Chapter 14

MODELING INOPERABILITY PROPAGATION USING BAYESIAN NETWORKS

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Abstract The modeling of critical infrastructure interdependencies is a challenging task. This paper discusses several interdependency modeling requirements and proposes a Bayesian network approach for modeling interdependencies and inoperability propagation. The approach is applied to a case study involving the Japanese critical infrastructure sectors. Survey data published by the National Institute of Land and Infrastructure Management and the Japanese National Information Security Center are used to generate conditional probability values for the Bayesian network. The approach has the flexibility to adapt to diverse critical infrastructure scenarios and interdependency structures.

Keywords: Inoperability propagation, Bayesian networks, risk assessment

1. Introduction

The modeling of critical infrastructure (CI) interdependencies is an important but challenging research problem. One of major requirements is adequate realistic data that can support the infrastructure modeling process [3]. However, data of sufficient detail, coverage and quality is not available for several critical infrastructure sectors. Due to the scarcity of data, many critical infrastructure modeling approaches are limited to certain domains, and most approaches are forced to engage scenario-based modeling.

This paper discusses the principal requirements for interdependency modeling and proposes an approach that uses a Bayesian network for interdependency modeling and inoperability propagation. The modeling approach is validated using a case study involving the Japanese critical infrastructure sectors.

2. Related Work

The input-output inoperability model (IIM) developed by Haimes and coworkers (see, e.g., [4]) is based on the economic equilibrium model of Leontief [6]. Several extensions to IIM have been proposed (see, e.g., [1, 10, 11]).

The IIM formulation uses static economic data from "make" and "use" matrices provided by the Bureau of Economic Analysis. This formulation assumes that a direct correlation exists between national economic input-output data and economic sector operability/inoperability. However, such a correlation represents a crude approximation of reality. As discussed in [2], national input-output data can represent economic sector dependencies that are insignificant in some cases. In the case of Japan, almost all the defined critical infrastructures correspond to utility service sectors. These sectors have insignificant input-output table values, but they have high degrees of physical and functional interdependence.

Setola, *et al.* [12] have introduced an alternative IIM formulation. Instead of using national economic input-output data, their formulation derives the interdependency coefficients using expert interviews, where the expert data is expressed and processed using a fuzzy set methodology. Macaulay [7] has proposed a similar quantitative method for modeling interdependencies, with an emphasis on the financial sector. In particular, Macaulay develops tornado charts of economic dependencies from national input-output data, and derives data flow matrices based on a survey of experts in public and private critical infrastructure entities.

IIM yields useful estimates of sector inoperability and provides a simple method for translating these estimates into financial losses for each sector and for the economy as a whole. Nevertheless, adequate data for interdependency modeling is difficult to obtain. In Japan, for example, there have been a considerable number of service interruptions – Japan experienced six major earthquakes from 2007 to 2009 alone; and numerous post-disaster reports and case studies are available. However, the problem is that there is very little data specifically related to infrastructure interdependencies. For this reason, a thorough review of published reports is recommended as an alternative to acquiring hard data.

3. Modeling Interdependencies

Our infrastructure interdependency modeling approach is designed to address the requirements of flexibility, generality and reliability. While IIM is regarded as the most convenient way of estimating the economic impact of certain disruptions, our model uses a Bayesian network as a buffer between initial perturbations and IIM to allow flexible adjustment and risk management intervention (Figure 1). The propagated inoperability values obtained using the Bayesian network are input to the IIM for economic loss estimation and impact assessment.

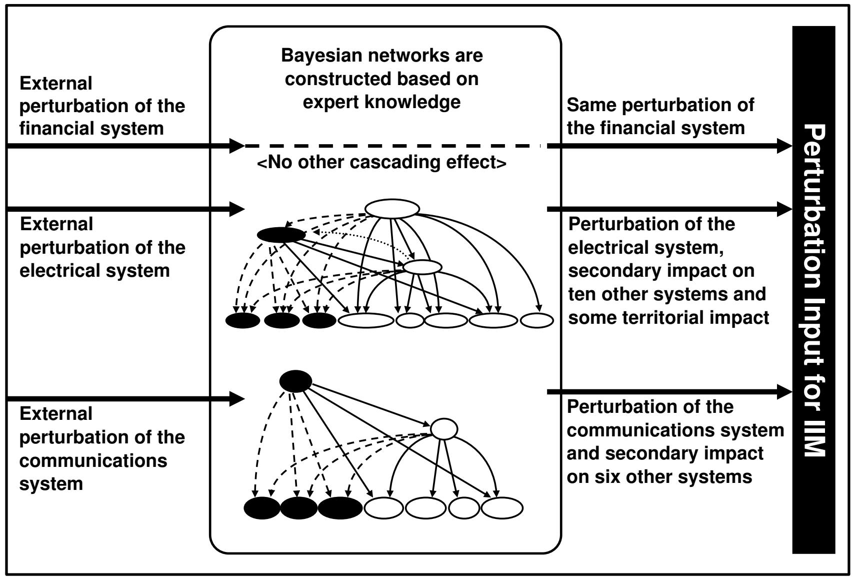

Figure 1. Bayesian network as a buffer between external perturbations and IIM.

We assume that the structure and strength of interdependencies change over time (daily, seasonal, etc.). The temporal changes may also occur during a disaster: outbreak period, emergency period and restoration period. The interdependencies during the outbreak period can be almost identical to those under normal conditions. However, the limited availability of resources during the emergency causes the interdependencies to be different from those during the outbreak period. Similarly, the interdependencies during the restoration period are different as a result of the recovery dynamics and resilience characteristics. Therefore, critical infrastructure interdependency modeling should address these situational dependencies and should adapt to the relevant disaster periods.

4. Data Sources

Our primary major data source for modeling critical infrastructure interdependencies was a 167-page technical report released in February 2009 by the National Institute of Land and Infrastructure Management (NILIM) of the Japanese Ministry of Land, Infrastructure, Transport and Tourism [5]. The report investigated the interdependencies between critical infrastructures in past disasters and presented the results in the form of tables and influence diagrams. The report has three major components: (i) data collection; (ii) two analytical models, one based on matrix equations and the other on system dynamics; and (iii) a simulation of earthquake damage spreading in the Tokyo metropolitan area. The data collection and matrix equations from the NILIM were used in our study.

Table 1. Dependencies during the Kobe and Niigata Chuetsu earthquakes.

Ref. No.	Influence Generated	Influence Received	Type	Details
1	Water	Health	Lifeline	8,850 m^3 of water had to be delivered by trucks for 47 days
16	Road	Water	Restoration	66.5% of employees could not reach work on the day of the disaster due to congestion
30	Water	Road	Alternative	Hospitals needed increased water delivery from 5-6 tons to 30 tons from locations as far as 7 km away
32	Elec.	Health	Lifeline	Failure of artificial respirators threatened sixteen lives; the respirators had to be operated manually
95	Water	Gas	Physical	Gas supply was halted to 12,463 locations due to water leakage into control systems
104	Comm.	Industry	Lifeline	One of two NTT Online Cable trunk lines between the computing center and the Kobe head office was cut
13	Road	Gas	Restoration	Gas supply system repairs in the Yamaguchi and Horikoe regions could not proceed for three days because of road damage
25	Gas	Waste	Functional	Sewage was used to cool pressurized gas
16	Comm.	Gas	Restoration	Vital SCADA data for the Nagaoka control center and Kawaguchi gas control unit was delayed by more than two hours

The data collection component of the NILIM report incorporates an exhaustive review of 65 reports on the Kobe earthquake and 52 reports on the Niigata Chuetsu earthquake. The unique CI-to-CI dependencies were extracted and categorized into the six groups listed below. Excerpts are listed in Table 1.

- **Physical Impact:** 18 cases
- **Functional Impact:** 33 cases
- **Restoration Delay:** 62 cases
- **Alternative Impact:** 43 cases
- **Common Failure:** 4 cases
- **Lifeline Impact:** 84 cases

Because it focuses on earthquake disaster management, the NILIM report does not cover all ten (officially-defined) Japanese critical infrastructures [9]. Nevertheless, it provides a good foundation for further interdependency analysis. Based on knowledge gained from literature surveys and government hearings, a survey questionnaire was created to assess the quantitative influence on the critical infrastructures.

Table 2. Survey results.

		Critical Infrastructure									Lifeline Services			
		Elec.	Gas	Water	Sewage	Comm.	Road	Rail	Harbors	Air	Transport	Finance	Health	Gov.
Critical Infrastructure	Elec.		1	3	8	4	9	16	12	8	12	8	12	16
	Gas	1		1	2	1	0	4	1	3	1	1	6	2
	Water	2	1		4	0	0	4	3	3	4	1	16	8
	Sewage	0	0	1		0	0	4	1	1	1	1	4	1
	Comm.	0	8	2	1		4	16	4	8	12	20	6	20
	Road	0	4	2	0	12		1	8	4	16	6	12	2
	Rail	0	1	0	0	0	6		3	4	4	2	0	2
	Harbors	0	3	0	0	0	0	0		0	1	0	0	12
	Air	0	0	0	0	0	0	0	0		1	0	0	0

The survey results are shown in Table 2. Each entry provides the influence of the row CI on the column CI (receiver). Note that the table shows the CI-to-CI influences as well as the influences on lifeline services.

Table 3. Influence matrix.

	Elec.	Gas	Water	Sewage	Comm.	Road	Rail	Harbors	Air
Elec.	0	0.016393	0.049180	0.131148	0.065574	0.147541	0.262295	0.196721	0.131148
Gas	0.016393	0	0.016393	0.032787	0.016393	0	0.065574	0.016393	0.049180
Water	0.032787	0.016393	0	0.065574	0	0	0.065574	0.049180	0.049180
Sewage	0	0	0.016393	0	0	0	0.065574	0.016393	0.016393
Comm.	0	0.131148	0.032787	0.016393	0	0.065574	0.262295	0.065574	0.131148
Road	0	0.065574	0.032787	0	0.196721	0	0.016393	0.131148	0.065574
Rail	0	0.016393	0	0	0	0.098361	0	0.049180	0.065574
Harbors	0	0.049180	0	0	0	0	0	0	0
Air	0	0	0	0	0	0	0	0	0

The CI-to-CI influence matrix (Table 3) was generated from Table 2 by normalizing the values based on the largest rowwise summation (= 61).

Table 4. Total dependency matrix.

	Elec.	Gas	Water	Sewage	Comm.	Road	Rail	Harbors	Air
Elec.	0.003027	0.060529	0.062064	0.139291	0.103214	0.185284	0.310372	0.249977	0.185895
Gas	0.017125	0.006658	0.018984	0.036822	0.019919	0.011660	0.079578	0.028158	0.061886
Water	0.033289	0.023033	0.003787	0.071028	0.005186	0.013347	0.082301	0.063595	0.062982
Sewage	0.000600	0.003098	0.016766	0.001303	0.001434	0.006833	0.067607	0.021723	0.022540
Comm.	0.003768	0.150483	0.039683	0.024776	0.021507	0.095532	0.284585	0.099075	0.169147
Road	0.003076	0.103339	0.042159	0.009882	0.202890	0.021722	0.080962	0.155817	0.106637
Rail	0.000625	0.029102	0.004504	0.001665	0.020331	0.100717	0.009461	0.065036	0.077227
Harbors	0.000842	0.049508	0.000943	0.001811	0.000980	0.000573	0.003914	0.001385	0.003044
Air	0	0	0	0	0	0	0	0	0

The DEMATEL method was used to obtain the total (direct + indirect) impact of the CI-to-CI influences. The resulting matrix is shown in Table 4.

Table 5. Total requirements of Japan's ten critical infrastructures.

	Elec.	Gas	Water	Finance	Rail	Logistics	Air	Comm.	Gov.	Health
Elec.	1.043578	0.025498	0.093584	0.008200	0.060693	0.011241	0.015587	0.015551	0.017824	0.024930
Gas	0.000534	1.012813	0.001717	0.001005	0.001095	0.000808	0.001316	0.001071	0.001191	0.003883
Water	0.001937	0.005211	1.105431	0.002248	0.006977	0.002976	0.003473	0.004135	0.004786	0.007713
Finance	0.059927	0.029559	0.034154	1.099556	0.232122	0.038274	0.071628	0.046012	0.020523	0.037563
Rail	0.002233	0.002142	0.002420	0.009354	1.003249	0.002407	0.002884	0.002962	0.006447	0.004207
Logistics	0.012923	0.020586	0.011587	0.008528	0.006226	1.006349	0.007863	0.015381	0.010985	0.013164
Air	0.000791	0.000630	0.000836	0.001372	0.000626	0.000505	1.005925	0.002804	0.001273	0.001525
Comm.	0.012735	0.016381	0.018865	0.032934	0.017441	0.015884	0.021257	1.154597	0.021695	0.017611
Gov.	0.001230	0.001310	0.001932	0.001498	0.000911	0.001205	0.002105	0.001109	1.000440	0.000994
Health	0.000007	0.000024	0.000054	0.000034	0.000030	0.000004	0.000006	0.000049	0.000014	1.023300

Table 5 shows the total industry-by-industry requirements for the Japanese critical infrastructures, which can be used to calculate the total industry requirements per dollar of industry output. This data, which was obtained from the input-output tables of Japan (Year 2000) published by the Statistics Bureau (Ministry of Internal Affairs and Communications), expresses the economic dependencies between critical infrastructures.

Figures 2 and 3 compare the operational dependencies obtained from Table 4 and the economic dependencies obtained from Table 5, respectively. Two indices are computed to enhance readability. The influence driving index (D) of a row infrastructure is the sum of the row entries. The influence receiving index (R) of a column infrastructure is the sum of the column entries. The indices D and R are plotted on the x-axis and y-axis, respectively.

The lifeline services (finance, health and government services) are omitted in the NILIM survey data (plotted diagram on the left); as a result, they appear to contradict each other. However, there are several interesting points to be discussed. Judging from its relative position, electricity is the high influence driving infrastructure in both figures. Communications in the right-hand-side diagrams (economic dependence) shows a high influence driving index similar to electricity. It underscores the similarity in the economic dependency patterns of electricity and communications while electricity has a much higher influence driving index than communications from the operational dependency point of

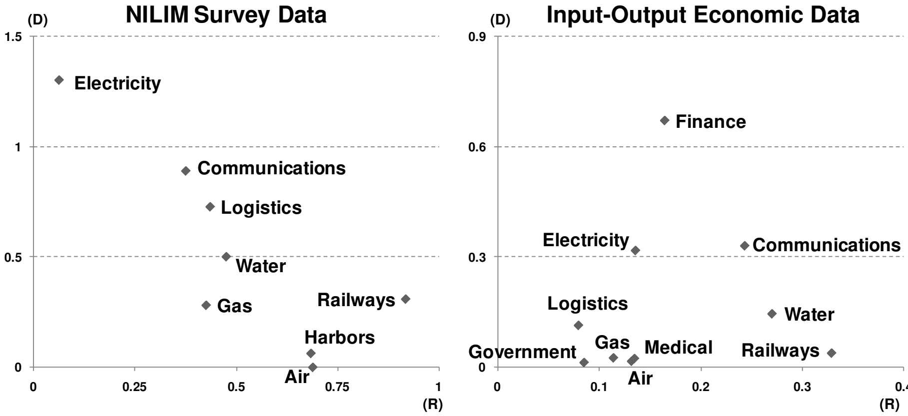

Figure 2. Influence driving (D) and receiving (R) comparison.

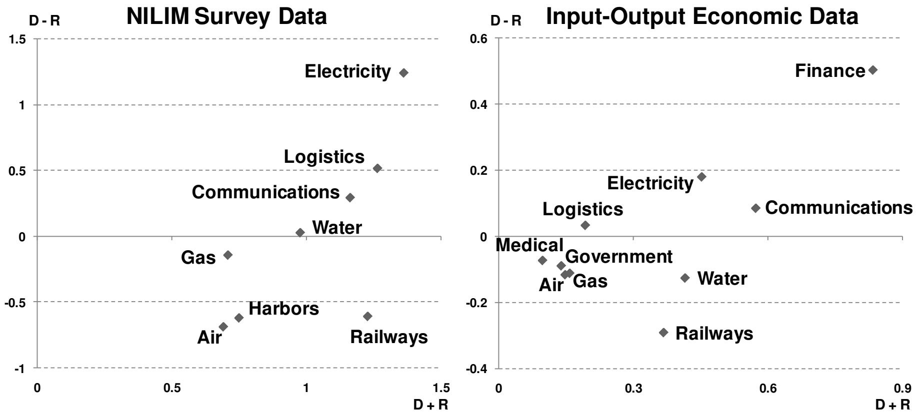

Figure 3. Net influence $(D - R)$ and strength of relation $(D + R)$.

view. Railways have the highest influence receiving indices from the economic and operational perspectives.

The net influence of a critical infrastructure is computed as $D-R$. If $D-R$ is positive, then the critical infrastructure has a net driving influence, otherwise it has a net receiving influence. The strength of relation of a critical infrastructure is computed as $D+R$. Note that $D-R$ and $D+R$ are used as the x-axis and y-axis, respectively, in Figure 4, which compares the operational and economic dependencies between critical infrastructures.

A net driving influence is observed for the electricity, communications and logistics infrastructures in Figures 2 and 3. The net influence of water is inconsistent because the NILIM survey considers operational and physical dependencies (water leakage into control systems is a serious threat after an earthquake). In the case of the $D+R$ metric, electricity and communications have anomalous results with respect to the economic and operational viewpoints. Communica-

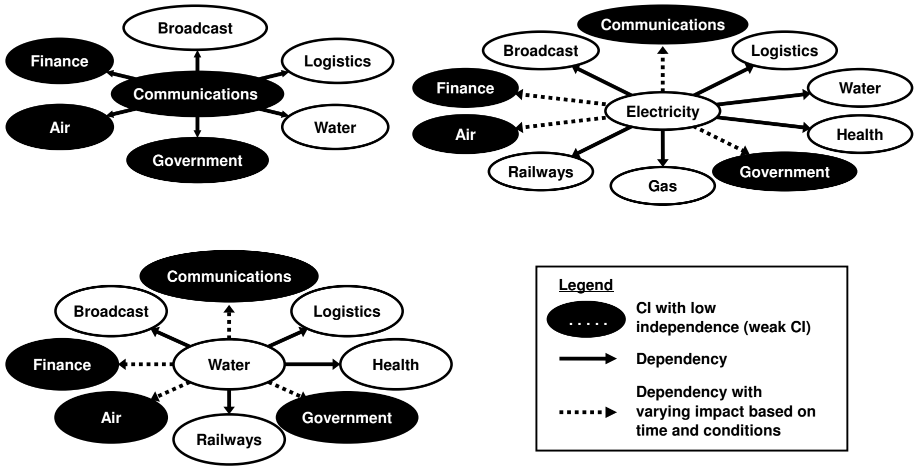

Figure 4. NISC interdependency analysis results.

tions in the right-hand-side diagrams (based on economic data) has a higher strength of relation than electricity, which reflects the higher investment in information technology by the communications sector. From an operational perspective, electricity is a fundamental requirement for every other critical infrastructure according to the NILIM survey. Logistics (road and transportation) has an insignificant strength of relation with respect to economic dependence. However, in the case of a disaster, road networks are vital for all the critical infrastructures, as demonstrated by the higher strength of relation in the NILIM survey.

Figure 4 shows the results of an interdependency analysis conducted by the Japanese National Information Security Center (NISC) [9]. The dark circles represent sectors with low dependencies (weak systems); the dotted arrows represent time-varying dependencies. Of the ten critical infrastructure sectors, broadcasting, railway, electricity, gas, medical services, water and logistics are termed as highly-independent (robust) systems. On the other hand, communications, finance, air transportation and government services are weak systems with low independence. Note that communications and broadcasting is defined as a single sector. However, they are treated separately because of their different dependency characteristics.

5. Causal Network

Figure 5 presents the causal network developed using the results of NISC's interdependency analysis. The diagram shows the first-level propagation of inoperability among the critical infrastructures. Quadrant I contains the major influence sectors – communications, electricity and water; any perturbation to one or more critical infrastructures in this quadrant will propagate to other critical infrastructures. Quadrant II contains communications and water to

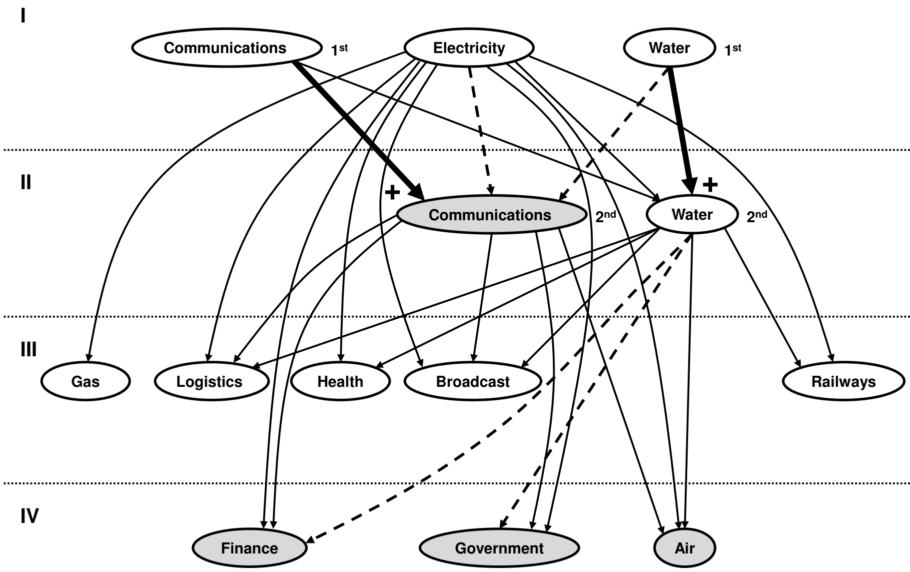

Figure 5. Causal network for Japan's critical infrastructures.

handle the interdependencies between the two infrastructures. The thick dark arrow between the first communications node in Quadrant I and the second communications node in Quadrant II expresses the fact that an inoperability perturbation in the first node (say 0.2) propagates to the second communications node as an identical value (0.2). If there are two external perturbations to communications and electricity of 0.2 and 0.2, respectively, then the propagated inoperability in the second communications node is the sum of 0.2 propagated from the first communications node and some portion of the inoperability influenced by electricity on communications. The nodes in Quadrants III and IV are infrastructures that have little or no influence on other infrastructures (that correspond to leaf nodes in the causal network). The critical infrastructures in Quadrant IV have low independence (i.e., they are weak systems) according to the NISC analysis.

Certain inconsistencies exist in the NILIM and NISC dependency results. The NILIM report focuses on earthquake damage spreading analysis and targets three types of dependency impact – physical, functional and restoration delay. On the other hand, the NISC study mainly focuses on the functional perspective. Our model focuses on the functional dependence and dependency structure of critical infrastructures during the disaster period.

6. Bayesian Networks

Bayesian networks provide a flexible formalism for expressing expert knowledge. Based on the causal network described above, we constructed a Bayesian network utilizing the influence matrices and qualitative assessments of CI-to-

CI dependencies presented in Section 4. Better results are obtained for a decision node with a larger number of states. However, it requires many more conditional probabilities and has a higher computational cost. For reasons of simplicity and for demonstration purposes, each node in the network is limited to having four states:

- **Normal:** The system is in a normal condition and is fully operational with an inoperability of 0.00.
- **Reduced:** The system is slightly perturbed and is 80% operational with an inoperability of 0.20.
- **Half:** The system is 50% operational with an inoperability of 0.50.
- **Down:** The system is completely out of service (0% operational) with an inoperability of 1.00.

We used Hugin Lite (version 6.8) to construct the Bayesian network for the first-order propagation of inoperability in the ten Japanese critical infrastructures. The network primarily targets functional dependencies and is modeled for a one-day period. The structure of the Bayesian network conforms to the NISC results and the influence levels (conditional probabilities) are based on the NILIM results and influence matrices. In addition, the qualitative assessments relied on the ratings and reasons provided by participants in the questionnaires, the functional impact obtained by mining data pertaining to previous disasters, interview notes, and NISC survey results such as the direct and time-varying impact and critical infrastructure interdependencies.

7. Future Tokyo Earthquake Case Study

Figure 6 shows the initial situation where all the critical infrastructures are in the normal operational state. In May 2006, the Tokyo Metropolitan Disaster Management Council [13] produced a damage estimate report for a predicted 7.3 magnitude earthquake occurring directly beneath Tokyo. This earthquake was assumed to occur together with a 6.9 magnitude quake beneath Tokyo Bay near the Shinagawa area [8].

Figure 7 shows the inoperability propagation due to a 6.9 magnitude earthquake. The results were obtained using estimated service disruptions of 20.5% to electricity and 18.2% to communications as the initial perturbations that were input to the Bayesian network.

Figure 8 shows the effects of a 7.3 magnitude earthquake in the same region. Estimated service disruptions of 48.6% to electricity and 38.4% to communications were used as the initial perturbations input to the Bayesian network. These external perturbations propagated into the other critical infrastructures creating varying levels of inoperability. The inoperability of communications increases from 48.6% to 58.3% due to its dependence on electricity and water supply. Of the other infrastructures, the financial system suffers the most with an inoperability of 9.5%.

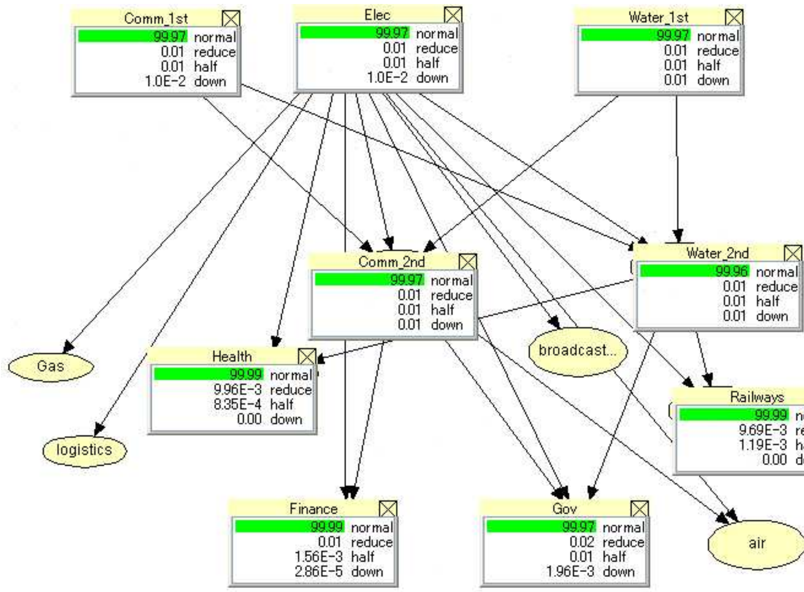

Figure 6. Initial situation in the critical infrastructure interdependency network.

8. Conclusions

The IIM is arguably the most popular method for estimating the economic impact of critical infrastructure disruptions. However, the Bayesian network described in this paper serves as a buffer between initial perturbations and the IIM, providing the flexibility to adapt to various scenarios and adjustments in interdependencies. The fidelity of the Bayesian network approach is, of course, dependent on the conditional probability assignments. The strength of the approach lies in its ability to combine expert judgment and objective data, and to refine the results as new data of higher quality becomes available.

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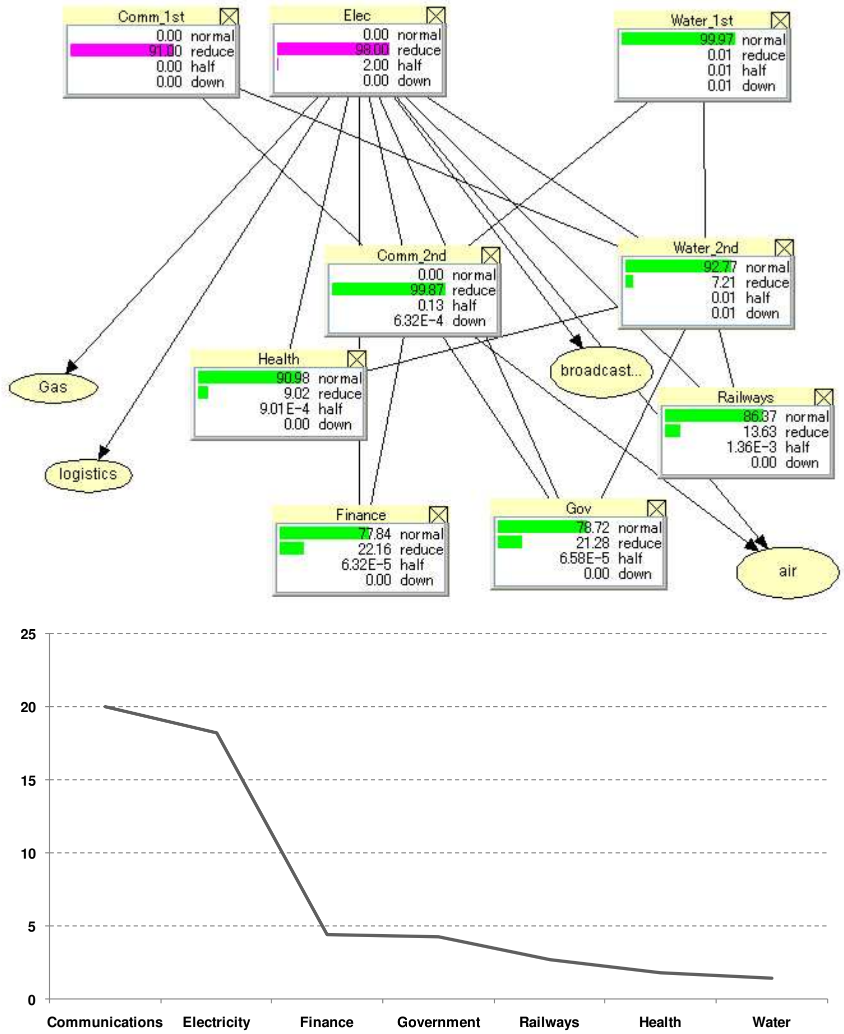

Figure 7. Inoperability propagation due to a 6.9 magnitude earthquake.

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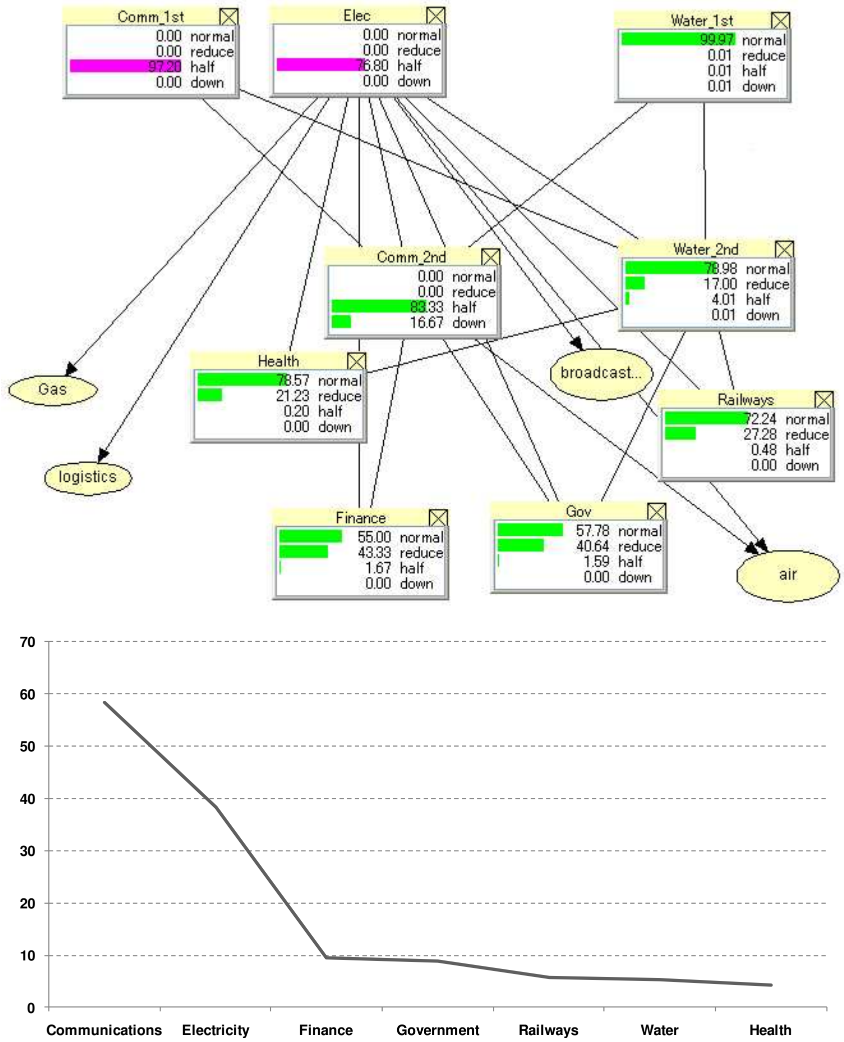

Figure 8. Inoperability propagation due to a 7.3 magnitude earthquake.

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