (MCS) is implemented to simulate the response of the sample networks under seismic conditions. The peak ground acceleration (PGA) level at each node is increased monotonically, and the PGV at each pipeline is calculated accordingly using the conversion formulation developed in [15]. Note that the references [15, 16] dealt with *CL*, while SFR analyses were conducted only in the reference [15].

5.2.1 Example 1: Water-Only Network

In analyzing water networks, one of the major differences between the proposed approach and that presented in [15, 16] is that individual pipelines are removed (i.e., a link-based approach) in the proposed approach, whereas in the model in [15, 16], the fragilities of pipelines that are adjacent to a water distribution node were combined into the water distribution node (i.e., a node-based approach). As a result, the model in [15, 16] requires that all pipelines connected to a node fail for connectivity loss to occur. The example in this section illustrates that this assumption results in underestimation of *CL* and *SFR*.

Consider the example network in Fig. 4. To allow for direct comparison of link and node removal, the network flow algorithms employed in [15, 16] for estimating *CL* and *SFR* are used in this example.

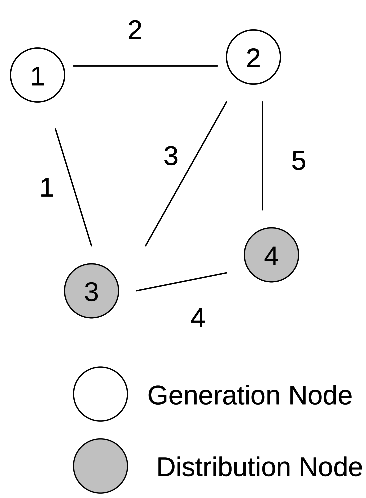

Figure 4. Water-only network for validation.

The results for this network are shown in Figs. 5-8. MCS with 500 samples was used to assess the seismic performance (i.e., *CL* and *SFR*) of this network. The results in

Figs. 5 and 6 illustrate that the proposed model yields a higher measure of system loss as a function of PGA. In this specific example, the failure of link 1, 3 and 5 disrupt the flow between generation and distribution nodes. The link-based model is able to capture this situation while the node-based model cannot. This difference resulted in the underestimation of *CL* and *SFR* when the network is analyzed using the model in [15, 16]. As shown in Figs. 7 and 8, the computational efficiency is approximately the same for both the node-based and link-based models.

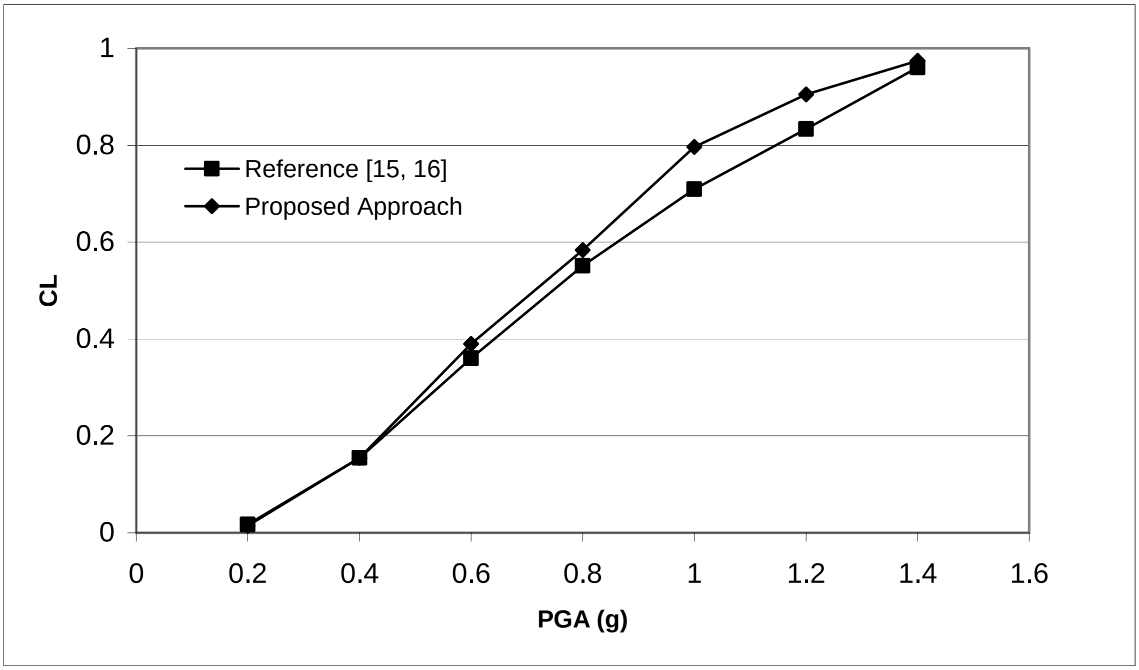

Figure 5. Mean CL for the water-only network.

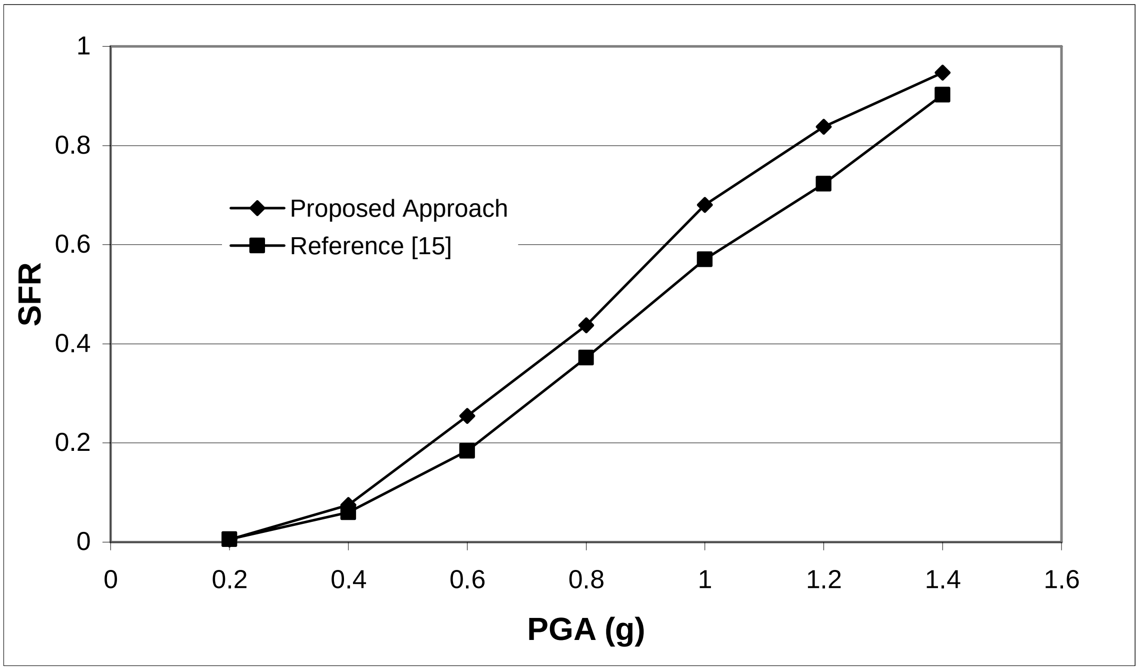

Figure 6. Mean *SFR* for the water-only network.

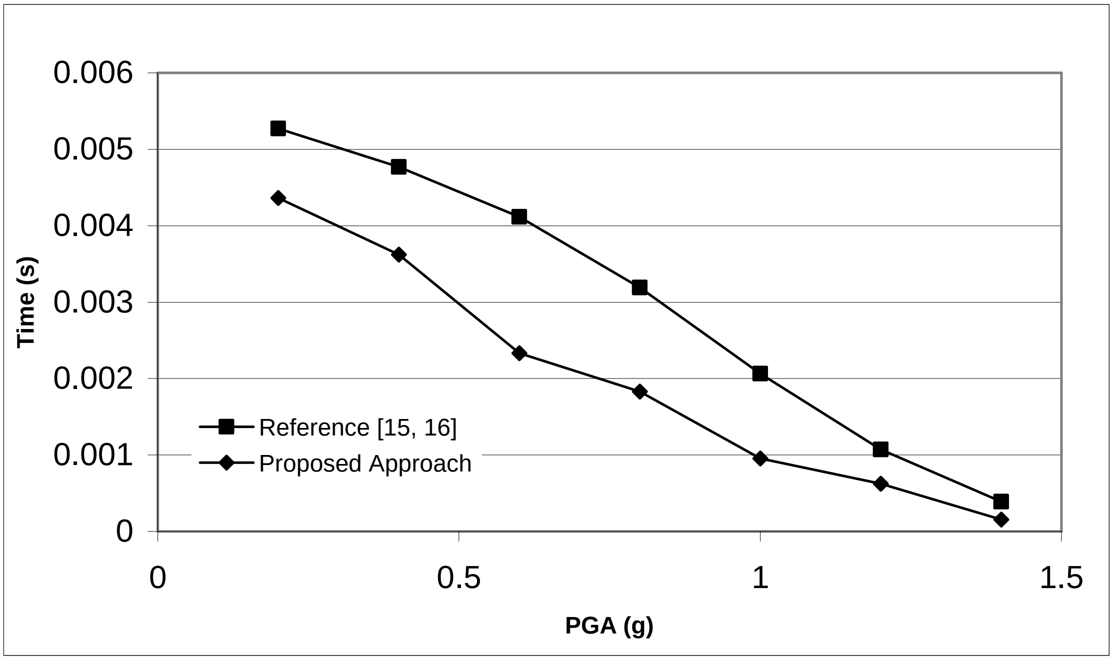

Figure 7. Average *CL* algorithm runtime for the water-only network.

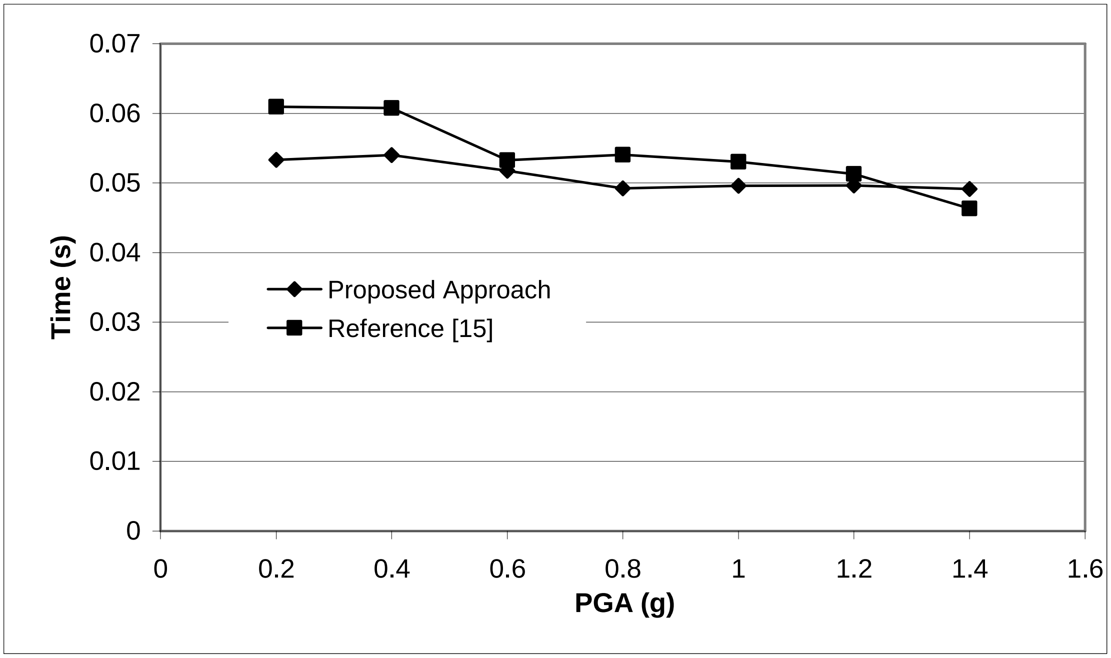

Figure 8. Average *SFR* algorithm runtime for the water-only network.

5.2.2 Example 2: Network with Transmission Nodes

If a power generation node fails, power distribution nodes that are supplied with electricity only from the power generation node are not functional even though the power distribution nodes survived under earthquakes. This nonfunctionality of the power distribution nodes may result in nonfunctionality of water nodes that are dependent on these power distribution nodes. For a power system that has transmission nodes, simulations (e.g., breadth first search) are required to determine if power distribution nodes are able to carry electricity from the power generators after a seismic event. To investigate whether both approaches can appropriately handle this case, the network shown in Fig. 9 was selected and analyzed. Note that “T” in Fig. 9 represents a transmission node.

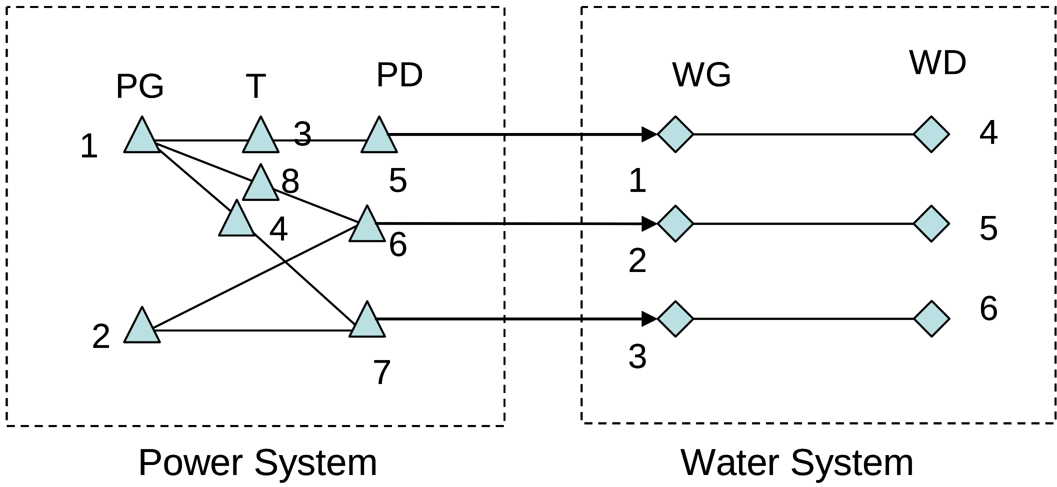

Figure 9. Example network for transmission node case.

Like the previous example, Monte-Carlo simulation (MCS) with 500 samples was used to assess the seismic performance. The reliability of backup power generator at each water generation node was decreased monotonically, in other words, interconnectedness level (i.e., the strength of dependency) increased for this example. The results for this system are shown in Figs. 10 and 11.

As shown in Figs. 10 and 11, the results from both models show that the *CL* and *SFR* increase as the interconnectedness level increases. However, the model in [15, 16] has higher network performance loss for this example network because it cannot account for cases where the generation nodes fail and transmission nodes exist between other generation nodes and the distribution nodes. To illustrate this issue in more detail, consider the network shown in Fig. 12. In the model in [15, 16], if a generation node fails from seismic forces, then this model looks to see if the neighbors of the generation node have

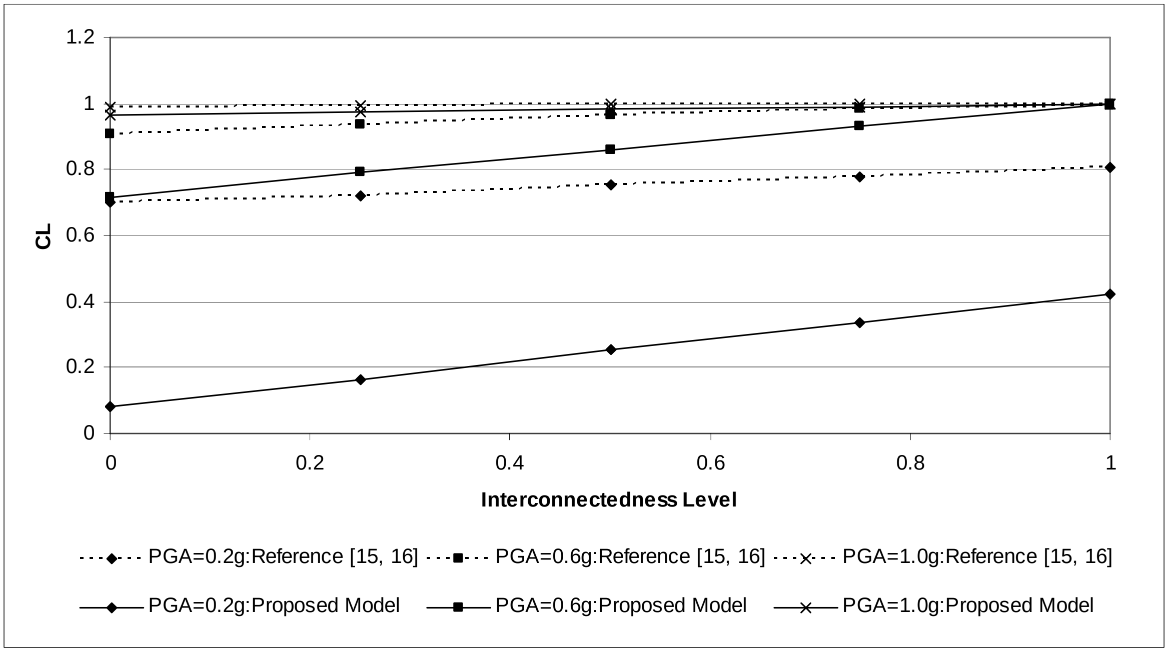

Figure 10. Mean *CL* of water network for transmission node case.

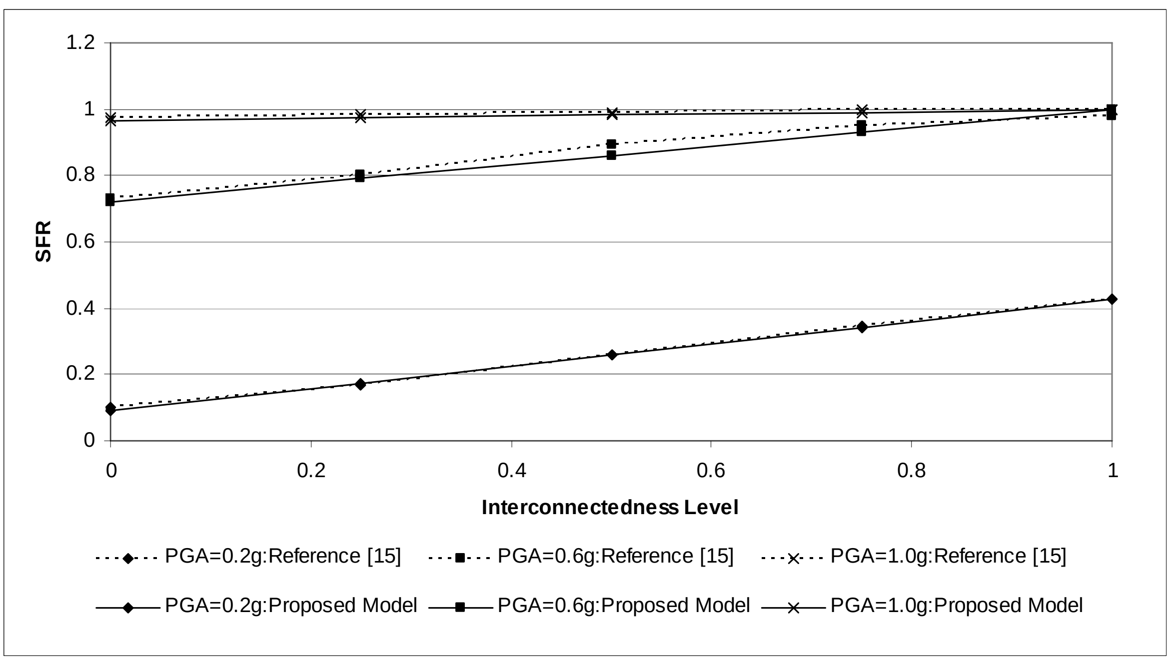

Figure 11. Mean *SFR* of water network for transmission node case.

links to other generation nodes. If there are none, then the model in [15, 16] assumes that water nodes which are dependent upon the neighbors of the power generation nodes fail. However, suppose that power generation node G2 fails after an earthquake, but power generation node G1 and water generation node G survive. In this case, the model in [15, 16] assumes that D cannot receive the electricity because the other neighbor of D is not a generation node. This will result in the possible removal of water generation node G while D still has flow from the power supply, G1. The analysis in this fashion overestimates the network performance loss although this approach is more computationally convenient. In contrast, the proposed model uses breadth first search algorithm to ensure the connectivity between generation and distribution nodes.

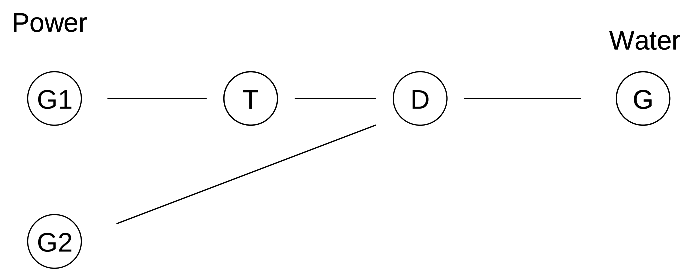

Figure 12. Example network for transmission node analytical comparison.

Note that *CL* at low PGA level from the model in [15, 16] is highly overestimated while the difference of *SFR* between both models are slight. The overestimation of *CL* from the model in [15, 16] is because this model assumes that every distribution node receives flows from all generation nodes under intact conditions. In this specific example, this assumption is not appropriate.

5.2.3 Example 3: Multiple Power Nodes per Water Node (MPPW)

This example focuses on the case when a node in the water network is dependent on multiple nodes in the power grid. To compare the results between the proposed approach and the model in [15, 16], the network shown in Fig. 13 was developed and analyzed.

Because the model in [15, 16] considers a water node to be subjected to interdependent effects if any of the power nodes that are able to feed flow into the water node is nonfunctional, this model is expected to underestimate water network performance.

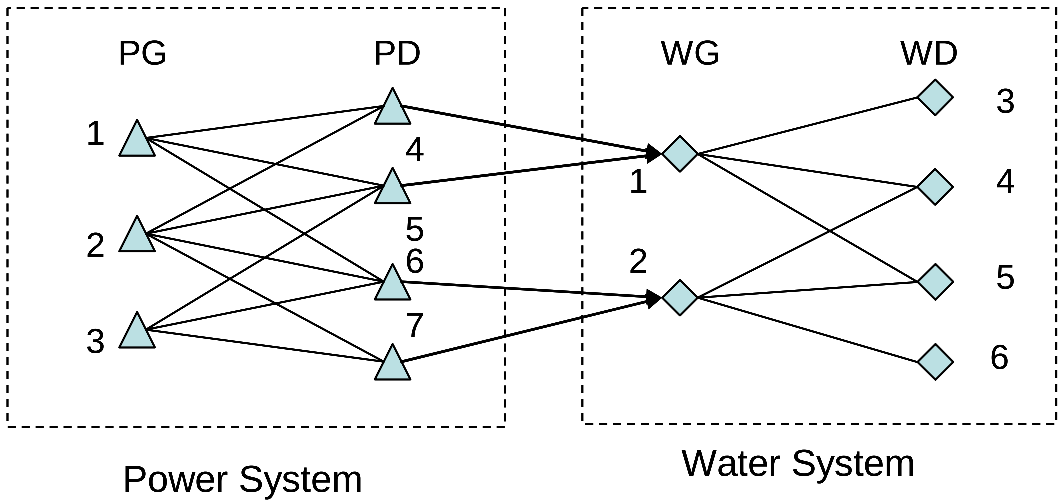

Figure 13. Example network for MPPW case.

For the analyses of this example, Monte-Carlo simulation (MCS) with 500 samples was performed with the interconnectedness level (i.e., the strength of dependency) increased monotonically. The results for this system are shown in Figs. 14 and 15 and the runtime of both models are compared in Figs. 16 and 17.

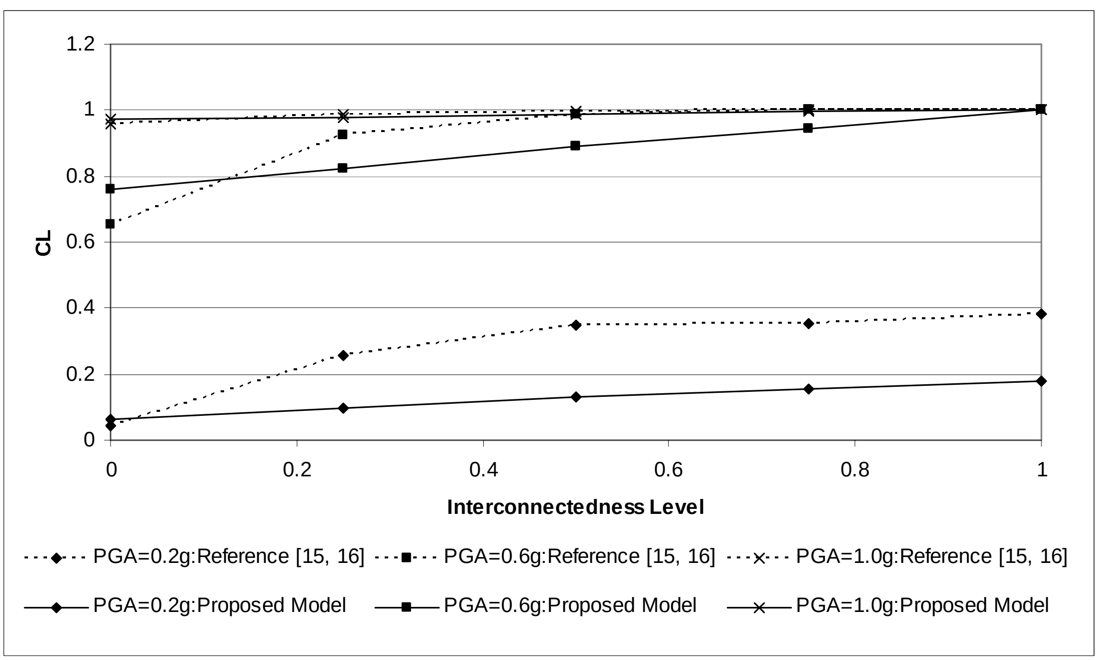

Figure 14. Mean *CL* of water network for MPPW case.

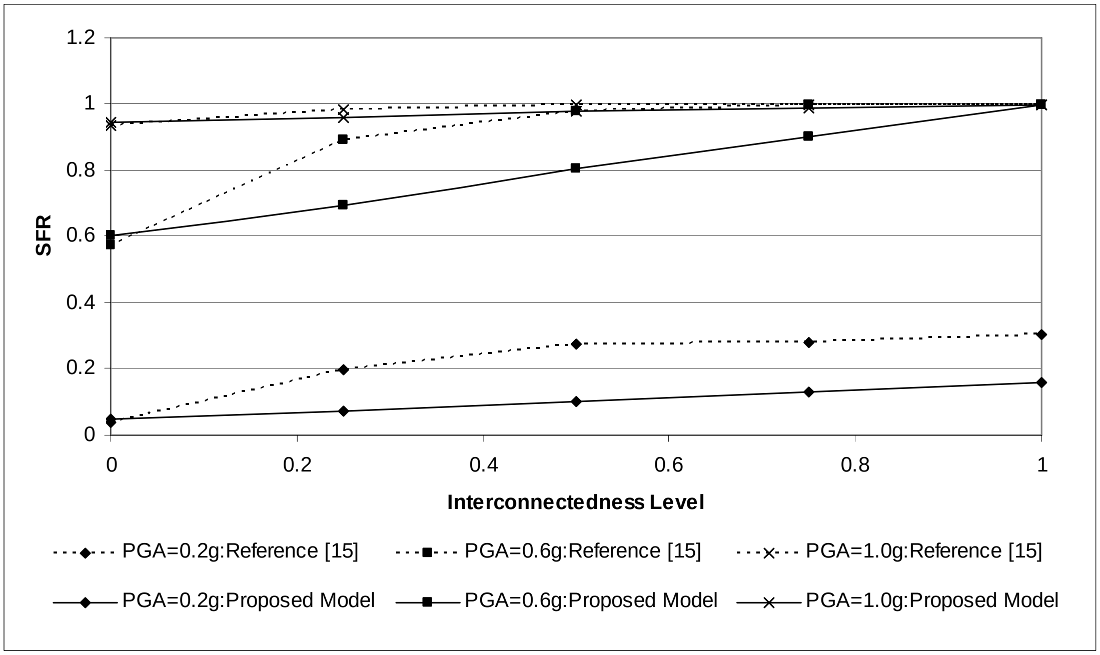

Figure 15. Mean *SFR* of water network for MPPW case comparison.

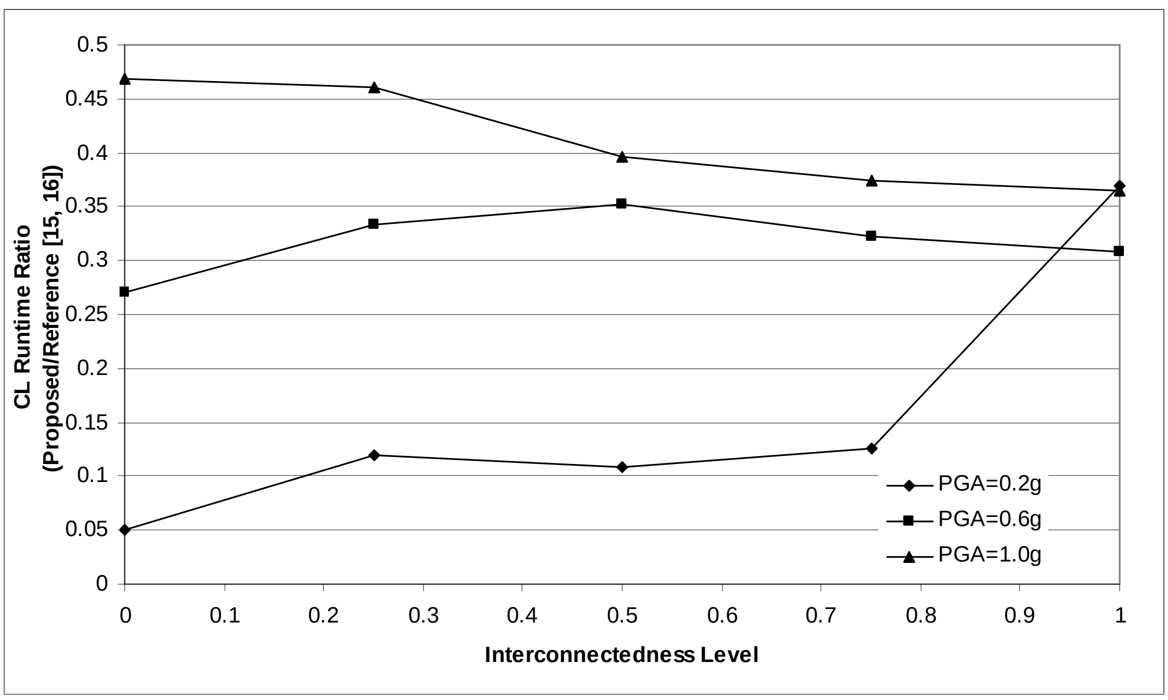

Figure 16. Runtime comparison of *CL* for MPPW case.

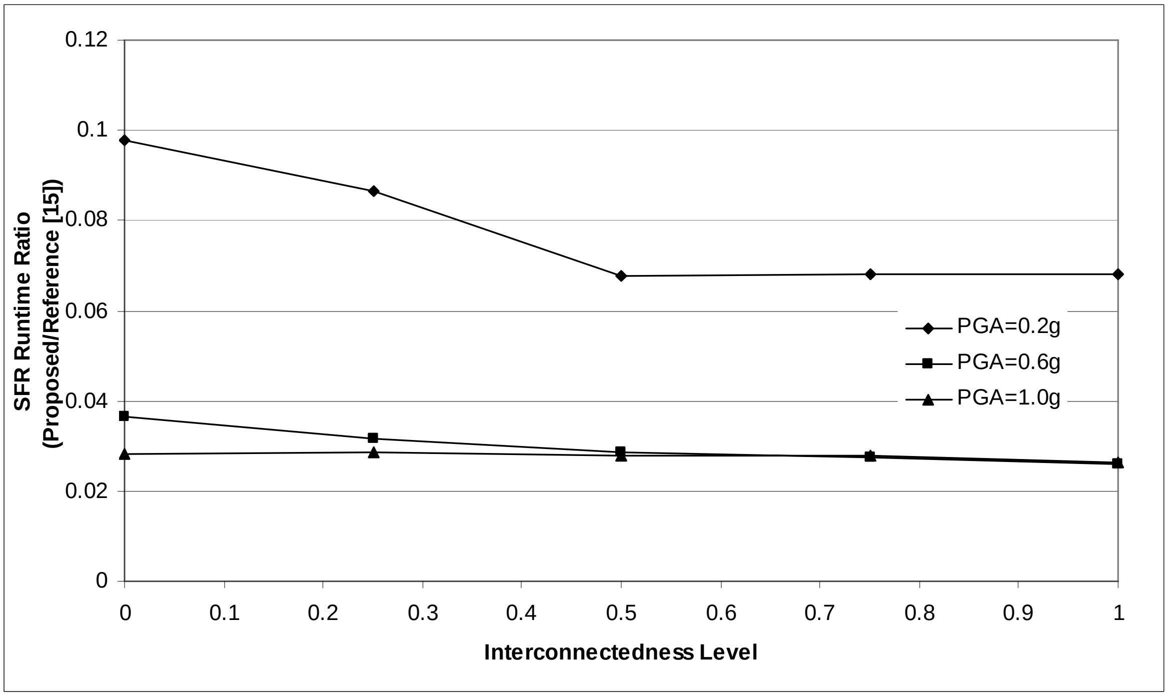

Figure 17. Runtime comparison of *SFR* for MPPW case.

As illustrated here, the model in [15, 16] overestimates *CL* and *SFR* at higher interconnectedness level because of the way that it determines dependency effect. This finding suggests that the results for this case would improve with the use of the proposed model. Runtime of both approaches are compared in Figs. 16 and 17. The computational efficiency of the proposed model is excellent, particularly for *SFR* due to the use of more efficient algorithms.

5.2.4 Example 4: Multiple Water Nodes per Power Node (MWPP)

In this example (Fig. 18), one power node feeds multiple water nodes. In the model [15, 16], if many water nodes are connected to one failed power node, all water nodes are assumed to be under the same dependency effect, which means that if one water node is considered to have failed, then the others also are considered to have failed. However, the proposed approach evaluates the interdependency effect considering the reliability of the backup power unit at each water node independently. Therefore, the proposed approach does not assume that all water nodes are under the same dependency effect.

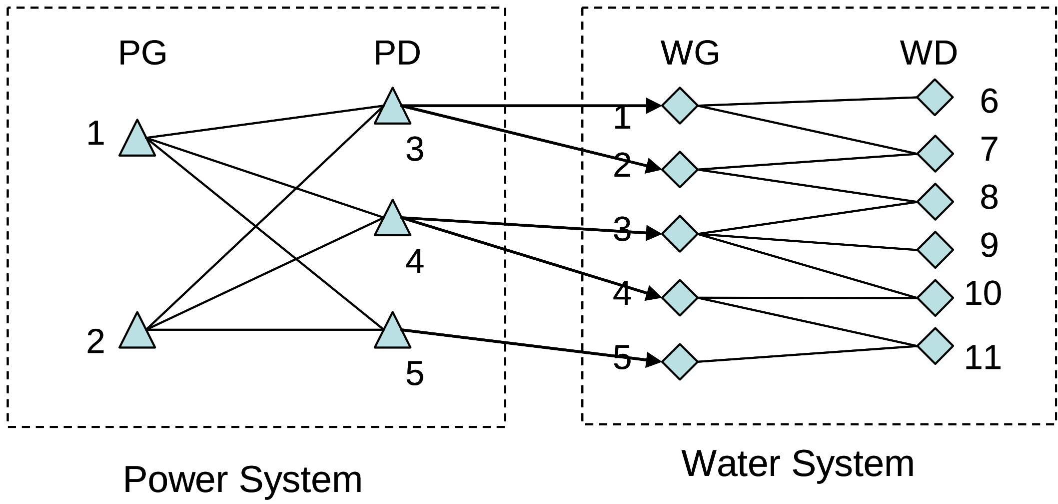

Figure 18. Example network for MWPP case.

Like previous examples, Monte-Carlo simulation (MCS) with 500 samples was used with the interconnectedness level (i.e., the strength of dependency) increased monotonically. The results for this system are shown in Figs. 19 and 20.

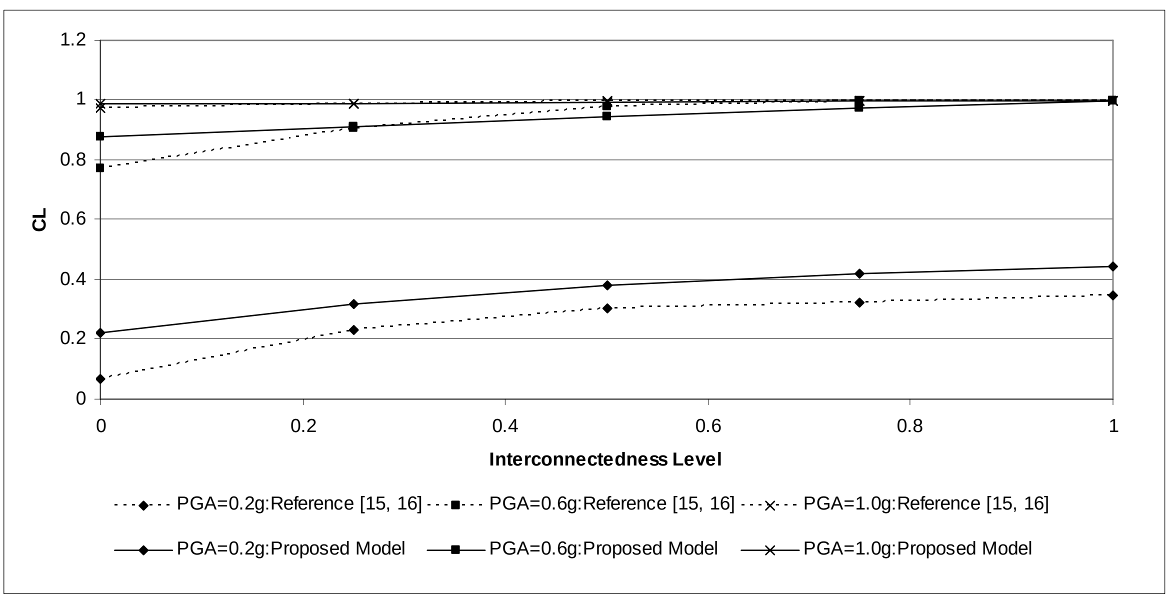

Figure19. Mean *CL* of water network for MWPP case.

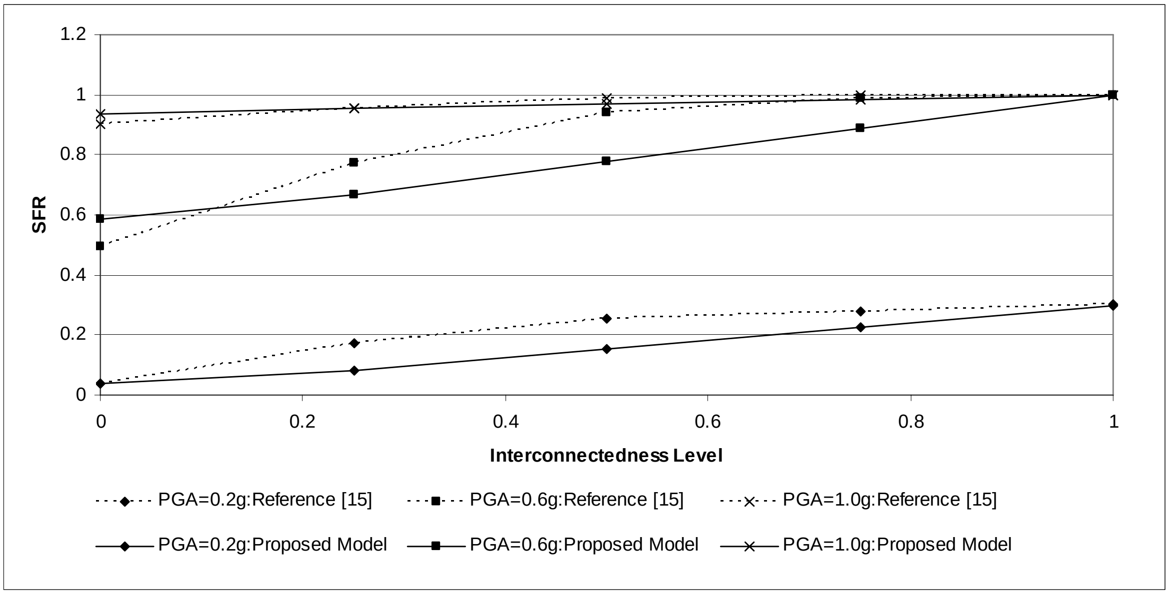

Figure 20. Mean *SFR* of water network for MWPP case.

These results show that the proposed approach produces higher performance loss estimates at zero interconnectedness level and the model in [15, 16] overestimates the performance loss at higher interconnectedness levels. The former is due to the link-based approach of the proposed model and the latter is due to the fashion that the model in [15, 16] evaluates the interdependency effects.

5.2.5 Example 5: Memphis Network

Both approaches are applied to a simplified Memphis water and power systems to estimate system performance. The networks have 49 water and 59 power nodes as shown in Figs. 21 and 22. For the water system, storage tanks and large pumps are modeled as the water generation nodes, and pipe intersections are modeled as the water distribution nodes. Gate stations are modeled as power generation nodes, and substations are modeled as power distribution nodes for the power grid. Each water generation node is dependent on at least one power distribution node.

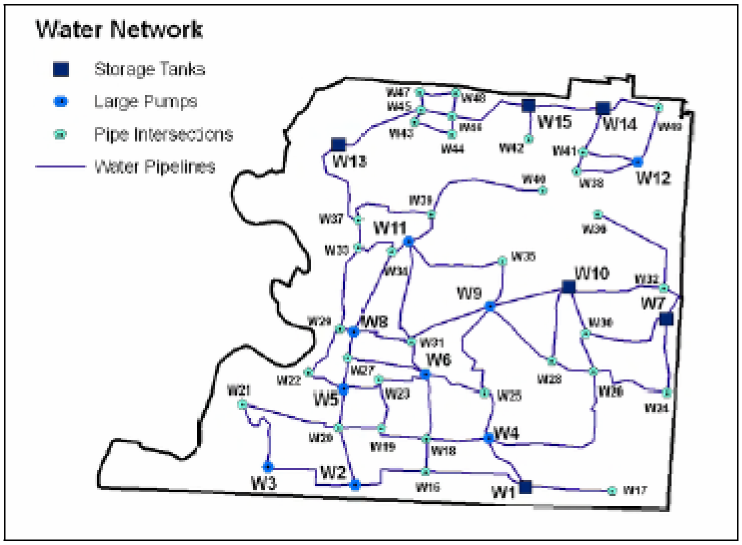

Figure 21. Memphis water network [16].

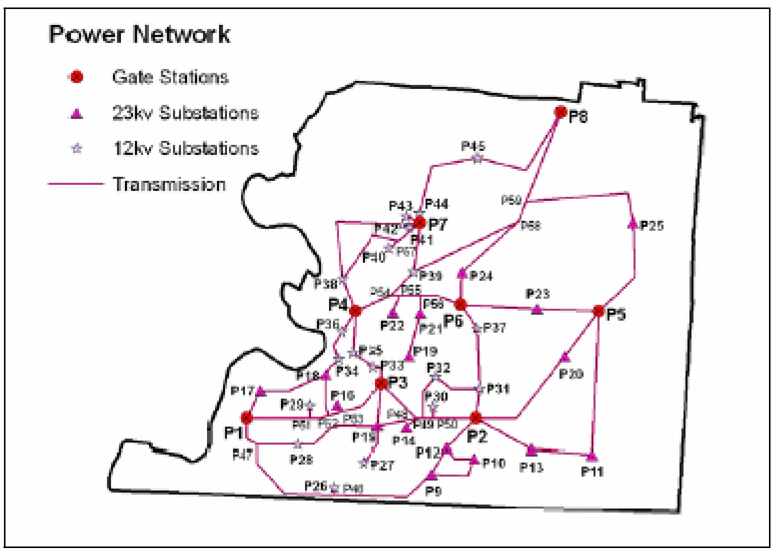

Figure 22. Memphis power network [16].

For the Memphis water and power networks, determination of which approach would yield higher system performance loss is difficult before carrying out the simulation due to their complexity. However, a few key characteristics can be investigated to estimate the difference of the system performance from both approaches:

1) The Memphis water network has many interconnected water distribution nodes. This characteristic implies that failure of pipelines would reduce network performance before the failure of every distribution node (see

Section 5.2.1). As a result, the model in [15, 16] is expected to underestimate the network performance loss.

2) The Memphis power network has many transmission nodes and only one case of a power node connected to multiple water nodes (and no cases of water nodes connected to multiple power nodes). These characteristics imply that the interdependency effects will be largely influenced by the transmission nodes. Therefore, the model in [15, 16] will overestimate the system performance loss.

These characteristics imply that the Memphis analyses will show a higher performance loss for the proposed model than the model in [15, 16] at the zero interdependency level, and that the performance from the model in [15, 16] will increase with respect to the proposed model as the interdependency level increases.

As previously mentioned, the references in [15, 16] modeled utility systems as undirected networks. However, an actual system is a heterogeneous mix of bidirectional and unidirectional links. Based on a series of discussions with an official[1] in MLGW, generation nodes (e.g., pumping stations and water tanks in water networks and gate stations in power grids) only allow power and water to flow from them under normal operating conditions although these nodes has an ability to change the direction of flow for re-routing. Unlike water pumping stations, water tanks can allow flow in both directions under normal conditions so that they can provide water to distribution nodes or water from distribution nodes can fill the tanks. Although these tanks allow bidirectional flow physically, we can assume that they can allow flow in one direction for network analyses because water from distribution nodes fills the tanks first and the tanks provide water to other distribution nodes. Therefore, the proposed model looks at utility systems as directed networks such that unidirectional links are modeled to send flow only from generation nodes to distribution or transmission nodes while two unidirectional links are modeled to carry bidirectional flow between distribution nodes or generation nodes. Note that if a generation node fails, water/power from other generation nodes can pass through the failed node to provide water/power to the affected area after emergency operations are performed.

To compare both the proposed model and the model in the references [15, 16] directly, Memphis water and power systems are modeled as undirected and directed ones and analyzed.

[1] Richard Bowker, Manager of Information Service: Memphis Light, Gas & Water

Monte-Carlo simulation (MCS) with 1000 samples was selected after convergence tests and used for the analyses with the interconnectedness level (i.e., the strength of dependency) increased monotonically. Note that while both models can consider spatial variation in the ground motion, this effect was not taken into account for simplification.

The comparison of the system performance and computational efficiency for undirected Memphis network are conducted and shown in Figs. 23-26. The *CL* and *SFR* analyses for the Memphis water and power networks illustrate both the phenomenon from the water network-only analyses that compared the proposed link removal to the node removal in the model in [15, 16], and the transmission node case for which the model in [15, 16] overestimates interdependent effects.

As shown in Figs. 23 and 24, the proposed model has higher network performance loss at lower interdependency levels, and at higher interdependency levels, the model in [15, 16] either catches up to the proposed model or increases at a faster rate as a function of interdependency. The results from the proposed approach indicate that the system performance loss increases as the strength of dependency (interconnectedness level) increases. These results clearly show that the neglect of dependency (or interdependency) effect will mislead the evaluation of seismic performance for lifeline systems which are interdependent with one another.

The runtime comparisons in Figs. 25 and 26 show that the algorithms used in the proposed model run fairly fast compared to the algorithms in the model in [15, 16].

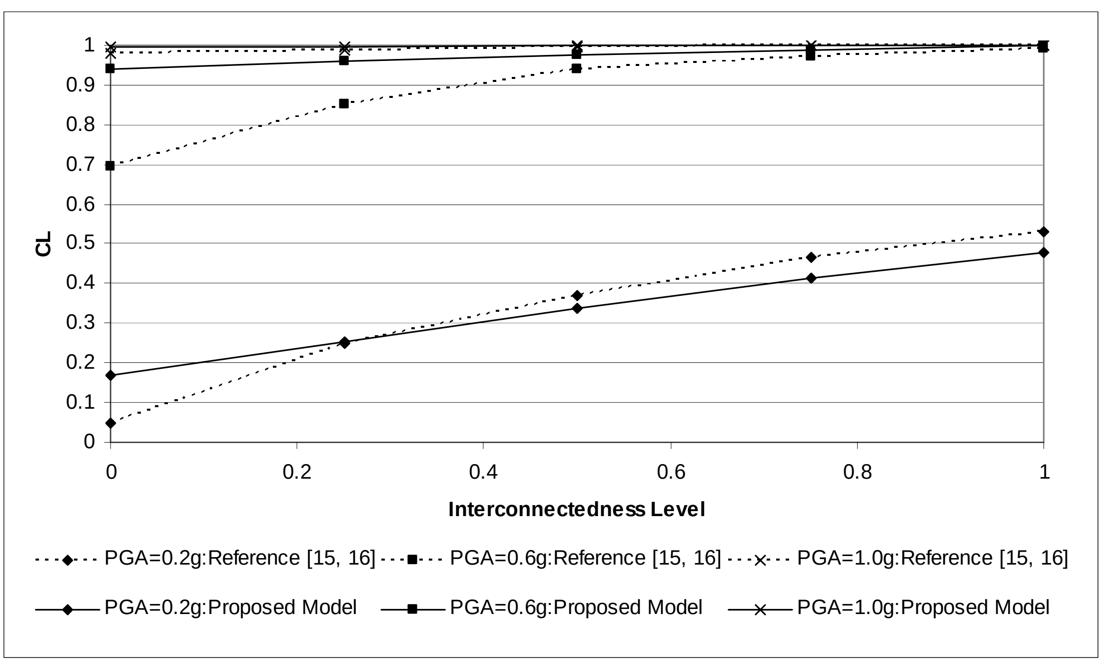

Figure 23. Mean *CL* for undirected Memphis water network.

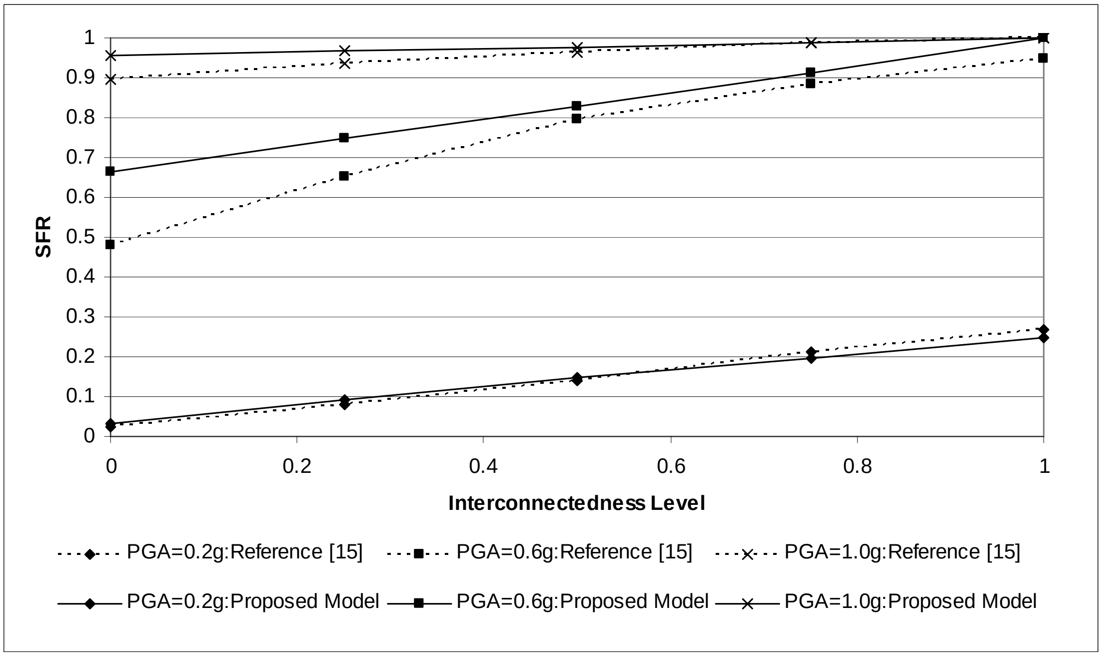

Figure 24. Mean *SFR* for undirected Memphis water network.

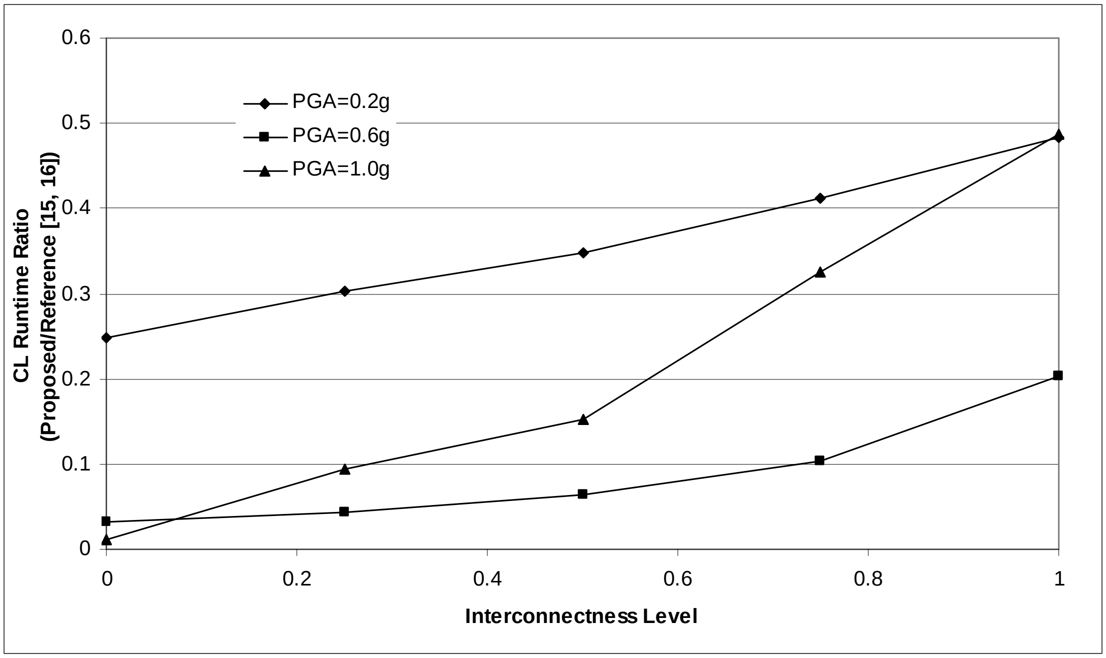

Figure 25. Runtime comparison of the *CL* for undirected Memphis networks.

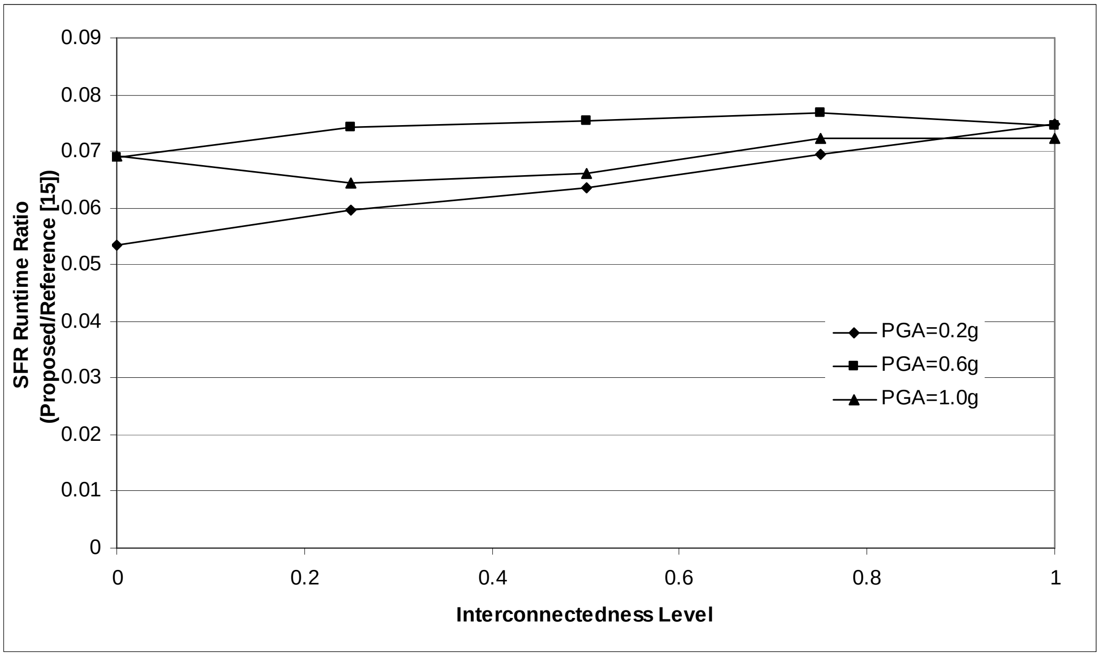

Figure 26. Runtime comparison of the *SFR* for undirected Memphis networks.

For the analyses of directed Memphis network, the assumption made in [15, 16], that all distribution nodes are able to get fed by all generation nodes, is not obviously appropriate. Therefore, the model in [15, 16] was modified to evaluate *CL* using Eq. (8). The comparison of the system performance for directed Memphis network are shown in Figs. 27-28. These results show the same trends as the results for undirected Memphis network.

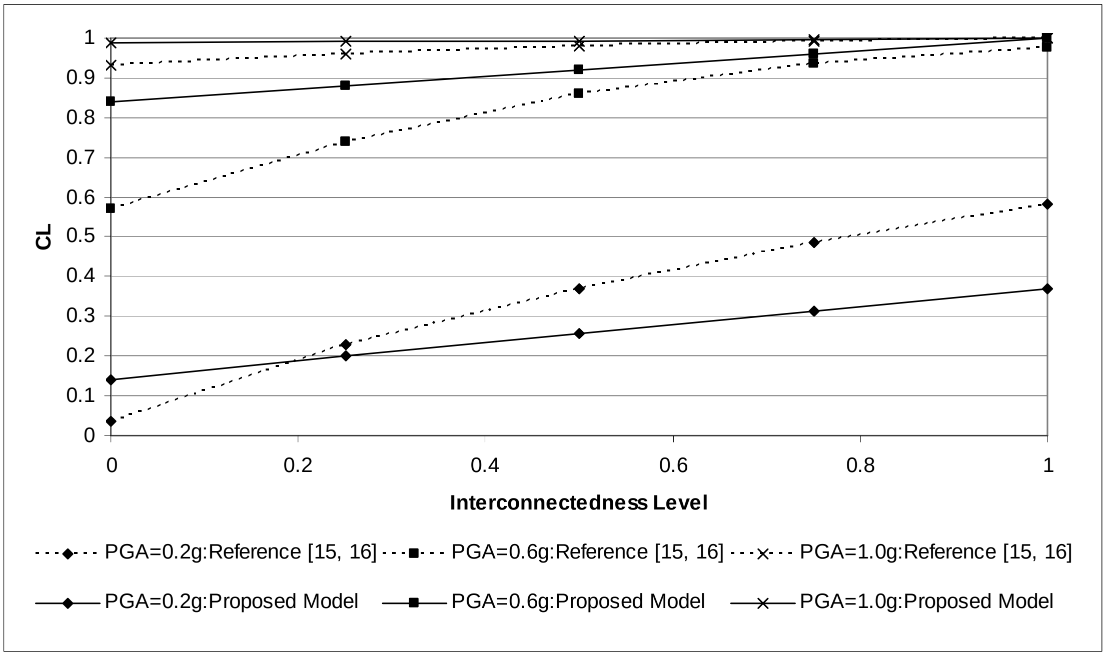

Figure 27. Mean *CL* for directed Memphis water network.

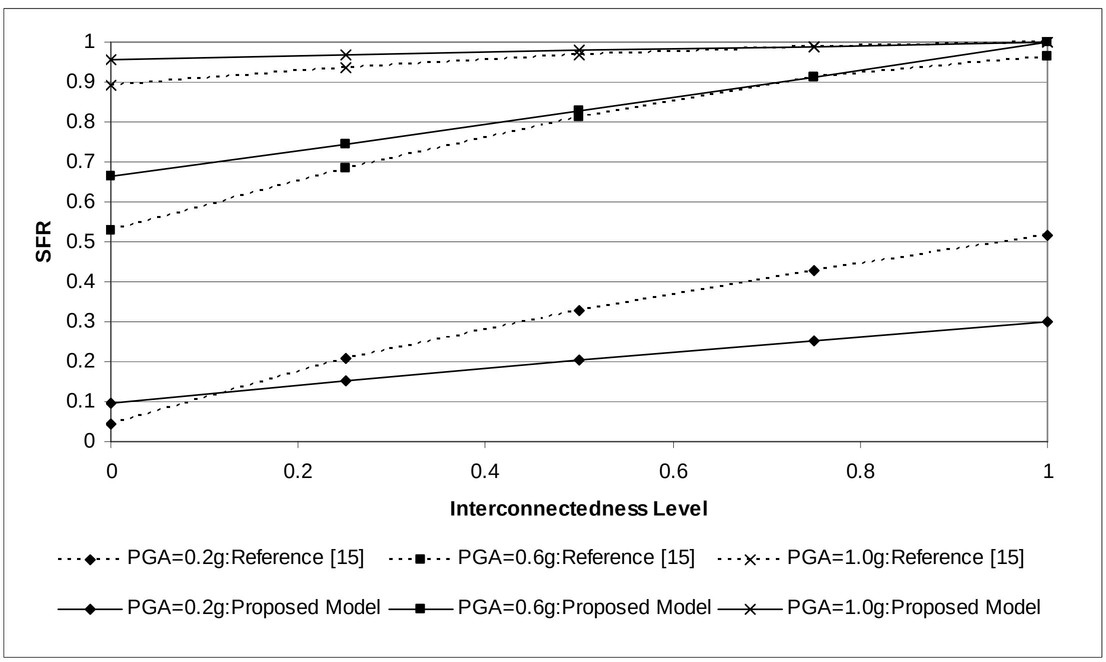

Figure 28. Mean *SFR* for directed Memphis water network.

6. CONCLUSION

This report presented a new approach to account for the interdependency effects in evaluating the seismic performance of lifeline systems. A probabilistic formulation was developed to accurately characterize interdependency between power and water grids. This probabilistic formulation and efficient network flow algorithms were implemented to assess the seismic performance of interdependent lifeline systems. The strength of interdependency (interconnectedness level) was given by the failure probability of the backup supply unit at a node that is dependent on nodes in other systems.

Example networks were developed and analyzed to demonstrate the difference between the proposed approach and that in a recently published work [15, 16]. Through a series of example analyses, the robustness and efficiency of the proposed approach were successfully demonstrated. The analysis for a simplified Memphis water and power grid demonstrated the importance of considering the interdependency effects in the seismic performance assessment of utility lifeline networks.

Key improvements in the proposed model include the consideration of improved interdependent failure mechanism and the use of efficient algorithms. Although both the proposed model and the model in [15, 16] capture the effects of interdependencies in analyzing network, the proposed model offers enhanced interdependent network response estimates. The discussions of flow direction in utility networks provided better understanding of the behavior of network systems under normal and emergency conditions. Utility systems are modeled as directed networks based on the discussions, which helped to estimate the seismic performance of the systems more accurately.

The resulting output of the proposed model provides useful insight in the preparedness of potential hazard and the establishment of effective mitigation actions. The proposed model will be implemented in MAEviz, the seismic loss estimation tool developed by Mid-America Earthquake (MAE) Center, for assessing a comprehensive seismic risk to critical infrastructures.

ACKNOWLEDGEMENTS

The authors would like to express their sincere gratitude to Prof. Leonardo Dueňas-Osorio of Rice University for his support in understanding his work and for his careful review of this manuscript. This study was undertaken as a part of the Mid-America Earthquake (MAE) Center research projects IT-1: Framework Development and RM-2: Systematic Treatment of Uncertainty. The MAE Center is a National Science Foundation

Engineering Research Center (ERC) funded by National Science Foundation Award No. EEC-9701785.

REFERENCES

1. Caltrans. The Continuing Challenge: The Northridge Earthquake of January 17, 1994. *Seismic Advisory Board Report*, California Dept. of Transportation, Sacramento, California, 1994.
2. Hall JF (ed.). Northridge earthquake of 17 January 1994: reconnaissance report. *Earthquake Spectra* 1995; 11 (Supple. C)
3. USHUD. *Preparing for the "Big One" - Saving Lives Through Earthquake Mitigation in Los Angeles, CA*, U. S. Department of House and Urban Development, 1995.
4. Chen WF, Scawthorn C (ed.). *Earthquake Engineering Handbook*, CRC Press, New York, NY, 2003.
5. Hwang H, Shinozuka M. Seismic performance assessment of water delivery systems. *Journal of Infrastructure Systems* 1998; 4(3):118-125
6. Kim YS, Spencer BF, Elnashai AS, Ukkusuri S, Waller ST. Seismic performance assessment of highway networks. *The 8th National Conference for Earthquake Engineering*, San Francisco, U.S.A., April 18-22, 2006.
7. Shinozuka M, Dong X, Chen TC, Jin X. Seismic performance of electric transmission network under component failures. *Journal of Earthquake Engineering and Structural Dynamics* 2007; 36(2):227-244.
8. Vanzi I. Seismic reliability of electric power networks: methodology and application. Structural Safety 1996; 18(4):311– 327.
9. Li J, He J. A recursive decomposition algorithm for network seismic reliability evaluation. *Earthquake Engineering and Structural Dynamics* 2002; 31(8):1525-1539.
10. Kang WH, Song J, Gardoni P. Matrix-based system reliability and applications to bridge networks. *Proceedings of 10th International Conference on Applications of Statistics and Probability in Civil Engineering (ICASP)*, Tokyo, Japan, July 31-August 3, 2007.
11. Axelrod A, Cohen MD. *Harnessing Complexity: Organizational Implications of a Scientific Frontier*. Free Press, New York, NY, 1999.
12. Rinaldi SM, Peerenboom JP, Kelly TK. Critical infrastructure interdependencies. *IEEE Control Systems* 2001; 21(6):11–25.
13. Amin M. Towards self-healing energy infrastructure systems. *IEEE Computer Applications in Power* 2001; 14(1):20–28.

14. Haimes YY, Jiang P. Leontief-based model of risk in complex interconnected infrastructures. *Journal of Infrastructure Systems* 2001; 7(1):12.
15. Dueňas-Osorio DO, Craig JI, Goodno BJ. Tolerance of Interdependent Infrastructures to Natural Hazards and Intentional Disruptions, *Mid-America Earthquake Center Report*, 2006.
16. Dueňas-Osorio DO, Craig JI, Goodno BJ. Seismic response of critical interdependent networks. *Earthquake Engineering and Structural Dynamics* 2007; 36(2): 285-306
17. Ahuja RK, Magnanti TL, Orlin JB. *Network Flows*, Prentice Hall, Upper Sadler River, NJ, 1993.
18. MAEC. http://mae.cee.uiuc.edu/software_and_tools/maeviz.html
19. FEMA. *HAZUS 99: Technical Manual*. Federal Emergency Management Agency, 1999.
20. Billinton R, Li W. *Reliability Assessment of Electrical Power System Using Monte Carlo Methods*, Plenum Press, New York, NY, 1994
21. O'Rourke MJ, Ayala G. Pipeline Damage Due to Wave Propagation, *Journal of Geotechnical Engineering,* 1993; 119(9).