Advances in Reliability, Safety and Security, Part 7 – Kołowrocki, Magryta-Mut (eds.)
© 2024 Polish Safety and Reliability Association, Gdynia, ISBN 978-83-68136-19-7 (printed), ISBN 978-83-68136-06-7 (electronic)

Advances in Reliability, Safety and Security

ESREL 2024
Monograph Book Series

Assessing Resilience In Urban Systems Using Dynamic Multi Regional Input Output Model

Xiuke Tang[a,b], Pradeep V. Mandapaka[a], Kang Tai[b,c], Edmond Y. M. Lo[a,b,d]

[a]*Institute of Catastrophe Risk Management, Interdisciplinary Graduate Programme, Nanyang Technological University, Singapore*
[b]*Future Resilient Systems Programme, Singapore-ETH Centre, Singapore*
[c]*School of Mechanical and Aerospace Engineering, Nanyang Technological University, Singapore*
[d]*School of Civil and Environmental Engineering, Nanyang Technological University, Singapore*

Abstract

Disruptions in a city's infrastructure systems usually propagate beyond the original impacted region and sector, resulting in direct and indirect losses that build up over time until the system completely recovers. In this paper, we focus on the dynamic resilience assessment during the recovery phase by modeling the fragility resulting from the multi-regional interdependencies in urban systems. The static and dynamic inoperability input-output model is adopted to assess the static and dynamic resilience under a fire accident that occurred in an oil refinery in the West region of Singapore. For the dynamic resilience assessment, the varying total output of the system during the recovery phase is adopted as the resilience indicator as it can serve as a consistent measure of the impact on different critical infrastructure systems. Moreover, we employ the input-output data and the region-specific initial disruptive data at the multi-regional level, which was not available before. With the help of the multi-regional data, the impact of the fire accident is illustrated at a multi-regional level and then compared with the single-regional (national) level. The higher level of details in the results of the dynamic resilience assessment at a multi-regional level reveal a less extreme minimum total output and longer recovery time than the results at the national level. Moreover, the initially impacted manufacturing (MANUF) sector suffers the largest economic loss, followed by the others (OTHSV) sector in both multi-regional study and single-regional study, showing the relative vulnerabilities of the respective infrastructure systems in a high-density urban system.

Keywords: input-output analysis, recovery dynamics, inoperability, multiple regions, urban resilience

1. Introduction

There are an increasing number of catastrophic disasters and disruption events that impact urban systems (Lam and Tai, 2018). Moreover, urban systems are becoming denser due to greater provision of more and better critical infrastructure (CI) and the increasing number of job opportunities attracting more population into urban areas (Curt and Tacnet, 2018). Therefore, the CI is growing more interdependent in the current high-density urban systems under this rapid urbanization phenomenon. Furthermore, with the cascading effect caused by interdependencies, a relatively small disruption of one CI system may lead to significant disruptions in the whole urban system. Thus, one of the main requirements for designing resilient infrastructures is in comprehending the fragility caused by system interdependencies.

The interdependencies among the CI systems can be categorized into geographic, physical, cyber, and logical interdependencies (Rinaldi et al., 2001). Some types of interdependencies (such as logical interdependencies) are quite difficult to identify or may not be apparent as the relevant data needed to quantify them are confidential or intangible. Thus, most methods of analysis such as network-based methods or agent-based methods can assess only one or two types of interdependencies and one or two CI systems (Ouyang, 2017). While they can assess individual CI systems in detailed spatial granularity, the overall relationships among the multiple different CI systems may be overlooked. Therefore, there is a need for a more complete model of the interdependencies among different CI systems, and this may be achieved through some economic models like the computable general equilibrium methods and input-output (IO) methods (Kelly, 2015). They can assess different kinds of interdependencies among the CI systems, but only at large scales, such as at the provincial or city level. The IO model, for instance, is widely used in disaster analysis in infrastructure systems.

The basic IO model can simulate only the static economic loss immediately after the disruption happens, but more can be done to develop a fuller picture of the resilience of the system. Firstly, it would be convenient to have a resilience indicator suitable for all CI. Secondly, the indicator fluctuates with time to represent the dynamic conditions after a disruption. Resilience indicators vary among different CI systems, such as the pump pressure level for a water supply system (Rehak et al., 2019). Consequently, the functionality or operability of each system is chosen to be the resilience indicator after the disruption happens. Santos (2006) and Santos and Haimes (2004) utilized the inoperability input-output model (IIM) based on Leontief's IO model to quantify economic losses due to demand reductions through the interdependency analysis between different CI systems. Moreover, to simulate the systems' performance along with time, the dynamic form IIM was introduced by Santos (2006). Santos (2006) employed the multi-criteria evaluation analysis and dynamic IO analysis to describe the magnitudes of the monetary loss and forecast future impacts with the North American Industry Classification System (NAICS). Santos and Haimes (2004) employed the dynamic IIM (DIIM) to assess the economic loss during the different temporal frames of recovery simulated by different recovery rates. With the conclusion from the risk-impact analysis, the recovery priority for investigated sectors was obtained. However, these studies were only applied at the system level rather than the facility level, and could not consider the spatial distribution within each CI system.

Due to the complexity of supply and demand activity within and among individual CI systems, the spatial distribution for each CI system plays a critical role in resilience analysis (Oliva et al., 2010). For the regional-level IO model, Hewings et al. (2001) and Irimoto et al. (2017) simulated the economic ripple effects of both international and interregional disruptions in different scenarios. Based on the existing models, Hewings et al. (2001) explored the income formation and output generation interdependence between inner-city communities and suburbs by dividing the Chicago metropolitan area into four subregions, identifying the strength of interdependence between regions with the interrelational income multiplier. Irimoto et al. (2017) focused only on the transport sector, highlighting the more vulnerable regions needing urgent disaster prevention by changing the input-output model's trade coefficients to simulate different scenarios. However, these studies could not incorporate the dynamic changes of the resilience indicator after the disruption happened.

Recently, there have been attempts to downscale the DIIM from the system level to the facility level by incorporating the DIIM with the network analysis (Tatar et al., 2022; Yu et al., 2020). Tatar et al. (2022) introduced the Functional Dependency Network Analysis (FDNA) into DIIM, which simulated the relationships between feeder and receiver nodes through the Strength of Dependency (SOD) and Criticality of Dependency (COD) relationships, and these required much data about the relationships among various CI sectors and the facilities. Moreover, some research incorporated the DIIM with the regionalized IO tables (IOT) (Crowther and Haimes, 2010; Yu et al., 2020). However, these studies are still at an early stage. This paper proposes a new way to downscale DIIM to smaller spatial granularity by incorporating multi-regional (MR) IOT, which can form a good starting point for some what-if and optimization studies for analyzing and enhancing the resilience of urban systems.

Section 2 of this paper describes the methodologies for the IIM and DIIM in the static form and dynamic form at a multiple regions level. Section 3 describes the data acquisition and the disruption event chosen for the case study. Section 4 presents the results and discussion. Section 5 presents the concluding remarks.

2. Methodologies

The methodology is based on the IO model which is widely used for disruption analysis at the system level, and the MRIOT for downscaling the system level to smaller spatial granularity.

2.1. Basic input-output (IO) model

The IO model was based on the Leontief IO analysis, rooted in the IOT, which is the crucial foundation for various extensions and applications, focusing on assessing the interdependencies in an economy (Miller and Blair, 2009). The economy can be categorized into multiple sectors, and each sector produces homogeneous products with a stable production structure after a disaster and throughout the recovery process. For the ease of data collection and research scope definition, the researched economy's area and period are predefined and work as spatial and temporal influencers.

The linkages between different sectors of the economy can be represented purely by the transaction flows, and serve as estimates of indirect and direct interdependencies. These transaction flows are the transactions among groups of industries (sectors) that consume goods and services (input) to produce other goods and services (outputs) with the assumption of constant returns to scale (Bierkandt et al., 2014).

The transaction data always come from interindustry transaction IOT constructed by official statistical authorities. In an interindustry transactions table (as shown in Fig. 1), the rows describe the distribution of a producer's output throughout the economy, and the columns represent the composition of inputs required by a particular industry to produce its output. The additional columns labeled Final Demand record each sector's sales to final markets for their output, such as personal consumption and sales to the federal government. The additional rows, labeled Value Added, account for the other (non-industrial) inputs to production, such as labor, depreciation of capital, indirect business taxes, and imports (Lin et al., 2017).

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="8">PRODUCERS AS CONSUMERS</td><td colspan="4">FINAL DEMAND</td></tr>
<tr><td>Agric.</td><td>Mining</td><td>Const.</td><td>Manuf.</td><td>Trade</td><td>Transp.</td><td>Service</td><td>Other</td><td>Personal Consumption Expenditures</td><td>Gross Private Domestic Investment</td><td>Govt. Purchases of Goods & Services</td><td>Net Exports of Goods & Services</td></tr>
<tr><td rowspan="8">PRODUCERS</td><td>Agriculture</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Mining</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Construction</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Manufacturing</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Trade</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Transportation</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Services</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Other Industry</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td rowspan="3">VALUE ADDED</td><td>Employees</td><td colspan="8">Employee compensation</td><td colspan="4" rowspan="3">GROSS DOMESTIC PRODUCT</td></tr>
<tr><td>Business Owners and Capital</td><td colspan="8">Profit-type income and capital consumption allowances</td></tr>
<tr><td>Government</td><td colspan="8">Indirect business taxes</td></tr>
</table>

Fig. 1. Input-Output Table (adapted from Miller and Blair, 2009).

The basic Leontief IO model was formulated based on the transactions among industrial sectors. The total output of each sector work from the sales to other sectors and the final market, so the equation for the output and sales relationship for each sector is as follows:

$$\mathbf{x} = \mathbf{Zi} + \mathbf{f} \tag{1}$$

$\mathbf{x}$: consists of x_i , total output (production) of sector i
$\mathbf{f}$: consists of f_i, total final demand for the output of sector i
$\mathbf{Z}$: consists of z_{ij}, industry sales by sector i to sector j
$\mathbf{i}$: a column vector of 1's (of same dimension as x)

To assess the relationships between the total output of each sector and the corresponding industry sales by one sector to another sector, the technological coefficient was introduced. The input from each sector i as a fraction of the total output of sector j forms the technical coefficient a_{ij}, as follows:

$$a_{ij} = \frac{z_{ij}}{x_j} \tag{2}$$

It is used for assessing interdependencies, representing the need for the output of sector i for producing a unit output of sector j. They can be summarized in the matrix form, represented by $\mathbf{A}$, as follows:

$$\mathbf{A} = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix} \tag{3}$$

Then, using the standard matrix algebra results for linear equations, the equation can be translated into the form below with an identity matrix $\mathbf{I}$:

$$\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{f} = \mathbf{Lf} \tag{4}$$

The $\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1}$ is known as the Leontief inverse or total requirements matrix, representing one unit change in final demand leading to the change in the total output.

2.2. Inoperability input-output model (IIM)

The inoperability input-output model (IIM) (Haimes and Jiang, 2001; Jiang and Haimes, 2004; Santos and Haimes, 2004) is a useful tool to assess the economic loss for an individual sector from a direct disruption. In the short run and under transient conditions, the equilibrium assumption may not always hold.

The classical form of IIM is as follows:

$$\mathbf{q} = \mathbf{A}^{*}\mathbf{q} + \mathbf{c}^{*} \tag{5}$$

The vector $\mathbf{q}$ represents the degraded output as a proportion of original output for each sector and $\mathbf{c}^{*}$ the degraded final demand divided by original final demand, and $\mathbf{c}^{*} = \widehat{\mathbf{x}^{-1}}\Delta\mathbf{f}$ where $\hat{\mathbf{x}}$ is the diagnoal form of sectoral output vector $\mathbf{x}$. $\mathbf{A}^{*}$ represents the normalized technical coefficient and $\mathbf{A}^{*} = \widehat{\mathbf{x}^{-1}}\mathbf{A}\hat{\mathbf{x}}$ where $\mathbf{A}$ is the technical coefficients used in the basic input-output model and $\mathbf{x}$ is the output for "Business As Usual" scenario from measuring the expected economic output without any disruption (Tatar et al., 2022).

2.3. Dynamic inoperability input-output model (DIIM)

For resilience assessment, how a system reacts to the disruption is also critical. It takes time for a system to respond, recover from and even adapt to a disruption. To assess the recovery of a multi-sectoral system, Haimes et al. (2005) proposed the dynamic IIM, which can be represented by the following:

$$\mathbf{q}^{\mathbf{t+1}} = \mathbf{q}^{\mathbf{t}} + \mathbf{K}(\mathbf{A}^{*}\mathbf{q}^{\mathbf{t}} + \mathbf{c}^{*\mathbf{t}} - \mathbf{q}^{\mathbf{t}}) \tag{6}$$

where $\mathbf{K}$ is defined as the recovery coefficients, which is also in the diagonal form with k_{ii}.

Numerous methods and thoughts for economic analysis are employed in IIM (Akhtar and Santos, 2012; Aviso et al., 2015; MacKenzie et al., 2012; Santos et al., 2013; Setola et al., 2009; Yu et al., 2020), assuming that after a certain period, the infrastructure will be non-operational, leading to economic consequences which is the counterfactual of the Business As Usual scenario.

2.3.1. Recovery coefficients

The diagonal element k_{ii} in $\mathbf{K}$ describes the ability of sector i to recover from imbalance in supply and demand induced by disruption, defined as follows:

$$k_{ii} = \frac{In[{q_i}^{0}/{q_i}^{t}]}{T_i}\left(\frac{1}{1 - {a_{ii}}^{*}}\right) \tag{7}$$

where T_i is the recovery time for sector i from an initial inoperability of ${q_i}^{0}$ to a desired post-recovery inoperability ${q_i}^{T_i}$ and ${a_{ii}}^{*}$ is the self-dependency element for sector i in $\mathbf{A}^{*}$ (Mandapaka and Lo, 2023).

The actual recovery time T_i for each sector when they face different extents of disruption and inoperability levels is based on corresponding historical data which is scarce. Thus, the most adopted method to quantify T_i is a probability approach which assume that the time T_i for a sector to recover from ${q_i}^{0} = 100\%$ to ${q_i}^{t} = 1\%$ follows a PERT distribution, which is a version of Beta distribution. Then, the most likely recovery time T_i for each sector can be obtained, which is a function of ${a_{ii}}^{*}$, given by the following:

$$T_i = \frac{15}{\sqrt{{a_{ii}}^{*}}} \tag{8}$$

2.3.2. Resilience indicator

After knowing the evolution of the inoperability level, the resilience indicator for different sectors can be defined as the post-disruption economic output for each time step for all sectors. That is because for different sectors representing the different CI, the resilience indicator may be different (Shaker et al., 2019). To align the resilience indicators, the total output for each sector (CI) is chosen as the resilience indicator, and for the resilience of the whole urban system, the post-disruption economic output for each sector in each time step is the resilience at that time step.

If the baseline annual output vector $\mathbf{x}$ is evenly distributed over 365 days, the inoperability vector $\mathbf{q}^{\mathbf{t}}$ at time t can be converted into post-disruption economic output $\widetilde{\mathbf{x}^{\mathbf{t}}}$ as follows:

$$\widetilde{\mathbf{x}^{\mathbf{t}}} = \frac{1}{365}(\mathbf{x} - \hat{\mathbf{x}} \times \mathbf{q}^{\mathbf{t}}) \tag{9}$$

2.4. DIIM extensions

The inoperability level for initial impacted sector should also be accounted for when obtaining the overall inoperability level, which is always represented by $\mathbf{p^t}$, representing the inoperability level caused by direct disruption. It is assumed that $\mathbf{p^t}$ is zero when some sectors in some regions are not impacted by the direct disruption, which usually follows the exponential functions or is modelled by actual data if available. The initial inoperability $\mathbf{q^0}$ is usually assumed equal to $\mathbf{p^0}$.

For the DIIM for multiple regions scenario, some research focused on modifying the equations with adding interregional trading coefficient when the MRIOT and the regional-specific disruption data is not available. The original MRIIM and MRDIIM is based on the multi-regional IO model which needs the transactions among various selling regions and purchasing regions for each sector, known as interregional trading coefficients. Through the interregional trading coefficients, the single regional IOT can be disaggregated to MRIOT, and the region-specific final demand reduction is also obtained. However, the MRIOT is available in our study, and the original inoperability/final demand used in this paper is also region-specific inoperability/final demand which are already distributed appropriately to the region. Thus, the equation for MRIIM and MRDIIM used in our work is the same as the single regional IIM and DIIM.

3. Five-region Singapore MRIOT and disruption description

3.1. Five-region Singapore MRIOT

Singapore is a sophisticated cosmopolitan city, with complex interdependencies among numerous CI sectors maintaining citizens' basic daily life. Moreover, Singapore is gradually facing higher population density and their related activities that may intensify the cascading effects under any disruption. Thus, there is a need for Singapore to more thoroughly identify and quantify interdependencies and reveal its resilience under specific disruptions that may have a higher probability of occurrence in Singapore. Apart from that, Singapore is also a well-segmented city, which means individual sub-regions in Singapore play different roles. That is because the detailed location distribution of each CI system also impacts the interdependencies and resilience of Singapore. Therefore, an MRIOT in smaller spatial granularity for Singapore is established to investigate the interdependencies in more detailed spatial scale and uncover the resilience for different regions within Singapore.

The five regions in the MRIOT of Singapore is West, North, East, Northeast, and Central regions. Moreover, the sectors in MRIOT are aggregated from 116 sectors in the national IOT to 12 sectors, listed in Table 1. The MRIOT is derived from the Singapore national IOT in 2010 close to the point in time when the disruption of interest took place since the national IOT for 2011 is not available.

Table 1: Sector categories.

Sectors in national IOT	Sectors in MRIOT	Abbreviations
1-3,47-50	Others	OTHSV
4-46	Manufacturing	MANUF
51-53	Construction	CONST
54-55	Wholesale and Retail Trade	WHRTL
56-63	Transportation and Storage	TRST
64-65	Accommodation and Food Service	FDB
66-69	Information and Communication	INFCM
70-77	Financial and Insurance Service	FNISR
78-79	Real Estate Service	RESV
80-89	Professional Service	PFSSV
90-97	Administrative and Support Service	ADM
98-116	Community, Social and Personnel Service	CSPSV

3.2. Disruption description

Singapore is one of the world's top locations for oil refining and is regarded as Asia's center of commerce (ExxonMobil, 2022). With a total capacity of 1.43 million barrels per day (bpd) in 2010, Singapore was the refiner of choice for 4.7% of the capacity in Asia Pacific and 1.5% of the global total (DOS, 2020). For example, ExxonMobil's refinery on Jurong Island, which has a capacity of 592,000 bpd, is one of the largest in the world and accounts for nearly 41% of Singapore's total refining capacity (Ern and Abdullah, 2014). With a processing capacity of up to 500,000 bpd, the Royal Dutch Shell refinery on Pulau Bukom Island is the first refinery in Singapore and accounted for 35% of the country's total refining capacity in 2010 (ExxonMobil, 2022).

On September 28, 2011, the Pulau Bukom refinery's largest pump house caught fire. Over the course of the following day, the fire spread and became a massive conflagration (Chua, 2011; Ern and Abdullah, 2014). Due to the size and intensity of the fire, the Singapore Civil Defense Force (SCDF) declared Operations Civil Emergency, the nation's official response plan for civil emergencies, and the refinery was gradually shut down as a safety measure (Chua, 2011). The fire was extinguished late on September 29, 2011, after 32 hours of coordinated efforts by the SCDF, Shell's firefighting crew, and multiple government agencies. The impacted facility was reverted to the refinery on October 2, but operations were halted for the following week. The lack of specific operational data makes it challenging to pinpoint the exact timeline for the refinery's return to normalcy.

The initial effects of the Pulau Bukom fire on the refinery sector are computed using a top-down methodology in the single regional level (Mandapaka and Lo, 2023), accounting for the sector's proportionate contribution to Singapore's GDP. The manufacturing (MANUF) sector's chemicals cluster, which also includes petrochemicals, petroleum, and other specialized chemicals, includes the production and refining activities. Since the analysis in this study was conducted using the IO data of 12 broadly grouped sectors, the initial impact is only assumed to affect the MANUF sector. In 2010, the chemicals cluster accounted for about 10.4% of the MANUF sector, with the sector contributing 22% to Singapore's SGD 327 billion GDP (DOS, 2020, 2022). Moreover, the Pulau Bukom refinery accounted for approximately 35% of the nation's total refining capacity. When these data are combined, the MANUF sector will initially experience the following daily impact: $1/365 * 0.35 * 0.104 * 0.22 * \text{SGD } 327{,}000 = \text{SGD } 7.17$ million. However, the daily output for the MANUF sector in West region where the Pulau Bukom island located is SGD 6.88 million, which is less than the initial loss obtained by top-down method, which is not in agreement with that the final demand being part of the daily output even though the daily output is similar to the final demand loss. The reason may be the inaccurate data for top-down method. Thus, we assume the initial loss is almost one day loss for MANUF sector in west region which is set as $0.99 * \text{SGD } 6.88 = \text{SGD } 6.81$ million.

4. Results and Discussion

4.1. Static IIM for MRIOT and national IOT

For the initial inoperability level, it is assumed to induce a reduction in final demand in manufacturing sector in West region. Thereby, the normalized demand reduction for the MANUF sector in west region, $c^*_{MANUF,West} = \Delta f_{MANUF,West}/x_{MANUF,West} = 6.81/6.88 = 99\%$. The initial demand reductions for all other sectors are set to zero. The initial demand reduction in MANUF sector in West region cascades to other sectors in other regions due to the interdependencies among different sectors in the various regions. The total sectoral inoperability for each sector in each region can be obtained by demand-side IIM from Section 2.2 (Equation (5)). Then, the total output and the resilience under the fire accident can be obtained by Equation (9).

The regional cumulative economic loss is shown in Fig. 2(a). The comparison between cumulative economic loss obtained by national IOT and MRIOT for each region in each sector is shown in Fig. 2(b). From the Fig. 2(a), the most influential region is still the initial impacted region – West region, whose output loss (about 8 million SGD) is almost eight times that of other regions, while the output losses for other regions are quite similar which are approaching SGD 1 million. From Fig. 2(a) and (b), the initial impacted sector – MANUF sector is the most impacted sector especially for the MANUF sector in West region, followed by OTHERS sector (OTHSV). From Fig. 2(b), the Central region has the strongest interdependencies with the West region since the output loss for MANUF and OTHSV sectors in Central region rank the second. The output losses for each region and each sector also reveal the resilience of each region and each sector under this fire accident. The directly impacted region and the sector have the least level of resilience under this physical fire accident, followed by the regions and sectors with large interdependencies with the directly impacted region and sector, such as OTHSV sector.

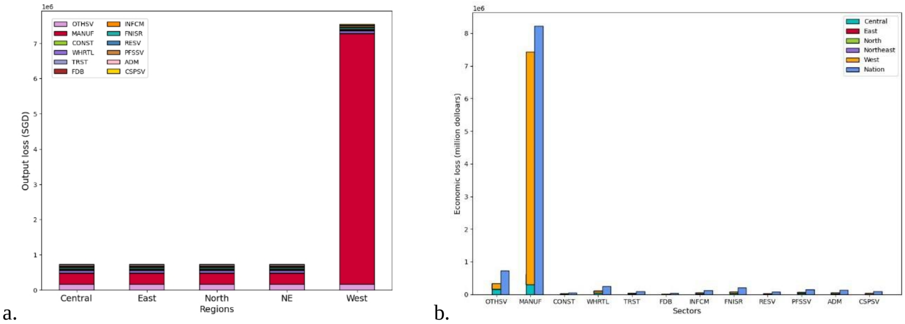

Fig. 2. (a) Cumulative economic loss for each sector in each region; (b) Cumulative economic loss for each region in each sector.

4.2. Dynamic DIIM for MRIOT and national IOT

To simulate the dynamic situation, the direct fire-induced impact is modified to simulate the real trajectory of the initial impacted MANUF sector in West region from September 28 (Day 0), when the refinery closed, to October 10 (Day 12), when it began operating at 20% inoperability after the disruption. As data on refinery recovery from October 11 (Day 13) till fully recovered is not available, an exponential scenario for slowly decaying (concave down) from Day 13 is assumed (Mandapaka and Lo, 2023). Thereby, the full trajectory for initially impacted MANUF sector in West region is as follows:

$$p_{MANUF,West}^{\boldsymbol{t}} = \begin{cases} p_{MANUF,West}^{\boldsymbol{0}}, & 0 \leq t \leq 11 \\ p_{MANUF,West}^{\boldsymbol{t}} * 0.8, & and t = 12 \\ \left(1 + e^{-\widetilde{K}_{MANUF}T_{MANUF}} - e^{-\widetilde{K}_{MANUF}(t-12-T_{MANUF})}\right)p_{MANUF,West}^{12}, & 13 \leq t \leq T_{MANUF} \\ 0, & t > T_{MANUF} \end{cases} \tag{10}$$

The inoperability levels for the various sectors in West region are shown in Fig. 3, with the inoperability level of MANUF sector rising to $p_{MANUF,West}^{\boldsymbol{0}}$ for the first 11 days, then falling to 80% of the $p_{MANUF,West}^{\boldsymbol{0}}$ at Day 12, and then follows a concave exponential function which represents the recovery path till it fully recovers after almost 175 days.

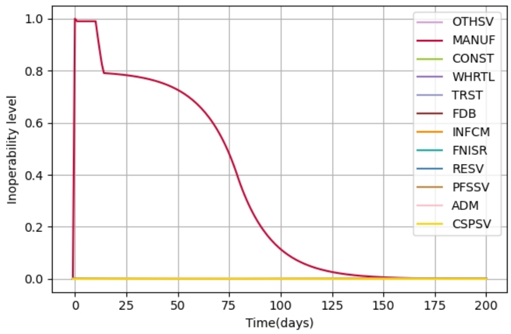

Fig. 3. Inoperability level for different sectors in West region.

The inoperability levels for various sectors in other regions are shown in Fig. 4(a) to (d). From the four graphs in Fig. 4, the most impacted sector in each region is still MANUF sector, followed by OTHSV sector, which is the same as the findings from the static IIM. However, the new thing is that the recovery times for these four regions are longer than those for the initial impacted region (West region), with the four regions spending almost 200 days to return to normal operability level. Fig. 4 (b) shows that North region incurs the highest inoperability level among the four other regions, followed closely by Central region.

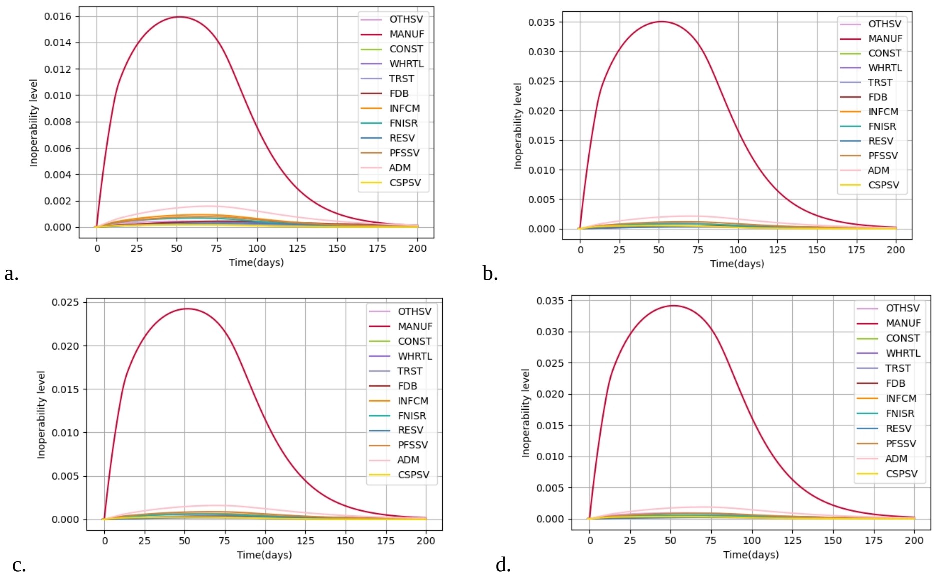

Fig. 4. Inoperability level for different sectors in (a) East region; (b) North region; (c) Northeast region; (d) Central region.

The total output for each time step during the recovery phase obtained by MRIOT and national IOT are shown in Fig. 5, which depicts the resilience triangle which in turn is a graphical representation of the recovery trajectory and the resilience for the whole system after the disaster.

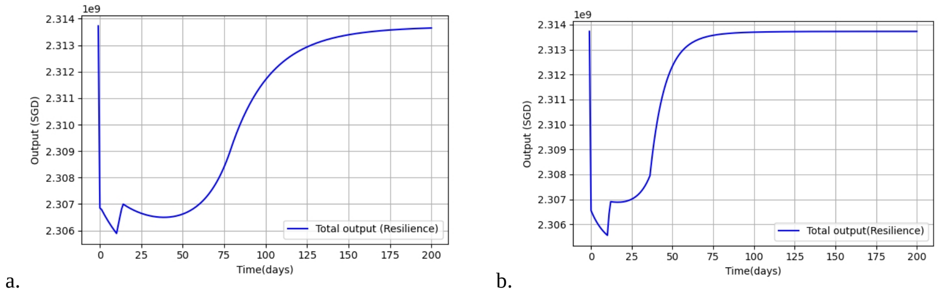

Fig.5. (a) Total economic loss obtained by MRIOT; (b) Total economic loss obtained by national IOT.

From the difference in recovery times between (a) and (b) in Fig. 5, the Singapore urban system recovers faster when the national IOT is adopted, with the economic loss and recovery propagating faster through the interdependencies in the national IOT while the interdependencies may be more complex in the MR urban systems within Singapore. Moreover, when the national IOT is adopted, the minimum total output during the recovery phase is smaller than when adopting the MRIOT. That is because in the national IOT, the interdependencies are stronger than the interdependencies in MRIOT due to the aggregation of the interdependencies in the national IOT, leading to lower minimum total output during the recovery phase.

5. Conclusion

As a sophisticated urban system with numerous CI systems for supplying citizens' daily necessities, Singapore faces challenges to maintain resilience under increasingly complex interdependencies. Small disruptions in one CI sector may lead to unexpected severe disruptions in the whole system due to cascading effects. Moreover, the location of each facility in each CI system also play an important role in the interdependencies. Thus, the resilience of an urban system should be investigated through a more detailed and complete network of the interdependencies among different regions and different sectors. Modeling the fragility via a dynamic analysis also helps to present a more complete picture of the resilience for this urban system. Through adopting the static IIM in a fire accident in West region of Singapore, the cumulative regional economic loss and the cumulative sectoral total economic loss are obtained. The initial impacted West region still suffered the largest economic loss, which made up almost two thirds of the total loss for the whole Singapore. For the sectoral loss, the initial impacted sector (MANUF sector) still suffered the largest loss, followed by the OTHERS sector (OTHSV sector), which is also aligned with the findings about the sectoral loss in DIIM.

Apart from the total economic loss in the whole year, how the economic losses are distributed over the whole year is also quite crucial since the resilience of a system is not only related to the total loss, but also related to how the system recovers from a disruption, which is essential for understanding how to enhance the resilience and conduct the rescue or reconstruction after a disruption. Thus, we adopted the DIIM to investigate the Singapore urban system recovery characteristics such as the duration, recovery path, peak inoperability, and lowest total output of this urban system after the fire accident in a single regional (national) scenario which treat Singapore as whole and only reveal the sectoral performance, and MR scenario which accounted for the detailed location distribution of each CI system.

Moreover, in our MR scenario, the MRIOT and MR disruption data are employed, which enable us to investigate a disruption that initially happen in one sector and at a smaller spatial granularity which then propagates to all other regions within the urban system. Due to the regional specific transaction data and disruption data being available, the MRIIM and MRDIIM used in our case study is the same as the single regional IIM and DIIM, which differs from past MR inoperability studies. Through the comparison between the resilience obtained by MR scenario and single regional scenario, the actual recovery of the MR system is slower than that in the single regional scenario, perhaps due to the more complex interdependencies present in the MR scenario. The ability to perform such studies may facilitate the development of more detailed rescue and reconstruction plans for disruptions and improve the resilience of urban systems.

The original contribution for this research is the MR scenario implementation for the high-density urban systems which divided the whole urban area into several regions with assigning specific function for each region. Previously, due to the unavailability of MRIOT at regional level within a city, the MR disaster impact cannot be investigated. Thanks to the implementation of the more detailed MRIOT, the complete picture of the propagation of the disaster is obtained and the accurate economic losses for each region and the whole urban system are obtained.

However, there are some limitations in this current work. For instance, the current MRIOT for Singapore is still at the five-region level whereas a 55-region level that corresponds to Singapore's urban planning zones may facilitate more accurate sectoral analysis and studies. Moreover, due to the absence of recovery data, the recovery path is simulated by an exponential function which may not follow closely the actual situation.

Acknowledgements

This work was done at the Institute of Catastrophe Risk Management, Interdisciplinary Graduate Programme, Nanyang Technological University. The research was conducted as part of the Future Resilient Systems project at the Singapore-ETH Centre, which was established collaboratively between ETH Zurich and the National Research Foundation Singapore. This research is supported by the National Research Foundation under its Campus for Research Excellence and Technological Enterprise (CREATE) programme.

References

Akhtar, R., Santos, J. R. 2012. Risk-based input–output analysis of hurricane impacts on interdependent regional workforce systems. *Natural Hazards, 65*(1), 391-405. doi:10.1007/s11069-012-0369-0

Aviso, K. B., Amalin, D., Promentilla, M. A. B., Santos, J. R., Yu, K. D. S., Tan, R. R. 2015. Risk assessment of the economic impacts of climate change on the implementation of mandatory biodiesel blending programs: A fuzzy inoperability input–output modeling (IIM) approach. *Biomass and Bioenergy, 83*, 436-447. doi:10.1016/j.biombioe.2015.10.011

Bierkandt, R., Wenz, L., Willner, S. N., Levermann, A. 2014. Acclimate—a model for economic damage propagation. Part 1: basic formulation of damage transfer within a global supply network and damage conserving dynamics. *Environment Systems and Decisions, 34*(4), 507-524. doi:10.1007/s10669-014-9523-4

Chua, A. 2011. Pulau Bukom Fire. *Available online: https://eresources.nlb.gov.sg/infopedia/articles/SIP$_$1868$_$2012-02-02.html (accessed on 20 August 2022).*

Crowther, K. G., Haimes, Y. Y. 2010. Development of the multiregional inoperability input - output model (MRIIM) for spatial explicitness in preparedness of interdependent regions. *Systems Engineering, 13*(1), 28-46.

Curt, C., Tacnet, J. M. 2018. Resilience of Critical Infrastructures: Review and Analysis of Current Approaches. *Risk Analysis, 38*(11), 2441-2458. doi:10.1111/risa.13166

DOS. 2020. Share Of Nominal Gross Value Added, By Industry. *SSIC, Available online: https://tablebuilder.singstat.gov.sg/table/TS/M015781 (accessed on 20 August 2022).*

DOS. 2022. National Accounts: Supply, Use and Input-Output Tables*., Available online: https://www.singstat.gov.sg/find-data/search-by-theme/economy/national-accounts/latest-data#SU-IOT (accessed on 20 August 2022).*

Ern, L. Y., Abdullah, A. 2014. Fighting the shell pulau bukom fire: Strategies that worked for the SCDF. *Home Team J. , 66–73*.

ExxonMobil. 2022. Singapore Refinery*., Available online: https://www.exxonmobil.com.sg/Company/Overview/Who-we-are/Singapore-Refinery*.

Haimes, Y. Y., Horowitz, B. M., Lambert, J. H., Santos, J. R., Lian, C., Crowther, K. G. 2005. Inoperability input-output model for interdependent infrastructure sectors. I: Theory and methodology. *Journal of Infrastructure systems, 11*(2), 67-79.

Haimes, Y. Y., Jiang, P. 2001. Leontief-based model of risk in complex interconnected infrastructures. *Journal of Infrastructure systems, 7*(1), 1-12.

Hewings, G. J., Okuyama, Y., Sonis, M. 2001. Economic interdependence within the Chicago metropolitan area: a Miyazawa analysis. *Journal of Regional Science, 41*(2), 195-217.

Irimoto, H., Shibusawa, H., Miyata, Y. 2017. *Evaluating the economic damages of transport disruptions using a transnational and interregional input–output model for Japan, China, and South Korea*.

Jiang, P., Haimes, Y. Y. 2004. Risk management for Leontief‐based interdependent systems. *Risk Analysis: An International Journal, 24*(5), 1215-1229.

Kelly, S. 2015. Estimating economic loss from cascading infrastructure failure: a perspective on modelling interdependency. *Infrastructure Complexity, 2*(1). doi:10.1186/s40551-015-0010-y

Lam, C. Y., Tai, K. 2018. Modeling infrastructure interdependencies by integrating network and fuzzy set theory. *International Journal of Critical Infrastructure Protection, 22*, 51-61. doi:10.1016/j.ijcip.2018.05.005

Lin, J., Tai, K., Tiong, R. L. K., Sim, M. S. 2017. Analyzing Impact on Critical Infrastructure Using Input-Output Interdependency Model: Case Studies. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering, 3*(4). doi:10.1061/ajrua6.0000919

MacKenzie, C. A., Santos, J. R., Barker, K. 2012. Measuring changes in international production from a disruption: Case study of the Japanese earthquake and tsunami. *International Journal of Production Economics, 138*(2), 293-302. doi:10.1016/j.ijpe.2012.03.032

Mandapaka, P. V., Lo, E. Y. M. 2023. Assessing Shock Propagation and Cascading Uncertainties Using the Input–Output Framework: Analysis of an Oil Refinery Accident in Singapore. *Sustainability, 15*(2). doi:10.3390/su15021739

Miller, R. E., Blair, P. D. 2009. *Input-output analysis: foundations and extensions*: Cambridge university press.

Oliva, G., Panzieri, S., Setola, R. 2010. Agent-based input–output interdependency model. *International Journal of Critical Infrastructure Protection, 3*(2), 76-82. doi:10.1016/j.ijcip.2010.05.001

Ouyang, M. 2017. A mathematical framework to optimize resilience of interdependent critical infrastructure systems under spatially localized attacks. *European Journal of Operational Research, 262*(3), 1072-1084. doi:10.1016/j.ejor.2017.04.022

Rehak, D., Senovsky, P., Hromada, M., Lovecek, T. 2019. Complex approach to assessing resilience of critical infrastructure elements. *International Journal of Critical Infrastructure Protection, 25*, 125-138. doi:10.1016/j.ijcip.2019.03.003

Rinaldi, S. M., Peerenboom, J. P., Kelly, T. K. 2001. Identifying, understanding, and analyzing critical infrastructure interdependencies. *IEEE control systems magazine, 21*(6), 11-25.

Santos, J. R. 2006. Inoperability input-output modeling of disruptions to interdependent economic systems. *Systems Engineering, 9*(1), 20-34. doi:10.1002/sys.20040

Santos, J. R., Haimes, Y. Y. 2004. Modeling the demand reduction input‐output (I‐O) inoperability due to terrorism of interconnected infrastructures. *Risk Analysis: An International Journal, 24*(6), 1437-1451.

Santos, J. R., May, L., Haimar, A. E. 2013. Risk-based input-output analysis of influenza epidemic consequences on interdependent workforce sectors. *Risk Anal, 33*(9), 1620-1635. doi:10.1111/risa.12002

Setola, R., De Porcellinis, S., Sforna, M. 2009. Critical infrastructure dependency assessment using the input–output inoperability model. *International Journal of Critical Infrastructure Protection, 2*(4), 170-178. doi:10.1016/j.ijcip.2009.09.002

Shaker, R. R., Rybarczyk, G., Brown, C., Papp, V., Alkins, S. 2019. (Re)emphasizing Urban Infrastructure Resilience via Scoping Review and Content Analysis. *Urban Science, 3*(2). doi:10.3390/urbansci3020044

Tatar, U., Santos, J. R., Thekdi, S. A. 2022. Managing Physical and Economic Risk for Systems with Multidirectional Network Interdependencies. *Risk Anal, 42*(5), 1106-1123. doi:10.1111/risa.13824

Yu, K. D. S., Aviso, K. B., Santos, J. R., Tan, R. R. 2020. The Economic Impact of Lockdowns: A Persistent Inoperability Input-Output Approach. *Economies, 8*(4). doi:10.3390/economies8040109