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Exploring Dynamic Inoperability Input-Output Modelling of Cascading Consequences in a Total Defence Perspective

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Summary
The purpose of this work was to explore how the so-called inoperability input-output model (IIM) can be used as a tool for investigating scenarios and resilience aspects in a Total Defence perspective. The results show that IIM with its dynamic formulation can provide insight to critical infrastructure resilience aspects not easily gained otherwise. To allow further exploitation of IIM for national resilience analyses, it is recommended to build a database of interdependency matrices for the functions and critical infrastructures that constitute the Total Defence system. This database should be applicable for a broad range of scenarios, in particular scenarios that are used for security and defence planning.

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1 Introduction

The defence of Norway is built upon three main lines of effort: (*i*) national defence, (*ii*) the collective defence provided through NATO and (*iii*) bilateral support and reinforcement arrangements with close allies (Norwegian Ministry of Defence, 2020, p. 4). These three lines of efforts are underpinned by a modern and well-prepared Total Defence concept that builds national resilience (Norwegian Ministry of Defence & Norwegian Ministry of Justice and Public Security, 2018).

Looking out towards 2040, the security situation is characterised by global challenges like climate change and long-term effects of the Covid-19 pandemic, fragmentation and contestation within communities, states and the international system as well as mismatch between the challenges and the ability to deal with them (Beadle, Diesen, Nyhamar, & Bostad, 2019; National Intelligence Council, 2021, pp. 1-3; NATO, 2020, pp. 16-21; Sellevåg *et.al.*, 2020). The situation is exacerbated not only by the proliferation of emerging and disruptive technologies that continue to add complexity to our critical infrastructures, but also by the historically fragmented governance of risks spanning several government departments (Helbing, 2013; Oughton, Usher, Tyler, & Hall, 2018). Conventional strategies where risks are analysed, evaluated and treated individually, leading to siloed risk management, are therefore becoming insufficient (Helbing, 2013).

The new security situation where nation states may face more intense and cascading challenges (National Intelligence Council, 2021, p. 1), calls for strengthened national and collective resilience (NATO, 2021). It has, however, been acknowledged for decades that understanding the fragilities induced by multiple interdependencies is generally considered as one of the major challenges when it comes to improving national resilience, including the resilience of critical infrastructures (Chang, 2009; Rinaldi, Peerenboom, & Kelly, 2001; Vespignani, 2010). The 2020–2021 Covid-19 pandemic has just reminded us of this fact. Future strategies for meeting the challenges should therefore build on the principles of resilience and adaptation (Hollnagel, Woods, & Leveson, 2006; National Intelligence Council, 2021, p. 3; Schulman, 2021; Woods, 2020).

In order to strengthen resilience efforts, there is a need to better understand the potential cascading consequences that follow disruptive events. For this purpose, several modelling and simulation approaches have been proposed (Ouyang, 2014). So-called network flow-based and agent-based methods allow for detailed modelling of critical infrastructures with substantial accuracy, but come with great computational cost and need large amounts of data that are not easily available. Holistic approaches, on the other hand, model how the service degradation within one infrastructure influence other infrastructures' ability to operate, but in an abstract and strategic-oriented manner with little computational cost (Ouyang, 2014; Setola, Rosato, Kyriakides, & Rome, 2016, p. 29).

One of the most successful holistic approaches is the economic theory-based inoperability[1] input-output model (IIM) (Haimes *et al.*, 2005b; Haimes & Jiang, 2001; Lian & Haimes, 2006; Santos & Haimes, 2004). The IIM has been successfully applied to cases like terrorism (Santos, 2006; Santos & Haimes, 2004), the impact of high-altitude electromagnetic pulse (Haimes, Horowitz, Lambert, Santos, Crowther, & Lian, 2005a), blackouts (Anderson, Santos, & Haimes, 2007), hurricanes (Crowther, Haimes, & Taub, 2007), cyber-attacks (Santos, Haimes, & Lian, 2007) and pandemics (Santos, 2020). IIM has also been used to analyse interdependencies between economic sectors in Italy (Setola, 2008) and Norway (Sellevåg, 2021).

The purpose of this work is to explore the usability of IIM to elucidate cascading consequences from disruptive events. On the basis of the findings, recommendations are made for how IIM can be used as a tool for investigating scenarios and resilience aspects in a Total Defence perspective.

This short report is organised as follows: A short review of the theory for IIM is provided in chapter 2. Then, the results from the application of the IIM with its dynamic formulation are presented and discussed in chapter 3. Finally, conclusions and recommendations for further work are presented in chapter 4.

[1] The term "inoperability" refers to "the inability of the system to perform its intended natural or engineered functions" (Haimes, Horowitz, Lambert, Santos, Lian, & Crowther, 2005b).

2 Theory

2.1 Infrastructure Dependencies and Interdependencies

Before discussing the IIM for modelling of cascading effects, it is worthwhile to review some of the literature on infrastructure interdependencies since cascading effects results from such interdependencies. Although several definitions for dependencies and interdependencies exists (Ouyang, 2014), one of the most widely accepted are the definitions provided by Rinaldi *et al.* (2001):

- *Dependency: "A linkage or connection between two infrastructures, through which the state of one infrastructure influences or is correlated to the state of the other"*

- *Interdependency: "A bidirectional relationship between two infrastructures through which the state of each infrastructure influences or is correlated to the state of the other"*

The concepts of infrastructure dependency and interdependency are illustrated in Figure 2.1.

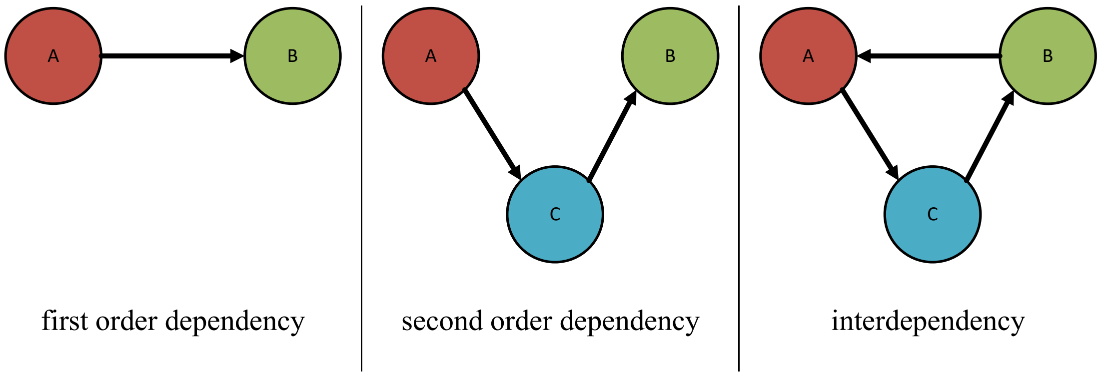


Figure 2.1 Illustration of dependency and interdependency (after Setola et al., 2016, p. 22)

On the basis of the abovementioned definitions, Rinaldi *et al.* (2001) proposed the following six dimensions for describing infrastructure dependencies:

- *Types of interdependencies*
- *Infrastructure environment* (*e.g.* economic, technical, social/political)
- *Coupling and response behaviour* (*e.g.* loose/tight)
- *Infrastructure characteristics* (*e.g.* organisational, operational)
- *Types of failures* (*e.g.* common cause, cascading, escalating)
- *State of operation* (*e.g.* normal, stressed/disrupted)

When it comes to *types of interdependencies*, such types can in its simplest case be characterised as *functional* (*i.e.* the operation of one infrastructure system is necessary for the operation of another system) or *spatial* (*i.e.* relating to the proximity of infrastructure systems) (Zimmerman, 2001). Rinaldi *et al.* (2001) characterised infrastructure types as:

- *Physical*; two infrastructures are physically interdependent if the state of each is dependent on the material output(s) of the other

- *Cyber*; the state of an infrastructure depends on information transmitted through the information infrastructure

- *Geographic*; infrastructures are geographically interdependent if a local environmental event can create state changes in all of them

- *Logical*; two infrastructures are logically interdependent if the state of each depends on the state of the other via a mechanism that is not a physical, cyber, or geographic connection

Other types of interdependencies have been defined as well (Ouyang, 2014). Common for many of them, including the types proposed by Rinaldi *et al.* (2001), is that they can be characterised as cause-based interdependencies. Recently, Goldbeck, Angeloudis and Ochieng (2019) have argued that an effect-based classification is more important for modelling purposes since interdependencies can yield similar effects despite having different causes. For this purpose, Goldbeck *et al.* (2019) proposed the following four types of effect-based dependency relations: (*i*) stochastic failure propagation, (*ii*) logic, (*iii*) asset utilisation and (*iv*) resource input dependencies. Stochastic failure propagation can for instance be caused by spatial proximity, while resource input dependencies relates to physical inputs or cyber dependencies. When it comes to logic dependencies or asset utilisation, we refer to Goldbeck *et al.* (2019) for details. For the purpose of applying the IIM, the interdependency types proposed by Zimmerman (2001), *i.e.* functional and spatial, provides sufficient understanding.

2.2 Dynamic Inoperability Input-Output Model

IIM for interdependent infrastructure sectors with its dynamic formulation has been described elsewhere (Haimes *et al.*, 2005b; Haimes & Jiang, 2001; Lian & Haimes, 2006; Santos & Haimes, 2004), so only brief details are given. The Leontief input-output model is given in Eq. (2.1). Here, x_i is the total production output of industry i, a_{ij} is the Leontief technical coefficient, *i.e.* the proportion of industry i's input to j with respect to the "as-planned" total production of j ($\hat{x}_j$), and c_i is the final demand for i's output (Haimes *et al.*, 2005b; Santos & Haimes, 2004).

$$\boldsymbol{x} = \boldsymbol{Ax} + \boldsymbol{c} \Leftrightarrow \left\{ x_i = \sum_j a_{ij} x_j + c_i \right\} \forall\, i \tag{2.1}$$

In the static demand-reduction IIM, Eq. (2.1) is transformed into Eq. (2.2) (Haimes *et al.*, 2005b; Santos & Haimes, 2004):

$$\boldsymbol{q} = \boldsymbol{A}^* \boldsymbol{q} + \boldsymbol{c}^* \Rightarrow \boldsymbol{q} = (\boldsymbol{I} - \boldsymbol{A}^*)^{-1} \boldsymbol{c}^* = \boldsymbol{S}\boldsymbol{c}^*, \tag{2.2}$$

where $\boldsymbol{I}$ is the identity matrix. The inoperability $\boldsymbol{q} \in [0, 1]^n$ is a vector specifying the normalised production losses for each of the n infrastructures that can be potentially realised after a prolonged demand-side perturbation $\boldsymbol{c}^* \in [0, 1]^n$ (Haimes *et al.*, 2005b; Santos & Haimes, 2004). An inoperability of $q_i = 0$ means that the production output of i is "as planned", while $q_i = 1$ implies that i is 100% inoperable (Santos & Haimes, 2004). Thus, infrastructure disruptions (which typically occur at the supply side) are modelled as a forced demand-reduction with impacts cascading to other sectors by backwards linkages (Kelly, 2015; Oosterhaven, 2017).

The $n \times n$ matrix $\boldsymbol{A}^*$ describes the interdependencies between the different infrastructure sectors. Each matrix element a_{ij}^* represents the fraction of inoperability that is transmitted by the j-th infrastructure to the i-th infrastructure, *i.e.* the first-order impact of j on infrastructure i (Setola, De Porcellinis, & Sforna, 2009). Since

$$\boldsymbol{S} = (\boldsymbol{I} - \boldsymbol{A}^*)^{-1} = \boldsymbol{I} + \boldsymbol{A}^* + \boldsymbol{A}^{*2} + \boldsymbol{A}^{*3} + \cdots, \tag{2.3}$$

we see that cascading (*i.e.* second- and higher-order) effects are captured by the IIM as long as $(\boldsymbol{I} - \boldsymbol{A}^*)$ is not singular.

To address the temporal behaviours of the infrastructure sectors in the response and recovery phases following a perturbation, a dynamic IIM (DIIM) has been formulated (Haimes *et al.*, 2005b; Lian & Haimes, 2006). In the dynamic Leontief input-output model, Eq. (2.1) takes the form given in Eq. (2.4) (Haimes *et al.*, 2005b):

$$\boldsymbol{x}(t) = \boldsymbol{Ax}(t) + \boldsymbol{c}(t) + \boldsymbol{B}\dot{\boldsymbol{x}}(t), \tag{2.4}$$

where $\boldsymbol{B}$ is a so-called capital coefficient matrix that measures the willingness to invest in resources for speeding up the recovery process, and $\dot{\boldsymbol{x}}(t)$ is the derivative of $\boldsymbol{x}$ with respect to time (t). If we define a matrix $\boldsymbol{K}$ such that $\boldsymbol{K} = -\boldsymbol{B}^{-1}$ (Haimes *et al.*, 2005b), Eq. (2.4) yields:

$$\dot{\boldsymbol{x}}(t) = \boldsymbol{K}[\boldsymbol{Ax}(t) + \boldsymbol{c}(t) - \boldsymbol{x}(t)], \tag{2.5}$$

or in the discrete form:

$$\boldsymbol{x}(k+1) - \boldsymbol{x}(k) = \boldsymbol{K}[\boldsymbol{Ax}(k) + \boldsymbol{c}(k) - \boldsymbol{x}(k)], \tag{2.6}$$

where k is the time step parameter. Transforming Eqs. (2.5) and (2.6) into the inoperability form yield the following equations:

$$\dot{\boldsymbol{q}}(t) = \boldsymbol{K}[\boldsymbol{A}^*\boldsymbol{q}(t) + \boldsymbol{c}^*(t) - \boldsymbol{q}(t)], \quad (2.7)$$

$$\boldsymbol{q}(k+1) - \boldsymbol{q}(k) = \boldsymbol{K}[\boldsymbol{A}^*\boldsymbol{q}(k) + \boldsymbol{c}^*(k) - \boldsymbol{q}(k)], \quad (2.8)$$

If the final demand $\boldsymbol{c}^*(t)$ is stationary (*i.e.* $\boldsymbol{c}^*(t) = \boldsymbol{c}^*$) and given the initial condition $\boldsymbol{q}(0)$, it can be shown (Haimes *et al.*, 2005b; Lian & Haimes, 2006) that the solution of Eq. (2.7) is:

$$\boldsymbol{q}(t) = (\boldsymbol{I} - \boldsymbol{A}^*)^{-1}\boldsymbol{c}^* + e^{-\boldsymbol{K}(\boldsymbol{I}-\boldsymbol{A}^*)t}[\boldsymbol{q}(0) - (\boldsymbol{I} - \boldsymbol{A}^*)^{-1}\boldsymbol{c}^*] \quad (2.9)$$

2.3 Demand-Reduction Dynamics and Dynamic Recovery

As argued by Lian and Haimes (2006), the two basic DIIM applications are *demand-reduction dynamics* and *dynamic recovery* following disruptive events. These two applications will be discussed in the following.

2.3.1 Demand-Reduction Dynamics

DIIM can be used to model how the demand-reduction varies with time following an initial perturbation until equilibrium is achieved. Under normal conditions, *i.e.* in the pre-event phase, the infrastructure sectors will be in their business-as-usual state. At $t = 0$ of the disruptive event, it is assumed that the infrastructure sectors are fully operational, *i.e.* $\boldsymbol{q}(0) = 0$, but there are perturbation to the normalised final demand ($\boldsymbol{c}^* > 0$). It can be shown (Lian & Haimes, 2006) that Eq. (2.9) becomes:

$$\boldsymbol{q}(t) = \left[\boldsymbol{I} - e^{-\boldsymbol{K}(\boldsymbol{I}-\boldsymbol{A}^*)t}\right](\boldsymbol{I} - \boldsymbol{A}^*)^{-1}\boldsymbol{c}^* \quad (2.10)$$

When $t \to \infty$, Eq. (2.10) takes the form of the static IIM (Eq. (2.2)):

$$\boldsymbol{q}(\infty) = (\boldsymbol{I} - \boldsymbol{A}^*)^{-1}\boldsymbol{c}^* \quad (2.11)$$

However, this only holds if the system governed by Eq. (2.7) is stable. This requires that the absolute value of the dominant eigenvalue of $\boldsymbol{A}^*$ is smaller than 1.

2.3.2 Dynamic Recovery

In the recovery phase of an incident, the operational level of the infrastructure sectors will be reduced. Consequently, $\boldsymbol{q}(0) > 0$. Under the assumption that the final demand of each sector is constant ($\boldsymbol{c}^* = 0$) (Lian & Haimes, 2006), Eq. (2.9) is reduced to:

$$\boldsymbol{q}(t) = e^{-\boldsymbol{K}(\boldsymbol{I}-\boldsymbol{A}^*)t}\boldsymbol{q}(0) \quad (2.12)$$

As $t \to \infty$, it is seen from Eq. (2.12) that $\boldsymbol{q}(t) \to 0$; that is, the infrastructure sectors return to their business-as-usual status.

2.3.3 Infrastructure Resilience Coefficient Matrix

The matrix $\boldsymbol{K} = \mathrm{diag}(k_i); k_i \in [0, 1)^n$ introduced in Eq. (2.5) is characterised as an *infrastructure resilience coefficient matrix* (Haimes *et al.*, 2005; Lian & Haimes, 2006). This matrix has different, yet related, interpretations in the response phase and in the recovery phase. In the response phase, the $\boldsymbol{K}$ matrix provides a measure for how fast each sector adjusts to an imbalance in supply and demand. Thus, a greater k_i value implies a more prompt adjustment of sector i's output in response to a change in final demand.

In the recovery phase, on the other hand, each element k_i measures the recovery rate of infrastructure sector i. The recovery rate can be assessed as follows: Let us assume that sector i is experiencing a disruptive event ($q_i(0) > 0$), and all other sectors are initially unaffected ($q_j(0) = 0,\ j \neq i$). By applying Eq. (2.12), the recovery of sector i becomes (Lian & Haimes, 2006):

$$q_i(t) = e^{-k_i\left(1-a_{ij}^*\right)t} q_i(0) \tag{2.13}$$

From Eq. (2.13) it can be shown that the infrastructure recovery rate can be estimated in accordance with Eq. (2.14) (Lian & Haimes, 2006):

$$k_i = \frac{\ln[q_i(0)/q_i(\tau_i)]}{\tau_i}\left(\frac{1}{1-a_{ii}^*}\right) = \left(\frac{\lambda_i}{\tau_i}\right)\left(\frac{1}{1-a_{ii}^*}\right) \tag{2.14}$$

Here, τ_i is the time it takes for the inoperability of sector i to reduce to some value $q_i(\tau_i)$ and $\lambda_i = \ln[q_i(0)/q_i(\tau_i)]$ is a recovery constant (see also Figure 2.2). The ratio (λ_i/τ_i) can be estimated by experts by assessing, *e.g.*, how long time it will take sector i to recover from 100 % inoperability ($q_i(0) = 1$) to 5 % inoperability ($q_i(\tau_i) = 0.05$). If for example it takes 30 days for sector i to recover from 100 % inoperability to 5 % inoperability and $a_{ii}^* \ll 1$, $k_i \approx \ln[1.0/0.05]/30 \approx 0.0996$. From Eq. (2.14) it is also easily seen that k_i increases with increasing a_{ii}^* value. Thus, if the interdependency index $\theta_i = 1 - a_{ii}^*$ of sector i can be decreased in a particular scenario, it will increase the recovery rate (Lian & Haimes, 2006). The same is the case if the τ_i value can be decreased. The recovery rate k_i of sector i is therefore influenced by both its own recovery rate and its interdependency with other sectors (Lian & Haimes, 2006). In many cases, however, it can be assumed that $a_{ii}^* \ll 1$, thus $\theta_i \approx 1$. The recovery rate is therefore primarily determined by the τ_i value.

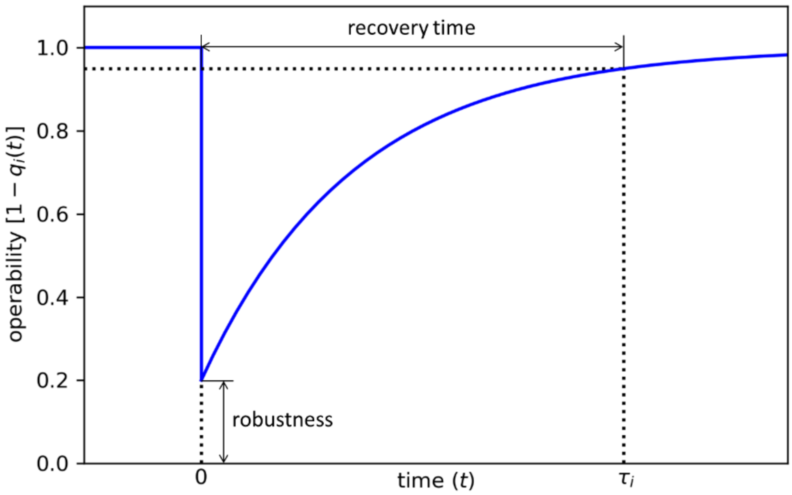


Figure 2.2 Illustration of the exponential recovery of infrastructure sector i *as governed by Eq. (2.13) following a disruptive event at time* $t = 0$*, where* τ_i *is the recovery time to 95 % operability (marked with dotted lines). The operability of sector* i *is defined as* $1 - q_i(t)$*, where* $q_i(t)$ *is the inoperability.*

2.4 Estimation of Interdependency Parameters

Several approaches have been proposed in the literature for estimating the IIM interdependency parameters (a_{ij}^*). Approaches based on physical connectivity (Haimes & Jiang, 2001), national account data (Haimes *et al.*, 2005b; Santos & Haimes, 2004) and expert assessments (Setola *et al.*, 2009) will be presented and discussed briefly in the following.

2.4.1 Physical-Based Model

In the original physical-based IIM that was developed by Haimes and Jiang (2001), infrastructure interdependencies were described on the basis of the physical connections between infrastructures i and j. If there are no physical connections between infrastructures i and j, $a_{ij}^* = a_{ji}^* = 0$. If there is a deterministic connection between i and j and a failure of infrastructure j definitely lead to a failure of infrastructure i, then $a_{ij}^* = 1$. Similarly, if a failure of j only leads to a 50 % drop in i's performance, then $a_{ij}^* = 0.5$. However, if the connection between i and j is stochastic,[2] all scenarios must be analysed and a statistical average must be taken to obtain a_{ij}^* and a_{ji}^* (Haimes & Jiang, 2001). Except for the simplest systems, enormous efforts are therefore

[2] That is, the connections appear to vary in a random manner.

required to collect such information. The application of the physical-based IIM is therefore hampered by the lack of data.

2.4.2 National Account Data

To account for the limitations of the physical-based IIM, it was therefore proposed to utilise economic data for interdependency analysis (Haimes *et al.*, 2005b; Santos & Haimes, 2004). At the national level, such data are readily available through national account data[3] provided by bureaus like Statistics Norway or the Bureau of Economic Analysis (BEA) in the United States. The assumption made is that the level of economic interdependency is the same as the level of physical and/or cyber interdependency (Haimes *et al.*, 2005b). Thus, the a_{ij}^* values can be calculated from the Leontief technical coefficients (a_{ij}) and the "as planned" total production ($\hat{x}_i$) values from the national account data (Eq. (2.15)):

$$a_{ij}^* = a_{ij}\frac{\hat{x}_j}{\hat{x}_i} \tag{2.15}$$

The advantage of using national account data is the thoroughness and quality of the data. Use of such data also allow for economic impact assessments (albeit with some limitations). The disadvantage of using national account data is that large disruptions may change the underlying structure of the economy and consequently also the Leontief technical coefficients (Kelly, 2015). To avoid such problems, the upper limit of $\boldsymbol{c}^*$ is therefore often limited to 0.1 (Santos & Haimes, 2004; Sellevåg, 2021; Setola, 2008). Thus, the effects of, *e.g.*, large-scale power outages or loss of telecommunication services will not be properly addressed. A second limitation is that economic interdependencies are only one dimension of infrastructure interdependencies (*cf.* section 2.1). A third limitation is that use of national account data only allows studies of the sectors that are included in the national account.

2.4.3 Expert Assessments

To address the limitations with the use of national account data, researchers have proposed to compute the a_{ij}^* values from sector-specific expert assessments (Setola *et al.*, 2009). In this approach the a_{ij}^* values are evaluated based on the direct (first order) consequences of an outage in infrastructure j on the operability of infrastructure i. For this purpose, an impact estimation table has been developed (Table 2.1). Consistent with the demand-reduction IIM assumptions, this approach takes advantage of the infrastructure operators' knowledge of the impacts of outages on their own infrastructures.[4] Thus, a_{ij}^* values can be estimated with rather good confidence. Furthermore, because the impact depends on the duration of inoperability, the approach proposed by Setola *et al.* (2009) is suited for addressing the temporal aspects of a disruptive event for different durations of the outage.

[3] National account data are tables describing the production and consumption of commodities of various economic sectors.
[4] Related to this, it is often difficult for infrastructure operators to estimate the downstream effects following a degradation or loss of their services.

Although infrastructure operators are knowledgeable about the effects of outages on own services, the expert assessments of the a_{ij}^{*} values will be affected by uncertainty. Setola *et al.* (2009) therefore proposed to use so-called fuzzy[5] numbers to capture this uncertainty from information on how confident the expert is in his or her assessment. Another approach would be to use the Delphi method (Helmer-Hirschberg, 1967).

Table 2.1 Impact estimation values (adapted from Setola et al., 2009)

Impact	Description	Value
Nothing	Event does not induce any effect on the infrastructure	0.000
Negligible	Event induces negligible and geographically-bounded consequences on services that have no direct impact on infrastructure operability	0.005
Very limited	Event induces very limited and geographically-bounded consequences on services that have no direct impact on infrastructure operability	0.008
Limited	Event induces limited and geographically-bounded consequences on services that have no direct impact on infrastructure operability	0.010
Some degradation	Event causes some degradation of the ability of the infrastructure to provide services in a geographic region	0.020
Modest degradation	Event causes modest degradation of the ability of the infrastructure to provide services in a geographic region	0.030
Significant degradation	Event causes significant degradation of the ability of the infrastructure to provide services in a geographic region	0.050
Provide only some services	Event causes the infrastructure to provide only some essential services in a geographic region	0.100
Nearly stop	Event causes the infrastructure to provide only some essential services nationwide	0.300
Complete stop	Event causes the infrastructure to be unable to provide services	0.500

[5] In two-valued logic statements are either true or false. Fuzzy logic is an extension of two-valued logic such that statements may have a degree of truth between 0 and 1 (*cf.* https://mathworld.wolfram.com/FuzzyLogic.html).

3 Results and Discussion

In the following, the use of DIIM for modelling cascading consequences following a disruptive event will be explored in a total defence perspective using a fictitious case study.

3.1 Case Description

The critical infrastructure sectors included in the case study are listed in Table 3.1. The case study is built on the basis of the Italian infrastructure case investigated by Setola *et al.* (2009), but where the defence, health and food supply sectors have been added. The interdependency $\boldsymbol{A}^*$ matrix for the critical infrastructure sectors is given in Table 3.2 and was generated from the impact values provided in Table 2.1 for an outage duration between six to twelve hours. As an example on how to interpret the a_{ij}^* values in Table 3.2, an outage of electricity that lasts between six to twelve hours will lead to some degradation of the ability of the health sector to provide services in a geographic region ($a_{\text{HEALTH,ELEC}}^* = 0.02$). The network topology for the case study is displayed in Figure 3.1. For simplicity, $\tau_i = 7$ days and $\lambda_i = 0.01$ were chosen for all sectors for computing the infrastructure resilience coefficient matrix (Eq. (2.14)).

Table 3.1 Critical infrastructure sectors included in case study

ID	Sector
DEFENCE	Defence sector (Armed Forces)
HEALTH	Health services
ELEC	Electricity supply
ECOM	Electronic communication and digital infrastructure services
FOOD	Food supply
WATER	Drinking water supply
FUEL	Fuel supply
FINANCE	Banking and financial market infrastructure services
LAND	Land transportation
SEAPORT	Port facilities
RAIL	Rail transportation
AIR	Air transportation
SAT	Satellite-based services

Table 3.2 IIM interdependency matrix (A^* matrix) for an outage period of 6 to 12 hours.

	DEFENCE	HEALTH	ELEC	ECOM	FOOD	WATER	FUEL	FINANCE	LAND	RAIL	SEAPORT	AIR	SAT
DEFENCE	0.020	0.008	0.008	0.010	0.005	0.010	0.020	0.005	0.008	0.008	0.005	0.020	0.050
HEALTH	0.000	0.020	0.008	0.010	0.008	0.050	0.010	0.005	0.020	0.005	0.005	0.050	0.005
ELEC	0.000	0.000	0.005	0.008	0.000	0.005	0.000	0.005	0.005	0.005	0.005	0.005	0.005
ECOM	0.000	0.000	0.050	0.050	0.000	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005
FOOD	0.000	0.000	0.050	0.020	0.008	0.020	0.005	0.050	0.020	0.010	0.008	0.008	0.005
WATER	0.000	0.000	0.010	0.010	0.000	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005
FUEL	0.000	0.000	0.100	0.050	0.000	0.005	0.005	0.050	0.020	0.020	0.020	0.005	0.005
FINANCE	0.000	0.000	0.100	0.100	0.000	0.005	0.005	0.050	0.005	0.005	0.005	0.005	0.005
LAND	0.000	0.000	0.008	0.008	0.000	0.005	0.030	0.008	0.050	0.008	0.005	0.005	0.008
RAIL	0.000	0.000	0.050	0.050	0.000	0.030	0.010	0.008	0.008	0.008	0.005	0.005	0.005
SEAPORT	0.000	0.000	0.100	0.050	0.000	0.005	0.005	0.010	0.008	0.050	0.008	0.005	0.005
AIR	0.000	0.000	0.100	0.100	0.000	0.030	0.030	0.010	0.008	0.020	0.005	0.050	0.300
SAT	0.000	0.000	0.005	0.005	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.008

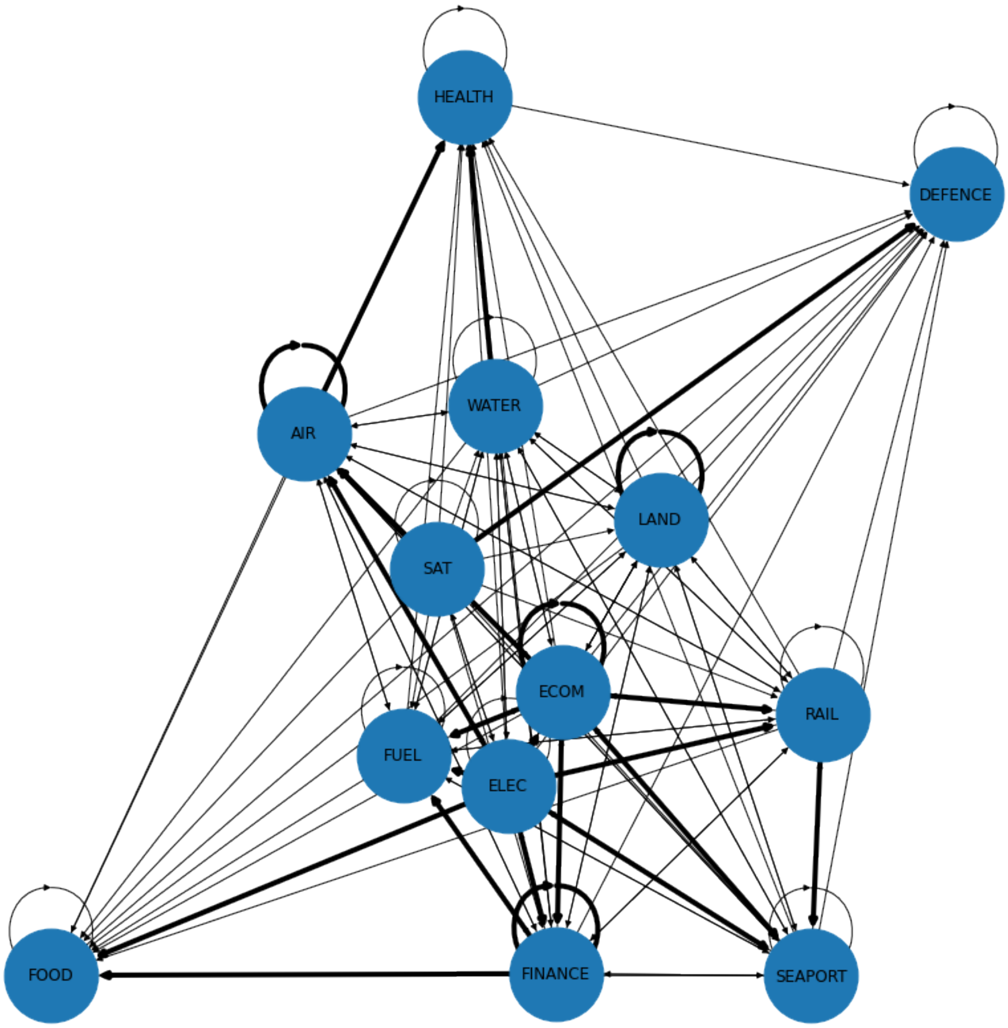


Figure 3.1 *Network topology for the case study described by the interdependency matrix in Table 3.2. The arrows shows the dependency relations* $j \rightarrow i$ *(thick lines symbolise dependency values for which* $a_{ij}^* \geq 0.05$*).*

3.2 Dependency Index and Influence Gain

The role of each infrastructure sector can be assessed by calculating the so-called dependency index (δ_i) and the influence gain (ρ_j). The dependency index is defined as given in Eq. (3.1) (Setola *et al.*, 2009):

$$\delta_i = \frac{1}{n-1}\sum_{j\neq i}^{n} a_{ij}^{*} \tag{3.1}$$

while the influence gain is defined as (Eq. (3.2)) (Setola *et al.*, 2009):

$$\rho_j = \frac{1}{n-1}\sum_{i\neq j}^{n} a_{ij}^{*} \tag{3.2}$$

Thus, the dependency index provides a measure of the fragility of the i-th sector to failures in the other sectors, while the influence gain expresses the j's ability to propagate inoperability to the other sectors (Setola *et al.*, 2009).

The dependency indices and influence gains for the case study are displayed in Figure 3.2 and Figure 3.3, respectively. As can be seen, air transportation is the most fragile sector towards failures in the other sectors for this fictitious case, while the electricity sector, electronic communications and satellite-based services exercise largest influence.

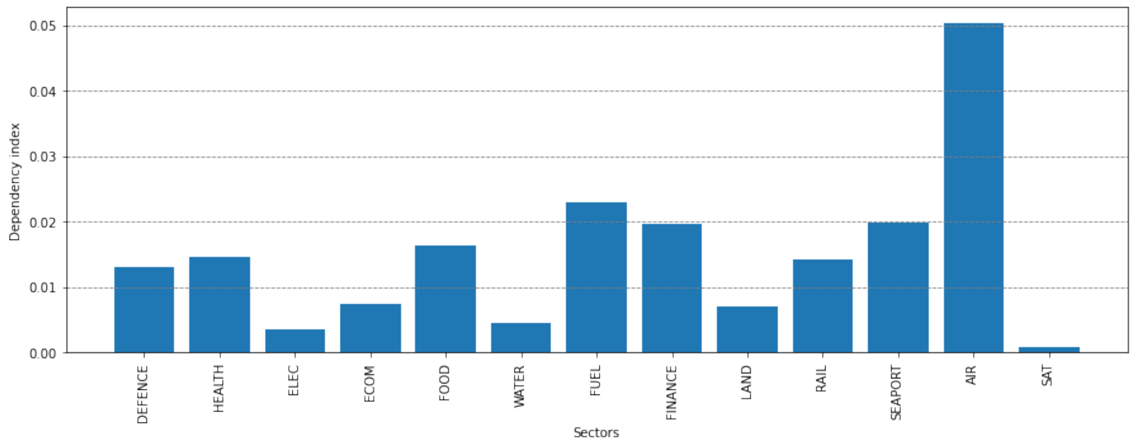


Figure 3.2 Dependency index for the case study described by the network topology given in Figure 3.1.

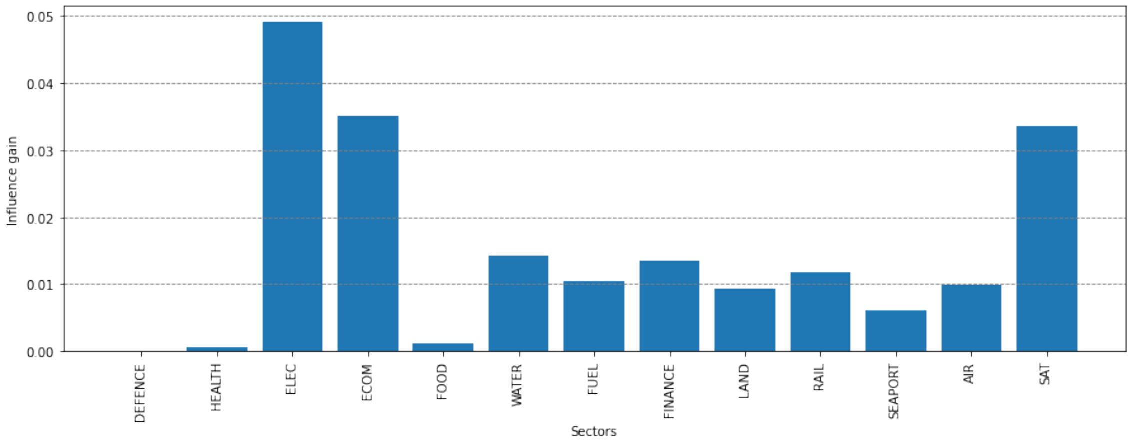


Figure 3.3 Influence gain for the case study described by the network topology in Figure 3.1.

3.3 Modelling of the Response Phase

Figure 3.4 shows the modelling results of the response phase following a notional disruption of electricity supply, electronic communications services, satellite-based services and banking and financial services. A c_k^* value of 0.5 was used in all experiments, where k is the perturbed sector. Only one sector was perturbed in each experiment.

The impact for each critical infrastructure sector (Q_i) can be calculated in accordance with Eq. (3.3):

$$Q_i = \int_0^{t_\mathrm{R}} q_i(t)\mathrm{d}t \tag{3.3}$$

where t_R is the duration of the response phase (here taken as the duration of the outage period, *i.e.* twelve hours). Thus, the total impact (Q_tot) for the whole system can then be calculated as (Eq. (3.4)):

$$Q_\mathrm{tot} = \sum_i Q_i \tag{3.4}$$

The impact values (Q_i and Q_tot) are displayed in Table 3.3. The largest Q_tot value during the response phase occurs when the electronic communications sector is perturbed, followed by the financial sector. It is somewhat surprising that the Q_tot is larger when the financial sector is perturbed compared to the electricity supply and satellite-based services sectors since the latter two exercise larger influence than the financial sector (Figure 3.3). This illustrates the importance of including second- and higher order interdependencies for understanding cascading effects.

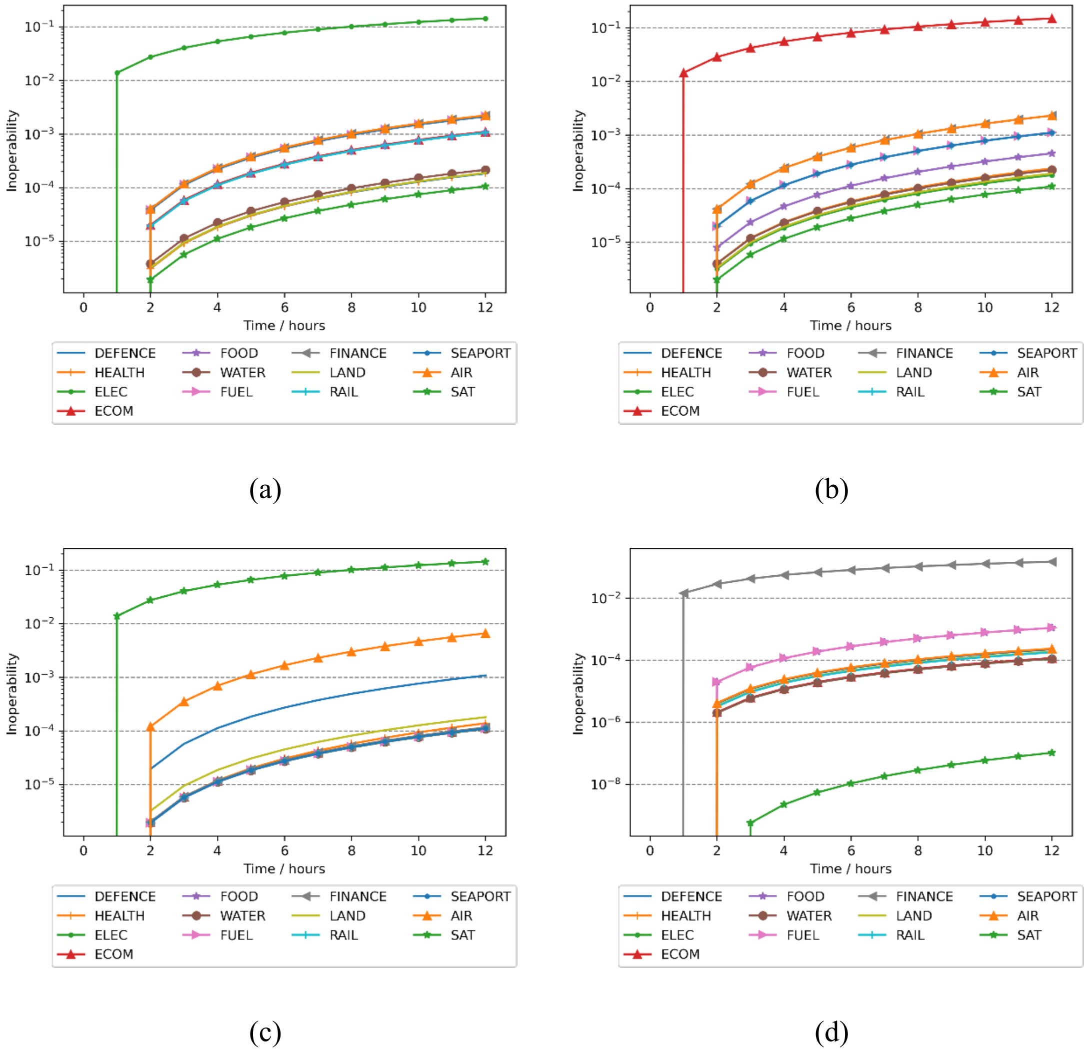


Figure 3.4 Inoperability as a function of time during the response phase following a notional disruption of (a) electricity supply, (b) electronic communications services, (c) satellite-based services and (d) banking and financial services ($c_k^* = 0.5$ was used in all experiments). The response phase equalled the twelve hour outage period for the k-th sector, where k is the perturbed sector.

Table 3.3 Impact for each infrastructure sector in the response phase following a twelve hours outage of the k-th sector.

Sector	Impact ($\boldsymbol{Q_i}$)			
	k = ELEC	$\boldsymbol{k}$ = ECOM	$\boldsymbol{k}$ = SAT	$\boldsymbol{k}$ = FINANCE
DEFENCE	0.001	0.001	0.004	0.001
HEALTH	0.001	0.001	0.001	0.001
ELEC	0.902	0.001	0.000	0.000
ECOM	0.004	0.945	0.001	0.001
FOOD	0.004	0.002	0.000	0.004
WATER	0.001	0.001	0.000	0.000
FUEL	0.009	0.005	0.000	0.004
FINANCE	0.009	0.009	0.001	0.945
LAND	0.001	0.001	0.001	0.001
RAIL	0.004	0.004	0.000	0.001
SEAPORT	0.009	0.005	0.000	0.001
AIR	0.009	0.009	0.027	0.001
SAT	0.000	0.000	0.905	0.000
$\boldsymbol{Q_{\text{tot}} = \sum_i Q_i}$	**0.953**	**0.983**	**0.941**	**0.959**

3.4 Modelling of the Recovery Phase

The recoveries of the critical infrastructure sectors for the four different experiments are shown in Figure 3.5, while the impacts are given in Table 3.4. The impact for each critical infrastructure sector was calculated from Eq. (3.3), except the integral was now over the whole period of the disruptive event, *i.e.* until the sectors were fully recovered.

Some noticeable effects can be observed for this fictitious case. Firstly, it takes in general more than 100 hours before the inoperability of the perturbed sector is less than 0.01 (1%). Thus, the recovery phase is significantly longer than the response phase. Secondly, even though the outage period ended after twelve hours, the inoperabilities of the sectors that are indirectly affected reach their maximum around 40 to 80 hours after the disruptive event started. Thus, the different sectors will be in different phases of the crisis due to the dynamics involved. Lastly, the total impact for the critical infrastructure system (Table 3.4) during the whole period of the disruptive event (*i.e.* when $t \to \infty$) follows the trends suggested by the influence gains of the sectors (Figure 3.3).

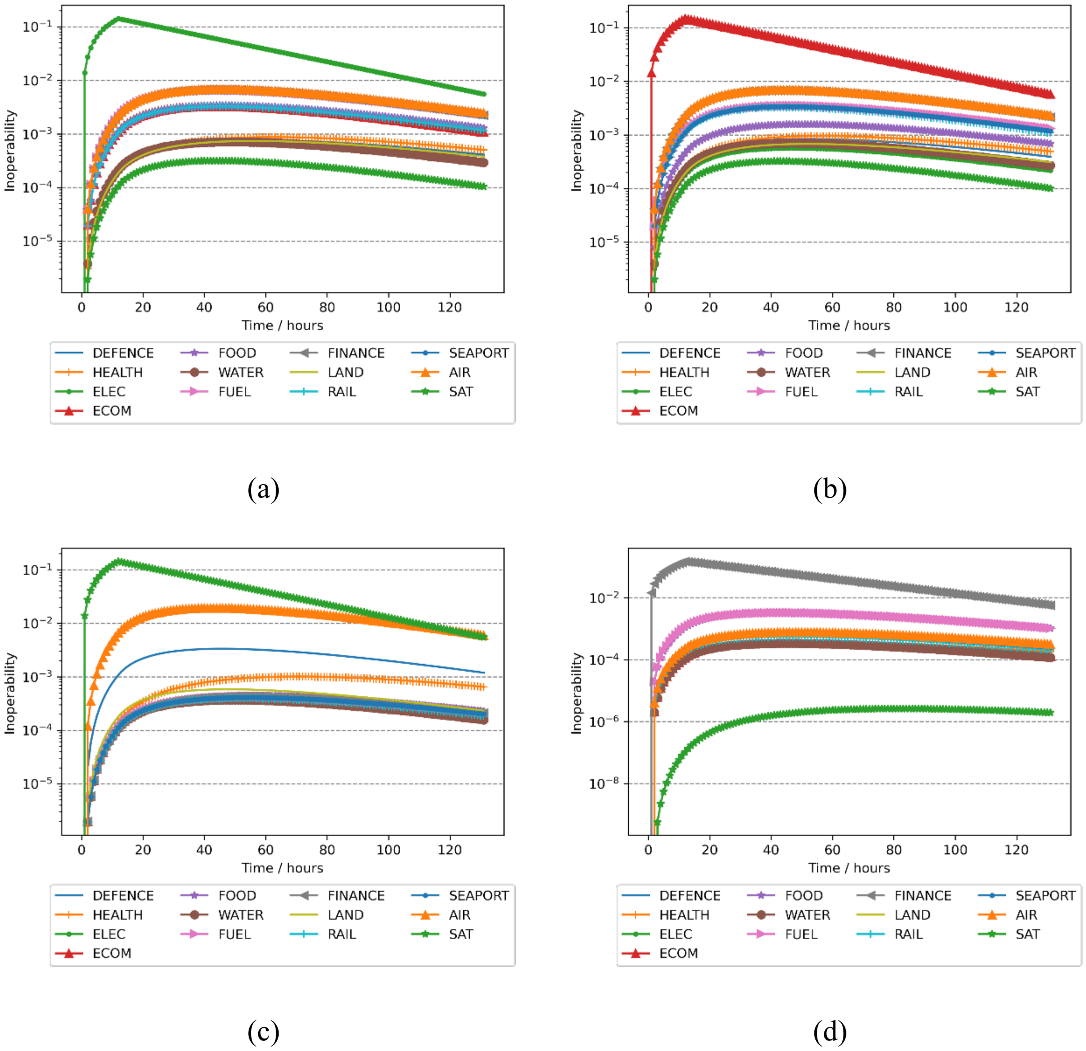


Figure 3.5 *Inoperability as a function of time during the response and recovery phases following a notional disruption of (a) electricity supply, (b) electronic communications services, (c) satellite-based services and (d) banking and financial services (c_k^*= 0.5 was used in all experiments). The response phase equalled the twelve hour outage period for the k-th sector, where k is the perturbed sector.*

Table 3.4 Impact for each infrastructure sector until fully recovered following a twelve hours outage of the k-th sector.

Sector	Impact ($\boldsymbol{Q_i}$)			
	k = ELEC	$\boldsymbol{k}$ = ECOM	$\boldsymbol{k}$ = SAT	$\boldsymbol{k}$ = FINANCE
DEFENCE	0.073	0.078	0.293	0.036
HEALTH	0.083	0.091	0.095	0.037
ELEC	5.913	0.051	0.033	0.028
ECOM	0.283	6.193	0.036	0.032
FOOD	0.301	0.145	0.042	0.278
WATER	0.064	0.063	0.034	0.030
FUEL	0.569	0.311	0.040	0.278
FINANCE	0.576	0.581	0.040	6.189
LAND	0.070	0.063	0.052	0.054
RAIL	0.286	0.286	0.037	0.050
SEAPORT	0.553	0.297	0.039	0.062
AIR	0.601	0.601	1.644	0.071
SAT	0.027	0.028	5.921	0.000
$\boldsymbol{Q_{\mathrm{tot}} = \sum_i Q_i}$	**9.398**	**8.786**	**8.305**	**7.144**

3.5 Risk-Cost-Benefit Analysis for Improving Resilience

In the following, we will investigate how the resilience of the critical infrastructure system as a whole can be increased by taking costs of different risk management options into consideration. We will do this by investigating how the recovery rate can be increased. Following Lian and Haimes (2006), a two-objective optimisation problem can be formulated for the risk-cost-benefit analysis (Eq. (3.5)):

$$\begin{aligned} &\underset{r_1,r_2,\dots,r_i,\dots,r_n}{\text{minimise}}\ Q_{\mathrm{tot}} = \sum_j \left(\int_0^\infty q_j\big(t, \boldsymbol{K}(r_1, r_2, \dots, r_i, \dots, r_n)\big) \mathrm{d}t \right) \\ &\underset{r_1,r_2,\dots,r_i,\dots,r_n}{\text{minimise}}\ C = C(r_1, r_2, \dots, r_i, \dots, r_n) \end{aligned} \tag{3.5}$$

Here, r_i is a finite set of n risk management options and C is the corresponding cost function for each option. Furthermore, the time is taken as zero ($t = 0$) when the outage period (twelve hours) is finished.

In the following, the risk-cost-benefit analysis will be illustrated by using disruption of electricity supply as an example. From Table 3.4 we see that the electricity supply and air transportation sectors suffer the largest impacts. A reasonable risk management strategy would then be to improve the recovery of these two sectors. Say for instance that the cost functions associated with reducing the τ_i values from seven days to five days are 75 and 25 for the electricity supply and air transportation sectors, respectively (the costs have arbitrary units). We can now define three different risk management options: r_{ELEC}, r_{AIR} and $r_{\text{ELEC+AIR}}$, having cost functions of 75, 25 and 100, respectively. The results from the risk-cost-benefit analysis are shown in Figure 3.6. As can be seen, little is gained for the critical infrastructure system as a whole by reducing the recovery time of the air transportation sector in addition to recovery time of the electricity supply sector for this fictitious case.

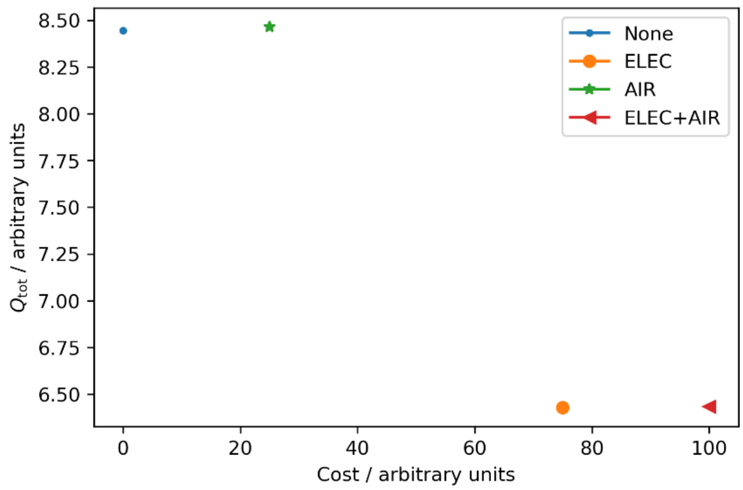
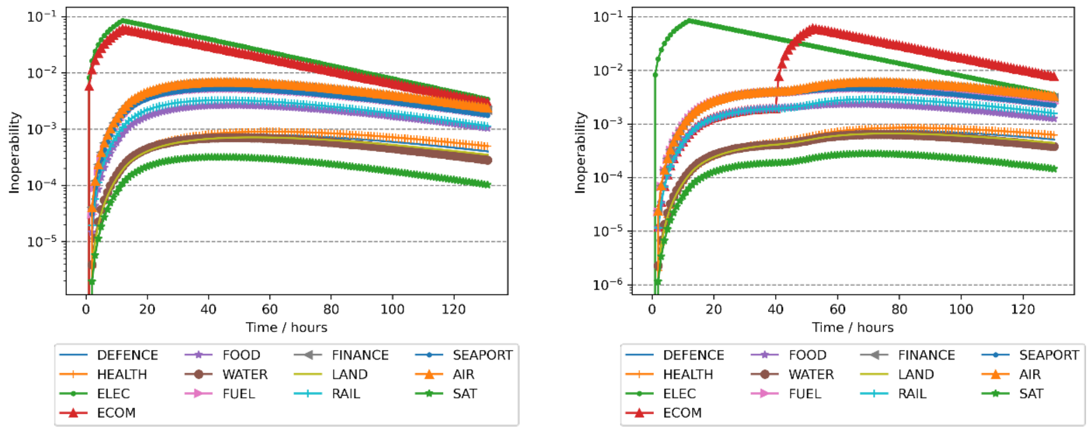


Figure 3.6 Risk-cost-benefit analysis of three different risk management options for reducing the recovery time after a disruption of the electricity supply sector.

3.6 Modelling of Multiple Disruptive Events

DIIM can also be used to model multiple disruptive events, *e.g.* malicious actions that are a part of a hybrid threat campaign (Cullen & Reichborn-Kjennerud, 2017).[6] Such events can occur simultaneously or there can be a time lag between two or several events.[7] Modelling results for each of the two types of scenarios are provided in Figure 3.7. In both cases the electricity supply and electronic communications sectors were perturbed with $c^*_{ELEC} = 0.3$ and $c^*_{ECOM} = 0.2$, respectively. In the first case, the electricity supply and the electronic communications sectors were perturbed simultaneously (Figure 3.7a), while in the second case there was a time lag between the perturbation of the two sectors (Figure 3.7b). From this, analyses similar to those made in sections 3.3–3.5 can for instance be carried out.

[6] This follows from $\boldsymbol{c}^* \in [0,1]^n$, where different disruptive events are described by different c^*_k values.
[7] In terms of hybrid threats, incidents occurring simultaneously can be considered as a so-called vertical escalation, while incidents that are separated in time would constitute a so-called horizontal escalation (Cullen & Reichborn-Kjennerud, 2017).



(a) (b)

Figure 3.7 Inoperability as a function of time for two disruptive events that (a) occur simultaneously or (b) with a time lag. The electronic supply and electronic communications sectors were perturbed in both experiments with $c^*_{ELEC} = 0.3$ *and* $c^*_{ECOM} = 0.2$*, respectively.*

4 Conclusions

A few conclusions can be made based on this exploratory work. As is evident from the modelling results, the cascading consequences following a disruptive event cannot easily be elucidated without the support of a modelling tool due to the second- and higher-order effects. For this purpose, DIIM is a simple, yet powerful tool for gaining cross-sectoral situational awareness. Further, DIIM can be used to inform risk-cost-benefit analyses when improving the resilience of the system of critical infrastructures.

The DIIM presented in this work is, however, affected by limitations. Firstly, only parts of the six infrastructure dependency dimensions proposed by Rinaldi *et al.* (2001) are covered by the model. Secondly, given that it is a linear model, nonlinear behaviours are not addressed. Thirdly, the a_{ij}^* technical coefficients are treated as constant in time. This is not a very good approximation for large-scale, long-term disruptive events since such events can change the system of critical infrastructures to such an extent that the a_{ij}^* coefficients also will change. Lastly, temporal behaviours are addressed, but using an exponential model which may not be an appropriate approximation for all cases. Care should therefore be exercised when interpreting the results.

Despite these limitations, DIIM can provide insight to critical infrastructure resilience aspects not easily gained otherwise. This is particularly the case for severe malicious actions that pose a threat to national security and target vulnerabilities across different sectors of the society since it is difficult to predict the consequences of such events. It is therefore recommended to continue to exploit DIIM as a tool for analysing scenarios that require a Total Defence approach.

To this end, it is recommended to build a database of interdependency matrices ($\boldsymbol{A}^*$ matrices) for the functions and critical infrastructures that constitute the Total Defence system. This database should be applicable for a broad range of scenarios, including security challenges, crises, military confrontations and armed conflicts, and in particular for scenarios that are used for security and defence planning. Furthermore, the database of interdependency matrices should take into account different outage periods for the services provided by the functions and critical infrastructures. To investigate the effect of existing and new preparedness efforts, such outage periods could for instance be: (*i*) less than 2 hours; (*ii*) 2–6 hours; (*iii*) 6–12 hours; (*iv*) 12–24 hours; (*v*) 24–72 hours; (*vi*) 3–7 days; (*vii*) more than 7 days. It is recommended that the interdependency matrices are generated using the methodology outlined in section 2.4.3.

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