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THE UNCERTAINTY AND SENSITIVITY ANALYSIS OF THE INTERDEPENDENT INFRASTRUCTURE SECTORS BASED ON THE SUPPLY-DRIVEN INOPERABILITY INPUT-OUTPUT MODEL

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Abstract. *In this paper, an uncertainty and sensitivity assessment method is developed for the Supply-driven Inoperability Input-output Model (SIIM). The SIIM model has been proposed to investigate the initiating perturbations related to the input factors (value-added) and understand the infrastructure interdependencies upon vicious external attacks or unfortunate natural disasters. This work extends the existing research work in the literature and incorporates the stochastic perturbations related to value-added to conduct the analysis. A four-sector example is provided in this paper and the Monte Carlo simulation and the variance-based sensitivity analysis method is used to demonstrate the construction of the proposed risk model.*
Keywords: Interdependent infrastructure sectors, Supply-driven IIM, Stochastic perturbations, Uncertainty and sensitivity assessment, Monte Carlo simulation

1. **Introduction.** With the rapid economic development, the interconnections among individual economic sectors have become increasingly strong. Interdependency – enhanced operations offer great convenience, reduced cost and high efficiency. However, technical complexity and the general lack of understanding of interdependent relationships within and among the infrastructures expose the systems to unknown risks and vulnerability. Disruptions occurring in one infrastructure sector can trigger the disruptions in another sector with magnifying effect. Consider the disastrous earthquake that occurred in Wenchuan, China, on May 12th, 2008. It caused devastating damage to buildings and public facilities, including transportation systems such as roads, railways and the airports. The infrastructure systems are so closely interconnected that the damage further affected every aspect of people's daily lives. It took a long time to pinpoint the source of the disruption and explain the reasons behind the disaster.

Interdependencies among infrastructure sectors generate new assurance challenges, which need to be addressed on several decision-making levels. The challenges involve multiple stakeholders and have been modeled from various perspectives. Scholz et al. (2012) [20] develop the risk and vulnerability definition from a decision-theoretic perspective. Farkas et al. (2013) [27] develop Sensitivity analysis in lightning protection risk management. The Inoperability Input-output Model (IIM) has been developed to understand infrastructure interdependencies (Percoco et al. 2006 [17,18]; Santos, 2006 [22]). The model offers a macro-level, deterministic, and equilibrium approach to modeling interdependencies among economic infrastructures, which are estimated from the input-output accounts (Lian and Haimes 2006, 2007 [14,15]; Haimes et al. 2005 [6,7]).

The supply-driven IIM presented by Leung (2007) [16] complements the demand-driven perspective of the demand-reduction IIM (Santos et al. 2007 [16]; Haimes and Jiang 2001 [5]). This perspective addresses the impact that relates to the supply of input factors (value added). The initial perturbation describes the events that regard the value added perturbation as the first-round perturbation, and it may trigger a change in output prices, which may further trigger the second-round perturbation (for example triggering the change in the final demand quantity). After a disaster occurs, the value added in the supply-driven IIM can be more easily controlled than the final demand, since the final demand perturbation may be affected by the psychological impact on consumers. Moreover, in the interdependent infrastructure systems, there are more supply-driven sectors than demand-driven ones, and the value added perturbation is the dominant feature in the supply-driven sectors upon an interrupt event (Xu et al. 2011 [24]).

The supply-driven IIM considers the value added perturbation. Xu et al. (2011) [24] have developed a static model into a dynamic one. The perturbations of value added are assumed to be deterministic in this supply-driven IIM. However, in the real world, most of the initial perturbations are stochastic. It is very difficult to find a deterministic solution (Barker et al. 2009, 2010 [10-12]). In this paper, a Stochastic Supply-driven IIM (S-IIM) is developed by extending the Supply-driven IIM and allowing the perturbations of the value added to take the form of probability distributions. Moreover, the method to conduct uncertainty and sensitivity analysis is developed for the supply-driven inoperability input-output model.

The rest of the paper is organized as follows. Preliminaries are described in Section 2. Section 3 presents the stochastic supply-driven IIM. Section 4 applies the Monte Carlo simulation to conduct the uncertainty assessment, and uses the global sensitivity analysis method to conduct sensitivity analysis. And then a four-sector economic system is presented to demonstrate the methods. Finally, the paper is concluded in Section 5.

2. **Preliminaries.** This section first presents the supply-driven input-output price model and then its extension in the literature, called supply-driven inoperability input-output model (Leung et al., 2007 [16]).

2.1. **The supply-driven input-output model.** The supply-driven perspective of the input-output model was introduced by Ghosh (1958) [3]. He contended that the supply factors become more important than the production and demand factors in the cases where the markets are monopolistic and when there is a general shortage of resources. There have been a variety of studies on the supply-driven model. However, there are also some arguments on the validity of its application to the economic analysis. Most arguments were discussed in the papers by Davar (1993) [2] and Zaghini (1971) [26].

The supply-driven input-output economic model is expedited by value added inputs rather than final demands. The input in terms of the observed monetary value of commodity flow (in dollars) from sector i to sector j is denoted as x_{ij}. The matrix of commodity flows is $X = (x_{ij})_{n\times n}$. The technical coefficient is defined in Equation (1):

$$a_{ij} = \frac{x_{ij}}{x_i} \tag{1}$$

Equation (2) is the traditional input-output Ghosh model:

$$x = A^{(s)}x + z \Rightarrow x = \left(I - A^{(s)}\right)^{-1} z \tag{2}$$

This relationship among all n sectors is represented as a matrix, as shown in Equation (2), where x is the vector of total inputs; $A^{(s)} = (a_{ij})^T_{n\times n} = \left(a^{(s)}_{ij}\right)_{n\times n}$ is the interdependency matrix derived from the economic input-output data, where $\left\{a^{(s)}_{ij}\right\}$ specifies the proportionality coefficient corresponding to the input from sector i to sector j, with respect to the total output of sector i; and z is the column vector of value added inputs such as labor, wages, taxes, income, and rental.

2.2. **Supply-driven inoperability input-output model.** The supply-driven static IIM was derived by Leung et al. [16], and the supply-driven static inoperability input-output model is given as

$$p = \left(I - A^{(s)*}\right)^{-1} z^* \tag{3}$$

where $A^{(s)*}$ is the interdependency matrix which is derived from the economic input-output data, z^* is the value added price perturbation vector, $\hat{z}$ is the value of nominal value added, and $\tilde{z}$ is the value of degraded value added after perturbation. We suppose that $(I - A^{(s)*})^{-1} = (b_{ij})_{n\times n}$, and

$$z^* = diag(\hat{x})^{-1} (\tilde{z} - \hat{z}) \tag{4}$$

$$p = diag(\hat{x})^{-1}(\tilde{x} - \hat{x}) \tag{5}$$

$$A^{(s)*} = diag(\hat{x})^{-1} A^{(s)} diag(\hat{x}) \tag{6}$$

where p is the vector of the cost change in output due to value added perturbation. The supply perturbation is expressed by vector z^*, whose elements represent the difference between the planned supply and the perturbed value added divided by nominal production, which is equivalent to the increase of value added as a proportion of total planned input.

2.3. **Variance-based sensitivity analysis.** The main idea of this method is to express the sensitivity through variance, and evaluate how the variance of such an input or group of inputs contributes to the variance of the output of a model.

Consider the model (Yu and Harris 2009 [23]; Jacques et al. 2006 [9]):

$$\begin{aligned} f &: R^n \to R \\ X &\mapsto Y = f(X) \end{aligned} \tag{7}$$

where Y is the output of a model, $X = (X_1, X_2, \cdots, X_n)$ is a vector of n independent inputs of the model, f is the model function. We define:

$$V_i = V\left[E(Y\,|X_i)\right] \tag{8}$$

$$V_{ij} = V\left[E(Y\,|X_i, X_j)\right] - V_i - V_j \tag{9}$$

$$V_{ijk} = V\left[E(Y\,|X_i, X_j, X_k)\right] - V_{ij} - V_{ik} - V_{jk} - V_i - V_j - V_k \tag{10}$$

The first-order sensitivity index is defined by:

$$S_i = \frac{V_i}{V(Y)} \tag{11}$$

The second-order sensitivity index is defined by:

$$S_{ij} = \frac{V_{ij}}{V(Y)} \tag{12}$$

Similarly, we can calculate higher order sensitivity index. The greater the index value is, the more important the variable or the group of variables is, which is linked to this index.

3. Uncertainty and Sensitivity Analysis. This section develops the theory and methodology based the supply-driven IIM to conduct the uncertainty and sensitivity analysis. Since the value added perturbation can be easily managed by the domain expert based on the expert probability assessments, the value added perturbation of the supply-driven uncertainty IIM is extended to take the form of the probability distribution.

3.1. The uncertainty analysis. Since the value added in the proposed supply-driven IIM is more controllable than the final demand after a disaster (based on the domain expert assessments), we assume that the increase of the value added in affected sectors are distributed triangularly. The triangular distribution is applied in various problems associated with risk analysis and uncertainty elicitation. The probability density function of triangular distribution is as follows (Barker and Haimes 2009 [10,11]):

$$f(x) = \begin{cases} \frac{2}{b-a}\frac{x-a}{c-a}, & a \le x \le c \\ \frac{2}{b-a}\frac{b-x}{b-c}, & c \le x \le b \\ 0, & \text{elsewhere} \end{cases} \tag{13}$$

And the cumulative distribution function of the triangular distribution is:

$$F(x) = \begin{cases} 0, & x \in [-\infty, a) \\ \frac{c-a}{b-a}\left(\frac{x-a}{c-a}\right)^2, & x \in [a, c] \\ 1 - \frac{b-c}{b-a}\left(\frac{b-x}{b-c}\right)^2, & x \in [c, b] \\ 1, & x \in [b, +\infty) \end{cases} \tag{14}$$

We can get the expected value and the variance of the triangular distribution:

$$E(x) = \frac{a+b+c}{3} \tag{15}$$

$$D(x) = \frac{1}{18}(a^2 + b^2 + c^2 - ab - ac - bc) \tag{16}$$

A price increase is the initiating event, and will cause other sectors to increase their production costs; again, this may or may not be able to be transformed to the increased costs on customers. It can be absorbed as the economic losses. The economic losses for each sector and overall economic losses are given in Equation (17) and Equation (18) [16,17]:

$$(Q_1, Q_2, \cdots, Q_n)^T = diag\,(\hat{x}_1, \hat{x}_2, \cdots, \hat{x}_n) \begin{pmatrix} p_1 \\ p_2 \\ \cdots \\ p_n \end{pmatrix} \tag{17}$$

$$Q = \hat{x}^T p \tag{18}$$

The Monte Carlo simulation is used to handle more complex calculations demanded by a larger set of sectors and general types of probability distributions. Through the Monte Carlo simulation, we can obtain the expected and the standard deviations values of the inoperability and the economic losses through the four-sector interdependent infrastructure system example. It gives the decision makers the insight into making the right decisions for risk management.

3.2. **The sensitivity analysis.** This section develops the variance-based global sensitivity analysis method (Iooss and Ribatet 2009 [8]; Volkova et al. 2008 [25]) to assess the uncertainty of the stochastic perturbation of value added of the supply-driven inoperability input-output model for the interdependent infrastructure systems.

Consider the supply-driven inoperability input-output model in the form of Equation (3). In general, we can rewrite Equation (3) as follows:

$$p = f\left(\left(I - A^{(s)*}\right)^{-1}, z^*\right) \tag{19}$$

The purpose of this paper is to assess the volatility in the stochastic elements of z^*. Suppose that the elements of z^* are effected by uncertainty and that the elements of $A^{(s)*}$ are known. Therefore, for the purpose of the sensitivity analysis, we can write Equation (19) as the following format:

$$p = f(z^*) \tag{20}$$

where z^* is the stochastic perturbation of the supply-driven inoperability input-output model. We can write the variance of the output as follows:

$$V(p) = E\left[V(p\,|z^*)\right] + V\left[E\left(p\,|z^*\right)\right] \tag{21}$$

In particular, the importance of z^* replies on how well z^* drives the changes in p, that is, how well $E(p\,|z^*)$ represents p. If the total variation in p is matched by the variability in $E(p\,|z^*)$ as z^* varies, then z^* could be a very important inter-industry linkage; that variation is measured by the term $V\left[E(p\,|z^*)\right]$. The term $E\left[V(p\,|z^*)\right]$ can be described as a prediction error, measuring the remaining variability in sector output. If we divide Equation (19) by the unconditional variance, we obtain the first-order sensitivity index of the value added decrease for sector i:

$$S_i\,|_p = \frac{V\left[E(p\,|z^*)\right]}{V(p)} = 1 - \frac{E\left[V(p\,|z^*)\right]}{V(p)} \tag{22}$$

Since the economic loss for each sector is:

$$Q = \hat{x}^T p = \hat{x}^T f(z^*) = g(z^*) \tag{23}$$

Similarly, we can obtain the first-order sensitivity index of the final demand decrease for sector i on the variance of the economic losses as follows:

$$S_i\,|_Q = \frac{V\left[E(Q\,|z^*)\right]}{V(Q)} = 1 - \frac{E\left[V(Q\,|z^*)\right]}{V(Q)} \tag{24}$$

4. **An Example.** The example in this section is used to illustrate the theory and the methodology of the uncertainty risk analysis using the supply-driven IIM. The model is extended to incorporate stochastic perturbations for the uncertainty and sensitivity assessment. Its fundamental analytical concepts and procedures are analyzed.

Example 4.1. *It is noted in the latest report from the Intergovernmental Panel on Climate Change that the temperature in China is rising and the extreme weather, including cyclones, droughts and floods, is on the increase. A massive flood struck the area along the Yangtze River in China this summer. The flood disaster destroyed the critical infrastructures, and the sectors such as electricity power grids, railway systems are negatively affected. Since these affected sectors had to pay higher costs to maintain normal operations, it is regarded as an increase in their value added component.*

We assume a four-sector interdependent infrastructure system for the city of Wuhan, which is comprised of (1) an electric power sector; (2) a railway transportation sector; (3) a water supply sector; and (4) a gas supply sector. Table 1 shows the transactions in terms of money-value flows. we suppose that the interdependent system is stable before

TABLE 1. The transaction balance in the four-sector economy (CNY)

	$j=1$	$j=2$	$j=3$	$j=4$	Demand c	Total output x
$i=1$ Electric power	175	280	280	140	350	1225
$i=2$ Rail Transportation	140	315	350	280	525	1610
$i=3$ Water supply	245	140	280	140	280	1085
$i=4$ Gas supply	175	280	105	280	175	1015
Value added z^T	490	595	70	175		
Total input x^T	1225	1610	1085	1015		

perturbation. In this table, an element in row i and column j represents the required input of services from sector i to j.

From Table 1, we get:

$$A^{(s)} = \left\{\frac{x_{ij}}{x_i}\right\}^T = \begin{pmatrix} 0.14 & 0.23 & 0.23 & 0.11 \\ 0.09 & 0.20 & 0.22 & 0.17 \\ 0.23 & 0.13 & 0.26 & 0.13 \\ 0.17 & 0.28 & 0.10 & 0.28 \end{pmatrix}^T = \begin{pmatrix} 0.14 & 0.09 & 0.23 & 0.17 \\ 0.23 & 0.20 & 0.13 & 0.28 \\ 0.23 & 0.22 & 0.26 & 0.10 \\ 0.11 & 0.17 & 0.13 & 0.28 \end{pmatrix} \tag{25}$$

The interdependent matrix of the four sectors is:

$$A^{(s)*} = diag(\hat{x})^{-1} A^{(s)} diag(\hat{x}) = \begin{pmatrix} 0.14 & 0.17 & 0.26 & 0.14 \\ 0.11 & 0.20 & 0.32 & 0.28 \\ 0.20 & 0.10 & 0.26 & 0.14 \\ 0.14 & 0.17 & 0.10 & 0.28 \end{pmatrix}^T = \begin{pmatrix} 0.14 & 0.11 & 0.20 & 0.14 \\ 0.17 & 0.20 & 0.10 & 0.17 \\ 0.26 & 0.32 & 0.26 & 0.10 \\ 0.14 & 0.28 & 0.14 & 0.28 \end{pmatrix} \tag{26}$$

$$\left(I - A^{(s)*}\right)^{-1} = (b_{ij})_{4\times4} = \left(I - \begin{pmatrix} 0.14 & 0.11 & 0.20 & 0.14 \\ 0.17 & 0.20 & 0.10 & 0.17 \\ 0.26 & 0.32 & 0.26 & 0.10 \\ 0.14 & 0.28 & 0.14 & 0.28 \end{pmatrix}\right)^{-1} = \begin{pmatrix} 1.57 & 0.65 & 0.60 & 0.55 \\ 0.58 & 1.72 & 0.47 & 0.59 \\ 0.89 & 1.10 & 1.84 & 0.69 \\ 0.69 & 0.99 & 0.64 & 1.84 \end{pmatrix} \tag{27}$$

Assume that both value added increases in sectors are distributed triangularly. Specifically, for sector 1, its value added increase is assessed to be a minimum of 10%, most likely 15%, and a maximum of 18%. For sector 2, the three-point estimates of minimum, most likely, and maximum are 15%, 20%, and 28%, respectively. In the example, the Monte Carlo simulation is used to generate the distributions of the inoperability and the economic losses for this interdependent infrastructure system.

4.1. **The uncertainty analysis.** Applying the supply-driven IIM in Equation (3), we denote $(I - A^{(s)*})^{-1} = (b_{ij})_{n\times n}$, the system equations of the four-sector economy can be written as follows:

$$\begin{cases} p_1 = b_{11}z_1^* + b_{12}z_2^* + b_{13}z_3^* + b_{14}z_4^* \\ p_2 = b_{21}z_1^* + b_{22}z_2^* + b_{23}z_3^* + b_{24}z_4^* \\ p_3 = b_{31}z_1^* + b_{32}z_2^* + b_{33}z_3^* + b_{34}z_4^* \\ p_4 = b_{41}z_1^* + b_{42}z_2^* + b_{43}z_3^* + b_{44}z_4^* \end{cases} \tag{28}$$

We have:

$$\begin{cases} E(p_1) = b_{11}E(z_1^*) + b_{12}E(z_2^*) + b_{13}E(z_3^*) + b_{14}E(z_4^*) \\ E(p_2) = b_{21}E(z_1^*) + b_{22}E(z_2^*) + b_{23}E(z_3^*) + b_{24}E(z_4^*) \\ E(p_3) = b_{31}E(z_1^*) + b_{32}E(z_2^*) + b_{33}E(z_3^*) + b_{34}E(z_4^*) \\ E(p_4) = b_{41}E(z_1^*) + b_{42}E(z_2^*) + b_{43}E(z_3^*) + b_{44}E(z_4^*) \end{cases} \tag{29}$$

Applying the Monte Carlo simulation to Equation (28) generates the distribution of the inoperability for individual sector as presented in Figure 1 to Figure 4. There are 10,000 samples conducted in the simulation.

The simulation results show that the expectation and the standard deviation of the four sectors' inoperability can be calculated. For example, as for the water supply sector, the expectation is 0.3583, which is close to the theoretical expectation of 0.3556, while the standard deviation is 0.0332. Similar results for other sectors can also be obtained and interpreted in the same way.

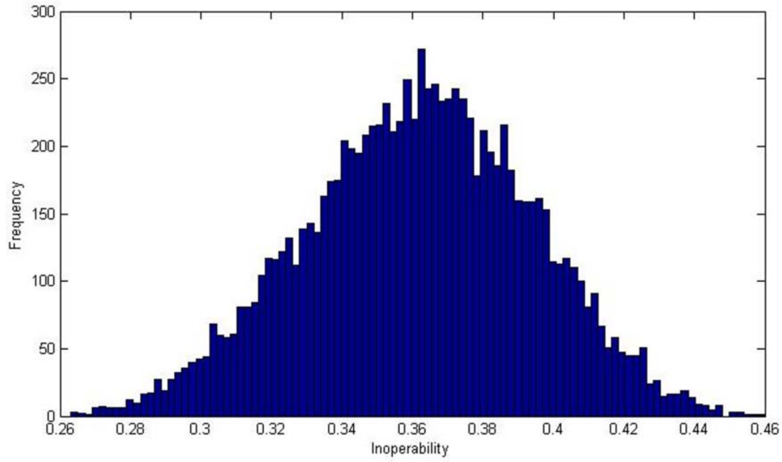

FIGURE 1. Inoperability distribution of the electric power sector (mean: 0.3618 std: 0.0322)

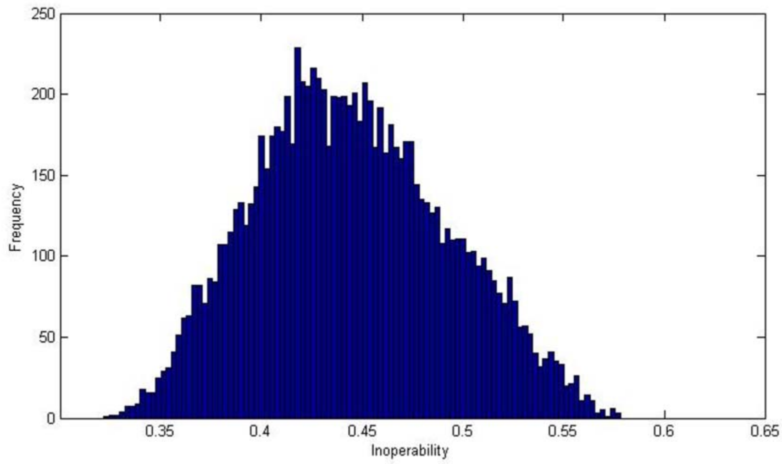

FIGURE 2. Inoperability distribution of the rail transportation sector (mean: 0.4447 std: 0.0478)

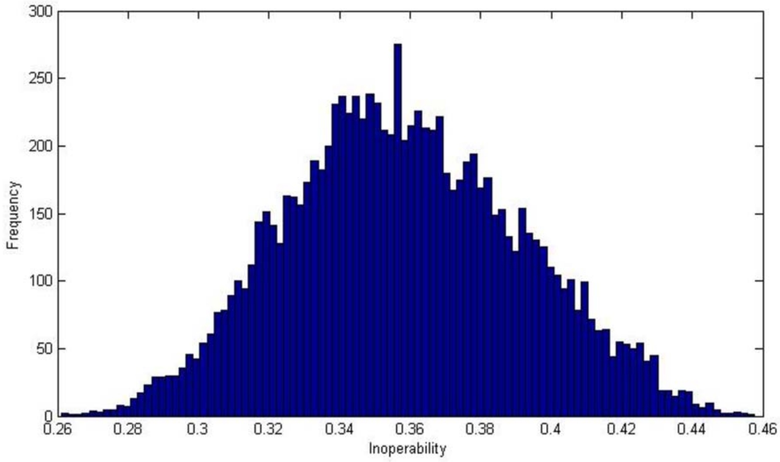

FIGURE 3. Inoperability distribution of the water supply sector (mean: 0.3583 std: 0.0332)

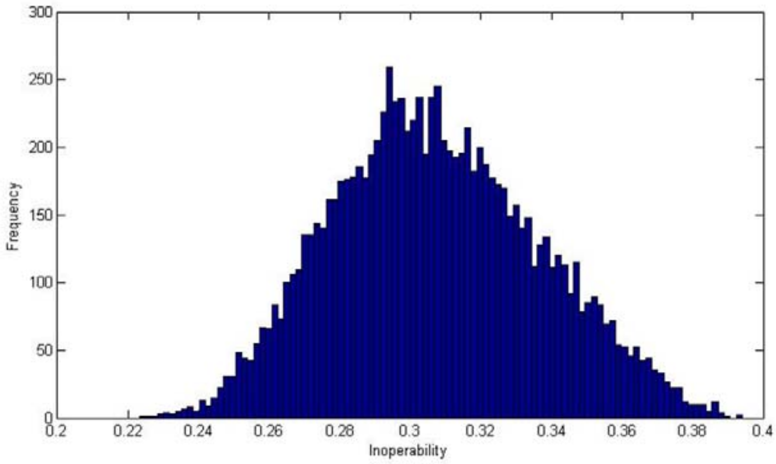

FIGURE 4. Inoperability distribution of the gas supply sector (mean: 0.3072 std: 0.0293)

Using the following equation, the economic loss for individual sector Q_i and the total economic loss Q can be computed from Equation (17) as follows:

$$(Q_1, Q_2, Q_3, Q_4)^T = diag(1225, 1610, 1085, 1015)p \tag{30}$$

$$Q = \hat{x}^T p = (1225, 1610, 1085, 1015)p \tag{31}$$

Based on Equations (29) and (30), through 10000 Monte Carlo simulation, Figure 5 shows the resulting distribution of the overall economic loss for the system.

From Figure 5, the Monte Carlo simulation results show that the expectation of the overall economic loss is CNY 1857.7 and the standard deviation is CNY 171.7057, which is close to the theoretical value. The results show the value of the infrastructure interdependency in the risk assessment process.

4.2. **The sensitivity analysis.** From the above section, we have:

$$V(z_1^*) = 0.00027, \quad V(z_2^*) = 0.00072 \tag{32}$$

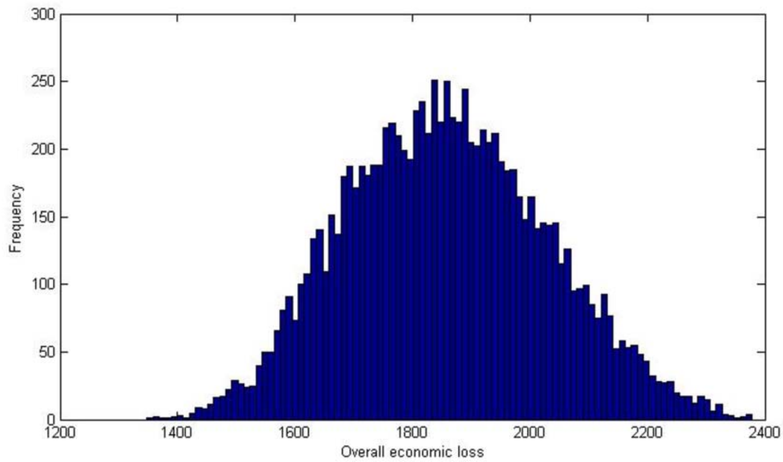

Figure 5. Distribution of the overall economic loss for the four sectors (mean: 1857.7 std: 171.7057)

From Equation (26), we have:

$$\begin{cases} p_1 = 1.57z_1^* + 0.65z_2^* \\ p_2 = 0.58z_1^* + 1.72z_2^* \\ p_3 = 0.89z_1^* + 1.10z_2^* \\ p_4 = 0.69z_1^* + 0.99z_2^* \end{cases} \tag{33}$$

The economic loss for individual sector:

$$Q = \hat{x}^T p = \hat{x}^T f(z^*) = g(z^*) \tag{34}$$

We have:

$$\begin{cases} Q_1 = x_1 p_1 = 1225\,(1.57z_1^* + 0.65z_2^*) \\ Q_2 = x_2 p_2 = 1610\,(0.58z_1^* + 1.72z_2^*) \\ Q_3 = x_3 p_3 = 1085\,(0.89z_1^* + 1.10z_2^*) \\ Q_4 = x_4 p_4 = 1015\,(0.69z_1^* + 0.99z_2^*) \end{cases} \tag{35}$$

$$S_i\,|_Q = \frac{V\,[E(Q\,|z^*)]}{V(Q)} = 1 - \frac{E\,[V(Q\,|z^*)]}{V(Q)} \tag{36}$$

Using the variance-based global sensitivity analysis and the Monte Carlo simulation results, the first-order sensitivity indexes is as follows:

For Q_1, we have:

$$S_{z_1^*} : S_{z_2^*} = 0.68 : 0.32 \tag{37}$$

For Q_2, we have:

$$S_{z_1^*} : S_{z_2^*} = 0.23 : 0.77 \tag{38}$$

For Q_3, we have:

$$S_{z_1^*} : S_{z_2^*} = 0.194 : 0.806 \tag{39}$$

For Q_4, we have:

$$S_{z_1^*} : S_{z_2^*} = 0.155 : 0.845 \tag{40}$$

Results in Equation (36) indicate that z_1^* is the most important factor for Q_1, which has the largest impact on the variance of Q_1. Results in Equations (37) to (39) indicate that z_2^* is the most important factor for Q_2, Q_3 and Q_4, which has the largest impact on the variance of Q_2 to Q_4. This will give decision makers some insight into making the right decisions for the risk management upon unexpected disruptive events.

5. **Conclusions.** This paper extends the supply-driven IIM to incorporate probabilistic dimensions to analyze the uncertainty and sensitivity of interdependent infrastructure sectors. In the case of the supply-driven uncertainty IIM, the distributions of the resulting economic loss and other impacts are represented as the triangular distribution for each of the initially affected sectors. And then the paper proposes the method in which the triangular distribution is used to represent risks. Given the distributions of initial inoperability of the sectors that are directly perturbed, the distribution of the overall loss of the economy is derived through the uncertainty supply-driven IIM. In this paper, the Monte Carlo simulation framework is utilized to derive the triangular distribution.

Sensitivity analysis is a useful tool when the uncertainty is present. The analysis examines the response of the outputs by exploring a finite region. Through the sensitivity analysis of the supply-driven uncertainty IIM, we can obtain the largest impact on the variance of variables, and thereby identify the key sectors (which indicate an industry with strong influence on the expansion of others in a system) for the purpose of risk management.

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