Proceedings of the 9th U.S. National and 10th Canadian Conference on Earthquake Engineering
Compte Rendu de la 9ième Conférence Nationale Américaine et
10ième Conférence Canadienne de Génie Parasismique
July 25-29, 2010, Toronto, Ontario, Canada • Paper No 1073

DESIGN OF INTERDEPENDENT INTERFACES FOR LIFELINE SYSTEMS USING RESPONSE SURFACE INVERSE RELIABILITY METHODS

X. Min[1] and L. Dueñas-Osorio[2]

ABSTRACT

Reliability-based design guidelines are necessary to achieve uniform levels of lifeline network performance. For this purpose, inverse reliability methods are explored in the context of geographically distributed networks. However, most of the lifeline network reliability design to date focuses on element strengthening and capacity increase without considering the topology of the overall networked system and without explicitly considering the interdependencies among different networks. Also, current lifeline system design almost exclusively emphasizes the negative effects of the interdependence on reliability of lifeline networks, which provides a single-sided view of the role of infrastructure coupling. A broader exploration of interdependence should also include the positive effects of interdependence to improve operation and control efficiency. In this paper, in order to fully consider the complexity of network system topology and accurately evaluate the duel influence of interdependence on the network reliability, response surface models (RSM) are employed for the representation of network performance. Inverse Reliability Method based on RSM approaches illustrates the challenges of satisfying conflicting design objectives such as interdependence reduction to avoid failure propagation, and interdependence increase to enhance infrastructure operation and control.

Introduction

Along with the worldwide urbanization and population concentration, lifeline systems, such as electrical power, water, natural gas, telecommunication networks, and transportation networks are now operated close to their design capacities while their stability control and topology have become more complex. Correspondingly, the reliability analysis, design, expansion and retrofit of lifeline network become increasingly important as well as increasingly difficult. Most previous studies on reliability-based design of lifeline networks are limited to the individual system level, while the effects of interdependence among different individual lifeline networks on system reliability has only drawn researchers' attention recently. Rinaldi et al.

[1] Ph.D. Student, Dept. of Civil and Environmental Engineering, Rice University, Houston, TX 77005
[2] Assistant Professor, Dept. of Civil and Environmental Engineering, Rice University, Houston, TX 77005

(2001) proposed a complex-adaptive system based method to evaluate the effect of external perturbations to interdependent lifeline systems including electric, water, telecommunication, oil, transportation, and gas networks. Dueñas-Osorio et al. (2007a, 2007b) developed a model for interdependent infrastructure systems in which the interdependence was determined by geographical immediacy and a probabilistic model of the strength of interdependent bonds between different networks. Rosato et al. (2008) use simplified DC power flow models to study interdependence between the electrical grid and telecommunication network under perturbation. Ouyang et al. (2009) looked into the interdependence effects between coupled power and gas networks. These past contributions have shed light on modeling interdependence lifeline networks. However, the current research on lifeline system interdependencies mainly focuses on the negative effects of coupling on infrastructure system performance (Rosato et al. 2008, Chang et al 2007, etc.). Dueñas-Osorio et al. (2007a, 2007b) demonstrate that interdependencies significantly increase the connectivity loss of lifeline systems under disaster conditions. A case study by Adachi and Ellingwood (2008) also reveals that serviceability of water distribution networks decreases when considering dependency on the power network. However, emphasis on the negative effects of interdependence overlooks an emerging purpose of interconnectedness, which is to enhance controllability and operation efficiency. Currently, different infrastructure systems are usually arranged in a more geographically interdependent fashion to take advantage of information technologies and alternative sources of data and communication exchange for more efficient and redundant operation. This paper demonstrates that the interdependence among different individual networks increases their connectivity loss when subjected to external disruptions, while keep their operation efficiency during normal operation regimens. A response surface model (RSM) based inverse reliability method is developed in this paper for interdependent seismic design of lifeline systems to achieve uniform performance, while explicitly considering network topological features and their interdependence interface to find the balance between positive and negative effects of system coupling on network reliability.

Metrics for Description of Network Interdependence Interface

To assess the effect of interdependence on the reliability of lifeline systems, topological metrics are needed first to explicitly describe the interconnection features between different networks.

Interdependence Strength

Interdependence strength (IS) is the coupling strength of interdependence bonds. It is represented by the conditional probability of failure (Dueñas-Osorio et al. 2007a), which can be expressed as:

$$IS = P(Failure\ N1_i \,|\, Failure\ N2_j) = p_{N1_i|N2_j} \qquad \text{for all } j \sim i \qquad (1)$$

Where $N1_i$ represents failure of the *i*th element of the network 1; $N2_j$ represents failure of the *j*th element in the network 2, and $p_{N1_i|N2_j}$ is the value of the conditional probability of failure of element *i* given failure of element *j*. The IS, can be tuned to explore all the possible coupling strengths between nodes from different networks, ranging from independence $p_{N1_i|N2_j} = p_{N1_i}$ to complete interdependence $p_{N1_i|N2_j} = 1$.

Interdependence Density

Interdependence density (ID) is the ratio of number of existing interdependent links to the number of all possible interactions between nodes from different network , which can be calculated by:

$$ID = \frac{\text{Number of interdependent links between network1 and network 2}}{n1 \times n2} \tag{2}$$

Where $n1$ is number of nodes in lifeline network1, $n2$ is number of nodes in network2, thus $n1 \times n2$ is number of all the possible links between the two networks. The parameter ID can also be tuned to represent different distribution density of interdependence bonds: from 0 to 1.0, where ID = 0 corresponds to the independent situation and ID = 1.0 corresponds to a case where there is a bond between each pair of nodes from different network.

Metrics for lifeline network Performance

The performance of the networks after exposure to seismic hazards is measured by the connectivity loss C_L, and the efficiency loss E_L, in this paper.

Connectivity Loss

Connectivity loss C_L is a parameter that quantifies the average decrease of the ability of distribution nodes to receive flow from generation nodes. The calculation of this parameter relies on the topological structure of the network, and to some extent relies on possible optimal flow patterns (Dueñas-Osorio et al., 2007a, Albert et al., 2004). Denote n_G the number of connecting paths from every generation node to any distribution node, n_D the number of all the distribution nodes, and n_G^i the number of generation units able to supply flow to distribution node i after a perturbation takes place. Then, C_L can be calculated as:

$$C_L = 1 - \frac{1}{n_D}\sum_i^{n_D}\frac{n_G^i}{n_G} \tag{3}$$

Where the averaging is done over every distribution vertex i of the network, and all the flow through each transmission line is assumed to be undirected.

Efficiency Loss

Efficiency loss E_L is a parameter that quantifies the ability of a network to keep its operation efficiency under perturbation relative normal operation states. Being consistent with the definition of efficiency in a single network, the interdependence efficiency, E, is defined as:

$$E = \frac{1}{n}\sum_{\substack{i \in net1 \\ j \in net2}}\frac{1}{d_{ij}} \tag{4}$$

Where n is the number of nodes in the network, d_{ij} is the shortest distance between nodes from different networks, which indicates the efficiency of communication between node *i* in network 1 and node *j* in network 2. Then, the efficiency loss is calculated by:

$$E_L = \frac{E_0 - E}{E_0} \tag{5}$$

Where E_0 is the interdependence efficiency of the network without perturbation; E is the interdependence efficiency of the network under perturbation. It should be noticed that the efficiency loss is a parameter measured for one network while taking into account interdependencies, but it is not a metric for the whole network of systems. It describes the efficiency of one network to communicate with another network in a system of lifeline systems.

Response Surface Model (RSM) based Inverse Reliability Method

The inverse reliability problem arises when it is necessary to determine the value of design parameters for a complex system given a desired reliability level. Many efficient methods to solve this problem have been proposed. Der Kiureghian et al. (1994) developed an iterative algorithm based on the Hasofer-Lind-Rackwitz-Fiessler (HLRF) algorithm to extend the method to general limit state functions. Li and Foschi (1998) introduced a Newton-Raphson algorithm for determining multiple design parameters for structural systems. The inverse reliability method adopted in this paper is based on the approach described in (Li and Foschi, 1998) but adapted to lifeline system applications. The limit state functions are implicit functions of the random design variables in lifeline system design, which make the classical inverse FORM method invalid in network-based reliability design because of the classic methods' requirements to evaluate the derivatives of the response function with respect to all random variables. To acquire an approximate explicit form of implicit response function of lifetime system networks, a design of experiment (DOE) based response surface (RS) model is used in this paper to enable adequate representations of complex network system behavior. The response surface method was introduced by Box and Wilson in 1951. The original idea of RS method is to use a series of designed experiments to obtain the most optimal response function to relate input and outputs. Rackwitz R. (1982) first applied the RS method in structural reliability assessment by fitting a polynomial at the limit state points to determine the tangent hyper plane of the failure boundary. Felix S. Wong (1985) used first-order polynomials with interaction terms as RS models to replace finite element code in reliability assessment of soil slopes. More recently, Cheng J. et.al (2009) used a polynomial-based response surface method to solve the inverse reliability problems of steel structures and compared the accuracy of the RS model and artificial neural network models to approximate actual limit state functions. The RS model adopted in this paper is based on the model described in (Cheng et.al, 2009).

Application Example

The lifeline examples in this paper correspond to the water and electrical power networks in Shelby County, Tennessee. After simplifications, both of the infrastructure systems are of comparable number of nodes and links, and are co-located to enable coupling. Figure 1 presents the topological structure of the selected networks (Dueñas-Osorio et al., 2007a):

Figure 1. Topological structure of the lifeline networks in Shelby County, TN: (a) electric power grid; and (b) potable water distribution networks

Figure 2 shows a sample of the seismic hazard in Shelby County with the power grid topology. The map presents seismic hazard contours in peak ground acceleration (PGA) for the most significant events at a hazard rate consistent with 10% probability of exceedance in 50 years.

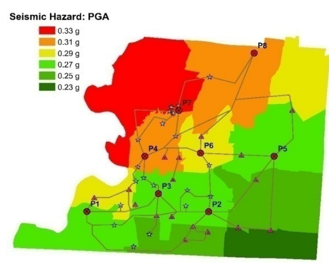

Figure 2. Hazard contours for the most significant events of de-aggregated probabilistic seismic hazard in Shelby County, Tennessee, U.S.A.

The power network contains nodes of four categories: high voltage gate substations, 23kv low voltage substations, 12kv low voltage substations, and general intersections of the transmission lines. Similarly, the water network includes distinct kinds of elements: pumping stations, elevated tanks, and junctions of the pipelines. For each kind of network component, there are unique probabilistic fragility curves, which capture the likelihood of exceeding specific limit states given a level of hazard intensity (typically in PGA units), and are traditionally fitted to lognormal probability distributions (Figure 3).

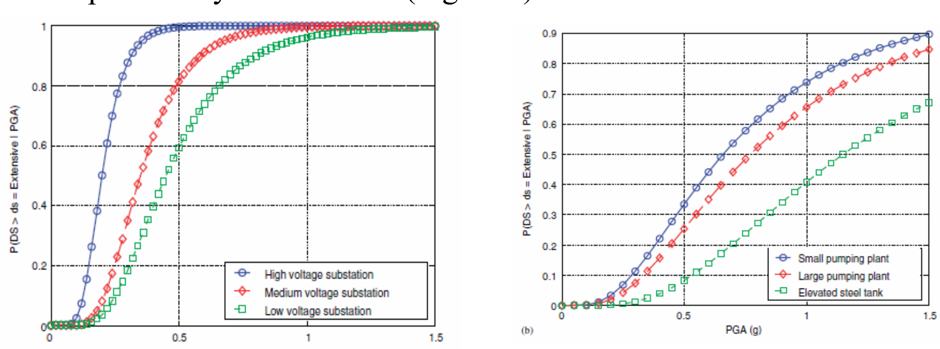

Figure 3. Fragility curves of network elements for an extensive damage limit state: (a) electric power grid; and (b) potable water distribution networks

Because the focus of this paper is to explore the interdependence interfaces for lifeline networked system, network interdependence style, or the settings for Interdependent strength (*IS*) and interdependent density *(ID)* have been chosen as design parameters. The performance of the networks after exposure to seismic hazards is measured by the connectivity loss C_L and the efficiency loss E_L, which allow prescribing system-level probability of failure P_f and the system reliability index β. The procedure in this example study is as follows: First, determine the range of values of the different possible levels for design parameters; then, use a sampling-based network reliability analysis algorithm code (Hernández-Fajardo and Dueñas-Osorio, 2009) to obtain the response of the network in terms of C_L and E_L for multiple levels of hazard intensity; based on the data acquired from the algorithm, find the response surface model and construct the limit state function of interdependent infrastructures. Finally, optimal design parameter levels can be determined by inverse reliability techniques. Also, note that this paper only considered the dependence of water availability on the serviceability of electrical power system. For simplicity, the dependence of power network operation on water network has not been included in the current research.

Interdependent network performance under seismic hazard

Design of experiment (DOE) technique is applied to choose the sampling points for network reliability analysis algorithm. Because there are only two design parameters, full factorial experiment will not require prohibitive computational efforts. Hence, a 9-level full factorial experiment has been chosen in this study. For interdependence strength and interdependence density, 9 different levels are considered in the simulation scenarios: 0.1~ 0.9 (every 0.1 intervals).

The response of network system performance (connectivity loss and efficiency loss) under seismic hazard has been determined by the reliability analysis algorithm code (Hernández-Fajardo and Dueñas-Osorio, 2009) for different IS and *ID* levels. Some of the results have been shown through the following figures.

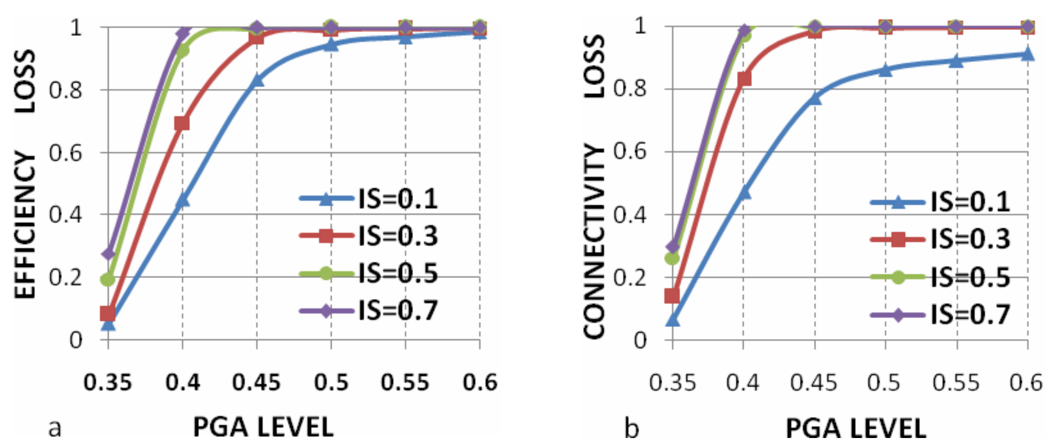

Figure 4. Network performance under different interdependence strength (ID=0.3)
(a) Efficiency Loss; and (b) Connectivity Loss

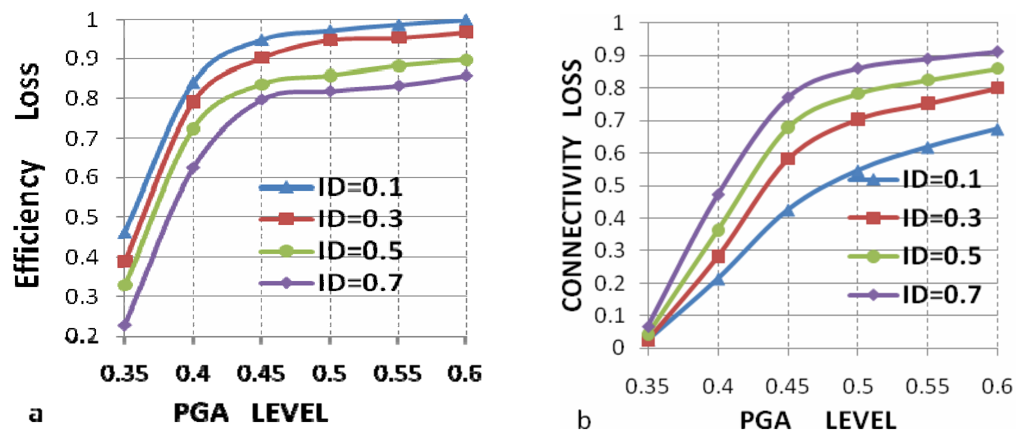

Figure 5. Network performance under different interdependence density (IS=0.3)
(a) Efficiency Loss; and (b) Connectivity Loss

From these figures it can be noticed that if the interdependence density level has been fixed, the increase of interdependence strength will lead to negative response in both network efficiency and connectivity. However, when the interdependence strength is fixed, an increase of interdependence density corresponds to an increase in connectivity loss, but a decrease in efficiency loss. This means a higher interdependence density level will help keep the operation efficiency but meanwhile will intensify the loss of network connectivity. This finding reveals the necessity to find the balance between positive and negative effects of system coupling on network reliability.

Response Surface Model

In this paper, the implicit response function is approximated by a simple and explicit polynomial function. After several trials of different types of function, it has been found that a pure quadratic polynomial model without interactive items can easily satisfy the accuracy of the approximation. In this application, IS and ID are the only design parameters. The response function at a given PGA level and for a given set of network component reliability properties is a function of IS and ID. The polynomial used to approximate the response function of network system is:

$$CL = a_0 + a_1 \times IS + a_2 \times ID + a_{11} \times IS^2 + a_{22} \times ID^2 \quad (6)$$

$$EL = b_0 + b_1 \times IS + b_2 \times ID + b_{11} \times IS^2 + b_{22} \times ID^2 \quad (7)$$

Limit State Function

Two limit state functions are considered in this paper: the loss of connectivity in the network, and the loss of efficiency in the network. When defining the limit state of the network system in connectivity loss, the limit state function is:

$$f = CL_{cr} - (a_0 + a_1 \times IS + a_2 \times ID + a_{11} \times IS^2 + a_{22} \times ID^2) \quad (8)$$

When defining the limit state of the network system in efficiency loss, the limit state function is:

$$f = EL_{cr} - (b_0 + b_1 \times IS + b_2 \times ID + b_{11} \times IS^2 + b_{22} \times ID^2) \tag{9}$$

CL_{cr} and EL_{cr} are critical connectivity loss and critical efficiency loss, which are allowable connectivity loss and efficiency loss values at the limit state. The *IS* and *ID* parameters are considered as uniformly distributed variables. Our objective is to find the values for *IS* and *ID*, such that the prescribed reliability index β is achieved for not exceeding the critical connectivity loss and critical efficiency loss under a certain seismic hazard.

Results and analysis

The inverse reliability procedure implemented in this paper can be synthesized in four steps: First, use the data set acquired by the network reliability analysis algorithm code for response surface modeling; then, use the response surface model to get the explicit limit state function; finally, use the inverse FORM method to find the mean value of infrastructure interface design parameters.

Choosing 50% as critical connectivity loss and critical efficiency loss, the data obtained from the network reliability analysis algorithm code are used to calculate the network-level probabilities of exceedance of the critical *CL* and *EL* parameters, which set the target values of β for the two limit states. Performing an inverse FORM procedure, the corresponding interdependence strength and interdependence density are found for the target β to be as follows:

Table 1. Inverse reliability analysis results (connectivity limit state)

PGA level	0.2	0.4	0.6	0.8
Interdependence strength, *IS*	0.4234	0.3342	0.2825	0.2217
Interdependence density, *ID*	0.3324	0.3043	0.2032	0.1424

Table 2. Inverse reliability analysis results (efficiency limit state)

PGA level	0.2	0.4	0.6	0.8
Interdependence strength, *IS*	0.3245	0.2984	0.2205	0.1743
Interdependence density, *ID*	0.5821	0.6321	0.6624	0.7055

For an increase of the seismic hazard intensity from 0.2 to 0.8, the design value for *IS* decreased 47.6% in the connectivity limit state and decreased 46.3% in the efficiency limit state. In terms of *ID*, the design value decreased 57.1% in the connectivity limit state, while increased 21.1% in the efficiency limit state (Tables 1 and 2). For interdependence strength, *IS*, the smaller value between the two design values for different target reliability levels can be taken as the final design value. But for interdependence density, the determination of the final design value should depend on an optima balance between the main C_L or E_L concerns at hand. For the combined concerns of connectivity and efficiency, a multi-attribute utility approach should be adopted as the final design value. This is work in progress.

Note that the interdependence strength is usually at a very high level for real-life networks. For instance, the interdependence strength between the power and water network in the application example is about 0.8. But from the results in the above tables, it can be seen the design values for the IS are relatively low in both connectivity reliability and efficiency reliability target performance: the maximum design values at different PGA level of the IS parameter are 0.42 in connectivity limit state and 0.32 in efficiency limit state. This highlights the need to reduce the interdependence strength in current practical network. Typically, the interdependence strength can be reduced by increasing the redundancy of the interdependence link.

In contrast to interdependence strength, in general, the *ID* level of real lifeline network is low. The *ID* level of the application example is about 0.1. However, from table 1 and 2, the minimum design value at different PGA level for the *ID* is 0.19 in connectivity limit state, and 0.58 in efficiency limit state. Both are larger than 0.1. Some measures should be taken to improve the density of interdependent links in current lifeline networks.

Conclusion

An inverse reliability procedure for designing the interface of lifeline networks considering the dual failure propagation and operational control effect of interdependence between different networks has been illustrated with practical network examples. The RSM-based inverse reliability method proves its efficiency and applicability in the application example. The results emphasize the fact that interdependence should be explicitly included in interface network design and should be considered from different perspectives in infrastructure system operation. The results of the application example also reveal the need to decrease the interdependence strength level and increase the interdependence density level in real life networks for effectively dealing with both connectivity and efficiency issues.

In this paper, the design for network systems has been simplified for testing the efficiency of RSM-based inverse reliability method and for evaluating the interdependence dual effect on network reliability. First, only two design parameters are considered in the current research. For a more comprehensive design space, additional design parameters should be included. Most importantly, the reliability of individual components in each network should be considered in designing. Second, the current reliability analysis and design should also be expanded to more than two systems with distinct interdependence style across them. For more complex situations, the current RSM-based inverse reliability method can be upgraded and enhanced in aspects like sampling method, RS model type, and interface topology among others. The metric to describe the interdependent style can also be enhanced. A joint metric for full description of interdependent style (*IS* and *ID*) is expected to be developed in future research.

Acknowledgements

The work presented in this paper has been funded in part by the National Science Foundation through grant CMM I-0748231.

References

Rinaldi, S. M., 2001. Critical infrastructure interdependencies, *IEEE Control Systems,* 21(6), 11-25.

Rosato, V. 2008. Modelling interdependent infrastructures using interacting dynamical models, International Journal of Critical Infrastructure, 4(1-2), 63-79

Adachi, T., and Ellingwood, B., 2008. Serviceability of earthquake-damaged systems: effects of electrical power availability and back-up systems on system vulnerability, *Reliab. Eng. Syst. Safety,* 93 (1), 78–88.

Albert R., Albert I., and Nakarado G. L. 2004, Structural vulnerability of the North American power grid, *Phys. Rev.,* E69, 025103®

Der Kiureghian Armen, Zhang, Y., and Li, C-C, 1994. Inverse reliability problem, *J. Engrg. Mech.ASCE*, 120(5), 1154-1159.

Dueñas-Osorio, L., Craig, J.I., and Goodno, B.J., 2007a. Seismic response of critical interdependent networks, *Earthquake Eng. Struct. Dyn*, 36 (2), 285–306.

Hernández, I., and Dueñas-Osorio, L., 2009. Time-sequential evolution of interdependent lifeline systems, *In Proceedings of the 10th International Conference on Structural Safety and Reliability (ICOSSAR)*, Osaka, Japan, September 12-17, 2009.

Li, H., and Foschi, R. O., 1998. An inverse reliability method and its application, *Structural Safety*, 20, 257–270.

Cheng J , Li Q.S. 2009. Application of the response surface methods to solve inverse reliability problems with implicit response functions. *Comput Mech*, 43, 451-459