TRABAJO ESPECIAL DE GRADO

MODELADO Y CUANTIFICACIÓN DE INTERDEPENDENCIAS DE SISTEMAS DE INFRAESTRUCTURA

Presentado ante la Ilustre
Universidad Central de Venezuela
en el marco del Convenio doble titulación
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Por el Br.:
Paredes Toro, Roger Luis
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Palabras Clave: Infraestructuras, Riesgo, Terremoto, Resiliencia, Monte Carlo.

Resumen.

Este trabajo de tesis de investigación presenta un algoritmo que utiliza datos de restauración y daño de componentes de sistemas de infraestructura (p. ej. Puentes, tanques de agua, subestaciones eléctricas) para estimar dependencia entre sistemas impactados por terremotos. Esta contribución se ubica en el contexto del desarrollo de métodos estandarizados para el diseño de estructuras que garantizan niveles adecuados de operación y seguridad no solo a nivel local, sino a nivel del sistema que dichas estructuras conforman. En este sentido, es existen casos documentados donde interdependencias, en la misma manera que la falla de un componente (p. ej. puente) perjudica a un sistema (transporte), la disrupción de un sistema perjudica a otros sistemas y el efecto en cadena que el daño directo genera se distribuye entre y a través de los sistemas. Algoritmos para predecir el performance de sistemas interconectados han sido propuestos. Sin embargo, la interdependencia entre sistemas se mantiene como una variable en donde análisis de sensibilidad de este parámetro han demostrado la gran magnitud en que análisis probabilísticos varían sus resultados.

Métodos alternativos para estimar la dependencia entre sistemas utilizan series temporales sosteniendo la hipótesis que dichos sistemas presentan fallas o son

restaurados en el tiempo de manera correlacionada. El método en este trabajo de tesis se basa sobre la hipótesis que las fallas y restauración de sistemas se correlaciona también en el espacio, ya que componentes a mayor proximidad geográfica tienden a fallar o recuperar funcionalidad de con cierta dependencia. El algoritmo presentado se basa en conceptos matemáticos y geoestatísticos como métricas para el cálculo de correlación entre dos variables y el método de Kriging.

Ya que este método se ha demostrado práctico para datos reales en un caso de estudio (Terremoto en la zona Talcahuano-Concepción en Chile en el 2010) que el autor de este manuscrito presentó recientemente en artículo científico de conferencia, esta contribución explora sistemas artificiales en un marco de experimentos computacionales usando teoría de grafos y el método de Monte Carlo. Los resultados de este análisis son satisfactorios y generalizan las conclusiones de resultados previos para el caso de estudio de Chile, avalando que la correlación espacial estima de manera consistente la dependencia entre sistemas de infraestructura interconectados.

POLITECNICO DI TORINO

MODELING AND QUANTIFICATION OF LIFELINE SYSTEM INTERDEPENDENCIES

By

Roger L. Paredes Toro

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

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ABSTRACT

This thesis concerns the development, testing, and study of a Kriging-based tool for quantifying interdependencies between lifeline systems, using spatially lagged correlations for measuring coupling, range, and location of interdependencies.

The need for modeling infrastructures, not as individual systems but as coupled systems, is widely acknowledged by the scientific community, and contributions in this subject currently come from a variety of approaches (e.g. Complex systems theory and network science); nevertheless, there are few model validation and calibration efforts to available case studies for ensuring their practical use and feasibility.

Additionally, there is a need for establishing the databases necessary for validation and calibration to real case studies. This thesis supports model validation and calibration by establishing preliminary guidelines for databases required and presents a Kriging-based approach to assess and quantify interdependence between lifeline systems. An emerging Kriging-based tool (Wu, Dueñas-Osorio, & Villagrán, 2012) represented a primary step towards quantifying spatial lifeline systems interdependence during their recovery, unveiling geographical and operational coupling patterns in the context of seismic threats; however, this application uses real and not specialized available databases, limiting its potential in face of what can be captured from richer and more dedicated databases.

This research expands on the geostatistical tool and present a more systematic approach, supporting recovery modelling and exploiting reconstruction information of utilities to quantify interdependence strength, range, and anisotropy across lifeline systems. Here, simple yet realistic recovery scenarios are used in order to exhaust the capabilities of this methodology when describing the recovery of interdependent networks, which gravitates mainly on

geographical, physical, and logistical coupling among utilities making use of local and global spatial-correlations. Then, we relate spatial correlation based metrics deriving from this approach to other network level properties from the graph theory perspective and depict intuitive connections using an experimental design approach. Lastly, we exemplify potential applications of this approach for powerful visualizations of recovery efforts for tracking progress and interdependence among lifeline systems.

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Also, I express my warm thanks to the close friends and family, for their support in nonacademic related subjects that have rendered my educational path with an ideal environment for favoring my professional and personal growth.

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1 INTRODUCTION

1.1 Motivation

Lifelines are a complex web of essential utility and transportation systems serving communities with goods and services; its constant operation is what creates the fabric of modern societies, which include urban networks like power, water, gas, transportation, and telecommunications systems. Nevertheless, the worldwide steady rise of population in urban areas, increasing demand of services, and expansion of lifelines have not been accompanied with a proper handling of interdependencies across systems, leaving societies in a gradually more vulnerable position to disruptive events.

Despite the efforts and significant progress through science and technology for improving resilience at the community scale, the costs emanating from lifelines disruptions continue growing. For example, in the United States, it is estimated that natural and man-made disaster events represent an average annual cost of $57 billion and many researchers claim that the trend in disaster losses is unstainable to the point that they will become more than what the government can afford (Gilbert, 2010).

In addition, there is evidence that developed countries' governments are not investing enough money to satisfy projected needs, resulting in greater losses. For instance, in the United States, the total documented cumulative gap between projected needs and likely investment in these critical systems will be $1.1 trillion by 2020 (ASCE, 2013). Also, surprisingly, it is common for developed countries not to apply available knowledge in their current policies (White, Kates, & Burton, 2002), which points out the huge gap that exist between research findings and policy makers.

Mitigating the socio-economic rupture of lifeline systems subjected to natural and man-made disruptions is difficult because of the uncertainty from the natural processes governing hazards and lack of information available for its study. In contributions from the research community, lifeline systems' modelers develop abstractions for conducting practical probabilistic performance assessments for supporting vulnerability mitigation strategies. In addition to this, they have proposed tools for aiding decision-makers in restoring infrastructure networks. Nevertheless, there is a gap between research findings and the prospects of their practical use; hence, there are no standardized methods for assessing the vulnerability and resilience of interdependent lifeline systems yet. For this reason, authors believe that the growing field of infrastructure networks modeling should aim to include validation and calibration exercises to real case studies.

Some of the challenges that model validation and calibration face are the availability of appropriate datasets and the means for conveying existing interdependencies (Rinaldi, Peerenboom, & Kelly, 2001) into the proposed models effectively. In this thesis, guidelines for the required datasets are provided and the theory of an emerging Kriging based approach (Paredes-Toro, Dueñas-Osorio, & Cimellaro, 2014; Wu et al., 2012) for quantifying interdependencies across lifeline is presented.

1.2 Interdependent lifeline systems' modeling

Based on the scope, recent models for the study of interdependencies across systems (Ouyang, 2014) can fall within the next two groups: forward analysis models and restoration models. The former models use probability theory to predict the response of interdependent infrastructural systems to natural and man-made hazards. The latter group of models focuses on the recovery of disrupted interdependent networks, and likewise, many contributions from different fields of studies are available.

Common approaches of forward analysis models for interdependent lifeline systems include economic theory, game theory, agent-based, and network based methods. For example, Haimes et al. (Haimes & Jiang, 2001) introduce an Inoperability Input-output Model (IIM) for infrastructures in order to study the risk of inoperability, a notion of unreliability for interdependent networks; Cagno et al. (Cagno, De Ambroggi, Grande, & Trucco, 2011) integrate the topologies to this approach. In addition to this, Zhang et al. (Zhang, Peeta, & Friesz, 2005) proposed an agent-based simulation that formulates the equilibrium analysis using game theory principles. Hernandez and Dueñas-Osorio (Hernandez-Fajardo & Dueñas-Osorio, 2011) proposed the Interdependence Fragility Algorithm (IFA), which employs network topologies and connectivity loss metric to perform statistical analyses in a simulation framework to assess interdependence strength; Buldyrev et al. (Buldyrev, Parshani, Paul, Stanley, & Havlin, 2010) also make use of the topologies but from an analytical perspective.

Likewise, restoration models of interdependent lifeline systems exhibit a wide range of approaches such as dynamical systems theory, complex systems theory, and network based. However, network based models are preferred in the context of supporting decision-makers since they consider practical aspects in real settings of lifelines reconstruction, such as demand of the commodities, limited resources, flow capacities, and costs of repairs and transportation. Among the network-based models, the research by Lee II and Wallace (Lee II, Mitchell, & Wallace, 2007) presents five types of interdependencies between infrastructure systems, namely, input dependence, mutual dependence, shared dependence, exclusive-or dependence, and co-located dependence. These interdependencies are then used to develop a network flows based mathematical model to guide the restoration of services. Similarly, Gonzales et al. (González, Dueñas-Osorio, Sánchez-Silva, & Medaglia, 2014) propose another decision support model, the Iterative Interdependent Network Design Problem (iINDP), an algorithm that finds the minimum-cost recovery strategy for a partially destroyed system solving a constrained optimization problem.

Despite the field study used for developing interdependent lifeline systems models, in forward analysis or recovery stage, the models rely on assumptions about coupling across infrastructure systems that later on translate into logical instances or numerical input. Since these assumptions have not been rigorously formalized for modelling, verification and validation is gaining attention (Farina, Graziano, Panzieri, Pascucci, & Setola, 2013). However, model validation and calibration to real case studies requires datasets and quantification tools that can integrate to modeling efforts. This study will focus on supporting model validation and calibration via quantification of interdependencies for informing probabilistic response models and decision-making support tools.

1.3 Interdependent networks and interdependencies

When a system i requires an input service from another system j in order to function, one can say that system i has a dependency on system j and the interconnectedness of systems i and j is unidirectional. Real networks however, exhibit dependencies in both directions; this is, one or more components in system i are dependent on system j, which in turn has one dependent component or more requiring input services from system i. The previous case is regarded as interdependent networks.

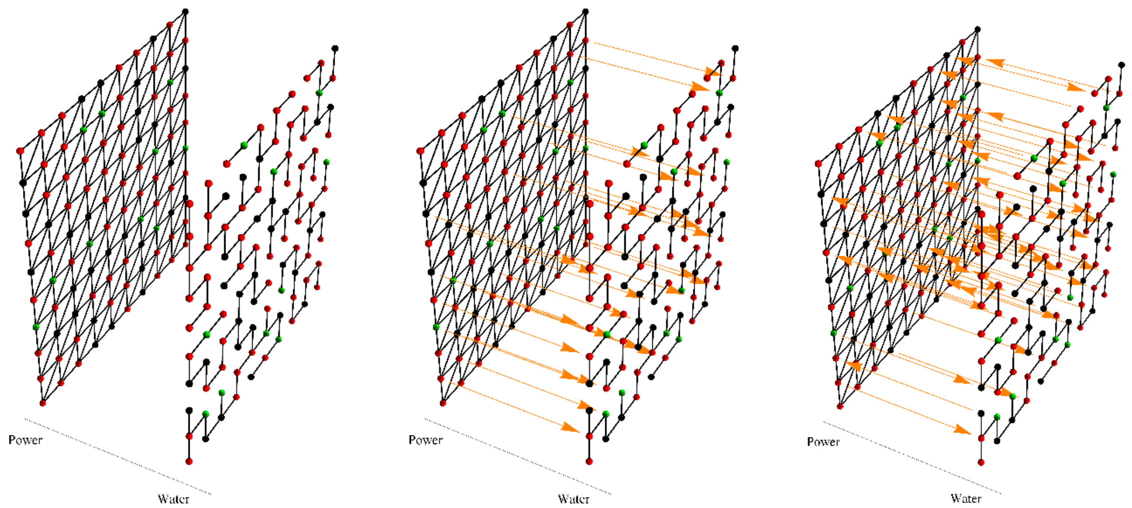


Figure 1Power and water networks presenting different levels of coupling. (a) Independent systems. (b) Dependent system. (c) Interdependent systems.

Edges connecting systems in Figure 1 are interdepdencies defining. a physical connection or more generally the flow of information. Of great importance at this point is the conceptualization of interdepencies by Rinaldi et al.(2001). In their work, they provide four flexible definitions of interdependence that allows unifying the terminology in the complex system's community . These are:

- Physical interdependence: whenever the state of each system is dependent on the material output(s) of another. A typical example is a water pumping station requiring electricity or a power generation facility that used water for cooling operations.
- Cyber Interdependence: whenever systems' states depend on information transmitted through an information infrastructure. For instance, some power generation systems are able to regulate they production according to demand levels, which in turn, are associated to other systems.
- Geographic Interdependence: whenever a single environmental event can influence the state of all systems or a subset of their components sharing a geographical location.

Natural and man-made hazards are good examples of this; for example, liquefaction braking water and gas pipes, fire, explosions, among others.

- Logical Interdependence: Whenever a mechanism that is not physical, cyber, or a geographic connection influence the state of systems.

1.4 Quantification of lifeline systems' interdependencies

Although a significant number of contributions can be found in the interdependent lifeline systems modeling field, less has been done in the quantification branch (Casalicchio & Galli, 2008). Available quantification methods include efforts to quantify direction of failures, escalation of cascading effects, coupling strength, and indexes for the degree of dependency and interdependency. Based on failure data, Zimmerman (R. Zimmerman, 2004) proposed a simple metric to determine the direction of interdependent failures, which from the viewpoint of an individual lifeline system, it is the ratio between the number of times being a cause of failure to the number of times being affected by failure. In addition, referring to power outages, Zimmerman and Restrepo (Rae Zimmerman & Restrepo, 2006) proposed a metric to determine whether cascading failures are escalating or attenuating in the context of power networks, consisting in the ratio of the duration of the electric power outage to the duration of a subsequent infrastructure failure that is dependent upon electric power. Moreover, in an effort to narrow the quantification efforts to the degradation of services or functionalities, Setola (Setola, 2010) proposes indexes that are a function of inoperability variations of infrastructures with respect to normal service conditions for quantifying intra-dependency and inter-dependency indexes, being the last one a non-reciprocal function for quantifying coupling of two interdependent systems. Less easily computed metrics are available in regards to the strength of coupling in the form of correlations. For instance, Mendonça et al. (Mendonça & Wallace, 2006) used Pearson's correlation coefficients to measure the degree of association across impacted infrastructures in the context of the 2001 World Trade Center Attack. In addition to this, Dueñas-Osorio et al. (Dueñas-Osorio & Kwasinski, 2012) derived coupling strengths for operational and logistical interdependencies using a time-series analysis approach.

1.5 Adopted methodology and thesis objectives

In an attempt for developing interdependence quantification tools that can be integrated into models (Ouyang, 2014), we present an enhanced Kriging Aided Spatial Correlation Algorithm (KASCA) (Paredes-Toro et al., 2014; Wu et al., 2012) for quantifying interdependencies across lifeline systems and support validation and calibration of network based models. Exploiting lifelines recovery information and using spatial correlations at different scales provides measures of coupling among systems and their components that serve as input for network based models (Hernandez-Fajardo & Dueñas-Osorio, 2011). In order to illustrate the effectiveness of the novel approach, computational experiments are conducted using idealized infrastructure networks and hazards scenarios for testing consistency with initial input conditions and interdependencies. In addition to this, the presented tools are accompanied with graphical representations of interdependencies that are intended to aid vulnerability mitigation efforts and decision-makers.

By focusing on studying failure and recovery patterns of interdependent networks, this study provides a better understanding on how the spatial configuration of interconnected networks and the hazard affect their coupled behavior during response or recovery efforts to disruptions. Additionally, quantifying spatial interdependencies between spatial networks helps refining algorithms that may fall short conceptualizing interdependencies, making it possible to calibrate models to real events as well as validate them.

The presented approach expands previous KASCA contributions (Paredes-Toro et al., 2014; Wu et al., 2012) acknowledging the temporal dimension, which is crucial for stablishing interdependence directionality in quantification efforts. Nevertheless, a full joint spatial-temporal analysis is not under the scope of this thesis, since it requires considering the physics governing natural processes of lifelines' operation (e.g. simulating lifelines' time of failure propagation of a damaged electrical substation supplying a water pumping station) in much detail. For this reason, the simulation framework referenced in this study assumes instantaneous communication and failure propagation across lifeline systems as found in the research of Hernandez-Fajardo et al.(Hernandez-Fajardo & Dueñas-Osorio, 2011); however, the reduced time scale of information and energy sharing found in lifeline systems justifies the instantaneous interaction assumption across systems.

To test validity of the presented Kriging-based approach to locate and quantify interdependencies without lacking generality, we perform a systematic analysis by means of an experimental design approach. The recovery scenarios that will be considered expands the space variables that are typically encountered in real case settings, particularly varying network topologies, performance parameters, and decision-making related variables.

The structure of the thesis is as follows. Section 2 describes the mentioned Kriging-aided approach, including their mathematical definitions, underlying assumptions, aims, and preliminary statements on its limitations. Moreover, some definitions from the graph theory perspective that will be useful in the next sections are reviewed. Section 3 offers a comprehensive summary of the enhanced KASCA-based interdependence metrics and visualizations, using toy models to exemplify their interpretations. Section 4 describe the simulation framework in the computational experiments for testing KASCA-based metrics and discuss the results, along with remarks about network properties influencing interdependencies. Section 5 presents conclusions from this contribution and outline ideas for future research.

2 BACKGROUND IN GEOSTATISTICS AND CONCEPTS IN GRAPH THEORY

In this section, we first present the mathematical definitions used in KASCA for quantifying interdependencies across lifeline systems. Secondly, some concepts in graph theory are outlined since the following sections will refer to a network-based simulation framework and the proposed tool is intended to inform interdependent network models using this approach. However, the results deriving from KASCA are general and provide measures of interdependence across lifelines that are useful when analyzing the resilience of infrastructure networks (e.g. Cimellaro et al. (Cimellaro, Solari, & Bruneau, 2014)).

2.1 Mathematical concepts

Before describing the algorithm, we introduce the concept of Kriging (Webster & Oliver, 2001) and correlation coefficients as metrics of association or coupling between systems (Dueñas-Osorio & Kwasinski, 2012; Mendonça & Wallace, 2006; Paredes-Toro et al., 2014; Wu et al., 2012). In addition to this, we assemble the previous definitions and present the algorithm for quantifying time and space interdependencies across systems and producing local cross-correlation maps, global cross-correlation maps(Paredes-Toro et al., 2014), and their temporal expansions as novelty.

2.1.1 Kriging

Kriging is a generic term for a range of least-squares methods to provide the best linear unbiased predictions; best meaning that they minimize the variance. In brief, Kriging performs estimations over non-sampled locations using prior knowledge (i.e. field observations); because of this, it is often referred to as a geostatistical spatial interpolator. Performing estimation with this technique involves solving a generally constrained optimization problem that leads to a system of equations called kriging system. In order to make the kriging system useful, one needs to model the spatial variability of the random field, or more specifically, formulate a variogram model.

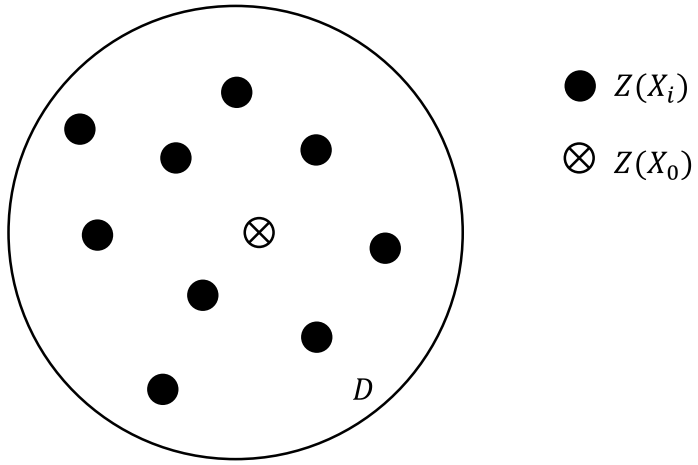


Figure 2. Distributed points on region D.

Before introducing the variogram, some considerations and definitions in regards to the random field $Z(X)$ observed at locations X_i, (with $i = 1,2,..,n$.) in a certain region D will be introduced (Figure 2). First, let us assume that the random field has a fixed expected value $E[Z] = \mu$ so that it is first order stationary. Second, consider that for any realization of $Z(X)$, there is a covariance structure that relates all observations at different locations as a function of their relative position so that one can say the random field is second order stationary or weak second order stationary if this is true for an enclosed region D (Figure 2). At his point, we can write the equations for the covariance between two observations occurring at relative distance h and the equation of the variogram, whose meaning will become more evident when relating it to the covariance.

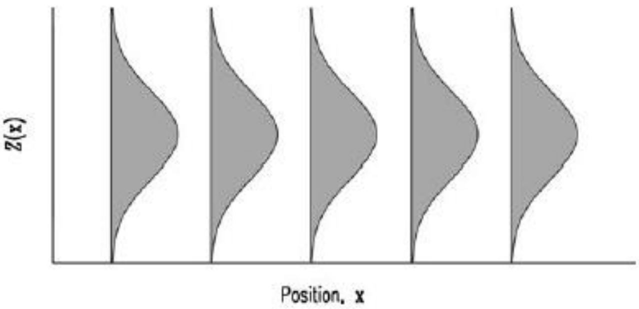


Figure 3. Standardized residuals at different locations in the network.

$$C(Z(X_1), Z(X_2)) = E[(Z(X_1) Z(X_2)] - \mu^2 \quad \text{(Eq. 1)}$$

After considering that the random field is second order stationary and the relative positions h of observations describes their spatial variability, the covariance can be written as:

$$C(h) = E[Z(X)Z(X+h)] - \mu^2 \quad \text{(Eq. 2)}$$

The variogram function describes the variability of observations at different locations or, in other words, the variance of the difference of observation pairs.

$$2\gamma\big(Z(X_1), Z(X_2)\big) = E\left[\big(Z(X_1) - Z(X_2)\big)^2\right] \quad \text{(Eq. 3)}$$

Which again, considering the second order stationary of the random field becomes:

$$2\gamma(h) = E[\big(Z(X) - Z(X+h)\big)^2] \quad \text{(Eq. 4)}$$

With some effort and following the previous considerations, the semi-variogram can be written in terms of the covariance as follows:

$$\begin{aligned} 2\gamma(h) &= E[Z(X)^2 + Z(X+h)^2 - 2Z(X)Z(X+h)] \\ &= (E[Z(X)^2] - \mu^2) + (E[Z(X+h)^2] - \mu^2) + (-2E[Z(X)Z(X+h)] + 2\mu^2) \end{aligned}$$

$$\gamma(h) = C(0) - C(h) \quad \text{(Eq. 5)}$$

The variogram function used for supporting kriging predictions will be a parametric curve fitted to an experimental variogram. The experimental variogram γ_E can be computed as [20]:

$$\gamma_E(h) = \frac{1}{2m(h)} \sum_{i=1}^{m(h)} \{Z(X_i) - Z(Xi_{i+h})\} \quad \text{(Eq. 6)}$$

Where $m(h)$ averages the variances of differences of measures separated at distances within the lag h. Computing $\gamma_E(h)$ for different lags h results into a set of points with coordinates (γ_E,h) that can be fitted by a parametric curve.

There are different models to fit the experimental variogram, however, they can be distinguished as bounded and unbounded models, being the later a group of models that allow the semivariogram to grow indefinitely as distance increases. Among the authorized models for fitting the experimental variogram that are common in the literature are the linear, spherical, exponential, Gaussian, and stable models (Wackernagel, 1995). The infrastructural recovery data in this study showed exponential and sigmoid shapes; hence, stable models were used as suggested in the literature (Webster & Oliver, 2001):

$$\gamma(h) = c\{1 - \exp\left[\left(-\frac{|h|}{r}\right)^{\alpha}\right]\} \quad \text{(Eq. 7)}$$

Where c represents the sill, r is parameter describing the range or length of correlation an α is another parameter of the function with constrain $0 \leq \alpha \leq 2$. The selected function is adjusted to the experimental variogram using weighted-least squares fitting and weights proposed by McBratney and Webster (McBratney & Webster, 1986).

After modeling the spatial variability of the random field under consideration, we can now formulate the kriging estimator:

$$\hat{Z}(X_0) = \sum_{i=1}^{n} \lambda_i Z(X_i) \quad \text{(Eq. 8)}$$

Where $\hat{Z}(X_0)$ is the estimate and λ_i is the kriging weights that corresponds to the sample $Z(X_i)$. Following the definition of kriging, the weights are calculated minimizing the error variance:

$$E\left[\left(Z(X_0) - \hat{Z}(X_0)\right)^2\right] = E\left[Z(X_0)^2 + \hat{Z}(X_0)^2 - 2Z(X_0)\hat{Z}(X_0)\right] \quad \text{(Eq. 9)}$$

Using Eq. 7 The error variance σ_E can be rewritten as:

$$\sigma_E = C(Z(X_0), \mathrm{Z}(X_0)) + \sum\sum_{j=1}^{n} \lambda_i \lambda_j C\big(Z(X_i), \mathrm{Z}(X_j)\big) - 2\sum_{i=1}^{n} \lambda_i C(X_0, X_\mathrm{i}) \quad \text{(Eq. 10)}$$

Or in terms of the variogram as:

$$\begin{aligned}\sigma_E &= C\big(Z(X_0), \mathrm{Z}(X_0)\big) + \sum\sum_{j=1}^{n} \lambda_i \lambda_j \,(C(0) - \gamma(Z(X_i), Z(X_j))) \\ &\quad - 2\sum_{i=1}^{n} \lambda_i \left(C(0) - \gamma\big(Z(X_0), Z(X_i)\big)\right) \\ &= \gamma(h) + C(h) + C(0) - \sum_{i=1}^{n}\sum_{j=1}^{n} \lambda_i \lambda_j \gamma\big(Z(X_i), Z(X_j)\big) - 2C(0) \\ &\quad + 2\sum_{i=1}^{n} \lambda_i \gamma\big(Z(X_0), Z(X_i)\big)\end{aligned}$$

$$\sigma_E = 2\sum_{i=1}^{n} \lambda_i \gamma(Z(X_0), Z(X_i)) - \sum_{i=1}^{n}\sum_{j=1}^{n} \lambda_i \lambda_j \gamma\big(Z(X_i), Z(X_j)\big) \quad \text{(Eq. 11)}$$

The other part of the kriging system is given by the constraints of the optimization problem, such as the unbiased condition of the kriging estimator.

Ordinary kriging (OK) is the most popular variant of Kriging and it serves well in most situations with its assumptions easily satisfied. That is why it is often regarded as the ‘work-horse’ of geostatistics (Oliver & Webster, 2014). It requires only knowledge of the variogram function and data for its implementation. It is also robust with regards to moderate departures from those assumptions and a less than an optimal choice of model for the variogram.

For satisfying the condition of unbiased estimator it must follow that:

$$\begin{aligned}E\big[Z(X) - \hat{Z}(X)\big] &= 0 \\ &= E[Z(X)] - \sum_{i=1}^{n} \lambda_i E[Z(X_i)] \\ &= (1 - \sum_{i=1}^{n} \lambda_i)\mu = 0\end{aligned}$$

$$\sum_{i=1}^{n} \lambda_i = 1 \quad \text{(Eq. 12)}$$

Now imposing the constraint in (Eq. 12 using a Lagrange multiplier, the error variance to be minimized becomes:

$$\sigma_E = 2\sum_{i=1}^{n} \lambda_i \gamma(X_i, X_0) - \sum_{i=1}^{n}\sum_{j=1}^{n} \lambda_i \lambda_j \gamma\left(X_i, X_j\right) - 2v\left(\sum_{i=1}^{n} \lambda_i - 1\right) \quad \text{(Eq. 13)}$$

Computing the partial derivatives of (Eq. 13) with respect to the $n + 1$ variables in the same equation (kriging weights λ_i and the Lagrange multiplier v) leads to the Kriging system of equations for computing the weights

$$\frac{\partial \sigma_e}{\partial \lambda_i} = 0, \qquad i = 1,2,\dots,n$$

$$\frac{\partial \sigma_e}{\partial v} = 0 \quad \text{(Eq. 14)}$$

The Kriging system is then:

$$\sum_{i=1}^{n} \lambda_i \gamma(X_i, X_j) + v = \gamma\left(X_j, X_0\right), \quad j = 1,2,\dots,n$$

$$\sum_{i=1}^{n} \lambda_i = 1 \quad \text{(Eq. 15)}$$

Which in matrix notation becomes:

$$\begin{bmatrix} \gamma\left(X_i, X_j\right) & \gamma\left(X_i, X_{j+1}\right) & \dots & \gamma(X_i, X_n) & 1 \\ \gamma\left(X_{i+1}, X_j\right) & \gamma\left(X_{i+1}, X_{j+1}\right) & \cdots & \gamma(X_{i+1}, X_n) & 1 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \gamma\left(X_n, X_j\right) & \gamma\left(X_n, X_{j+1}\right) & \dots & \gamma(X_n, X_n) & 1 \\ 1 & 1 & \cdots & 1 & 0 \end{bmatrix} \begin{bmatrix} \lambda_i \\ \lambda_i + 1 \\ \vdots \\ \lambda_n \\ v \end{bmatrix} = \begin{bmatrix} \gamma\left(X_0, X_j\right) \\ \gamma\left(X_0, X_{j+1}\right) \\ \vdots \\ \gamma(X_0, X_n) \\ 1 \end{bmatrix} \quad \text{(Eq. 16)}$$

This spatial interpolation technique presents a series of advantages with respect to the others, such as accounting for the relative position of sampling points and the so-called screen effect. The first relates to the property of assigning more weight to isolated samples than to those that are clustered, and the second is the property of assigning less weight to samples laying behind closer samples.

2.1.2 Correlation coefficient as measures of interdependence

The next measures of linear and nonlinear dependency are used to study the correlation between two sets concerning different lifelines and containing repair times prior full system restoration at different locations.

2.1.2.1 Pearson's correlation coefficient

Pearson's correlation coefficient has already been used as a measure of association to quantify the degree of interdependence between infrastructure systems (Mendonça & Wallace, 2006; Paredes-Toro et al., 2014; Wu et al., 2012). Pearson's rho coefficient (Rodgers & Nicewander, 1988) describes the degree of linear correlation between two sets of data, and it is a generally accepted metric to quantify interdependence.

$$\rho = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{[\sum(X_i - \bar{X})^2 \sum(Y_i - \bar{Y})^2]^{1/2}} \qquad \text{(Eq. 17)}$$

In this thesis, sets X and Y contain times of repairs prior to the full restoration of lifeline systems i and j at specific locations.

2.1.2.2 Rank correlation coefficients

Since the presented methodology attempts to capture not only the intensity of coupling but also its spatial distribution and range, rank correlation coefficients such as Kendall's tau and Spearman's rho are used to quantify nonlinear dependency of lifeline systems.

Again, in function of all n^2 pairs of sets X and Y, Kendall's tau is defined as (Johnson & Gibbons, 1973):

$$T = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} U_{ij}V_{ij}}{\left[\left(\sum_{i=1}^{n}\sum_{j=2}^{n} U_{ij}^2\right)\left(\sum_{i=1}^{n}\sum_{j=1}^{n} V_{ij}^2\right)\right]^{0.5}} \qquad \text{(Eq. 18)}$$

With $U_{ij} = sgn(X_j - X_i)$ and $V_{ij} = sgn(Y_j - Y_i)$. Where,

$$sgn(u) = \begin{cases} -1 & if\ u < 0 \\ 0 & if\ u = 0 \\ 1 & if\ u > 0 \end{cases}$$

Spearman's rho coefficient is defined as:

$$R = 1 - \frac{6\sum_{i=1}^{n} D_i^2}{n(n^2-1)} \qquad \text{(Eq. 19)}$$

Where,

$$D_i = rank(X_i) - rank(Y_i)$$

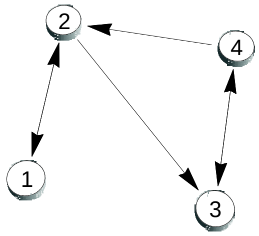
2.2 Basic concepts and terminology in graph theory

In infrastructural engineering, lifeline systems are considered interconnected spatially distributed components in which flow of services and commodities take place. The geographical, topological, and flow information of a network can be mathematically represented with a graph. Denoted $G(V, E)$, a graph is formed by a set V of vertices and a set E of edges (Figure 4a). Each edge e_i contains one or two terms of set V to indicate its endpoint(s). An alternative representation of the topological information of a graph is the adjacency matrix A (Figure 4b), a square matrix with as many rows and columns as number of vertices in the graph. The entry at row i and column j is the multiplicity of the adjacency from vertex V_i to V_j (Newman, 2010). In this thesis, only simplicial graphs (Gross & Tucker, 2001) are considered (i.e. no self-loops and multiple edges are allowed); however, directed edges are permitted. Thus, thee entries in the adjacency matrix can be defined as follow:

$$a_{ij} = \begin{cases} 1 & if\ there\ is\ an\ edge\ connecting\ vertices\ i\ and\ j \\ 0 & Otherwise \end{cases}$$

Using the previous expression for filling adjacency matrix's entries results into a symmetric square matrix. However, one can indicate direction of connectivity (Figure 4) modifying the previous expression as follows.

$$a_{ij} = \begin{cases} 1 \; if\ there\ is\ an\ edge\ from\ vertex\ i\ to\ j \\ 0 \qquad\qquad Otherwise \end{cases}$$



$$A = \begin{pmatrix} 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 \end{pmatrix}$$

Figure 4. Basic concepts in graph theory. (a) Directed graph and its (b) Adjacency matrix.

An important definition when describing the connectedness of graph is the concept of a path. A path is the combinatorial analog of a continuous image of a line segment. This is, for a given source and terminal nodes, a succession of vertices and edges serves as a path to connect them. In Figure 4a, there is a path between vertices 1 and 4 ($V = \{1,2,3,4\}$; $E = \{\{1,2\},\{2,3\},\{3,4\}\}$). Common algorithms for finding paths or deciding their existence are Dijkstra and Tarjan's strongly connected components. Finding paths become relevant in the study of infrastructure networks since they recognize internal connection routes or loss of functionality of components in the aftermath of a perturbation.

Another relevant concept is planarity of graphs. A planar graph is a graph that can be drawn in the plane in such a way that its edges meet only at their end vertices, if they meet at all (Barthélemy, 2011; Clark & Holton, 1991). Planarity in infrastructure networks is common because physical objects form graph's edges, and thus, overlapping connections are not always possible or cost effective.

In addition to convenient mathematical representations, graph theory and network science past studies compare properties of real networks to those of hypothetical models (Brando, Lin, Giovinazzi, & Palermo, 2012; Brummitt, D'Souza, & Leicht, 2012; Cardillo, Scellato, Latora, & Porta, 2006; Hines, Blumsack, Sanchez, & Barrows, 2010; Lhomme, Serre, Diab, & Laganier, 2013; Yazdani & Jeffrey, 2010). This is relevant to lifeline systems' modelers for developing robust vulnerability assessment methods and for designing networks that are more resilient by studying the space of variables influencing lifelines' response to disruptions (e.g. Network redundancy and robustness). In this study, we use spatial models considering lattice-like structures (Watts & Strogatz, 1998) and random geometric graphs (Díaz, Penrose, Petit, & Serna, 2001), and for both ,we consider their extreme topological formations (Cardillo et al., 2006) (Figure 5): Greedy Triangulations (GT) and Minimum Spanning Trees (MST).

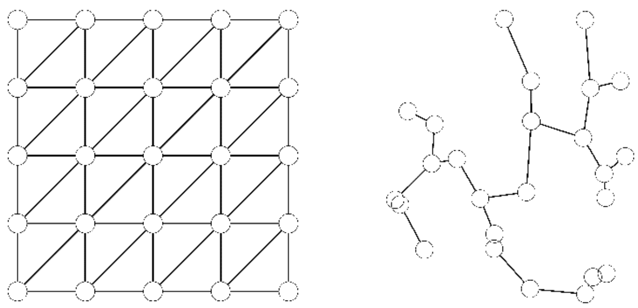


Figure 5. Example network models. (a) Lattice-like structure with a GT approximation as topological formation. (b) Random geometric structure with a MST topology.

3 KRIGING AIDED SPATIAL CORRELATION ALGORITHM (KASCA)

In this section, we first describe the algorithm for quantifying intensity and range of spatial correlations among lifeline systems. Two main subroutines fallow a data preparation phase: the computation of Kriging restoration surfaces filling space in a polar mesh-like distribution, and the computation of spatially lagged auto-correlations and cross-correlations. In addition, spatially distributed coupling intensities are derived to support utility and emergency managers with recommendations on location and allocation of resources. Lastly, we present remarks in the theory, assumptions, and limitations of this approach.

3.1 Kriging restoration surfaces

Let us assume that a pair of lifelines are damaged after some disruptive event and time of repairs prior full restoration at different locations of the systems are known. Typically, these are available through utility operator's records of outage time of components prior their restoration, and given that they are spatially distributed they provide field observations for studying the spatial variability of systems' restoration.

Considering the time of repairs prior full restoration of system i sampled at location j as the field observations of the random variable $Z_i(X_j)$, it is possible to start the variogram formulation as follows. First, one should compute the variogram estimator $\gamma_E(h) = \frac{1}{2m(h)}\sum_{i=1}^{m(h)}\{Z(X_i) - Z(Xi_{i+h})\}$ (Eq. 6). Secondly, using a weighted least-squares approach, covariance or variogram models (e.g. $\gamma(h) = c\{1 - \exp\left[\left(-\frac{|h|}{r}\right)^{\alpha}\right]\}$ (Eq. 7) are fitted to the variogram estimator. In this study stable models were considered at the end, after finding out for several cases that they provide the lowest mean squared residuals. In addition, the non-linear regression was performed using the Levenberg–Marquardt and the weights considered are those proposed by Cressie & Wikle (2011) For more detailed steps and guidelines computing the variogram refer to the literature cited in the previous section.

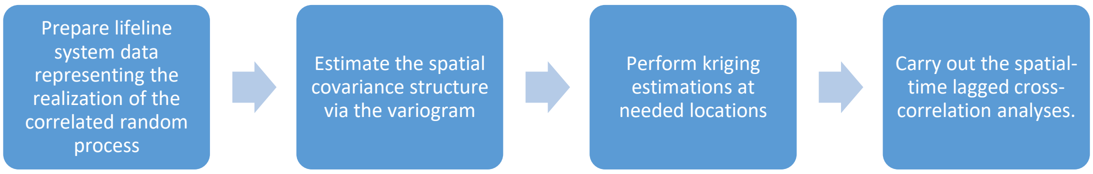
After modeling the spatial variability of systems' restoration, it is possible to perform Kriging interpolation at unknown locations. For reasons that are going to become clearer in the next section, a Kriging surface representing system's i time of repairs prior full restauration across a region is formed by estimates computed in a polar mesh-like structure around each field observation. Cross-estimates are computed too, this is, using the variogram and field observations of a complementary system j to perform Kriging interpolation, estimates are computed again around field observations of system i.

3.2 Spatial correlation analysis

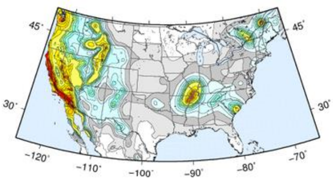
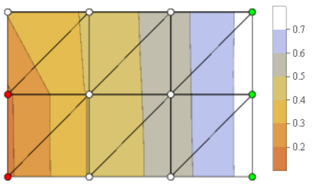
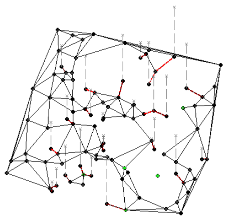
Here we show how to derive spatially lagged auto-correlations and cross-correlations for generating global correlation maps function of relative position considering distance and direction, and global correlation plots function of relative position considering distance only. The general idea that will be extended to derive global correlation maps and plots is that of creating a vector filling it with restoration times of system i at certain locations (e.g., where its components are located) and create another vector containing restorations of system j at the same locations using Kriging estimates. The resulting value will be the global strength of coupling between systems $I_{str(i,j)}$, that can be regarded as a measure of dependency of system j to system i. We take the previous notion of co-located correlation one step further by replacing the second vector with one filled with Kriging estimations at relative positions $h(r_i, \theta_i)$ with respect to the ones considered in the first vector. Filling with lagged coupling strength estimates $I_{str(i,j)}\big(h(r_i, \theta_i)\big)$ a polar mesh-like grid we now can verify rich heterogeneity in spatial dependency.

In addition to global correlation maps and plots, we compute their analogs local correlation maps and plots. After learning correlation range sin during global analysis, a new local polar mesh is used for deriving Kriging estimates around field observations matching location of system's components. Again, crossed Kriging estimates are computed across lifeline systems for enabling the computation of cross-correlations. The sets of vectors to be considered in $\rho = \frac{\sum(X_i-\bar{X})(Y_i-\bar{Y})}{[\sum(X_i-\bar{X})^2\sum(Y_i-\bar{Y})^2]^{1/2}}$ (Eq. 17-$R = 1 - \frac{6\sum_{i=1}^{n} D_i^2}{n(n^2-1)}$ (Eq. 19 refer to one vector filled with Kriging estimates around field observation $Z_i(X_j)$ at relative positions following the new local polar mesh distribution and using geostatistical information of system i, and another vector with Kriging estimates matching previous locations but using the geostatistical information of a complementary system j.

3.3 Summary and theory of the algorithm



The emerging KASCA methodology considers the state of a network, measured based on a performance quantity, as a realization of a random field in the two dimensional Euclidean space. This consideration allows intra-dependence studies when topological information from networks is not available, and allows interdependent spatial analyses by estimating a spatial covariance structure from field data, however the network space is not considered and the topological effect is expected to be recovered via spatial correlations with the coupling range. As it will be shown later, the covariance structure will be substituted by the variogram, a model of the spatial variability that can be obtained from failure and recovery data.

Natural or man-made process	Space of variability		KASCA assumed variability
Seismic Demands		Euclidean	Euclidean
Component Failure probabilities and serviceability rates		Euclidean and Network	Euclidean
Component Recovery times		Euclidean and Network	Euclidean

For instance, Figure 6-a depicts a network after a disruptive event indicating damaged arcs in red disconnecting some demand nodes from supplying nodes. Figure 6-b shows in red again the minimum arcs that were recovered to reconnect the isolated demand nodes to the network and find a path to the supplying nodes. Figure 6-c shows the same network with some line segments normal to the plane containing the network; the length of this normal line segments are proportional to the time of disconnection between the disruption and the recovery, in fact, they can only be seen for demand nodes that were disconnected after the disruptive event. Since each component has a mean recovery time and a standard deviation that can be obtained via numerical probabilistic approaches (such as Monte Carlo simulation), one can work with the normalized residuals (Figure 3) satisfying the constant mean condition for applying OPK.

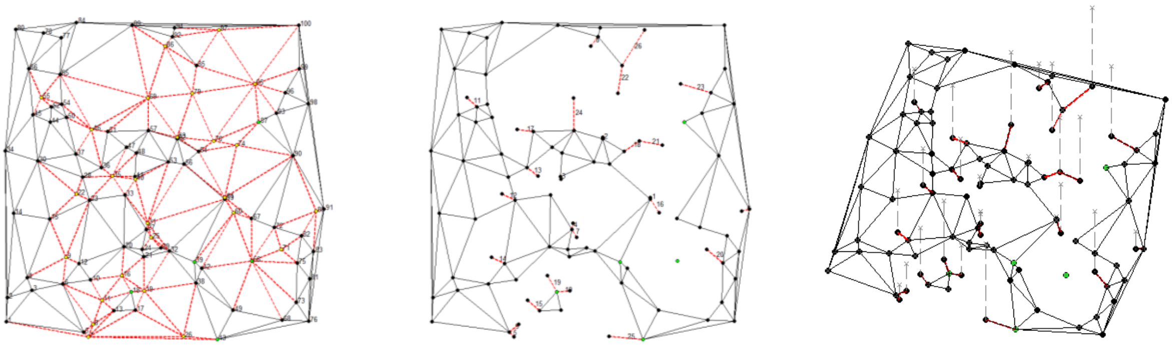


Figure 6. A network consisting on supplying and demand nodes. (a) Partially disrupted network (in Red) after an earthquake. (b) The minimum recovered arcs and components to ensure recover connectivity. (c) Normal segments to the plane containing the network indicate times required for resuming operation at nodes.

4 SIMULATION FRAMEWORK FOR TESTING KASCA

In this section, we describe the simulation framework adopted in this thesis for generating restoration data of lifeline systems subjected to seismic perturbations. First, the modeling approach considered for evaluating interconnected lifeline systems' response to an earthquake scenario in the literature is outlined. Secondly, the recovery strategy for deriving time of repairs prior full system restoration of omponents is described. Lastly, results from applying KASCA to the simulated recovery data is presented.

4.1 Interdependent lifeline system's response to an earthquake scenario.

The first step of the simulation framework used in this thesis is generating independent networks using the models reviewed in section 2. We start from lattice-like (Watts & Strogatz, 1998) and random geometric (Díaz et al., 2001) structures to establish the spatial configuration of components to later adapt their topologies to extreme cases in planar networks. The algorithms for generating lattice-like graphs and random geometric networks are not of great relevance since the final topology of networks is complemented or degraded to obtain Greedy Triangulations (GT) and Minimum Spanning Trees (MST) respectively. Conversely, the algorithms used in this thesis for computing these extreme topological models are the greedy algorithm (Devadoss & O'Rourke, 2011) for computing GTs and Kruskal's algorithm (Buhl et al., 2006) for computing MST's. Briefly, the greedy algorithm consists of adding non intersecting edges to the initial network until maximizing the number of triangulations possible we the prescribed conditions; however, edges that connect nodes along the convex hull that are not immediate neighbors are neglected here. These edges of great length are rare in real networks and for this reason here we consider approximations of greedy triangulations. In regards to the algorithm for generating MSTs, it consists in subtracting all edges from a graph and ranking them with respect to their length such that they are included again testing for each, however, that no cycles are created in the graph with their inclusion. In addition to network science aspects of lifelines generated in this simulation approach, there are operational characteristics to consider in order to make them represent real lifelines. We randomly flag vertices as part of one of three representative groups of most lifelines distributing services to communities: generation, distribution, and transmission or intersection. The proportion of nodes assigned to each group follows that found in the literature (Ouyang, Dueñas-osorio, & Asce, 2011; Poljanšek, Bono, & Gutiérrez, 2012).

What follows in this simulation framework is defining the physical interconnections between systems. These are typically established using service areas but here we simply connect systems' components needing external services with the nearest component providing that service in a complementary network. This approach is realistic in the sense that in real networks, demand vertices are supplied from the nearest distribution network component (e.g. Electricity substations and telecommunication tower antennas).

Defined all interdependent lifeline systems, we now provide a geographical context in which the seismic hazard is present. In the field of infrastructure networks, the Shelby county earthquake has been used (Adachi & Ellingwood, 2008) for studying lifelines' response to seismic perturbations and for applications of models supporting decision-makers. In this thesis, the Shelby county earthquake is used to derive seismic demands but lifelines considered are those generated as stated previously. Here we provide a general description on how seismic demands were generated. For more details Adachi & Ellingwood, 2008, 2009:

- Select an attenuation law from the literature, select the parameters that better adjust to the location of interest, and compute seismic demands at components' locations. Here we adopt the attenuation laws proposed by Atkinson & Boore (1995) which offer parameters that were computed for Easter North America.

- Select fragility curves for lifelines components. Here we used those suggested by FEMA.
- Compute failure probabilities of components using their fragility curves and seismic demands estimated using the attenuation laws.

To evaluate the network response, a cyclic-based interdependence is considered for the failure propagation under the assumption of instantaneous communication of failure and information across systems. This is, after evaluating components' loss of operation through connectivity analyses for each system, these are iteratively reevaluated considering external disconnections as new source of damage at each cycle until reaching a steady state for all systems. For each state, evaluate connectivity of vertices for the next cases: generation nodes are operating if they did not fail distribution nodes and transmission nodes are in operation if they are connected to a not failed generator node.

Once component's failure probabilities are known, it is possible to simulate lifeline's response to the ground motion. The simulation of the mean response that will be evaluated with the Kriging approach is as follows:

- Generate pseudo random numbers to simulate for n realizations components' state up/down (i.e. not failed or failed).
- Compute the connective coming from direct damage and using the cyclic-based approach update interdependence induced failures. The iterative procedure is done until reaching a steady state of the system.
- At the, we are given a network whose failed and/or disconnected components are known.

5 TESTING AND ANALISYS OF KRIGING BASED TOOLS BY COMPUTATIONAL EXPERIMENTS

In this section, we outline the analyses carried out by the KASKA approaches to test the influence of functional and network level properties on the quantified interdependence measures as well as the robustness of the quantification method. In the end of the section, we analyze the results obtain in the light of confirming KASCA validity for measuring degree of coupling across lifeline systems' via spatial correlations.

Previous results from applications of KASCA on real networks where interpreted taking into account their spatial layout only. Nevertheless, an impact due to network level properties on the performance of lifelines systems is warranted but their connections to spatial properties were not completely understood in the context of the previous methodology.

We use the KASKA approach on idealized networks, specifically for extreme models, Minimum Spanning Trees (MST) and Greedy Triangulations (GT). This approach depicts how the quantified spatial correlation metrics are intrinsically related to network properties such as the algebraic connectivity and the spectral gap. Then, we confirm our remarks using models among these limit cases, to expose the sensitivity of the metrics to the mentioned properties.

We should clarify that the use of idealized scenarios for simulating failure and recovery data is not a limitation for this study; it is instead, a systematic study of how interdependencies can be released on failure and recovery phases and identifying crucial parameters governing them.

The space of variables to be study form the network science perspective are:

- Spatial distribution of components according to the network model considered.

- Meshedness coefficient considering extremal topological formations, in particular a greedy triangulation approximation and minimum spanning tree.
- Coupling level established ranging the percentage of vertices requiring external connections, this is, have dependency with outside systems' components.

In regards to the functional parameters, these are fixed to a proportion commonly found in real networks.

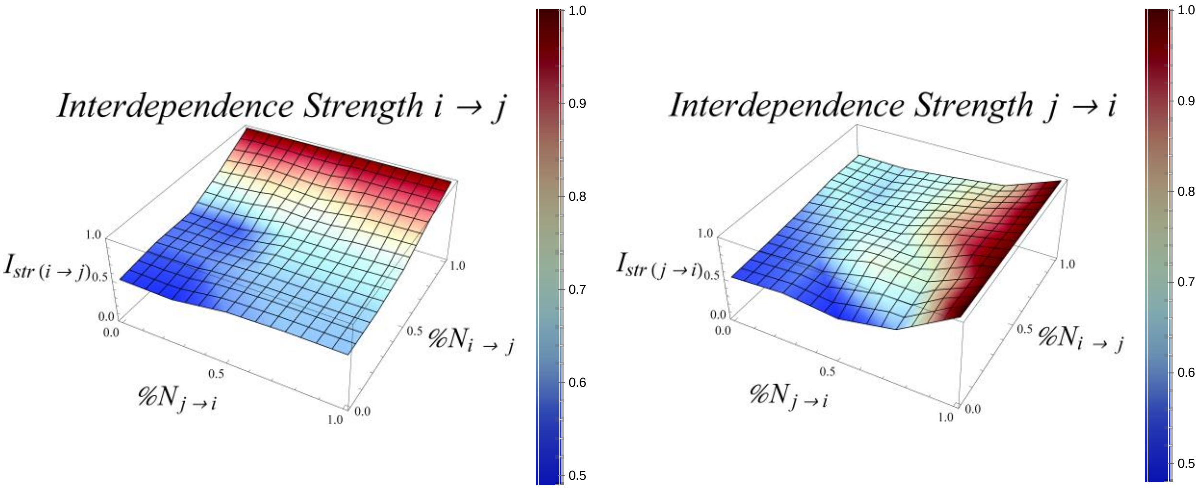


Figure 7. Interdependence strengths obtained using KASCA for different levels of coupling.

5.1 Discussion and analysis of results

Here, the global response is used to verify KASCA's validity for deriving coupling strengths. For low percentage of removed nodes and edges, the Interdependence length degrades rapidly on the GT. MST exhibits 150% more interdependence length.

Depending on the intensity of the event, GT networks exhibit fast decaying interdependence strength and, when the intensity of the event increases, this behavior tends to the one displayed by MST networks. This was the expected behavior, since from one model to the other, network properties such as the Meshedness coefficient (a measure of redundancies in the system) condition the minimum number of network components to recover. However, when the intensity of the event is high enough, total destruction of both networks is expected and if a minimal functional level of the network is the target on the recovery efforts, similar actions take place in both networks due to their shared spatial setup.

6 CONCLUSIONS AND FUTURE RESEARCH

The results of this study confirm the applicability of the kriging based techniques to quantify spatial interdependencies across systems from failure and recovery data of utilities for supporting model validation and calibration. Also, we show that the emerging kriging based techniques can be used to visualize failure and recovery data to aid operators or emergency managers envisioning interdependent phenomena among multilayered networks in time and space via volume rendering techniques.

The enhanced Kriging-based tools supports that interdependencies across systems are heterogeneous in space, as found by Wu et al. (Wu et al., 2012) after using recovery data in the context of the 2010 Mw 8.8 Chile Earthquake. However, in this study time is addressed and there is control over the interdependencies being activated, and since, does not suffer from the statistical noise coming from different interdependencies manifesting simultaneously (e.g. change of decision pattern in the course of recovery due to resource availability, among other statistical distortions encountered when applying KASCA to real non specialized data (Paredes-Toro et al., 2014; Wu et al., 2012). The fact that a network can vary its configuration due to disruptions or its recovery clearly implies that interdependencies are not only heterogeneous in space, but in time as well.

It is clear then that interdependencies are spatial-temporal dependent relationships that can manifest through the network phases (service conditions, exceptional event, and recovery actions) as a function of the event, networks fragility, degree of coupling.

This technique covers results provided by other empirical approaches that aim to capture frequent and significant failure patterns (McDaniels, Chang, Peterson, Mikawoz, & Reed, 2007) and other correlation analyses (Dueñas-Osorio & Kwasinski, 2012) via interdependence length and strength estimations. However, the main advantage of the proposed methods is that it quantifies and locates in space interdependencies between interconnected networks that can easily be mapped to the modeling practices. Having a complete understanding of the interdependence model assumptions and their implications is determinant to verify that a certain model has an holistic abstraction of the possible coupled behavior of lifeline systems, and when it is not the case this method suggest calibrations that can be translated into the model.

Figure 7 demonstrate how taking time into account for the computation of correlations is able to capture coupling strengths and physical their directionality (not to be confused with spatial directionality). This represents a major advance respect the classical method that.

This thesis has demonstrated the validity of computing spatial correlations of networks' restoration to derive coupling measures that consider their directionality. However, the presented tool was sensitive to superposition of interdependencies (Figure 7). Future research should aim to consider filtering methods of data to discard spurious correlations. In addition, future efforts pursuing spatial techniques should integrate fully time for a joint Spatial-Temporal method. A sequential approach would capture in time intensity, length, spatial and functional directionalities due to physical and logical interdependencies, verifying that they are functions of the event and the decision-making process for a given interdependent network.

The classical approach of this method provided length and directionalities of correlations. The interdependence length obtained via global averaged correlation plots represents a comprehensive measure of the influence extension that recovery efforts had over the network. Also, directionality of the recovery scheme was captured by means of the global correlation maps, suggesting that positive and negative correlations where closely related to functional and logistical spatial interdependencies respectively.

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