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NEW MODELS FOR ESTIMATING INTERDEPENDENCIES AND RECOVERY OF INFRASTRUCTURE SYSTEMS

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ABSTRACT

Modern urban systems consist of complex subsystems embedded in intricate networks with interdependencies. Whenever a natural hazardous event strikes these urban systems, disruptions originate and propagate through these interdependencies, forming cascades of failure, and increasing the extent of the impact caused by the disaster. Thus, much research effort has been invested in the study of interdependent infrastructure systems. Recently, a number of studies have used available infrastructure or service restoration data to estimate the coupling strength between system components.

This work presents four models for quantifying interdependencies between infrastructures, which can also be used to simulate the restoration of the entire system after a shock, such as an earthquake, and that can be mathematically fit to system restoration data. The proposed models are inspired by different assumptions about how disruptions propagate through infrastructures and how these infrastructures restore their functionality. Model fitting is done by matching the predicted restoration rate to the empirical restoration rate data, using the least squares criterion. The proposed models are tested for a selection of restoration data associated with six major earthquakes from Japan, New Zealand, and Chile. It is shown that the models effectively reproduce the original restoration curves and how the models may be used to estimate the restoration a system of infrastructures under an arbitrary initial shock.

Keywords: interdependencies, critical infrastructure systems, infrastructure restoration, data science

1. INTRODUCTION

Urban and national systems are comprised of social and technical subsystems embedded in intricate networks that present interdependencies, allowing the propagation of disruptions, heightening the overall fragility of the combined systems (Rinaldi et al. 2001; Buldyrev et al. 2010; Bashan et al. 2013; Ouyang 2014). Thus, a large body of research work has been dedicated to the study of this phenomenon, making use of a diverse variety of methodological approaches, including system dynamics models, agent-based models, network topology and flow models, economic models, graphical models, empirical indicators, frequent failure patterns, and more (Ouyang 2014). Since research relying on highly detailed models, such as network-based and agent-based approaches, require considerable amounts of data, coarser approaches have been particularly popular. The latter often rely on the concept of coupling strength (Parshani et al. 2010; Liu et al. 2016), which refers to the extent the functionality of one element (a node, a subsystem) depends on another. Approaches such as the Inoperability Input-Output model (Haimes and Jiang 2001; Haimes et al. 2005) and similar (Tsuruta et al. 2008; Pinnaka et al. 2015) rely heavily on a pre-estimated coupling strength. However, the quantification of this strength is not part of these models.

Several works have attempted to quantify coupling strength, for example, by eliciting expert knowledge (Correa-Henao et al. 2013; Muller 2012), by using data on sales between economic sectors (Barker and Santos 2010), and by using records on co-failing components (Chou and Tseng 2010).

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Lately, however, a number of works have attempted to quantify coupling strength from infrastructure restoration data. The method proposed in Dueñas-Osorio and Kwasinski (2012) has been particularly popular, since it has been used and extended by a number of works (Cimellaro et al. 2014; Zorn and Shamseldin, 2016; Krishnamurthy et al. 2016). In this method, the coupling strength between two time series of functionality is quantified by doing the following: (i) the logarithm is applied to each series, to reduce their skewness; then (ii) each series is differenced twice to remove trends; and (iii) the coupling strength is estimated from the ratio between the maximum lagged cross-correlation between the series (say, $|\rho(s,s',t_*)|$, where s and s' are the series being compared, and t_* is the optimal lag), and a function of the squared-root of the lag (say, $\sqrt{\max(|t_*|,1)}$ or $1+\sqrt{|t_*|}$). Unfortunately, measuring coupling strength in this manner does not inform an infrastructure restoration model.

1.1 Contributions of this work

This work proposes four models for estimating the joint recovery of interdependent infrastructure systems by estimating their interdependence from the time series of functionality. The models assume that the restoration rate of each infrastructure depends on the current degree of functionality of all the infrastructures of the system. Fitting of the models is done by optimizing the least-squares criterion of the restoration rate. Six infrastructure restoration datasets collected from the literature, which describe the functionality of three or more infrastructures after major earthquakes, are then used to compare the suitability of the models at reproducing the restoration of infrastructure systems.

This paper is organized as follows: Section 2 describes the restoration datasets used in this work; Section 3 proposes four different models for the restoration rate of the infrastructures; Section 4 evaluates the models against the collected datasets; and Section 5 states the conclusions and outlines the future work.

2. RESTORATION DATASETS

A thorough literature search was performed to collect data regarding the restoration of infrastructure systems after an earthquake. Functionality time series were collected for six major earthquakes in three subduction zones in the world: Chile, Japan, and New Zealand. The collected datasets contain time series of functionality that were compiled for three or more infrastructures recorded in the same time period, spanning the same spatial areas, and whose recovery would take more than three days. Having data over a very short period of time, with non-overlapping spatial areas, or from a single infrastructure would not permit the models to estimate interdependencies.

The following six recorded infrastructure restoration processes were considered in this work:

1. The 1995 Hanshin, Japan earthquake. This earthquake had magnitude Mw 6.9 and occurred January 17, 1996. The associated dataset contains functionality data of the power, gas, and water infrastructures, for a period of 82 days, starting at the onset of the event (Nojima 2012). This earthquake was caused by an inland crustal rupture, not by subduction activity.

2. The 2003 Mid-Niigata, Japan earthquake. This earthquake had magnitude Mw 6.6 and occurred October 24, 2003. The dataset contains functionality data of the power, gas, and water infrastructures, for a period of 46 days, starting at the onset of the disaster (Kajitani and Sagai 2009).

3. The 2010 Maule, Chile earthquake. This earthquake had magnitude Mw 8.8 and occurred February 27, 2010. It became the third strongest earthquake to be recorded by modern instruments to date[3]. The dataset contains restoration data for the Maule and Bio Bio regions of Chile and reports the functionality of the power distribution and both fixed and mobile telephony (Dueñas-Osorio and Kwasinski 2012). For the Maule region, recovery of these systems took four days (although the series spans two weeks), and for the Bio Bio region, the

[3] March 5, 2018.

data spans 18 days. Hereafter, data on both regions are considered two different datasets in this work.

4. The 2011 Christchurch, New Zealand earthquake. This earthquake had magnitude Mw 6.2 and occurred February 22, 2011. The dataset contains restoration data of the power, gas, water, and telecommunications infrastructures, as well as hospital services (healthcare) for a period of 29 days (Zorn and Shamseldin 2016). It is the richest dataset of the list, containing five infrastructures, which contrasts the other that contain only three.

5. The 2011 Tohoku, Japan earthquake. This Mw 9.1 earthquake that occurred March 11, 2011, is the second largest earthquake recorded by modern instruments to date. The associated dataset contains functionality data of the power, gas, and water infrastructures, for a period of 78 days, starting from the onset of the disaster (Nojima 2012, Cimellaro et al. 2014). This dataset was patched in this work; on day 29, there was a sudden loss of electricity due to an aftershock. Since this was corrected immediately, the power time series was patched on day 29, replacing the original data with the average of days 28 and 30.

6. The 2016 Kumamoto, Japan earthquake. This earthquake had magnitude Mw 7.0 and occurred April 16, 2016. The dataset contains functionality data of the power, gas, and water infrastructures, for a period of 31 days, starting from the onset of the disaster (Nojima and Maruyama 2016).

3. SYSTEM RESTORATION MODELS

This work is concerned with modeling the restoration of interdependent infrastructures systems through their restoration rate. To state this mathematically, let $x_i(t)$ denote the degree of functionality of infrastructure *i* in a system of *n* infrastructures, and let $x(t)=(x_1(t), x_2(t), \ldots, x_n(t))^T$ be the column vector of all $x_i(t)$. By definition, $x_i(t)$ ranges from 0 to 1, where 0 means that the infrastructure has lost all functionality, while 1 means that the infrastructure is completely functional. The concept of functionality is used in a rather loose manner here; it can be replaced by related concepts, such as serviceability, integrity, availability, operability, and operativity.

With these definitions, this work models the restoration rate of infrastructure systems using

$$x(t+1)=x(t)+\Phi(x(t)), \tag{1}$$

where the functional form of Φ describes how the interdependencies manifest in the restoration rate of each infrastructure. Note that this recurrence model states that the recovery rate of the system depends on the *current* functionality of the infrastructures, neither on their recovery rate nor on another aspect of the history of their recovery.

In practice, Equation 1 will be replaced by the following recurrence,

$$x_i(t+1)=\min\{\ 1,\ x_i(t)+\Phi_i(x(t))\ \}, \tag{2}$$

which prevents the entries of $x(t)$ from being greater than 1.

In the following, we describe the four functional forms adopted for Φ: linear (LIN), in which the restoration rates of the infrastructures depend linearly on the rest; relative linear (REL), in which the relative growth rate of each infrastructure depends linearly on the current state of the rest; gap-relative linear (GAP), in which the growth rate of each infrastructure is proportional to the remaining functionality and their linear combination; and multiplicative (MUL), which is based on fuzzy logic concepts. All these models are deterministic and meant to be fitted under the least-squares criterion.

3.1 LIN: Linear restoration rate model

This model states that the recovery rate of each infrastructure may be assumed as a linear combination of the current degree of functionality of the infrastructures. This model is thus written as

$$\Phi^{LIN}(x) = a + Bx, \tag{3}$$

where a is an n-dimensional vector and B is an $n \times n$-dimensional matrix. The entries of a and B cannot be negative. This model is then equivalent to the dynamic Inoperability Input Output model in discrete time (Lian and Haimes 2006).

The entries of the B matrix represent the coupling strength between the infrastructures. The entry located in row i and column j, i.e. element (i,j), represents the contribution of infrastructure i on the restoration of infrastructure j.

3.2 REL: Relative linear restoration rate model

This model states that the *relative* restoration rate of an infrastructure linearly depends on the current degree of functionality of the other infrastructures, which can be stated as

$$\frac{x_i(t+1) - x_i(t)}{x_i(t)} = a_i + b_i^T x(t), \tag{4}$$

which, in turn, is equivalent to

$$x_i(t+1) - x_i(t) = x_i(t)\left(a_i + b_i^T x(t)\right). \tag{5}$$

For this case, Φ can therefore be stated as

$$\Phi^{REL}(x) = x * (a + Bx), \tag{6}$$

where symbol '$*$' stands for the element-wise multiplication (also known as Hadamard or Schur product), and a and B have the same dimension as in the linear case. The entries of a and B cannot be negative.

3.3 GAP: Gap-relative linear restoration rate model

This model is similar to REL, except that it is inspired on the following observation: infrastructure restoration rates tend to diminish as functionality nears full restoration. In other words, the difference $x_i(t+1) - x_i(t)$ seems to be increasing on the gap $1 - x_i(t)$. Consequently, under this model, the growth rate can be written as

$$\frac{x_i(t+1) - x_i(t)}{1 - x_i(t)} = a_i + b_i^T x(t), \tag{7}$$

which is equivalent as stating

$$\Phi^{GAP}(x) = (1 - x) * (a + Bx), \tag{8}$$

where vector a and matrix B have the same dimension as in the previous cases. Again, the entries of a and B cannot be negative.

3.4 MUL: Multiplicative restoration rate model

The last model for the restoration rate is inspired on logic. Let us use an example to explain the insight behind it. Suppose that there is a system of n infrastructures, and, in particular, that infrastructure 1 depends on infrastructures 2, 3, and 4. Let p_i be a truth-value formula that is true if and only if infrastructure *i* is *functional*, stating implicitly that an infrastructure is either fully functional or non-functional. Now, if the restoration of infrastructure 1 depends on the restoration of infrastructures 2, 3, and 4, then this can be written as

$$r_i = \neg p_i \wedge p_2 \wedge p_3 \wedge p_4, \tag{9}$$

where r_1 is true if the conditions for recovery are met, and $\neg p_1$ is included to state that a fully functional infrastructure does not need to recover. If the propositional variables p_i are replaced by binary variables $q_i \in \{0,1\}$ such that $p_i \Leftrightarrow (q_i = 1)$, then the previous formula can be rewritten as

$$g_1 = (1 - q_1) \cdot q_2 \cdot q_3 \cdot q_4, \tag{10}$$

where g_1 is the binary equivalent to r_1. This example can be generalized quite easily; if binary variable $u_{ij} = 1$ if and only if the restoration of infrastructure *i* depends on the functionality of infrastructure *j*, then the following formula generalizes Equation 10,

$$g_i = (1 - q_i) \prod q_j^{u_{ij}}. \tag{11}$$

The previous example sets the ground for proposing the following restoration rate model,

$$\Phi_i^{MUL}(x) = a_i (1 - x_i)^{c_i} \prod x_j^{b_{ij}}, \tag{12}$$

which can be restated in terms of linear algebra as

$$\log_* \Phi^{MUL}(x) = \log_*(a) + c^T \log_*(1 - x) + B \log_*(x), \tag{13}$$

where a and c are n-dimension vectors, B is an $n \times n$-matrix, and $\log_*$ is the component-wise logarithm. This model basically generalizes Equation 11 by: (i) relaxing the binary variables q_i to use the whole range between 0 and 1 as x_i; (ii) giving relative importance to the terms through exponentiation, and allowing the exponents to be greater than 1; and (iii) stating that the restoration rate is proportional to this relaxed logic formula.

The entries of *a*, *B*, and *c* cannot be negative, with *a* and *c* being strictly positive.

3.5 Model fitting

The models are fitted using the restoration rate $x_i(t+1) - x_i(t)$, not the values of $x_i(t)$. The latter would require integrating the models and calibrating the coefficients to make the calibrated curves match the restoration data. The former approach, however, it is simpler to fit and does not control the propagation of estimation errors, which is a feature, since it permits the fair comparison of the models. The different Φ-functions model the restoration rates, and, if they are adequate, they will approximate the entire restoration curves.

The models are fitted to minimize the least-squares criterion,

$$\min \sum_t \|\Phi(x(t)) - (x(t+1) - x(t))\|^2. \tag{14}$$

The restoration rate models were programmed in Python and optimized using the `leastsq` routine in `scipy`'s `optimize` package, which minimizes the provided function using Newton's method with numerical approximations of the gradient and the Hessian. Thus, the routine is sensitive to sudden higher order (nonlinear) local changes in the provided function.

4. EXPERIMENTS

Each of the models was fitted to all the restoration datasets, and then, starting from the same initial loss of functionality of each infrastructure, the joint restoration of the system was estimated. Then, the root mean squared error was computed. This is described by the following pseudocode:

(1) For each dataset $(x_1, \ldots, x_n) \in Datasets$:

(2) For each model $M \in \{LIN, REL, GAP, MUL\}$:

(3) Find parameters $\theta = (a, B, c)$ from

$$\theta = \text{argmin}_\theta \sum_t \|\Phi_M(x(t);\theta) - (x(t+1) - x(t))\|^2,$$

(4) Compute the estimated restoration $\tilde{x}(t)$ from

$$\tilde{x}(0) = x(0),$$
$$\tilde{x}(t+1) = \tilde{x}(t) + \Phi_M(x(t);\theta)$$

(5) Compute the root mean squared error RMSE from

$$RMSE_M = \sqrt{\frac{1}{nT} \sum_t \|\tilde{x}(t) - x(t)\|^2},$$

where T is the number of days considered in the restoration period.

The curves that resulted from the simulated restoration, as well as the original data, are displayed in Figure 1. The charts illustrate how some models could reproduce some original curves, but could not adequately reproduce others. For example, the LIN model could properly reproduce the 2010 Maule/Maule restoration curves, but it could not reproduce the 2004 Mid-Niigata curves. It is apparent that the REL model does not reproduce well the restoration data.

In contrast, the GAP and MUL models seemed able to reproduce the original restoration data more closely than the LIN and REL models. To determine how well these perform with the available data, the estimated RMSE are displayed in Tables 1 and 2. Table 1 shows the original RMSE for each model and dataset, while Table 2 shows the *overestimation* of the RMSE for each model and dataset. The overestimation is defined as the ratio between the RMSE of the model and dataset divided by the smallest RMSE for the dataset.

Table 1. RMSE of each model and each restoration scenario (event).

	Model			
Earthquake	**LIN**	**REL**	**GAP**	**MUL**
1996 Hanshin	0.110	0.670	0.111	0.081
2004 Mid-Niigata	0.066	0.064	0.034	0.022
2010 Maule/Maule	0.239	0.229	0.226	0.207
2010 Maule/Bio Bio	0.237	0.493	0.221	0.178
2011 Christchurch	0.109	0.162	0.074	0.074
2011 Tohoku	0.110	0.469	0.135	0.137
2011 Kumamoto	0.112	0.683	0.137	0.113

The underperformance of the LIN model suggests that the model of Lian and Haimes (2006) might not be adequate for estimating the recovery of interdependent systems, in spite of the popularity of the IIO model. Nevertheless, when the MUL model does not outperform the rest, the LIN model does, suggesting that these models capture situations that the other cannot.

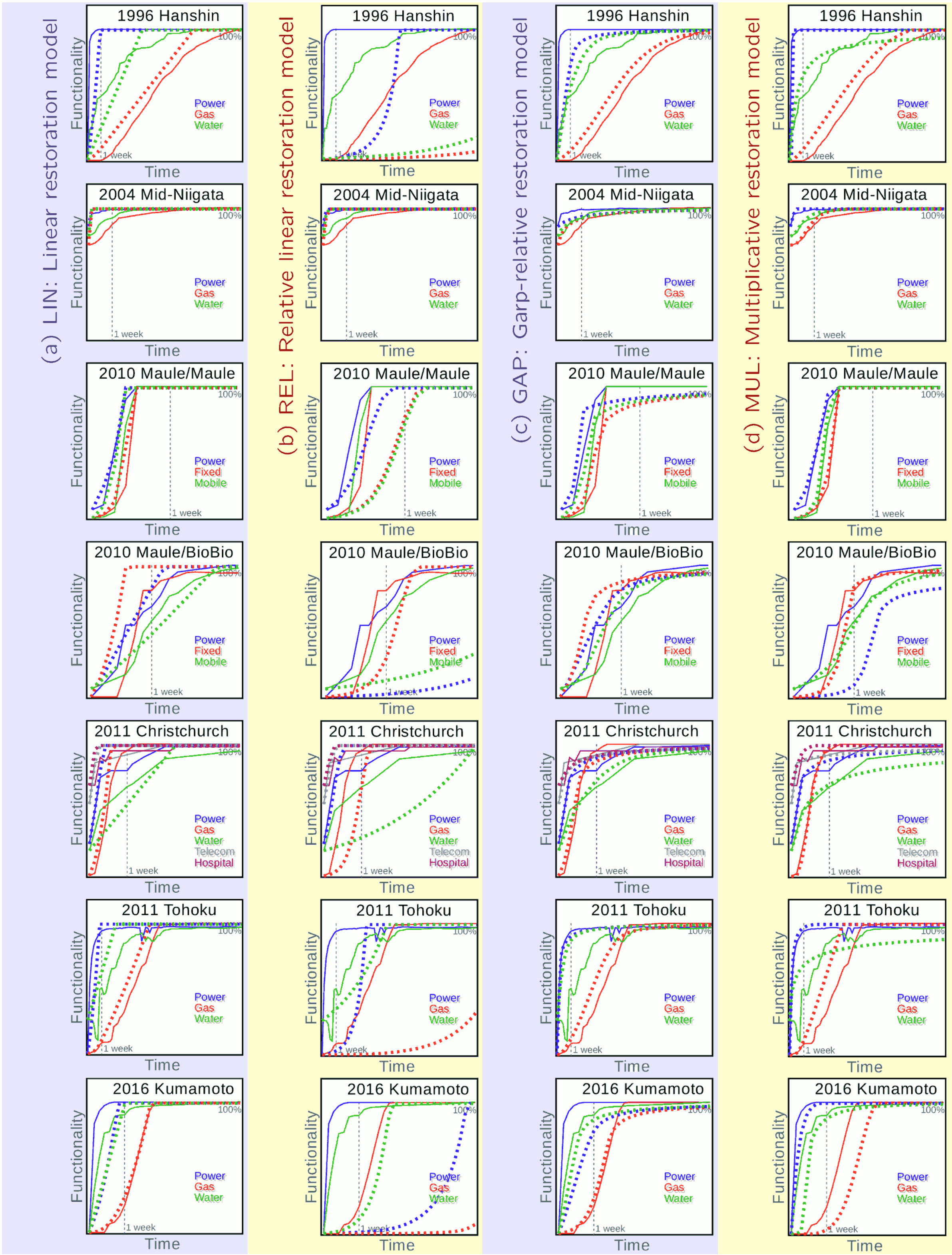

Figure 1. Comparison between the original and the estimated restoration data by the four models. In each plot, the corresponding earthquake (e.g. 1996 Hanshin), the original data (solid lines), and the estimated restoration (dotted lines) are displayed. Within a plot, lines of the same color represent the same infrastructure.

Table 2. Relative overestimation of the RMSE of each model versus the best (least) RMSE for each event.

	Model			
Earthquake	**LIN**	**REL**	**GAP**	**MUL**
1995 Hanshin	130.2%	825.6%	137.3%	100.0%
2004 Mid-Niigata	296.1%	283.6%	151.6%	100.0%
2010 Maule/Maule	115.8%	111.1%	109.5%	100.0%
2010 Maule/Bio Bio	133.2%	276.6%	123.8%	100.0%
2011 Christchurch	147.7%	220.5%	100.5%	100.0%
2011 Tohoku	100.0%	425.7%	122.2%	124.0%
2016 Kumamoto	100.0%	612.1%	123.2%	101.3%
Average	**146.2%**	**393.6%**	**124.0%**	**103.6%**

As mentioned before, strong non-linearities usually lead the optimization procedure to arrive at poor local minima. Therefore, the optimization was performed in multiple stages by: first allowing the parameters to range between 0 and 0.75, then between 0 and 1.75, and finally between 0 and 10. The optimal solution achieved in each stage was used as the initial solution for the next one. Optimizing in several successive stages improved the fit of all the restoration models with the exception of LIN, whose RMSE remained the same regardless of the optimization method used. (Since LIN is linear, fitting it to data requires solving traditional linear regression.)

5. CONCLUSIONS

Cities are supported by the operation of intricate networks that present complex interdependencies. In general, services and infrastructures depend on each other to be able to provide their functionality. These interdependencies increase the fragility and reduce the healing capacity of urban systems. Such is the case since network fragility is increased due to the ability of disruptions to propagate through these interdependencies, which can result in cascades of failures at a large scale. Moreover, the restoration processes of these systems also depend on the functionality of underlying infrastructures, in that the cascades of failure also affect the healing capacity of cities. Both phenomena are detrimental to the resilience of urban systems, it is hence necessary to understand the extent to which infrastructures depend on each other and the influence that each of these interdependencies has on the resulting resilience of cities.

This work proposed and evaluated four mathematical models for simulating the restoration of interdependent infrastructure systems. These models attempt to reproduce the restoration rate of each infrastructure by using different assumptions on how the interdependencies manifest during restoration. By proper fitting, the models may also measure the strength of the interdependence between the systems, conditional to the adequacy of the models. Six earthquake restoration datasets collected from the literature were used to evaluate and compare the proposed models, finding that one of them clearly outperformed the rest in terms of squared error. The best performing model is based on propositional logic formulas, generalized to continuous functions.

This work has several limitations. First and foremost, the proposed models are extremely simple and have only been fitted to a few small datasets. The models could become more complex if the datasets had considered more infrastructures. Experimental validity also requires testing on more datasets, which are, unfortunately, scant. Another limitation arises from the problem of identifiability: optimization of the proposed models might lead to different local optima, yet there is no way to distinguish which solution is better or worse than another. This extends to the problem of identifying which model is more *true* than the rest (although one model clearly stood out in terms of performance). The models are also limited in that they are not statistical. The introduction of randomness would transform them into full stochastic processes, making them more adequate for simulation. Finally, this work did not introduce proper fitting algorithms for the models; black-box numerical optimization is known to be suboptimal and might have hindered the performance of the proposed restoration models.

Overcoming the aforementioned limitations should be the subject of future work.

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