



**POLITECNICO**  
MILANO 1863  
DIPARTIMENTO DI ENERGIA

# **Risk Assessment and Management of Interdependent Critical Infrastructures**

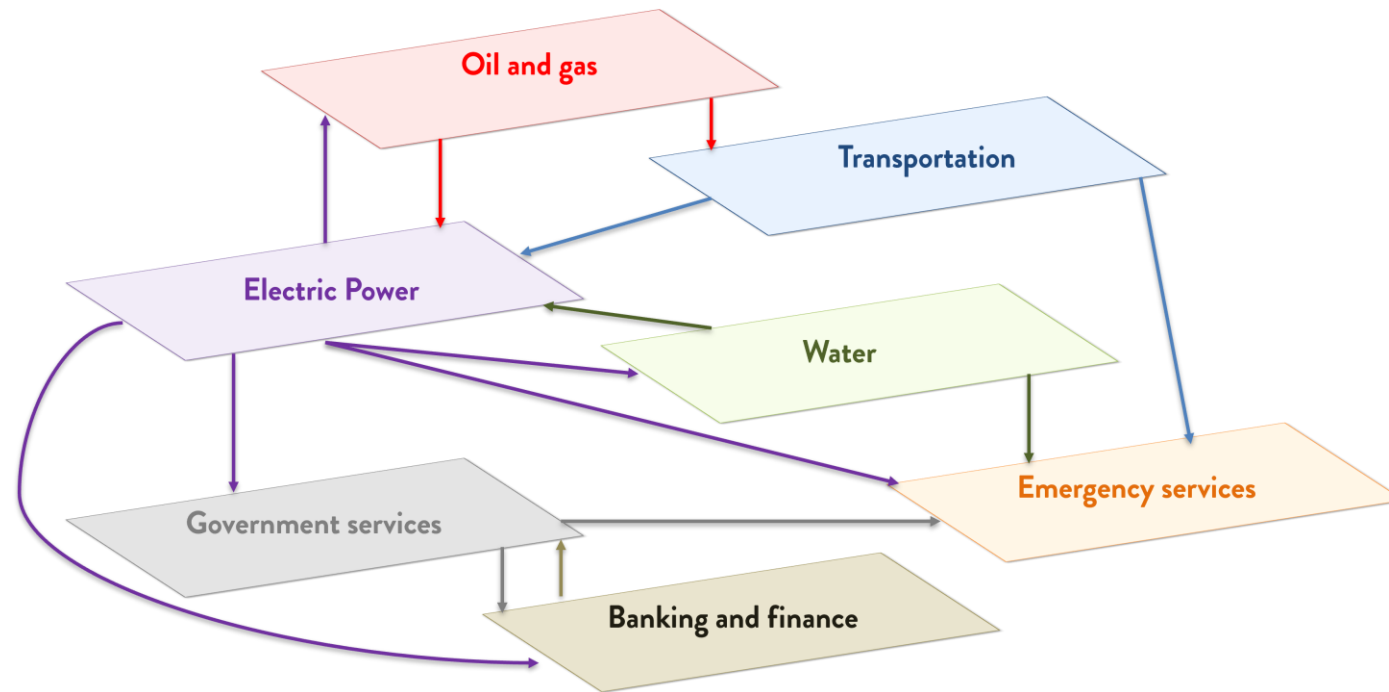
## 1. Interdependencies between Critical Infrastructures

- 1.1 Why Model Interdependencies?
- 1.2 Approaches Available to Model Interdependencies

## 2. Hybrid Approach to Model Interdependencies

- 2.1 Economic Theory-based Model: DIIM
- 2.2 Graph Theory-based Model
- 2.3 Application Example: Random Failures
- 2.4 Application Example: Natural Hazard Effects

# 1.1 Why Model Interdependencies?





# 1. Interdependencies between Critical Infrastructures

## 1.1 Why Model Interdependencies?

**Critical Infrastructures** describes assets that are **essential** for the functioning of a society and economy [1]



- By 2030, **60%** of the world's population will live in urban areas,
- This growth creates **technical and economic challenges** for CIs owners and **systems of systems planners**,
- Future cities will strain current safety and security engineering models
- New and complex **cascading failure** modes will emerge due to unforeseen system behaviours

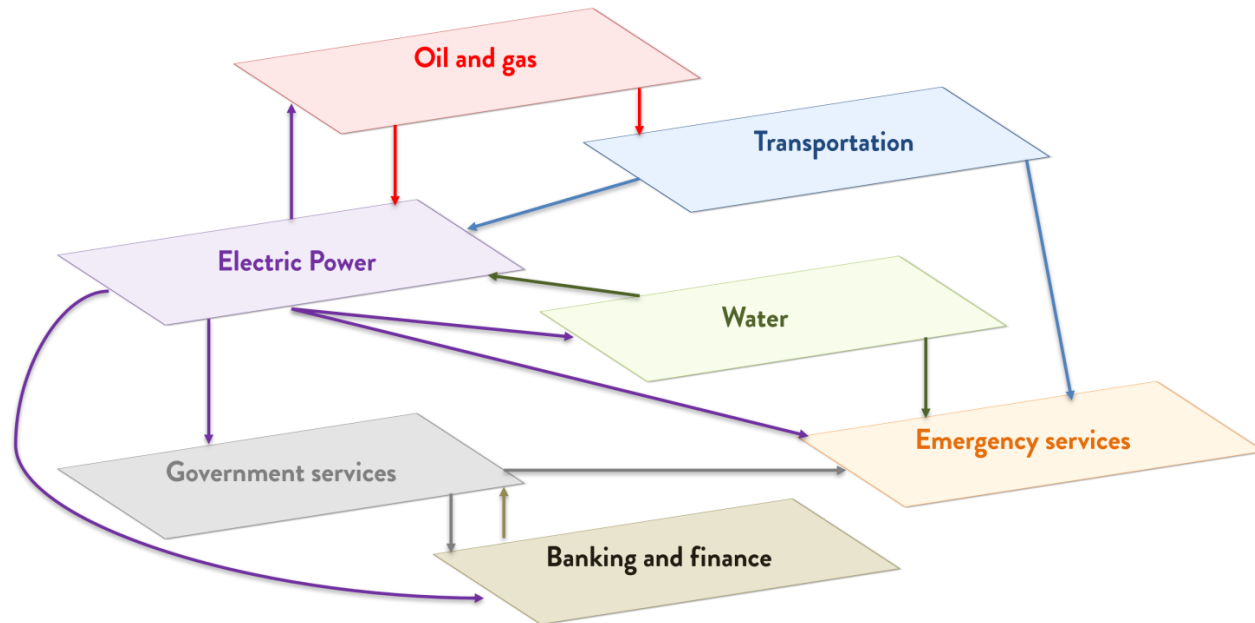
[2]



# 1. Interdependencies between Critical Infrastructures

## 1.1 Why Model Interdependencies?

In an interconnected world, hidden interdependencies between infrastructures often become evident during hazard events, making it crucial to model them to understand vulnerabilities and ensure resilience



The Great Texas Freeze [3]

The *2021 Texas Winter Storm* caused power grid failures, disrupting water and gas systems, affecting **5.2 million homes**, with damages reaching **\$195 billion** and over **700 fatalities**



Rio Grande do Sul, Brazil floods response [4]

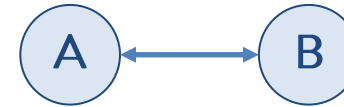
In early *2024*, *Southern Brazil* was hit by extratropical cyclones and flooding after a dam collapse, affecting **28.8 million people** and causing **\$20.4 billion** in damages, with power outages in the region, road closure, and airport shutdowns

# 1. Interdependencies between Critical Infrastructures

## 1.1 Why Model Interdependencies?



A **dependency** is a *unidirectional relationship* in which the functioning of one infrastructure is influenced by another



An **interdependency** is a *bidirectional relationship* in which two or more infrastructures mutually influence each other's state

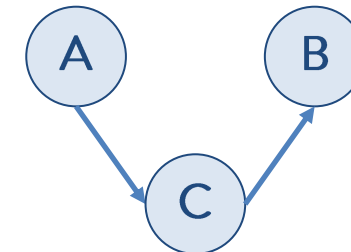
Dependencies between two infrastructures may be **direct** or **indirect**:

First order dependency



B depends directly on A

Second order dependency



B depends on A through another infrastructure C

[5]

# 1. Interdependencies between Critical Infrastructures

## 1.1 Why Model Interdependencies?





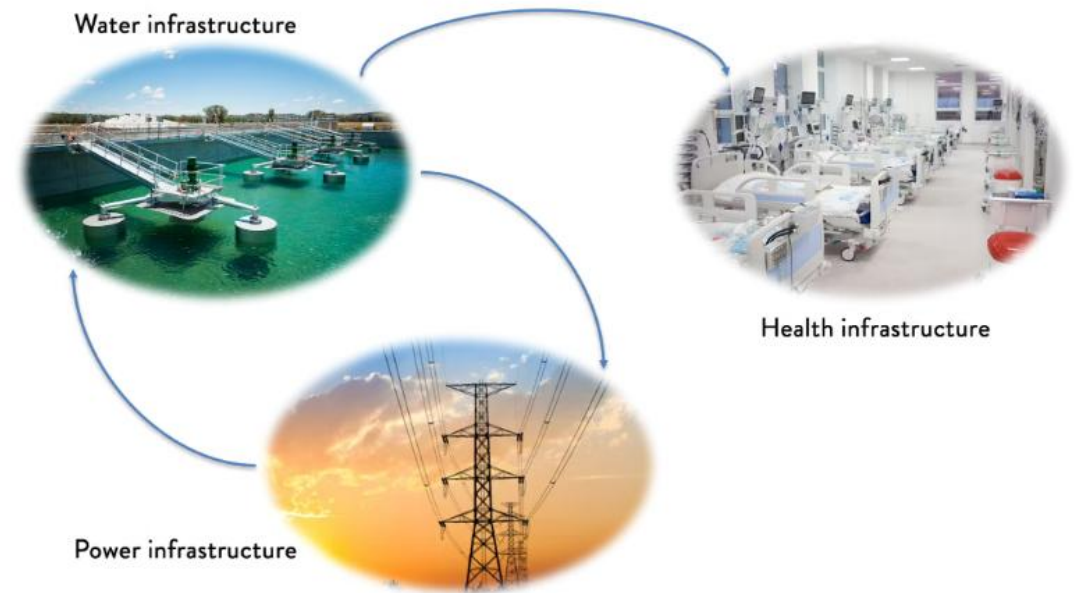
# 1. Interdependencies between Critical Infrastructures

## 1.1 Why Model Interdependencies?

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## Understanding Infrastructure Dependencies



# 1. Interdependencies between Critical Infrastructures

## 1.1 Why Model Interdependencies?

The interdependency literature adopts **different** planning horizons



System-of-Systems Planner

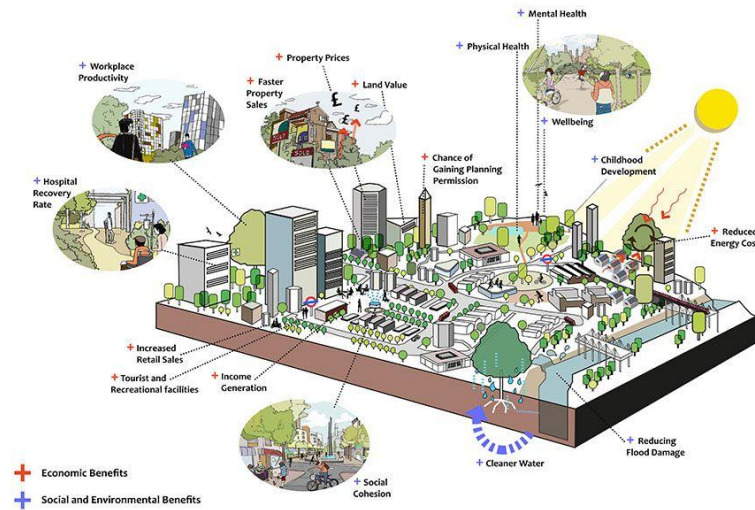


Owner or Operator of an infrastructure

# 1. Interdependencies between Critical Infrastructures

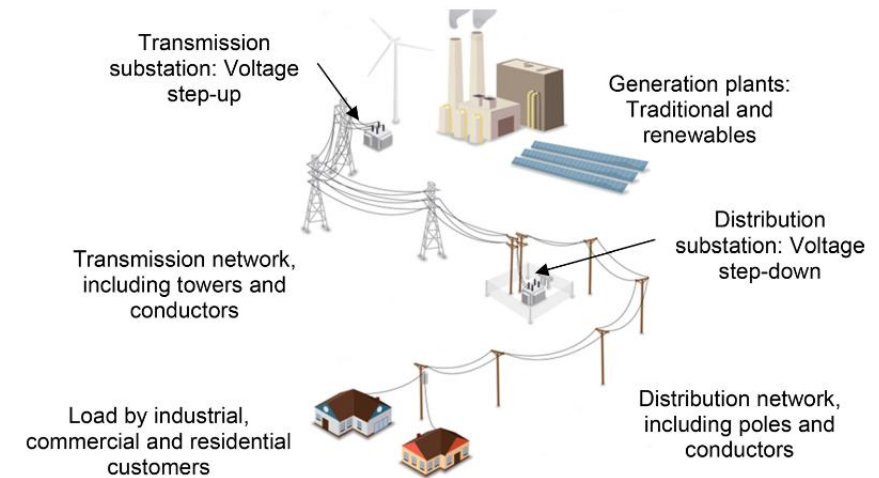
## 1.1 Why Model Interdependencies?

The interdependency literature adopts **different** planning horizons



### System-of-Systems Planner

- What are the expected **economic losses** of an extreme event in the region?
- Which is the **most critical industry** in terms of inoperability?
- How can we **expand networks** to introduce redundancies in the most vulnerable locations?



### Owner or Operator of an infrastructure

- What is the **change in resilience** of my CI when adding a security barrier?
- What is the **expected cost** of adding a security barrier?

[6]



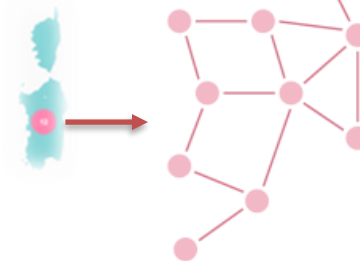
# 1. Interdependencies between Critical Infrastructures

## 1.1 Why Model Interdependencies?

**Holistic approaches** provide strategic insights for system-of-systems planners



### Interdependency between CIs



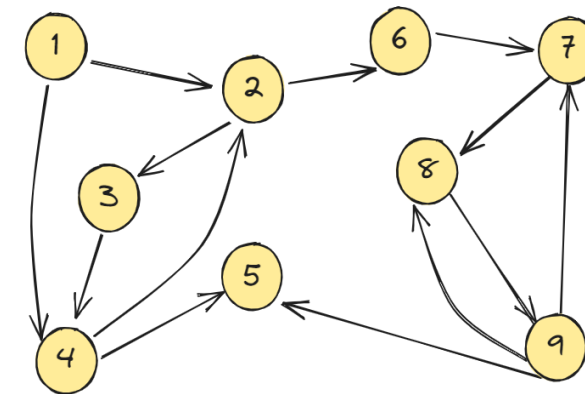
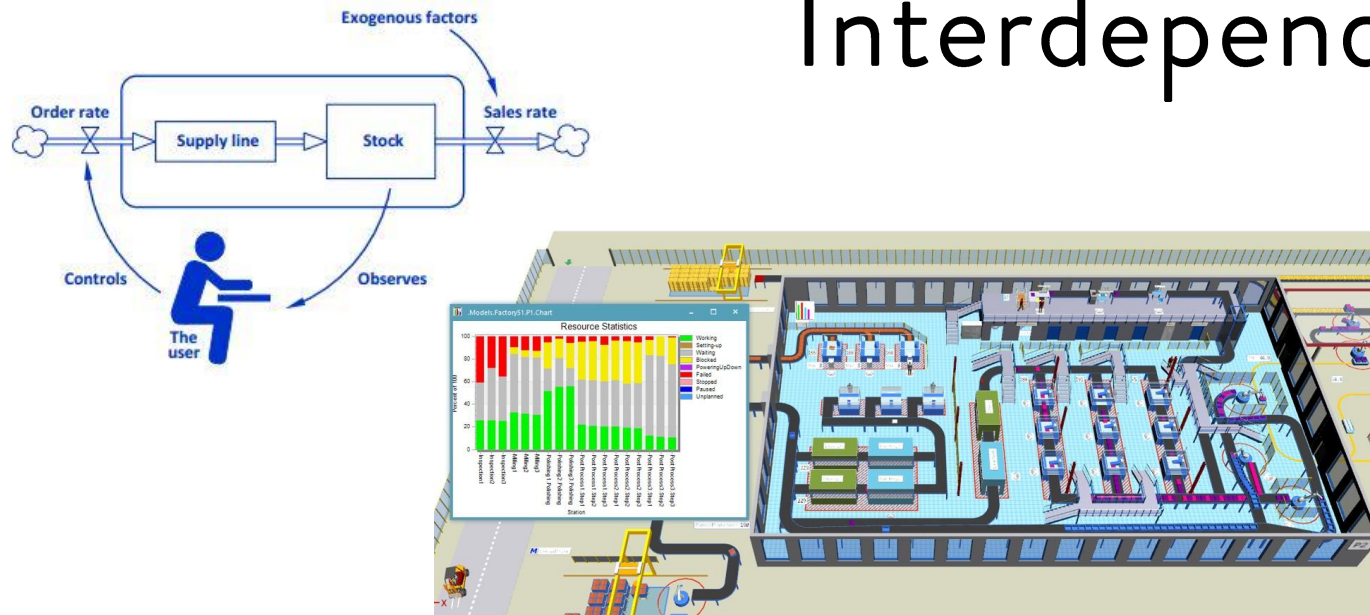
**Reductionist approaches** provide information to system operators for optimizing infrastructure layout, safety measures, and resilience within a CI

# 1. Interdependencies between Critical Infrastructures

## 1.1 Why Model Interdependencies? - References

- [1] Loggins, R., Richard G. L., Mitchell, J., Sharkey, T., and Wallace, W.A. (2019). CRISIS: Modeling the Restoration of Interdependent Civil and Social Infrastructure Systems Following an Extreme Event. *Natural Hazards Review* 20(3):1–21. doi: 10.1061/(asce)nh.1527-6996.0000326.
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# 1.2 Approaches Available to Model Interdependencies

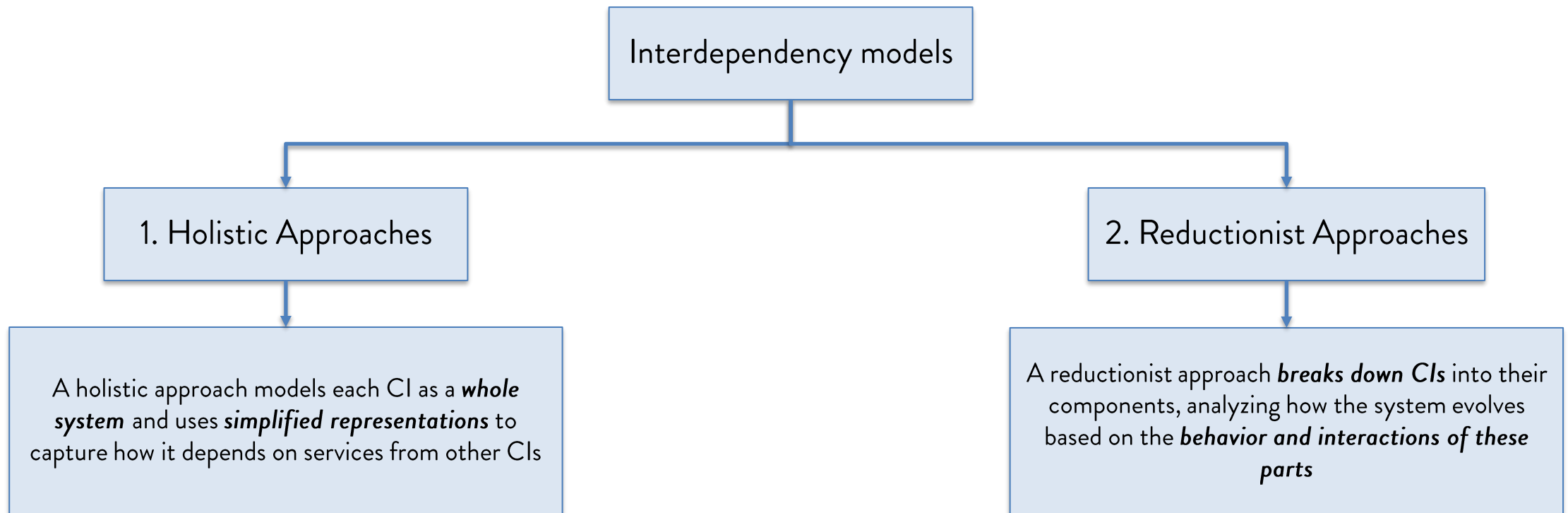




# 1. Interdependencies between Critical Infrastructures

## 1.2 Approaches Available to Model Interdependencies

Models can be classified into **two main categories** based on **how they capture** dependencies and interdependencies



# 1. Interdependencies between Critical Infrastructures

## 1.2 Approaches Available to Model Interdependencies

### 1. Holistic Approaches

#### 1.1 Survey-based table

*This involves collecting **expert opinion** through surveys to assess dependencies and interdependencies between CIs.*



The representation of interdependency is simple and intuitive



Results are specific to the surveyed event and community

### Toward Disaster-Resilient Cities: Characterizing Resilience of Infrastructure Systems with Expert Judgments

Stephanie E. Chang, Timothy McDaniels, Jana Fox, Rajan Dhariwal, and Holly Longstaff

Sector	Estimated Service Disruption Level			Service Disruption Level Scale	
	0 Hours	72 Hours	2 Weeks		
Electric power	Severe Disruption	Moderate Disruption	Low Disruption	No Loss	No service disruption
Communications	Severe Disruption	Moderate Disruption	Low Disruption	Low Disruption	Low extent & Low impact disruptions; may be ongoing
Water	Severe Disruption	Moderate Disruption	Low Disruption	Moderate Disruption	Low extent & High impact or High extent & Low impact disruptions
Transportation (Intraregional)	Severe Disruption	Moderate Disruption	Low Disruption	Severe Disruption	High extent & High impact disruptions
Transportation (Interregional)	Severe Disruption	Moderate Disruption	Low Disruption		
Healthcare	Severe Disruption	Moderate Disruption	Low Disruption		
Government	Moderate Disruption	Moderate Disruption	Low Disruption		
Natural Gas	Moderate Disruption	Moderate Disruption	Low Disruption		
Wastewater	Severe Disruption	Moderate Disruption	Low Disruption		

# 1. Interdependencies between Critical Infrastructures

## 1.2 Approaches Available to Model Interdependencies

### 1. Holistic Approaches

#### 1.2 Correlation-based table

*This utilizes correlation coefficients, such as **Pearson** and **cross-correlation coefficients**, to quantify how CIs are interconnected, using data on system **failures and recovery patterns over time***



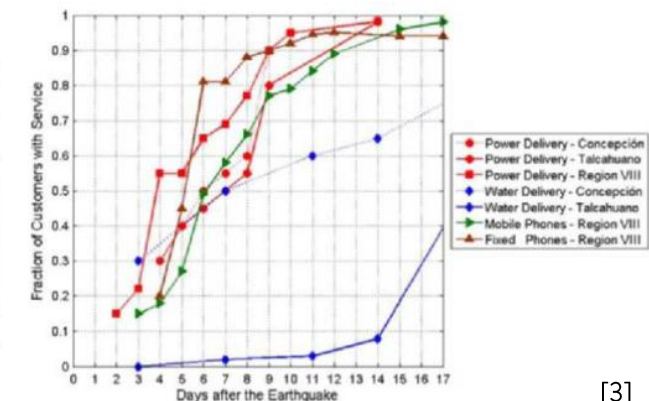
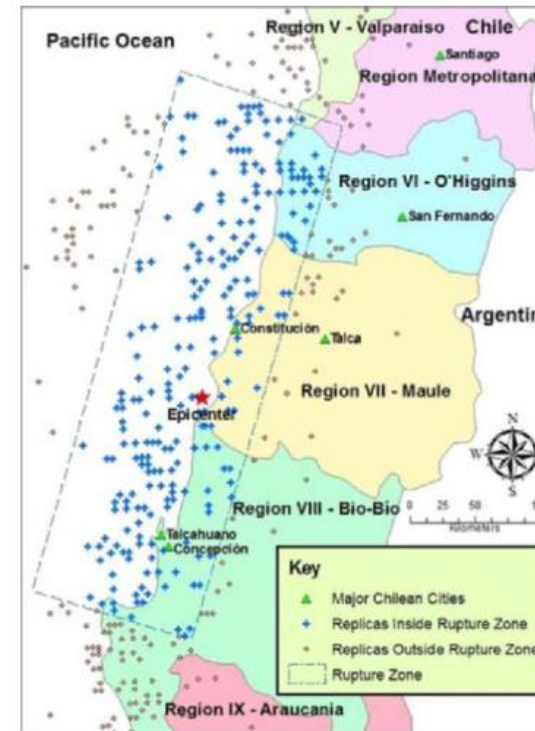
Utilizes statistical coefficients to analyse historical data on failures and recovery



Interpretation requires expert analysis, introducing potential bias

### Quantification of Lifeline System Interdependencies after the 27 February 2010 $M_w$ 8.8 Offshore Maule, Chile, Earthquake

Leonardo Dueñas-Osorio, M. EERI, and Alexis Kwasinski





# 1. Interdependencies between Critical Infrastructures

## 1.2 Approaches Available to Model Interdependencies

1. Holistic Approaches

Assessing the economic ripple effects of critical infrastructure failures using the dynamic inoperability input-output model: a case study of the Taal Volcano eruption

Joost Santos<sup>a</sup>, Krister Ian Daniel Z. Roquel<sup>b</sup>, Albert Lamberte<sup>c</sup>, Raymond R. Tan<sup>d</sup>, Kathleen B. Aviso<sup>d</sup>, John Frederick D. Tapia<sup>d</sup>, Christine Alyssa Solis<sup>c</sup> and Krista Danielle S. Yu<sup>c</sup>

### 1.3 Economic theory-based models

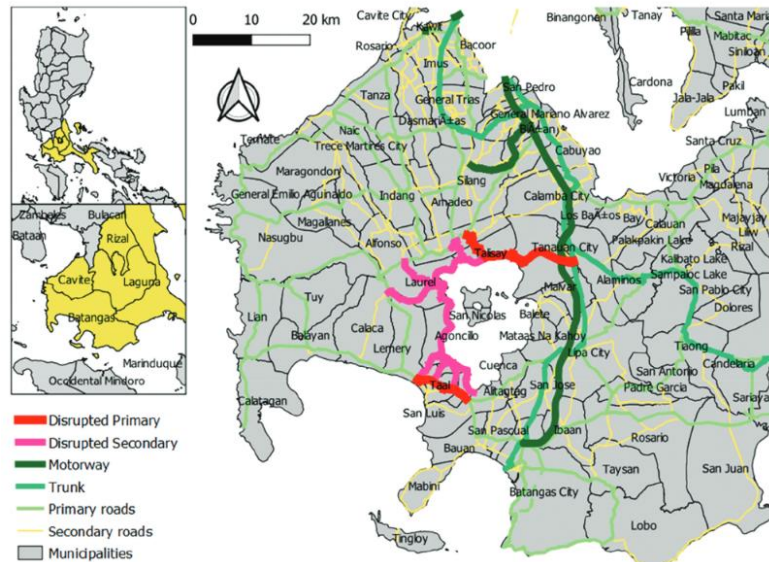
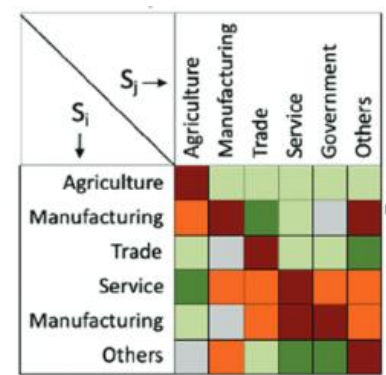
These models use *linear equations* to evaluate economic interactions, supporting policy development and disaster planning



Supports economic policy development and disaster response planning



Focuses mainly on economic impacts at the system level



# 1. Interdependencies between Critical Infrastructures

## 1.2 Approaches Available to Model Interdependencies

### 1. Holistic Approaches

### 1.4 System dynamics

*These models are used to understand the **nonlinear behavior** of complex systems over time, helping to analyze CI interactions and evolution*



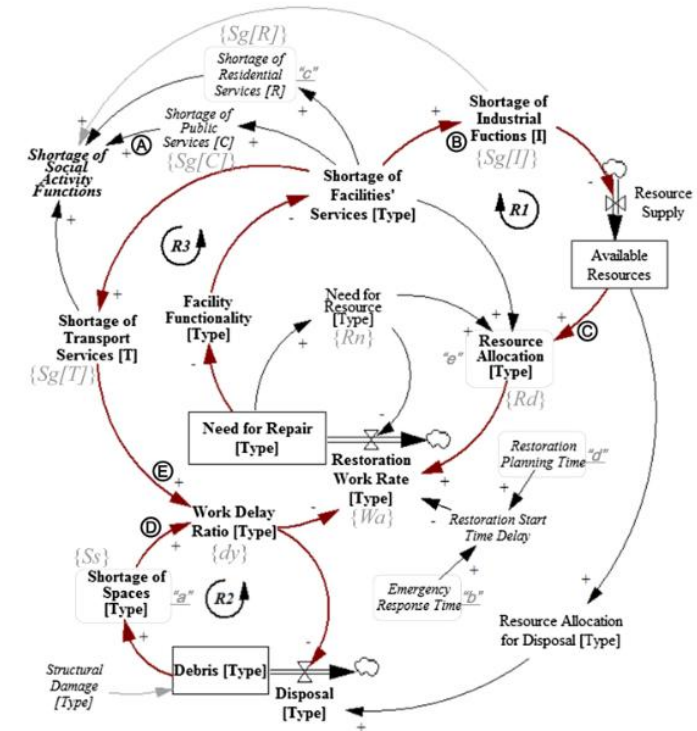
Provides insights into complex systems behaviors over time using causal-loop and stock-flow diagrams



Limited in uncertainty quantification and difficult to validate

## Postdisaster Interdependent Built Environment Recovery Efforts and the Effects of Governmental Plans: Case Analysis Using System Dynamics

Sungjoo Hwang, S.M.ASCE<sup>1</sup>; Moonseo Park, A.M.ASCE<sup>2</sup>; Hyun-Soo Lee, A.M.ASCE<sup>3</sup>; SangHyun Lee, M.ASCE<sup>4</sup>; and Hyunsoo Kim, S.M.ASCE<sup>5</sup>



[5]

# 1. Interdependencies between Critical Infrastructures

## 1.2 Approaches Available to Model Interdependencies

### 1. Holistic Approaches

### 1.5 Data-driven models

*Data-driven frameworks leverage **vast amounts of accessible data**, such as news and social media, to analyze resilience and manage disasters effectively*



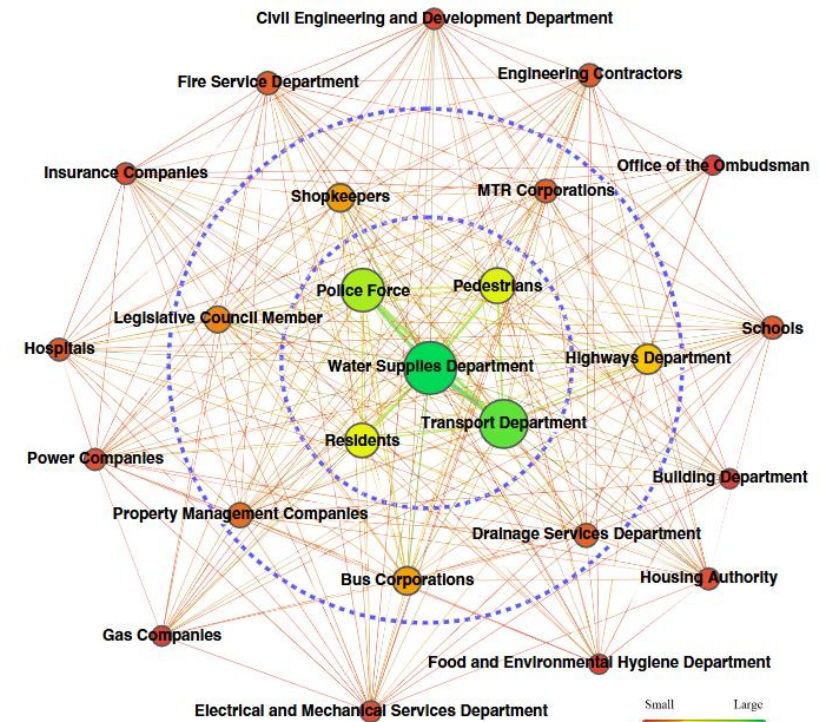
Capable of integrating diverse data sources



Relies heavily on large amounts of data, which may be unavailable or inconsistent

## Delineating Infrastructure Failure Interdependencies and Associated Stakeholders through News Mining: The Case of Hong Kong's Water Pipe Bursts

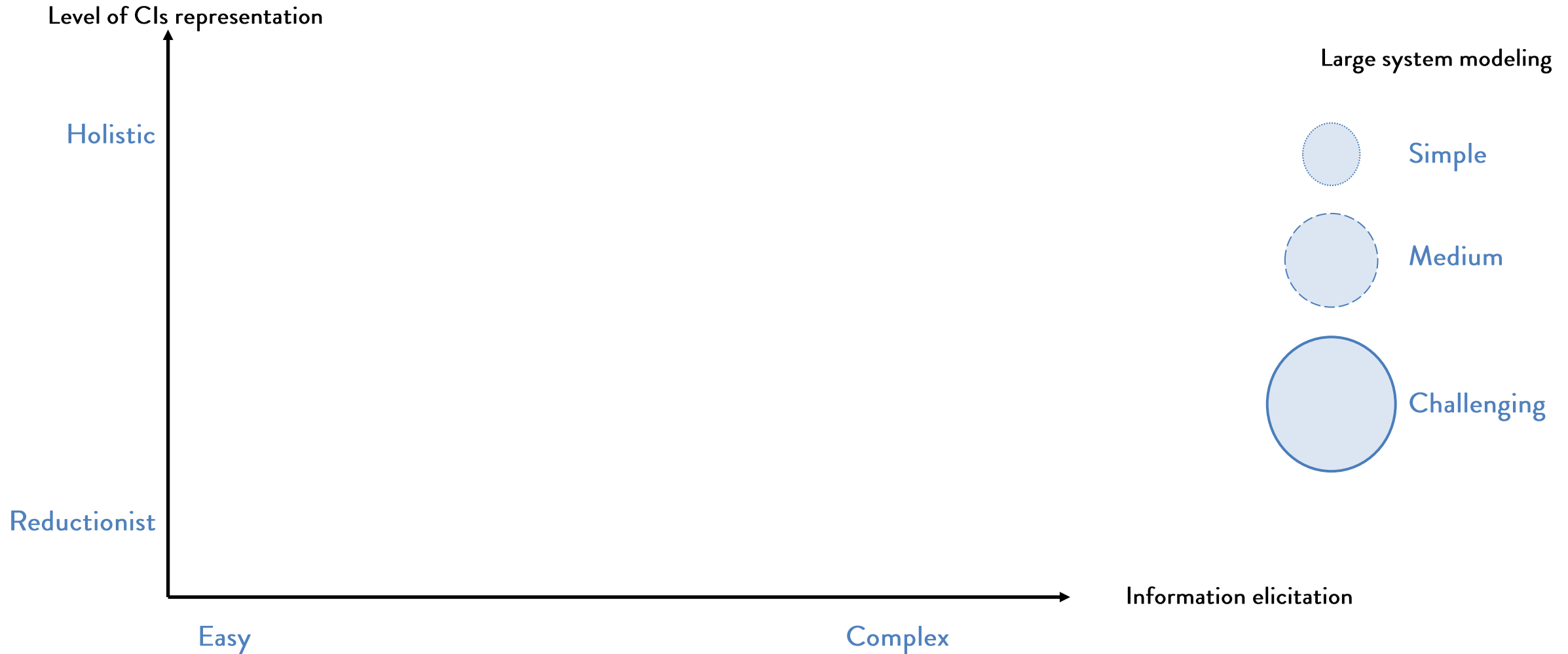
Shenghua Zhou, S.M.ASCE<sup>1</sup>; S. Thomas Ng, Ph.D.<sup>2</sup>; Yifan Yang<sup>3</sup>; and J. Frank Xu, Ph.D.<sup>4</sup>



[6]

# 1. Interdependencies between Critical Infrastructures

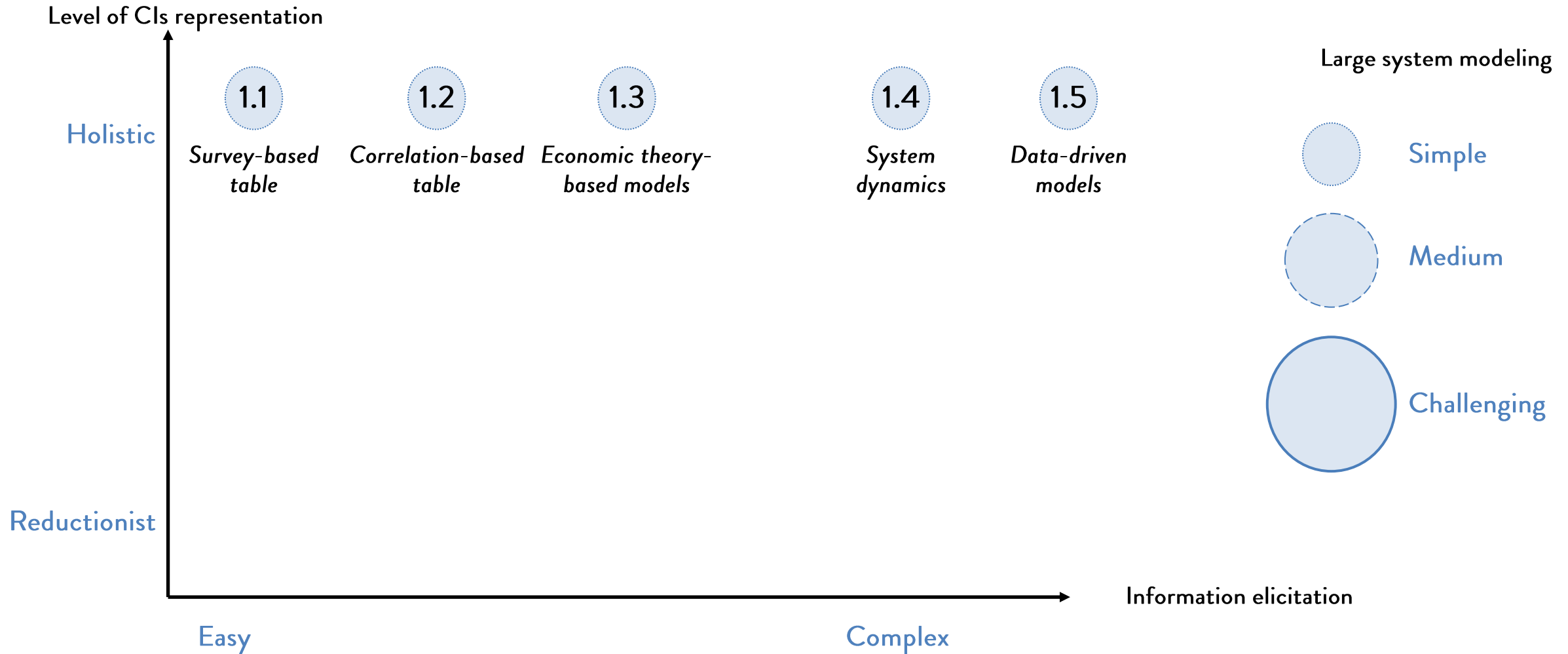
## 1.2 Approaches Available to Model Interdependencies





# 1. Interdependencies between Critical Infrastructures

## 1.2 Approaches Available to Model Interdependencies



# 1. Interdependencies between Critical Infrastructures

## 1.2 Approaches Available to Model Interdependencies

### Vulnerability of Smart Grids with Variable Generation and Consumption: a System of Systems Perspective

Enrico Zio, *Senior Member, IEEE*, and Giovanni Sansavini



[7]

## 2. Reductionist Approaches

### 2.1 Graph theory-based models

*These models use **matrices**, such as joint adjacency and probability matrices, to map interdependencies within networked systems*



Local interactions of the CI are considered



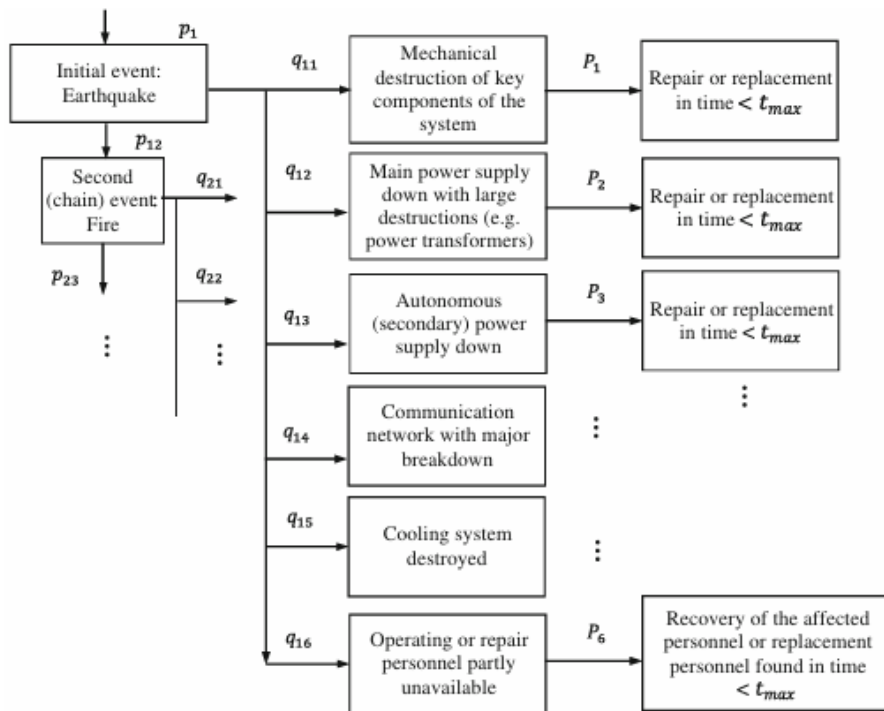
Requires extensive knowledge of network topology and node/link characteristics

# 1. Interdependencies between Critical Infrastructures

## 1.2 Approaches Available to Model Interdependencies

### Defining resilience using probabilistic event trees

Horia-Nicolai L. Teodorescu<sup>1,2</sup>



## 2. Reductionist Approaches

### 2.2 Discrete event simulation

*This approach models intricate dependencies within CIs as a sequence of distinct events, using sequential, conditional logic and causal relationships to assess failure probabilities under specific conditions*



Provides clear visualization of causal relationships and event progressions

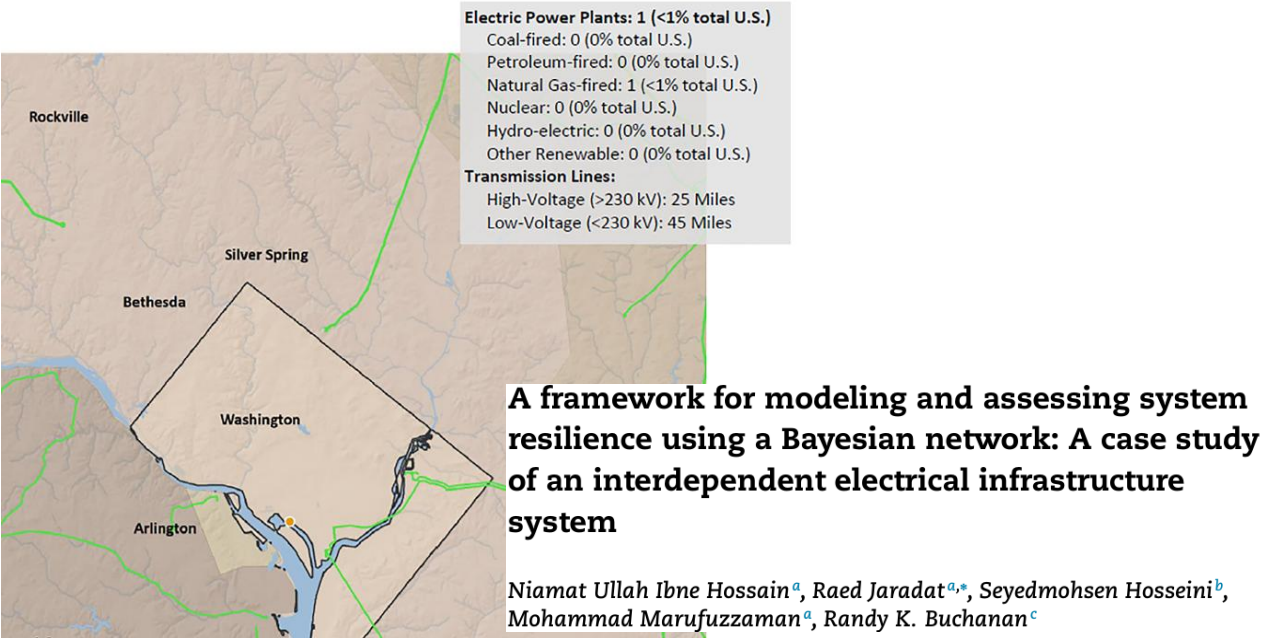


Can be computationally intensive

[8]

# 1. Interdependencies between Critical Infrastructures

## 1.2 Approaches Available to Model Interdependencies



## 2. Reductionist Approaches

### 2.3 Bayesian networks

*This approach models conditional dependencies using probabilistic graphs and Bayesian inference, making it effective for assessing causation and interdependency modeling*



Effectively models and assesses causal relationships within interdependencies

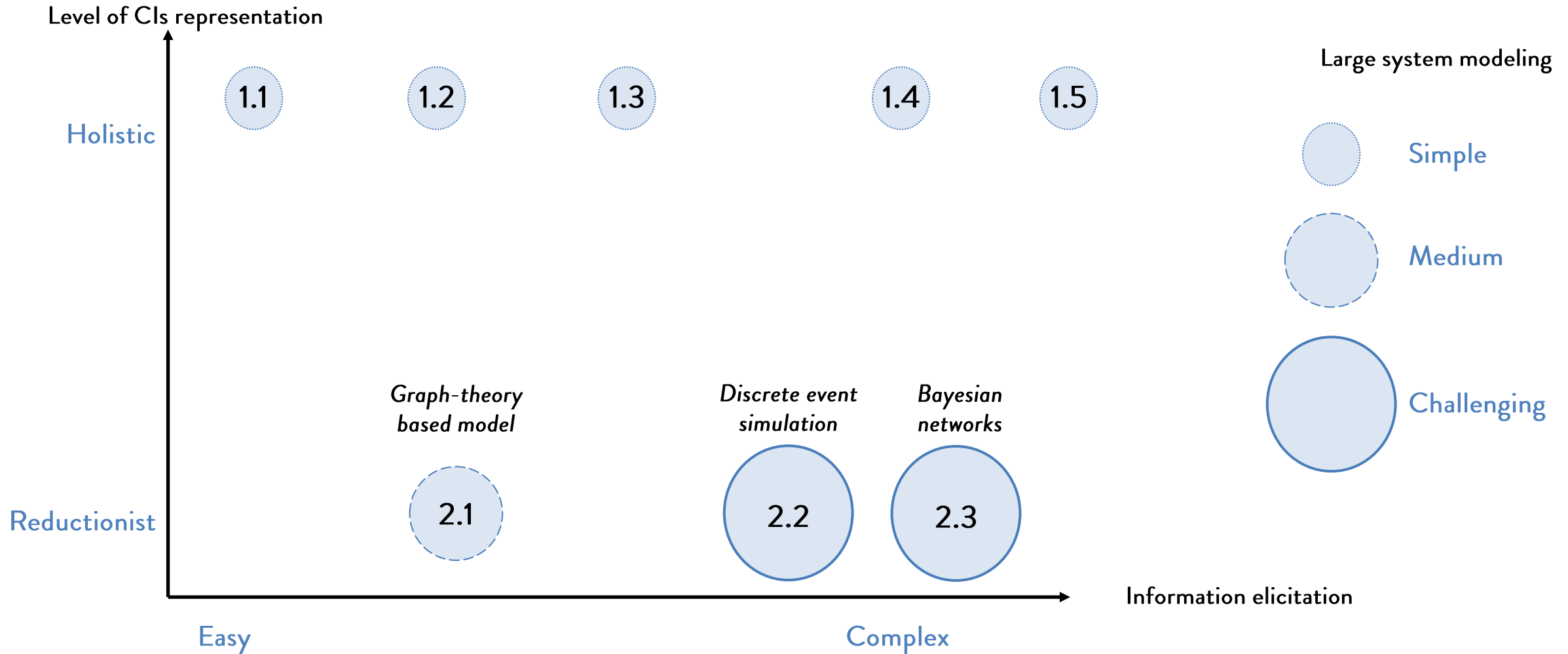


Becomes increasingly computationally complex as nodes are added



# 1. Interdependencies between Critical Infrastructures

## 1.2 Approaches Available to Model Interdependencies

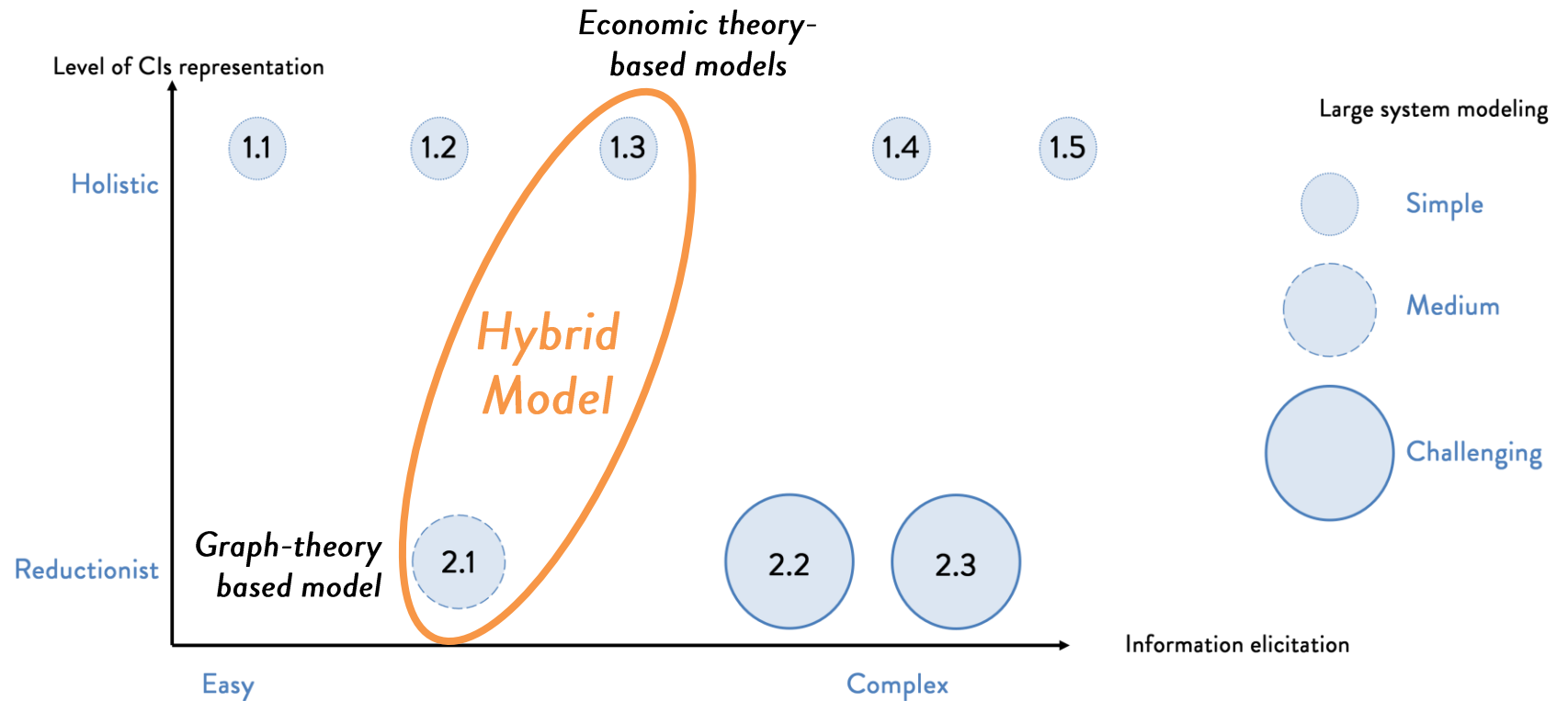


# 1. Interdependencies between Critical Infrastructures

## 1.2 Approaches Available to Model Interdependencies

A *hybrid approach* is needed to support planners and operators, *combining scalability for strategic planning with detailed insights into individual CIs*

Our model combines *graph-based and economic approaches* to capture physical interdependencies and quantify cascading effects for resilience planning



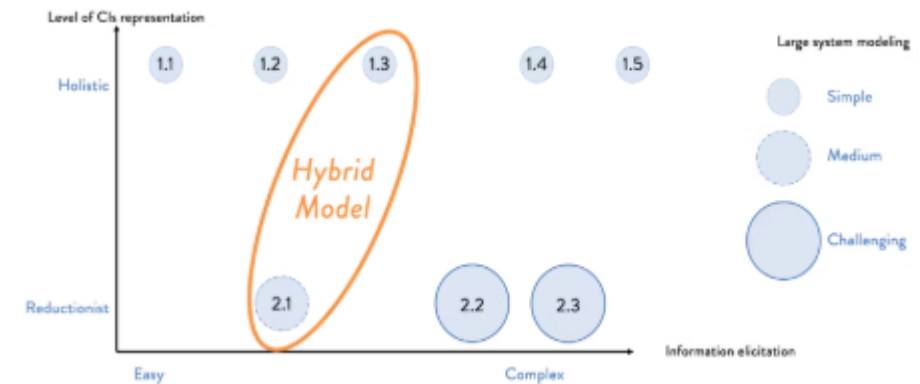
# 1. Interdependencies between Critical Infrastructures

## 1.2 Approaches Available to Model Interdependencies

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Read each scenario and match it with the most appropriate modeling approach



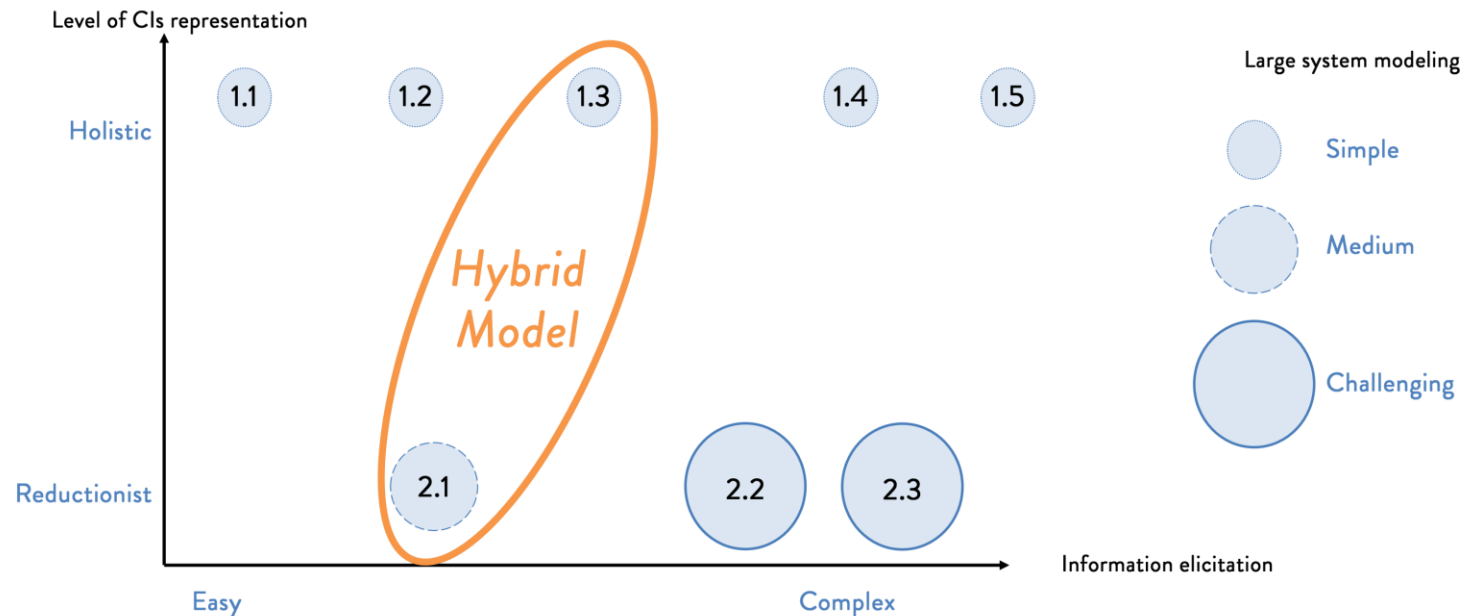
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## 1.2 Approaches Available to Model Interdependencies - References

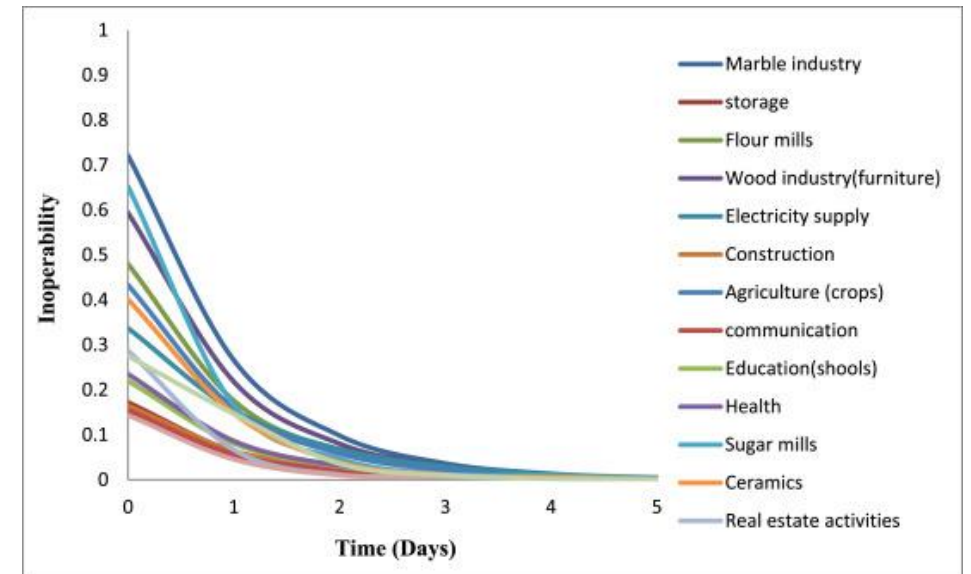
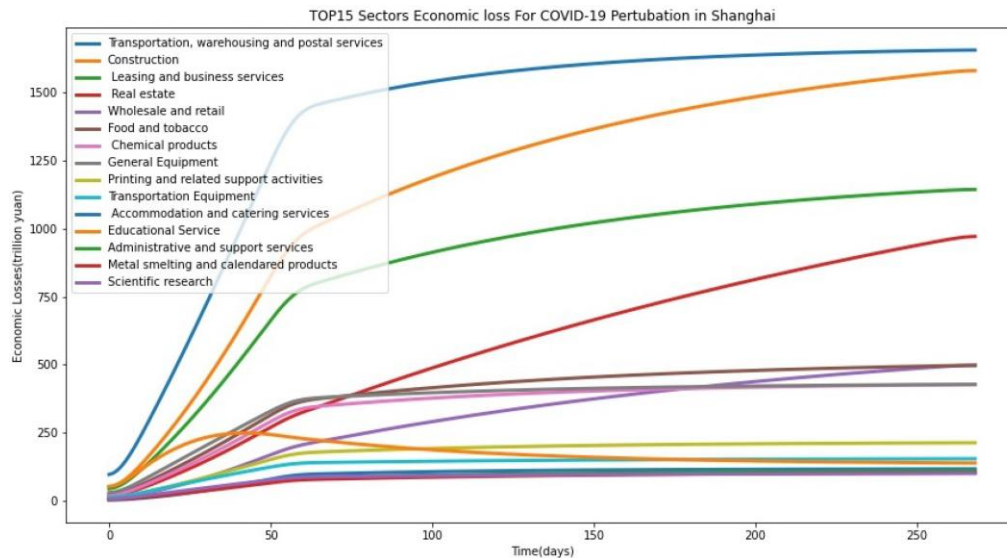
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## 2. Hybrid Approach to Model Interdependencies



## 2.1 Economic Theory-based Model: DIIM



## 2. Hybrid Approach to Model Interdependencies

### 2.1 Economic Theory-based Model: DIIM

[1]

The **Leontief Input-Output Analysis** was developed by economist **Wassily Leontief**; this method analyzes how **economic sectors** depend on one another.

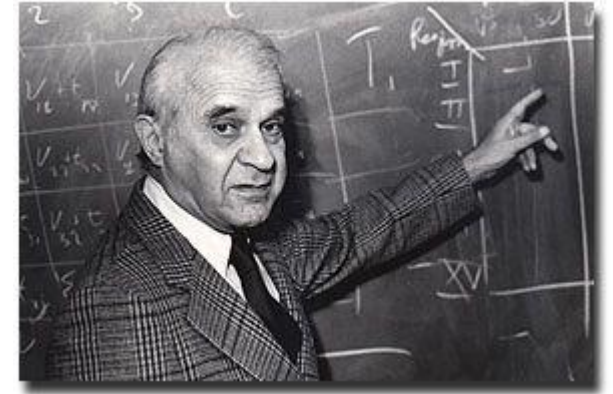
It is based on a **matrix model** that describes how the **output** from one industry becomes **input** for others.

Matrix of **technical coefficients**,  $a_{ij}$  represents how much from industry  $j$  is needed to produce 1 unit in industry  $i$

$$\bar{x} = \bar{A}\bar{x} + \bar{c}$$

**Final demand** vector, i.e.,  $c_i$  is the final demand for industry  $i$

**Total production output** vector, i.e.,  $x_i$  is the total production output for industry  $i$



He was awarded the Nobel Prize in 1973 for his work

All terms are expressed in units of output, and the model assumes linear production relationships

## 2. Hybrid Approach to Model Interdependencies

### 2.1 Economic Theory-based Model: DIIM

[1]

$$\bar{x} = \bar{\bar{A}}\bar{x} + \bar{c} \rightarrow (\bar{\bar{I}} - \bar{\bar{A}})\bar{x} = \bar{c} \rightarrow \bar{x} = (\bar{\bar{I}} - \bar{\bar{A}})^{-1}\bar{c}$$

We solve this equation to find how much total production is needed in each industry to meet final demand, considering the interdependencies between industries

Imagine we have 3 industries: Food (F), Energy (E) and Transport (T).  
The interaction between them can be represented by the following matrix:

$$\bar{\bar{A}} = \begin{bmatrix} 0.1 & 0.2 & 0.1 \\ 0.3 & 0.1 & 0.2 \\ 0.2 & 0.1 & 0.1 \end{bmatrix}$$

If the final demand is  $\bar{c} = \begin{bmatrix} 100 \\ 50 \\ 80 \end{bmatrix}$

Can you determine the total production vector  $\bar{x}$ ?



## 2. Hybrid Approach to Model Interdependencies

### 2.1 Economic Theory-based Model: DIIM

[1]

$$\bar{x} = \bar{A}\bar{x} + \bar{c} \rightarrow (\bar{I} - \bar{A})\bar{x} = \bar{c} \rightarrow \bar{x} = (\bar{I} - \bar{A})^{-1}\bar{c}$$

$$\bar{A} = \begin{bmatrix} 0.10 & 0.20 & 0.10 \\ 0.30 & 0.10 & 0.20 \\ 0.20 & 0.10 & 0.10 \end{bmatrix} \quad \bar{c} = \begin{bmatrix} 100 \\ 50 \\ 80 \end{bmatrix} \quad \bar{I} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$(\bar{I} - \bar{A}) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} - \begin{bmatrix} 0.10 & 0.20 & 0.10 \\ 0.30 & 0.10 & 0.20 \\ 0.20 & 0.10 & 0.10 \end{bmatrix} = \begin{bmatrix} 0.90 & -0.20 & -0.10 \\ -0.30 & 0.90 & -0.20 \\ -0.20 & -0.10 & 0.90 \end{bmatrix}$$

$$(\bar{I} - \bar{A})^{-1} = \begin{bmatrix} 0.90 & -0.20 & -0.10 \\ -0.30 & 0.90 & -0.20 \\ -0.20 & -0.10 & 0.90 \end{bmatrix}^{-1} = \begin{bmatrix} 1.26 & 0.30 & 0.21 \\ 0.49 & 1.26 & 0.33 \\ 0.33 & 0.21 & 1.19 \end{bmatrix}$$

$$\begin{bmatrix} 1.26 & 0.30 & 0.21 \\ 0.49 & 1.26 & 0.33 \\ 0.33 & 0.21 & 1.19 \end{bmatrix} \begin{bmatrix} 100 \\ 50 \\ 80 \end{bmatrix} = \bar{x}$$

Compute the total production

$x_F, x_E, x_T$

## 2. Hybrid Approach to Model Interdependencies

### 2.1 Economic Theory-based Model: DIIM

[1]

$$\bar{x} = \bar{A}\bar{x} + \bar{c} \rightarrow (\bar{I} - \bar{A})\bar{x} = \bar{c} \rightarrow \bar{x} = (\bar{I} - \bar{A})^{-1}\bar{c}$$

$$\bar{A} = \begin{bmatrix} 0.10 & 0.20 & 0.10 \\ 0.30 & 0.10 & 0.20 \\ 0.20 & 0.10 & 0.10 \end{bmatrix} \quad \bar{c} = \begin{bmatrix} 100 \\ 50 \\ 80 \end{bmatrix} \quad \bar{I} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$(\bar{I} - \bar{A}) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} - \begin{bmatrix} 0.10 & 0.20 & 0.10 \\ 0.30 & 0.10 & 0.20 \\ 0.20 & 0.10 & 0.10 \end{bmatrix} = \begin{bmatrix} 0.90 & -0.20 & -0.10 \\ -0.30 & 0.90 & -0.20 \\ -0.20 & -0.10 & 0.90 \end{bmatrix}$$

$$(\bar{I} - \bar{A})^{-1} = \begin{bmatrix} 0.90 & -0.20 & -0.10 \\ -0.30 & 0.90 & -0.20 \\ -0.20 & -0.10 & 0.90 \end{bmatrix}^{-1} = \begin{bmatrix} 1.26 & 0.30 & 0.21 \\ 0.49 & 1.26 & 0.33 \\ 0.33 & 0.21 & 1.19 \end{bmatrix}$$

$$\begin{bmatrix} 1.26 & 0.30 & 0.21 \\ 0.49 & 1.26 & 0.33 \\ 0.33 & 0.21 & 1.19 \end{bmatrix} \begin{bmatrix} 100 \\ 50 \\ 80 \end{bmatrix} = \bar{x} = \begin{bmatrix} 157.8 \\ 138.4 \\ 138.7 \end{bmatrix}$$

The Food industry must produce **157.8 units**,  
the Energy industry must produce **138.4 units**, and  
the Transport industry must produce **138.7 units**,

To meet the final demand of **100, 50, and 80**  
respectively, considering interdependencies

# 2. Hybrid Approach to Model Interdependencies

## 2.1 Economic Theory-based Model: DIIM

How to obtain the Leontief coefficient matrix?



	Cotton	...
F	100	
G	120	
H	90	

	S	T	W
Cotton	170	85	45
Polyester	30	95	165
⋮			

## 2. Hybrid Approach to Model Interdependencies

### 2.1 Economic Theory-based Model: DIIM

	Cotton	...		S	T	W
F	100		Cotton	170	85	45
G	120		Polyester	30	95	165
H	90		⋮			
	310			250	320	510

$$a_{FS} = \frac{100}{310} \times \frac{170}{250} = 0.22$$

$$a_{FT} = \frac{100}{310} \times \frac{85}{320} = 0.09$$

$$a_{FW} = \frac{100}{310} \times \frac{45}{510} = 0.03$$

What are the values of  $a_{GT}$  and  $a_{HW}$ ?

$$a_{GT} = \frac{120}{310} \times \frac{85}{320} = 0.10$$

$$a_{HW} = \frac{90}{310} \times \frac{45}{510} = 0.03$$

## 2. Hybrid Approach to Model Interdependencies

### 2.1 Economic Theory-based Model: DIIM

[2]

2001

$$\bar{x} = \bar{\bar{A}}\bar{x} + \bar{c} \longrightarrow \text{LEONTIEF-BASED MODEL OF RISK IN COMPLEX INTERCONNECTED INFRASTRUCTURES}$$

By Yacov Y. Haimes<sup>1</sup> and Pu Jiang<sup>2</sup>

*Inoperability* vector of critical infrastructure, i.e.,  $q_i$  is the inability (expressed as a percentage) of the  $i$ -th CI to operate correctly

$$\bar{q} = \bar{\bar{A}}\bar{q} + \bar{c}$$

*Perturbation* vector, i.e.,  $c_i$  is the initial perturbation affecting the  $i$ -th CI due to external factors

Matrix of *interdependency coefficients*,  $a_{ij}$  represents the fraction of inoperability that the  $j$ -th CI contributes to the  $i$ -th CI due to their interdependencies

*Inoperability Input-output Model*



## 2. Hybrid Approach to Model Interdependencies

### 2.1 Economic Theory-based Model: DIIM

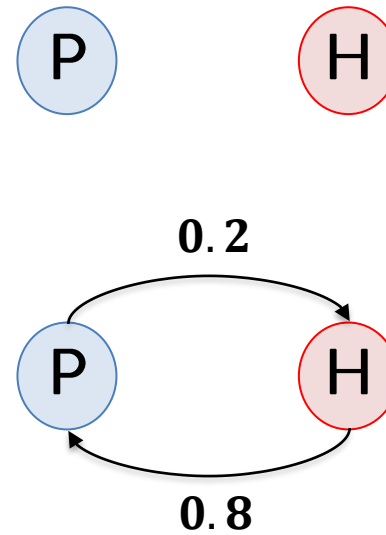
[2]

To show how to apply the Inoperability Input-output Model (IIM), we will solve the following example.

Imagine we have *two infrastructures*.

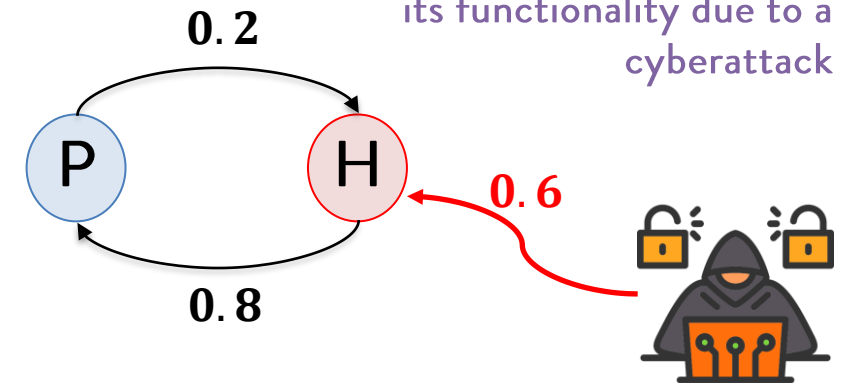
The inoperability is represented by  $q_P$  and  $q_H$

Suppose a failure in infrastructure H causes infrastructure P to become 80% inoperable, and a failure in infrastructure P causes infrastructure H to become 20% inoperable



Then  $\bar{A} = \begin{bmatrix} 0 & 0.8 \\ 0.2 & 0 \end{bmatrix}$

Now suppose that infrastructure H loses 60% of its functionality due to a cyberattack



*Estimate the inoperability of both infrastructures*

## 2. Hybrid Approach to Model Interdependencies

### 2.1 Economic Theory-based Model: DIIM

[2]

$$\bar{q} = \bar{\bar{A}}\bar{q} + \bar{c} \quad \bar{\bar{A}} = \begin{bmatrix} 0 & 0.8 \\ 0.2 & 0 \end{bmatrix} \quad \bar{c} = \begin{bmatrix} 0 \\ 0.6 \end{bmatrix}$$

$$\begin{bmatrix} q_P \\ q_H \end{bmatrix} = \begin{bmatrix} 0 & 0.8 \\ 0.2 & 0 \end{bmatrix} \begin{bmatrix} q_P \\ q_H \end{bmatrix} + \begin{bmatrix} 0 \\ 0.6 \end{bmatrix}$$

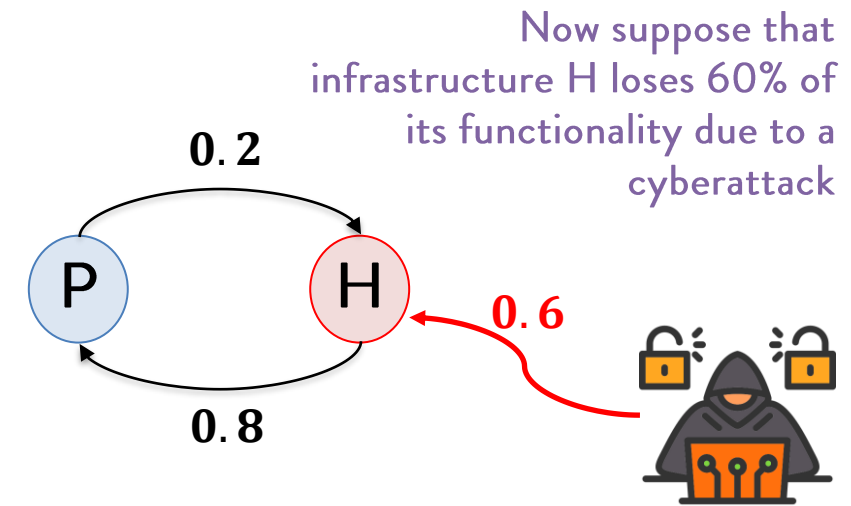
$$\begin{bmatrix} q_P \\ q_H \end{bmatrix} = \begin{bmatrix} 0.8q_H \\ 0.2q_P + 0.6 \end{bmatrix}$$

$$\begin{bmatrix} q_P \\ q_H \end{bmatrix} = \begin{bmatrix} 0.571 \\ 0.714 \end{bmatrix}$$

Note that inoperability of infrastructure *P* is **0.571**, even though it was not directly attacked.

This effect is purely due to the **interdependency** between the two infrastructures.

The inoperability of infrastructure *H* also increases by **0.114** due to its interdependency with infrastructure *P*



Estimate the inoperability of both infrastructures

## 2. Hybrid Approach to Model Interdependencies

### 2.1 Economic Theory-based Model: DIIM

[2]

Given the following description of interactions between four infrastructures, identify which interdependency matrix correctly represents the scenario

If the **power plant** fails completely, then the **transportation system** can perform only 60% of its functionality, whereas both the **hospital** and the **grocery store** cannot operate at all.

$$\bar{\bar{A}} = \begin{bmatrix} 0 & 0.9 & 0 & 0 \\ 0.4 & 0 & 0 & 0 \\ 1 & 0.8 & 0 & 0 \\ 1 & 0.9 & 0 & 0 \end{bmatrix}$$

If the **transportation system** fails completely, meaning workers and deliveries cannot reach their destinations, the **power plant** and the **grocery store** can each operate at only 10%, and the **hospital** at 20%.

$$\bar{A} = \begin{bmatrix} 0 & 0.9 & 0 & 0 \\ 0.6 & 0 & 0 & 0 \\ 1 & 0.8 & 0 & 0 \\ 1 & 0.9 & 0 & 0 \end{bmatrix}$$

On the other hand, the inoperability of the **hospital** or **grocery store** does not affect the operation of the **power plant** or the **transportation system**, nor do they significantly affect each other.

$$\bar{\bar{A}} = \begin{bmatrix} 0 & 0.1 & 0 & 0 \\ 0.6 & 0 & 0 & 0 \\ 1 & 0.2 & 0 & 0 \\ 1 & 0.1 & 0 & 0 \end{bmatrix}$$

## 2. Hybrid Approach to Model Interdependencies

### 2.1 Economic Theory-based Model: DIIM

[3]

Using the interdependency matrix, it is possible to estimate two indices:

#### Dependency index

$$\delta_i = \sum_{j=1}^n a_{ij}$$

measures how much infrastructure  $i$  depends on other infrastructures

- A **higher value** means infrastructure  $i$  becomes **highly inoperable when others fail**. It is less robust.
- A **lower value** means it can **maintain functionality** even when others are disrupted.

#### Influence index

$$\theta_j = \sum_{i=1}^n a_{ij}$$

measures how much infrastructure  $j$  influences the inoperability of others

- A **higher value** means failures in infrastructure  $j$  can cause **widespread disruptions**.
- A **lower value** means its failure has **limited impact** on other infrastructures.

## 2. Hybrid Approach to Model Interdependencies

### 2.1 Economic Theory-based Model: DIIM

Given the following interdependency matrix (ordered as: Power plant, Transportation system, Hospital, Grocery store), estimate the *dependency* and *influence* indices for each infrastructure.

*Which infrastructure is the least robust, and which one has the greatest influence on the others?*

$$\bar{A} = \begin{bmatrix} 0 & 0.9 & 0 & 0 \\ 0.4 & 0 & 0 & 0 \\ 1 & 0.8 & 0 & 0 \\ 1 & 0.9 & 0 & 0 \end{bmatrix}$$

Infrastructure	Dependency index ( $\delta_i$ )	Influence index ( $\theta_j$ )
Power plant	0.9	2.4
Transportation system	0.4	2.6
Hospital	1.8	0
Grocery store	1.9	0

*Least robust:* Grocery store

*Greatest influence:* Transportation system



## 2. Hybrid Approach to Model Interdependencies

### 2.1 Economic Theory-based Model: DIIM

[4]

2005

$$\bar{q} = \bar{\bar{A}}\bar{q} + \bar{c} \longrightarrow \text{Inoperability Input-Output Model for Interdependent Infrastructure Sectors. I: Theory and Methodology}$$

Yacov Y. Haimes, F.ASCE<sup>1</sup>; Barry M. Horowitz<sup>2</sup>; James H. Lambert, M.ASCE<sup>3</sup>; Joost R. Santos<sup>4</sup>; Chenyang Lian<sup>5</sup>; and Kenneth G. Crowther<sup>6</sup>

$$\bar{q}(t + 1) - \bar{q}(t) = \bar{\bar{K}}[\bar{\bar{A}}\bar{q}(t) + \bar{c}(t) - \bar{q}(t)]$$

Matrix of *resilience coefficients*,

$k_{ii}$  measures the recovery rate of the  $i$ -th CI, i.e., how quickly the  $i$ -th CI can recovery from inoperability.  
Larger coefficients correspond to faster infrastructure recovery

*Dynamic Inoperability Input-output Model*

## 2. Hybrid Approach to Model Interdependencies

### 2.1 Economic Theory-based Model: DIIM

[5]

## How to obtain the resilience coefficients?

$$k_{ii} = \frac{1}{T_i(1 - a_{ii})} \ln \left( \frac{q_i(0)}{q_i(T_i)} \right)$$

$q_i(0)$  the initial inoperability of the  $i$ -th CI;

$q_i(T_i)$  the inoperability that decision-makers of the  $i$ -th CI would like to achieve;

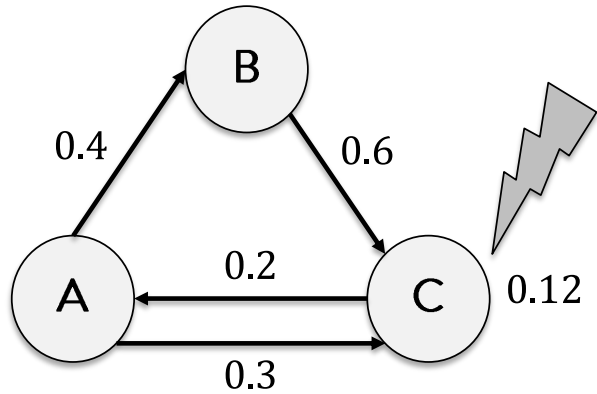
$T_i$  the required time to reach  $q_i(T_i)$ ;

If  $T_i$  is estimated by experts as the time required for the  $i$ -th CI to reduce its inoperability from 100% to a negligible value such as 1%, then:

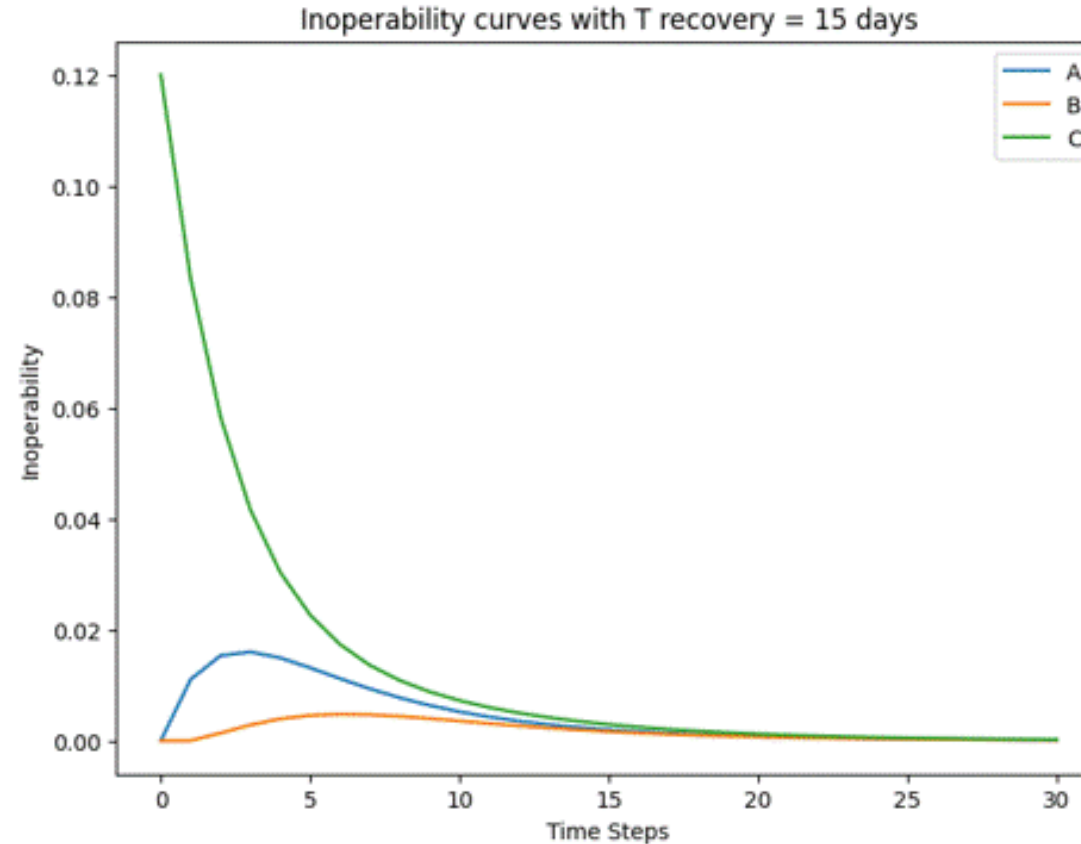
$$\ln \left( \frac{q_i(0)}{q_i(T_i)} \right) = \ln \left( \frac{1}{0.01} \right) = \ln(100)$$

## 2. Hybrid Approach to Model Interdependencies

### 2.1 Economic Theory-based Model: DIIM



$$\bar{A} = \begin{bmatrix} 0 & 0 & 0.3 \\ 0.4 & 0 & 0 \\ 0.2 & 0.6 & 0 \end{bmatrix}$$



$$\bar{K} = \begin{bmatrix} 0.31 & 0 & 0 \\ 0 & 0.31 & 0 \\ 0 & 0 & 0.31 \end{bmatrix}$$

## 2. Hybrid Approach to Model Interdependencies

### 2.1 Economic Theory-based Model: DIIM

#### [6] Static and dynamic metrics of economic resilience for interdependent infrastructure and industry sectors

Raghav Pant<sup>a</sup>, Kash Barker<sup>b,\*</sup>, Christopher W. Zobel<sup>c</sup>

<sup>a</sup> Environmental Change Institute, Centre for the Environment, University of Oxford, Oxford, UK

<sup>b</sup> School of Industrial and Systems Engineering, University of Oklahoma, Norman, OK 73019, USA

<sup>c</sup> Department of Business Information Technology, Virginia Polytechnic Institute and State University, VA, USA

Sample **A** matrix from the BEA 2011 input-output accounts.

IOCode	Commodities/industries Name	11 Agriculture	22 Utilities	23 Construction	48TW Transportation
11	Agriculture	0.1949842	0.0000011	0.0010711	0.0000444
21	Mining	0.0027765	0.1331650	0.0083818	0.0014131
22	Utilities	0.0154424	0.0002903	0.0032619	0.0028235
23	Construction	0.0044906	0.0107309	0.0007315	0.0075727
31G	Manufacturing	0.2005193	0.0080531	0.2442287	0.1873453
42	Wholesale trade	0.0475103	0.0010087	0.0232085	0.0135453
44RT	Retail trade	0.0018242	0.0000471	0.0359828	0.0047366
48TW	Transportation and warehousing	0.0215651	0.0341889	0.0134875	0.0862129
51	Information	0.0006798	0.0008374	0.0060602	0.0049617
FIRE	Finance, real estate	0.0782274	0.0066511	0.0300241	0.0548634
PROF	Professional services	0.0103202	0.0129371	0.0812154	0.0614684
6	Educational services	0.0021031	0.0000422	0.0000136	0.0000766
7	Arts, entertainment	0.0010167	0.0029302	0.0026978	0.0082843
81	Other services	0.0019078	0.0004941	0.0130497	0.0053673
G	Government	0.0002524	0.0001314	0.0000283	0.0105593

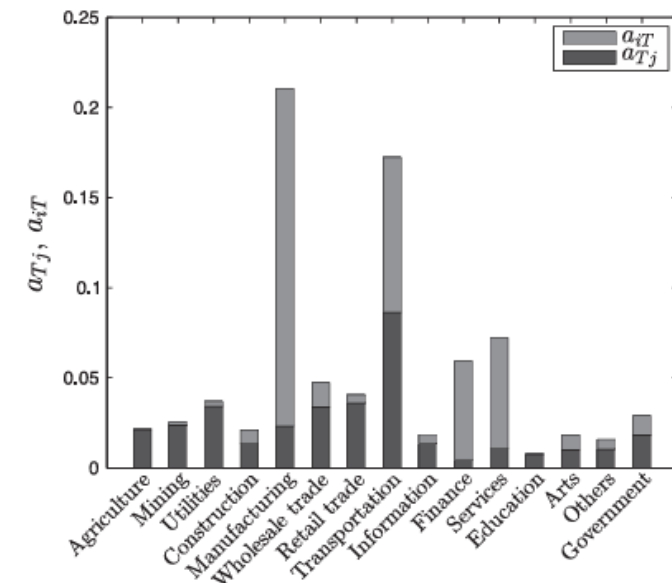



Fig. 1. Sample relationship among the Transportation sector and others.

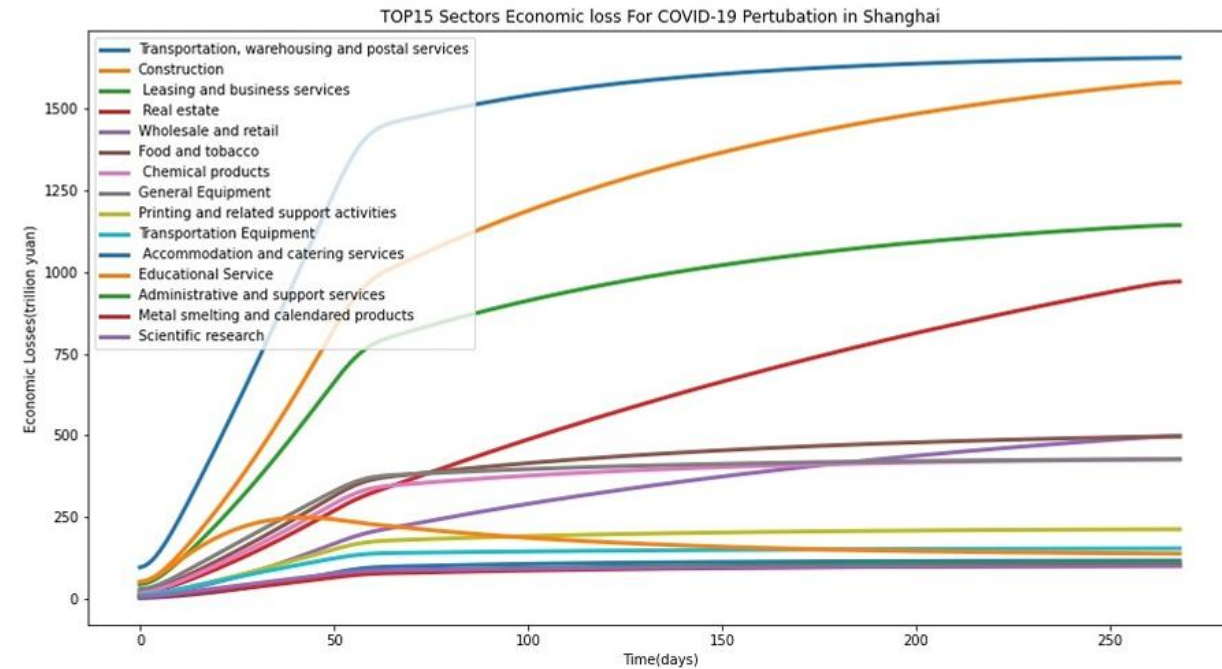
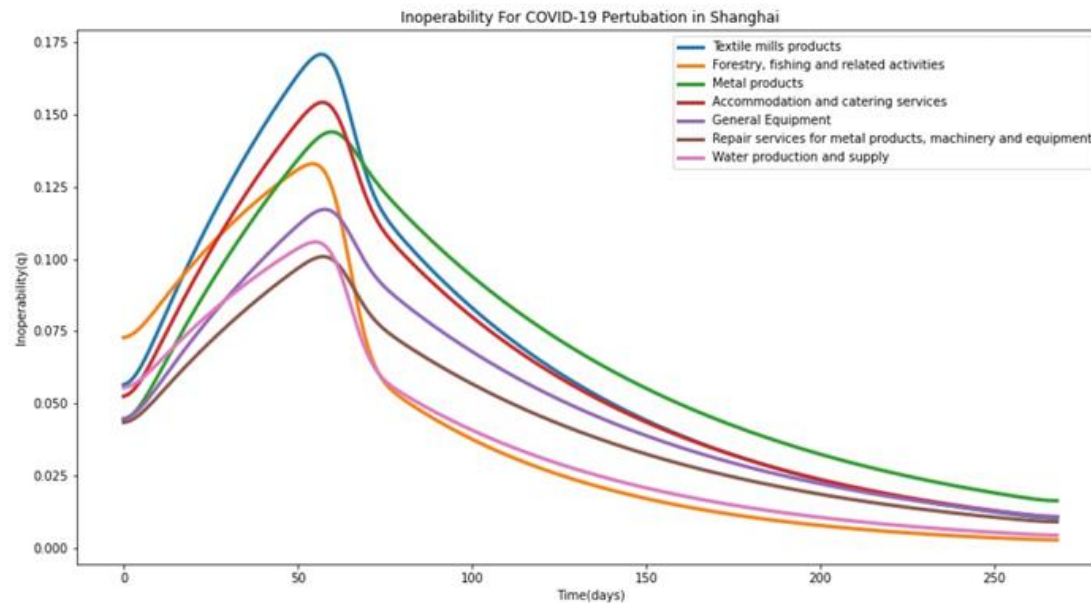
## 2. Hybrid Approach to Model Interdependencies

### 2.1 Economic Theory-based Model: DIIM

[7] Article

# A Demand-Side Inoperability Input–Output Model for Strategic Risk Management: Insight from the COVID-19 Outbreak in Shanghai, China

Jian Jin \*  and Haoran Zhou





## 2. Hybrid Approach to Model Interdependencies

### 2.1 Economic Theory-based Model: DIIM

#### [8] Critical infrastructure dependency assessment using the input-output inoperability model

Roberto Setola<sup>a,\*</sup>, Stefano De Porcellinis<sup>a</sup>, Marino Sforza<sup>b</sup>

<sup>a</sup> Complex Systems and Security Laboratory, University Campus BioMedico, Rome, Italy

<sup>b</sup> TERN - Italian Transmission System Operator, Rome, Italy

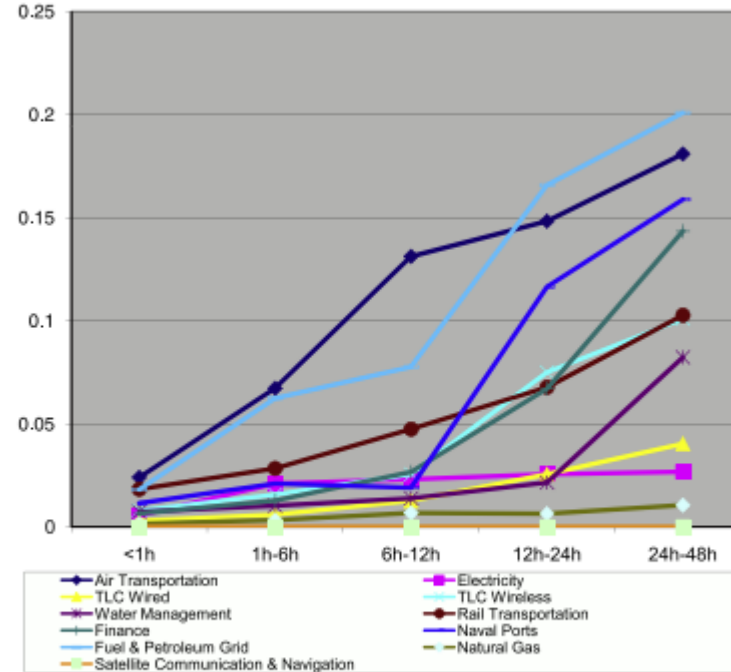


Fig. 4 - Dependency indices  $\delta_i$  for various outage periods.

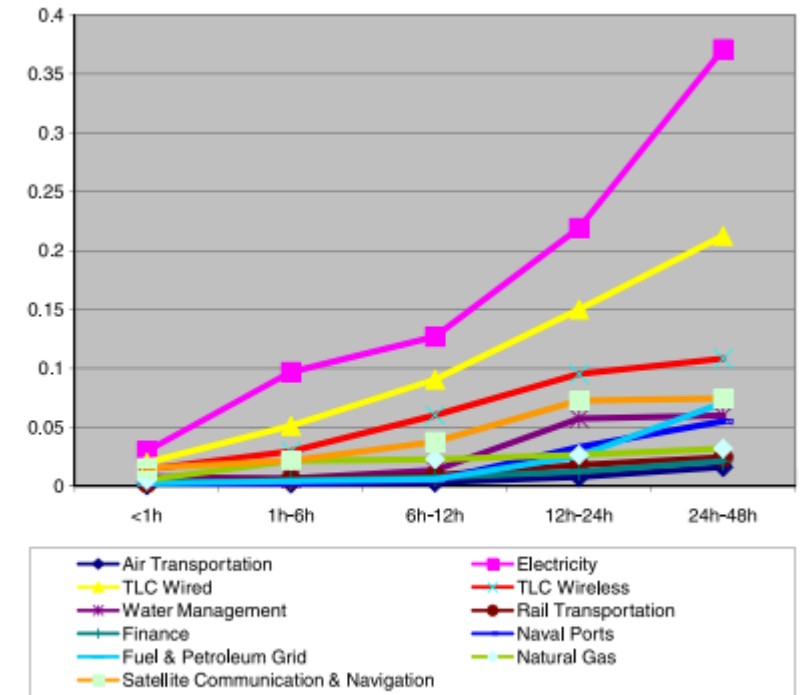


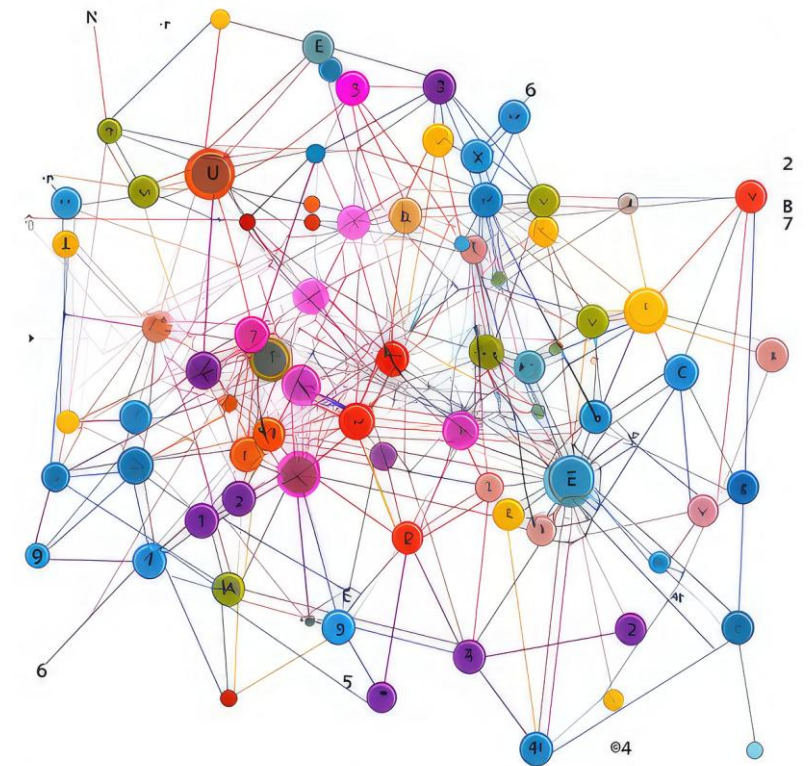
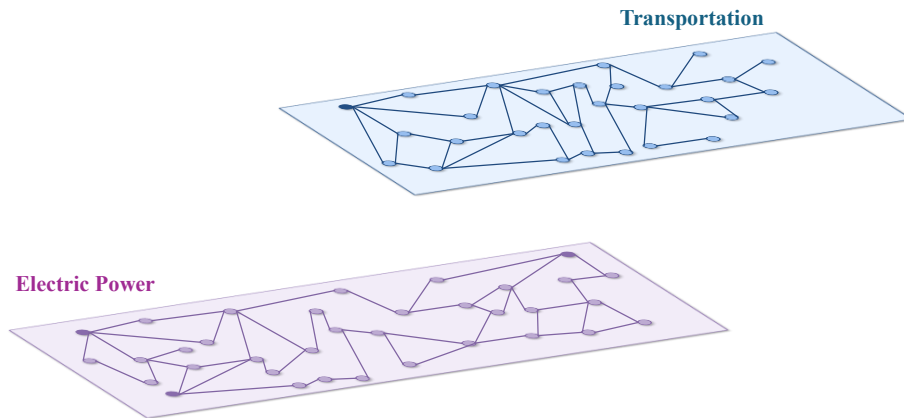
Fig. 5 - Influence gains  $\rho_j$  for various outage periods.

## 2. Hybrid Approach to Model Interdependencies

### 2.1 Economic Theory-based Model: DIIM - References

- [1] Leontief, W. (1966). Input-Output Economics. Oxford University Press, Oxford, United Kingdom. <https://liremarx.noblogs.org/files/2020/02/Wassily-Leontief-Input-Output-Economics-Oxford-University-Press-USA-1986.pdf>
- [2] Haimes, Y., & Jiang, P. (2001). Leontief-based Model of Risk in Complex Interconnected Infrastructures. *Journal of Infrastructure Systems*, 7(1), 1-12.
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- [4] 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. [https://doi.org/10.1061/\(asce\)1076-0342\(2005\)11:2\(67\)](https://doi.org/10.1061/(asce)1076-0342(2005)11:2(67))
- [5] Lian, C., & Haimes, Y. Y. (2006). Managing the risk of terrorism to interdependent infrastructure systems through the dynamic inoperability input-output model. *Systems Engineering*, 9(3), 241-258. <https://doi.org/10.1002/sys.20051>
- [6] Pant, R., Barker, K., & Zobel, C. W. (2013). Static and dynamic metrics of economic resilience for interdependent infrastructure and industry sectors. *Reliability Engineering & System Safety*, 125, 92-102. <https://doi.org/10.1016/j.res.2013.09.007>
- [7] Jian, J., & Zhou, H. (2023). A Demand-Side inoperability Input-Output model for strategic risk Management: Insight from the COVID-19 outbreak in Shanghai, China. *Sustainability*, 15(5), 4003. <https://doi.org/10.3390/su15054003>
- [8] Setola, R., De Porcellinis, S., & Sforza, M. (2009). Critical infrastructure dependency assessment using the input-output inoperability model. *International Journal Of Critical Infrastructure Protection*, 2(4), 170-178. <https://doi.org/10.1016/j.ijcip.2009.09.002>

## 2.2 Graph Theory-based Model



## 2. Hybrid Approach to Model Interdependencies

### 2.2 Graph Theory-based Model

ETH zürich



## Complexity theory and centrality measures

Giovanni Sansavini  
Reliability and Risk Engineering Lab  
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RRE  
Reliability and Risk Engineering

ETH Zurich – Prof. Dr. Giovanni Sansavini | 16.05.2025 | 1

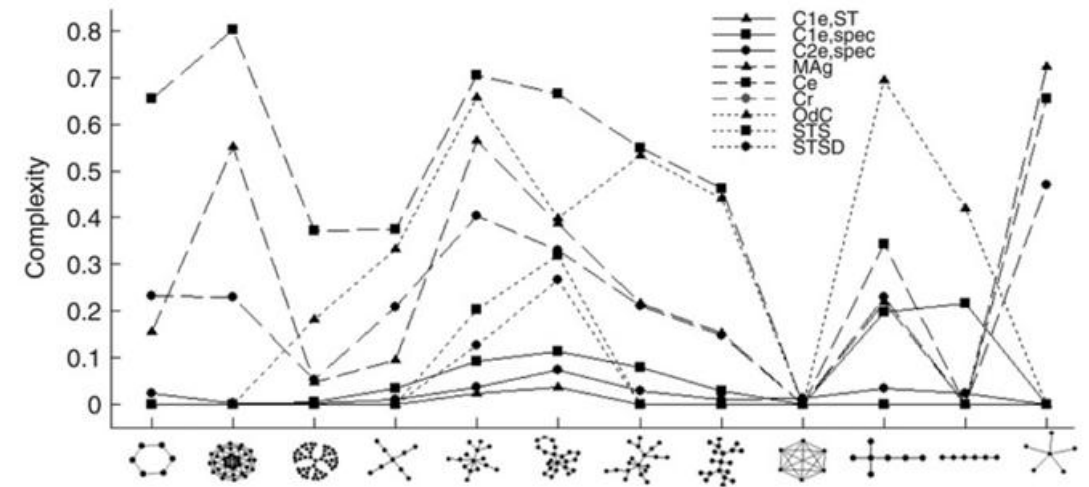
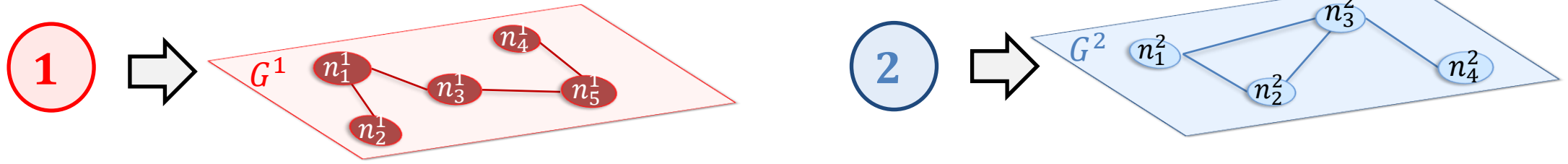


Fig. 4. Complexities of different test graphs.

## 2. Hybrid Approach to Model Interdependencies

### 2.2 Graph Theory-based Model

Network of the infrastructure 1 and the infrastructure 2

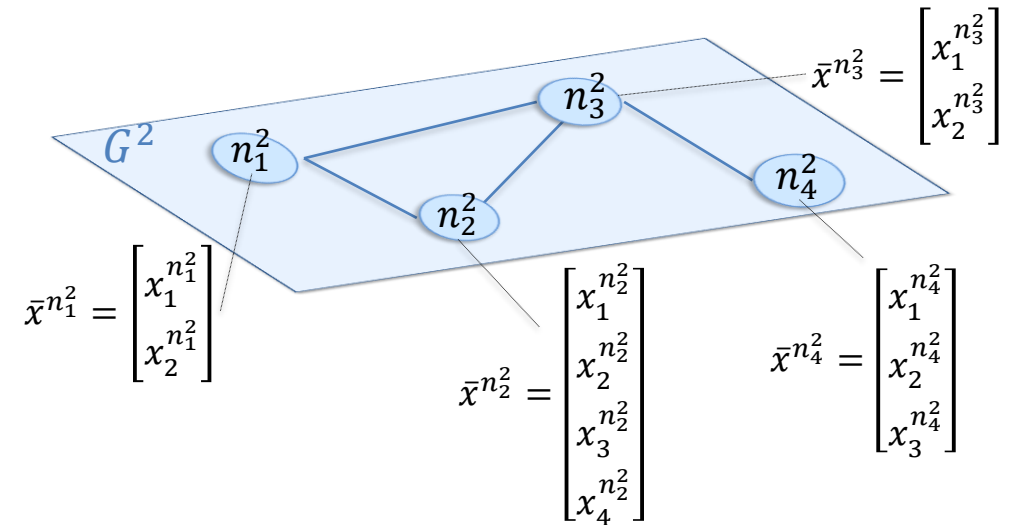
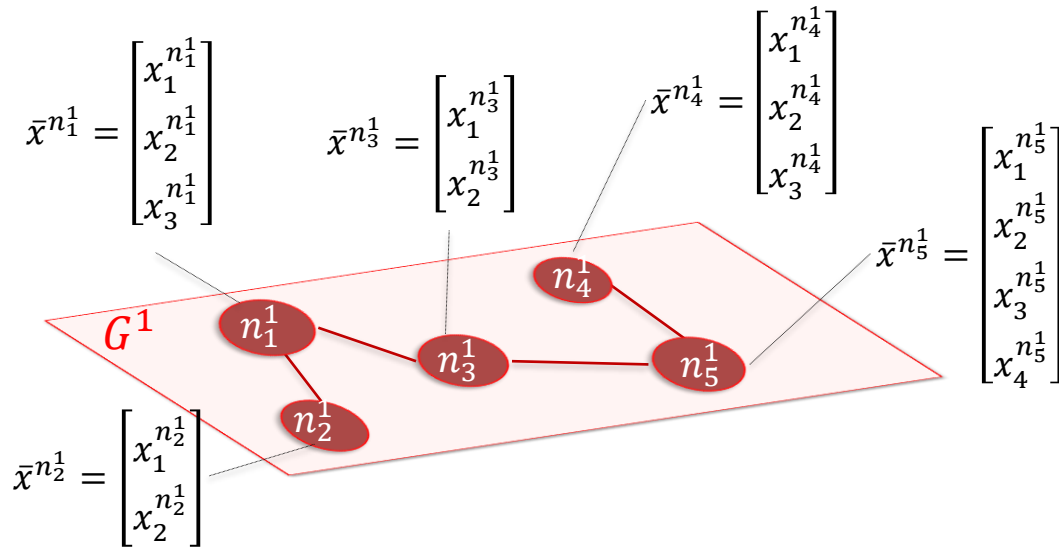




## 2. Hybrid Approach to Model Interdependencies

### 2.2 Graph Theory-based Model

State vector for each node of Infrastructure 1 and Infrastructure 2

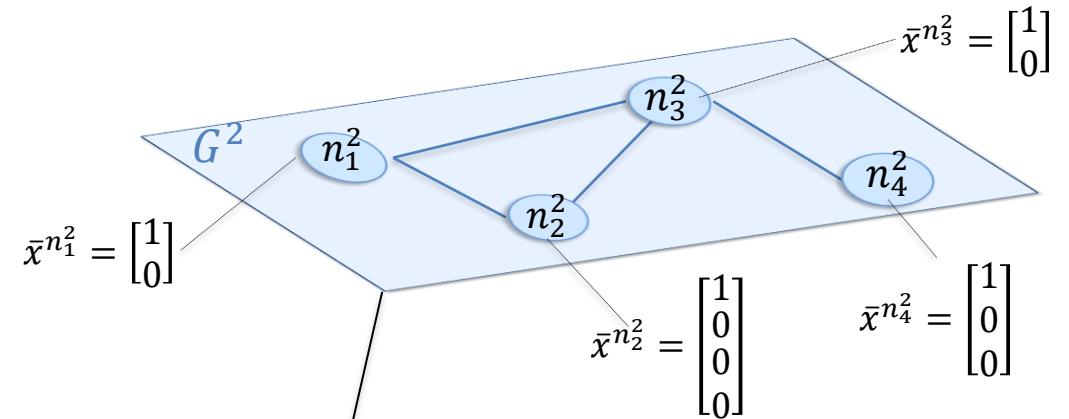
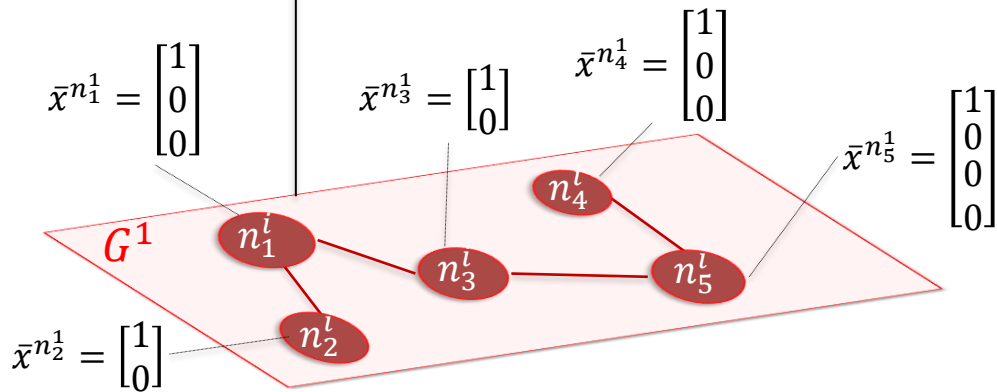


## 2. Hybrid Approach to Model Interdependencies

### 2.2 Graph Theory-based Model

Demands  $D(X_1^1)$  and  $D(X_1^2)$  of infrastructure 1 and infrastructure 2 in their perfect functioning states

$$X_1^1 = \phi(\bar{x}^{n_1^1}, \bar{x}^{n_2^1}, \bar{x}^{n_3^1}, \bar{x}^{n_4^1}, \bar{x}^{n_5^1}) \rightarrow D(X_1^1)$$

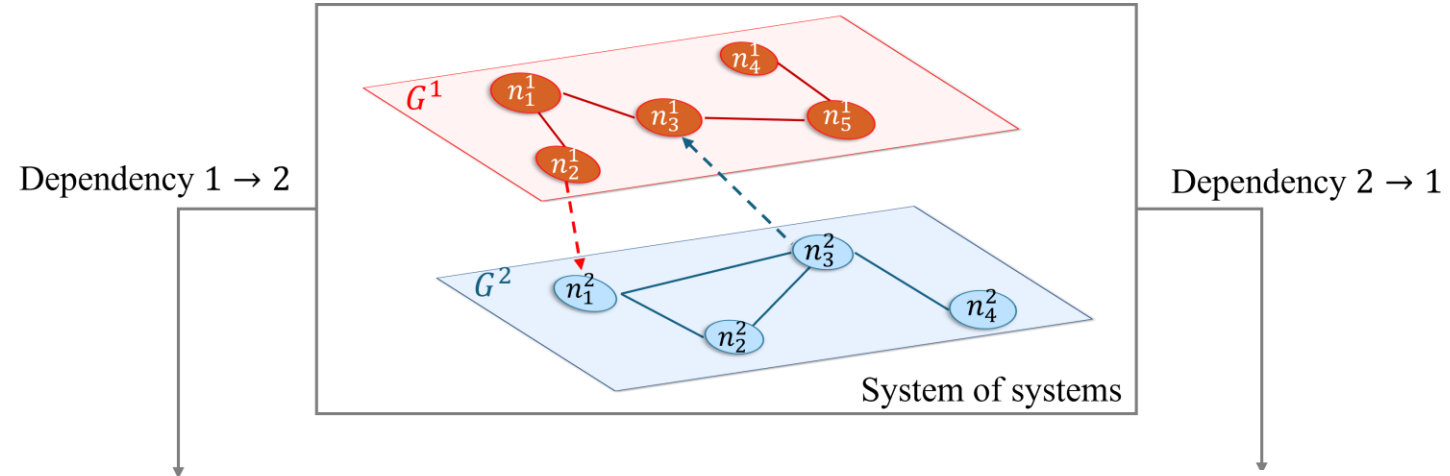


$$X_1^2 = \phi(\bar{x}^{n_1^2}, \bar{x}^{n_2^2}, \bar{x}^{n_3^2}, \bar{x}^{n_4^2}) \rightarrow D(X_1^2)$$

## 2. Hybrid Approach to Model Interdependencies

### 2.2 Graph Theory-based Model

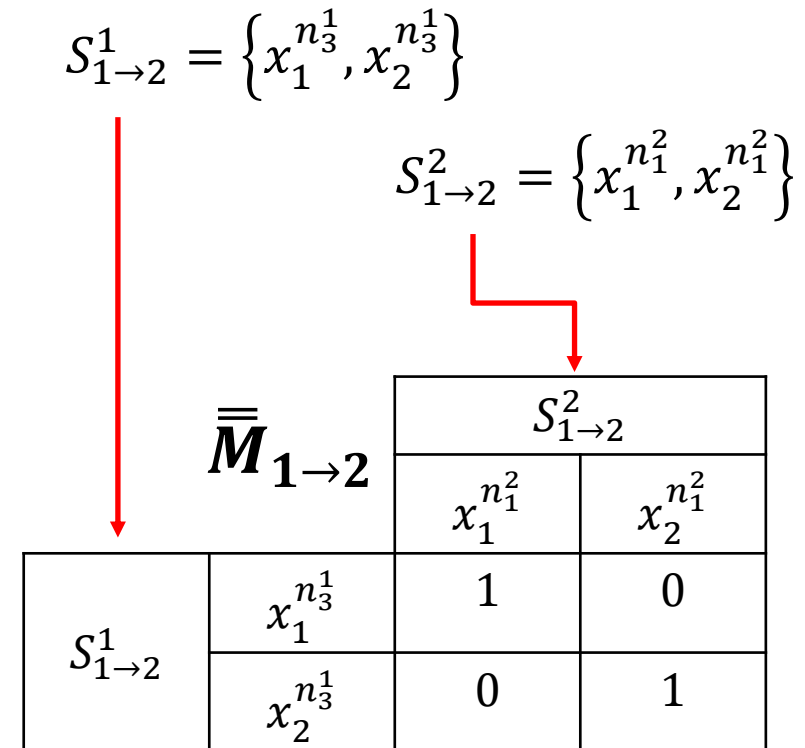
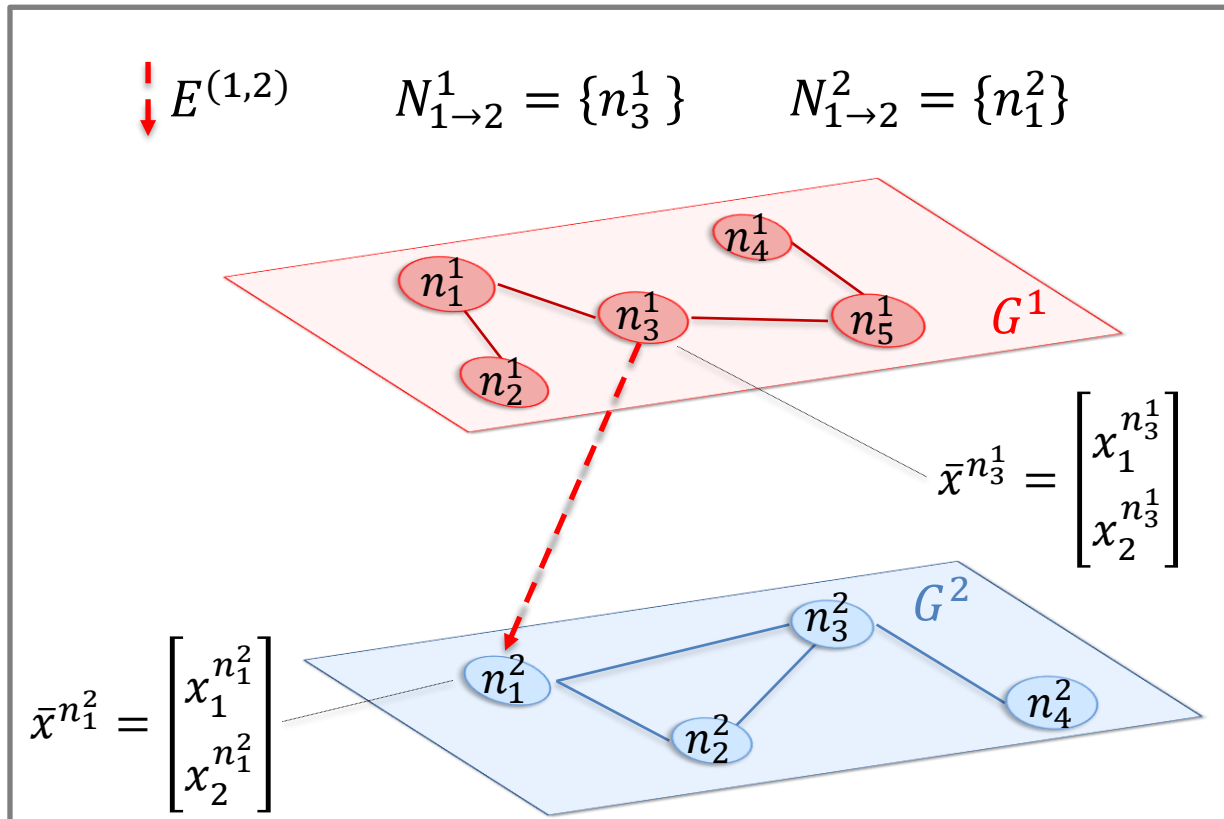
Connectivity between the infrastructure 1 and the infrastructure 2



## 2. Hybrid Approach to Model Interdependencies

### 2.2 Graph Theory-based Model

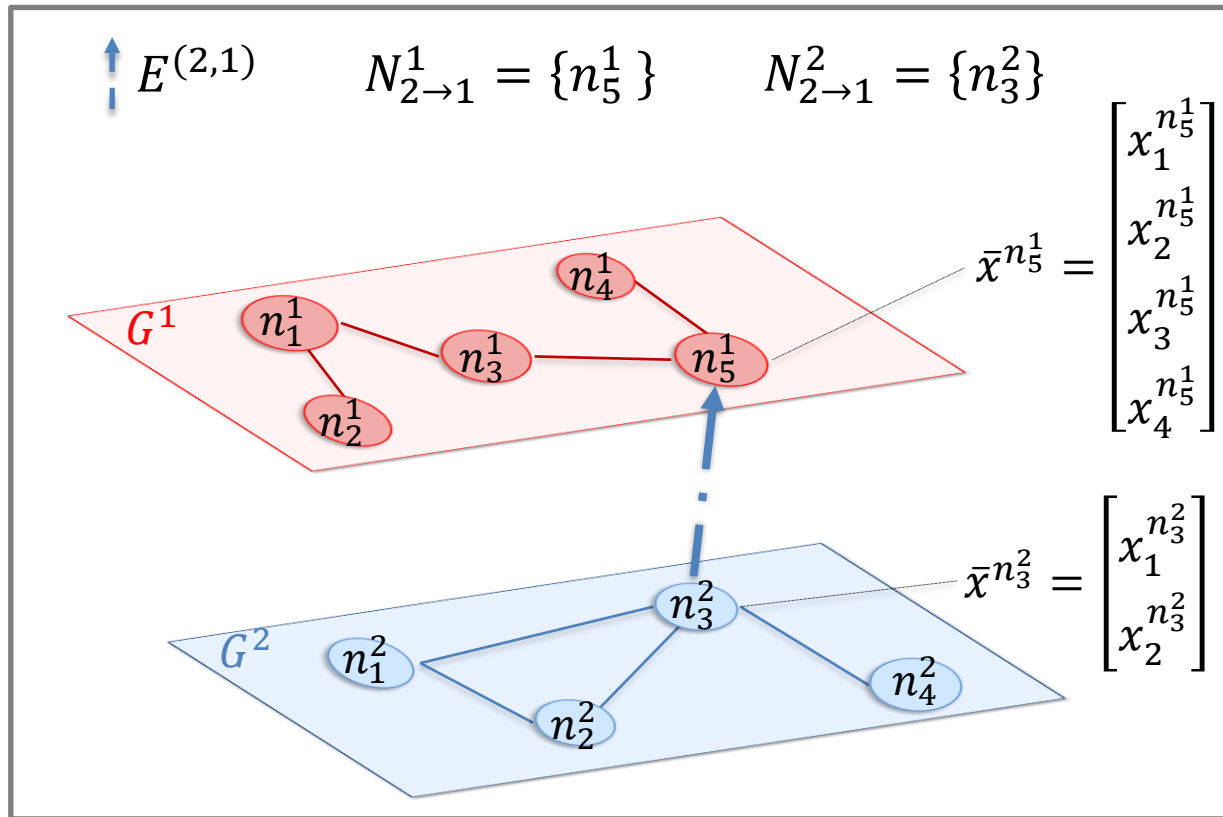
Dependency  $1 \rightarrow 2$



## 2. Hybrid Approach to Model Interdependencies

### 2.2 Graph Theory-based Model

Dependency  $2 \rightarrow 1$



$$S_{2 \rightarrow 1}^2 = \{x_1^{n_3^2}, x_2^{n_3^2}\}$$

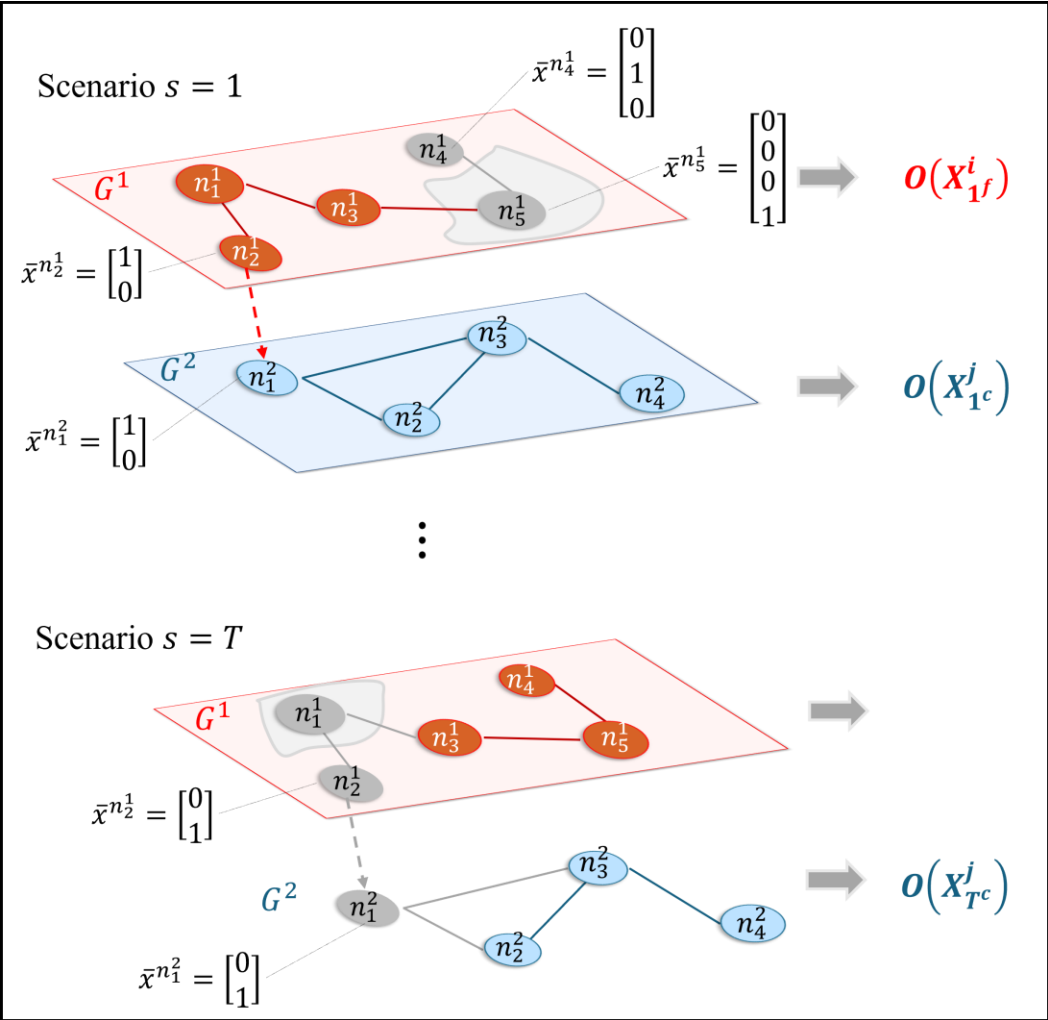
$$S_{2 \rightarrow 1}^1 = \{x_1^{n_5^1}, x_2^{n_5^1}, x_3^{n_5^1}, x_4^{n_5^1}\}$$

$$\bar{\bar{M}}_{2 \rightarrow 1}$$

		$S_{2 \rightarrow 1}^1$			
		$x_1^{n_5^1}$	$x_2^{n_5^1}$	$x_3^{n_5^1}$	$x_4^{n_5^1}$
$S_{2 \rightarrow 1}^2$	$x_1^{n_3^2}$	1	0	0	0
	$x_2^{n_3^2}$	0	0	1	0

# 2. Hybrid Approach to Model Interdependencies

## 2.2 Graph Theory-based Model



Estimation of values in the conditional probability matrix  $\bar{\bar{R}}_{1 \rightarrow 2}$

Diagram illustrating the estimation of values in the conditional probability matrix  $\bar{\bar{R}}_{1 \rightarrow 2}$ .

Row vector  $r^1$  (red) is defined as:

$$r^1 = \left\{ \begin{matrix} [0, 0.2], \\ (0.2, 0.6], \\ (0.6, 0.9], \\ (0.9, 1] \end{matrix} \right\}$$

Column vector  $r^2$  (blue) is defined as:

$$r^2 = \left\{ \begin{matrix} [0, 0.3], \\ (0.3, 0.8], \\ (0.8, 1] \end{matrix} \right\}$$

The matrix  $\bar{\bar{R}}_{1 \rightarrow 2}$  is a 4x3 matrix where the rows are indexed by  $r^1$  and the columns are indexed by  $r^2$ .

	$[0, 0.3]$	$(0.3, 0.8]$	$(0.8, 1]$
$[0, 0.2]$	1	0	0
$(0.2, 0.6]$	0.25	0.55	0.20
$(0.6, 0.9]$	0.15	0.45	0.40
$(0.9, 1]$	0	0.3	0.7



## 2. Hybrid Approach to Model Interdependencies

### 2.2 Graph Theory-based Model

Quantification of interdependency coefficients  $a_{21}[r^1]$

$a_{21}$	
$[0, 0.2]$	$(0.3 \times 1) + (0.8 \times 0) + (1 \times 0)$
$(0.2, 0.6]$	$(0.3 \times 0.25) + (0.8 \times 0.55) + (1 \times 0.2)$
$(0.6, 0.9]$	$(0.3 \times 0.15) + (0.8 \times 0.45) + (1 \times 0.4)$
$(0.9, 1]$	$(0.3 \times 0) + (0.8 \times 0.3) + (1 \times 0.7)$

Estimation of values in the conditional probability matrix  $\bar{\bar{R}}_{1 \rightarrow 2}$

$$r^2 = \left\{ \begin{array}{l} [0, 0.3], \\ (0.3, 0.8], \\ (0.8, 1] \end{array} \right\}$$
$$\downarrow r^2$$

$$r^1 = \left\{ \begin{array}{l} [0, 0.2], \\ (0.2, 0.6], \\ (0.6, 0.9], \\ (0.9, 1] \end{array} \right\}$$

	$[0, 0.3]$	$(0.3, 0.8]$	$(0.8, 1]$
$[0, 0.2]$	1	0	0
$(0.2, 0.6]$	0.25	0.55	0.20
$(0.6, 0.9]$	0.15	0.45	0.40
$(0.9, 1]$	0	0.3	0.7

## 2. Hybrid Approach to Model Interdependencies

### 2.2 Graph Theory-based Model

$\bar{\bar{A}}_1$ 

	2
$[0, 0.2]$	0.3
$(0.2, 0.6]$	0.72
$(0.6, 0.9]$	0.81
$(0.9, 1]$	0.94

$r^1$

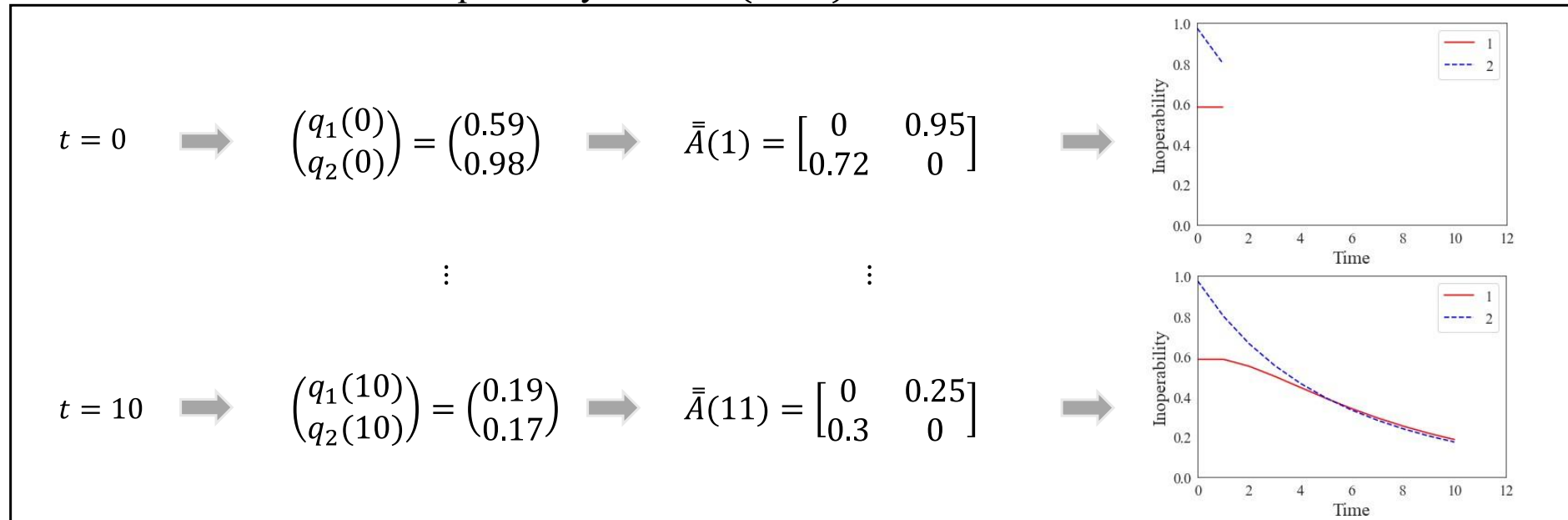
$\bar{\bar{A}}_2$ 

	1
$[0, 0.3]$	0.25
$(0.3, 0.8]$	0.60
$(0.8, 1]$	0.95

$r^2$

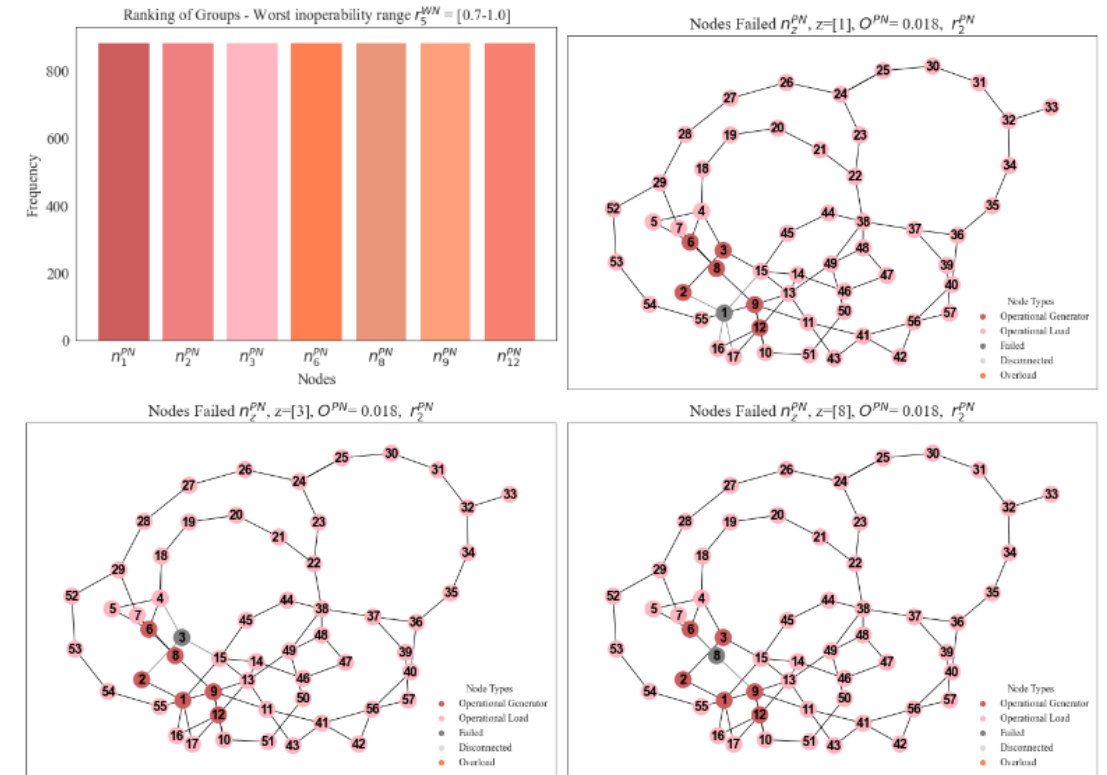
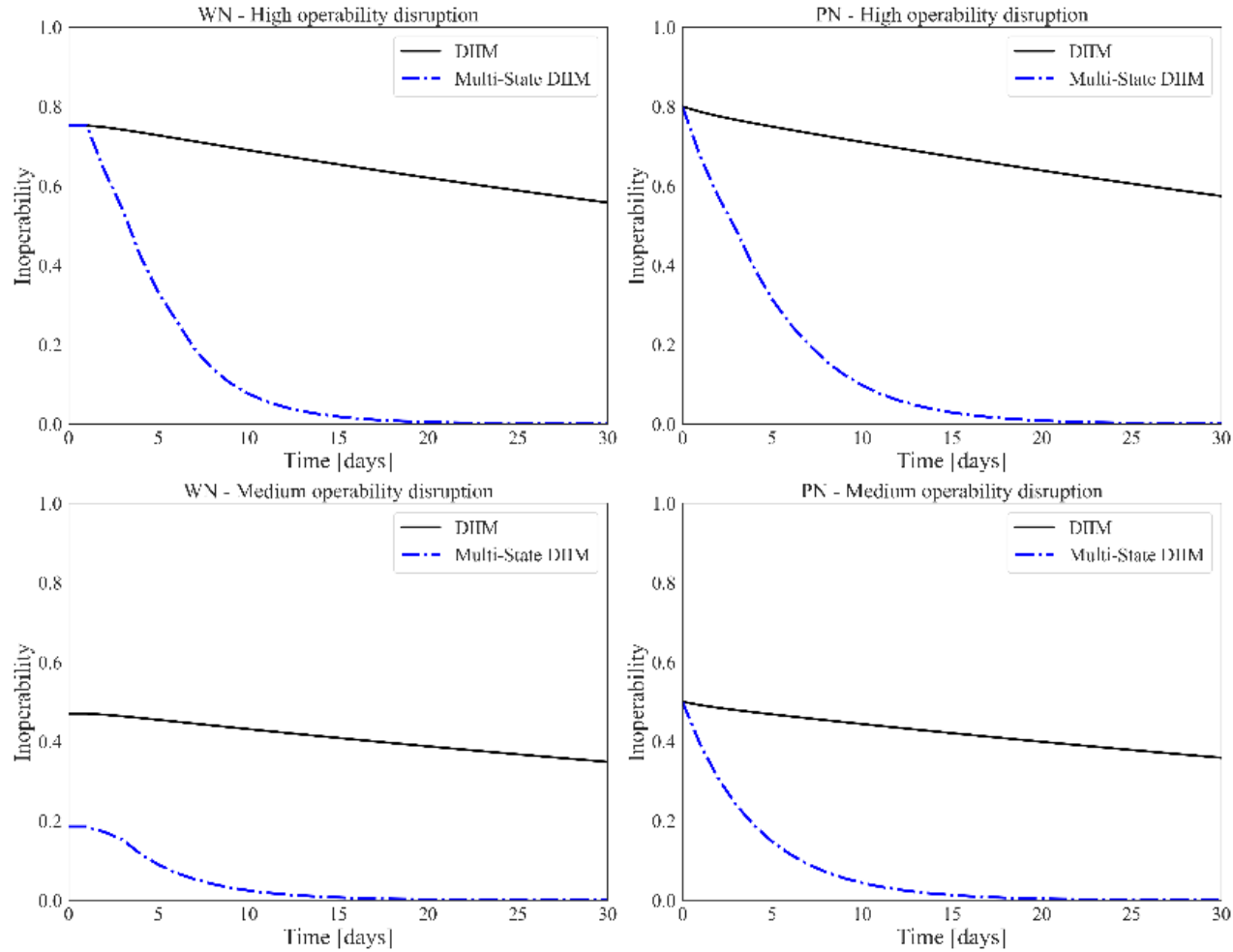
$$\bar{\bar{A}}(t+1) = \begin{bmatrix} 0 & a_{12}(q_2(t)) \\ a_{21}(q_1(t)) & 0 \end{bmatrix}$$

DIIM with Multi-state interdependency matrix  $\bar{\bar{A}}(t+1)$



## 2. Hybrid Approach to Model Interdependencies

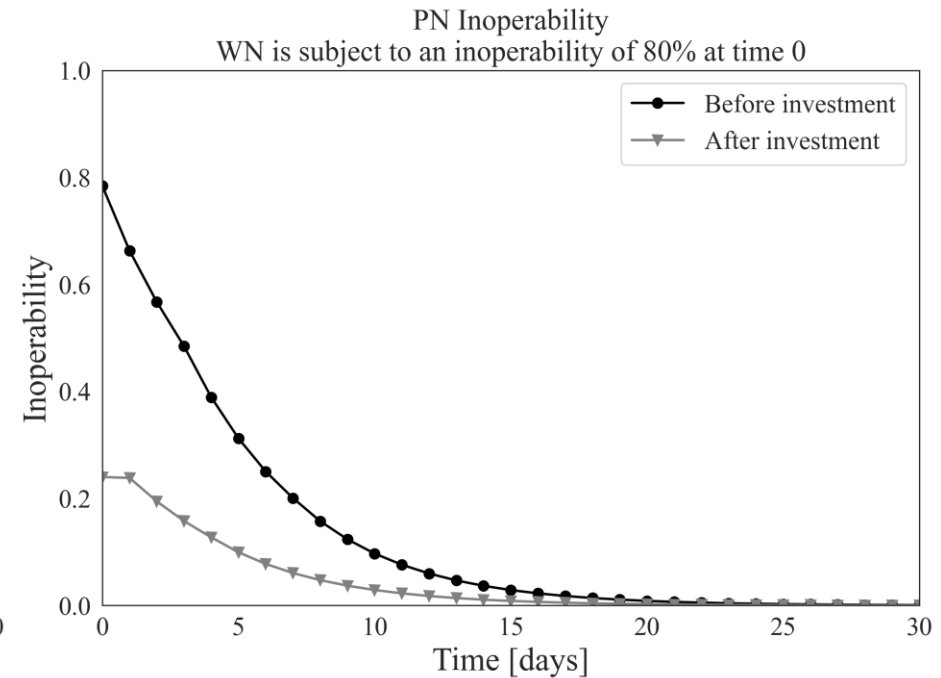
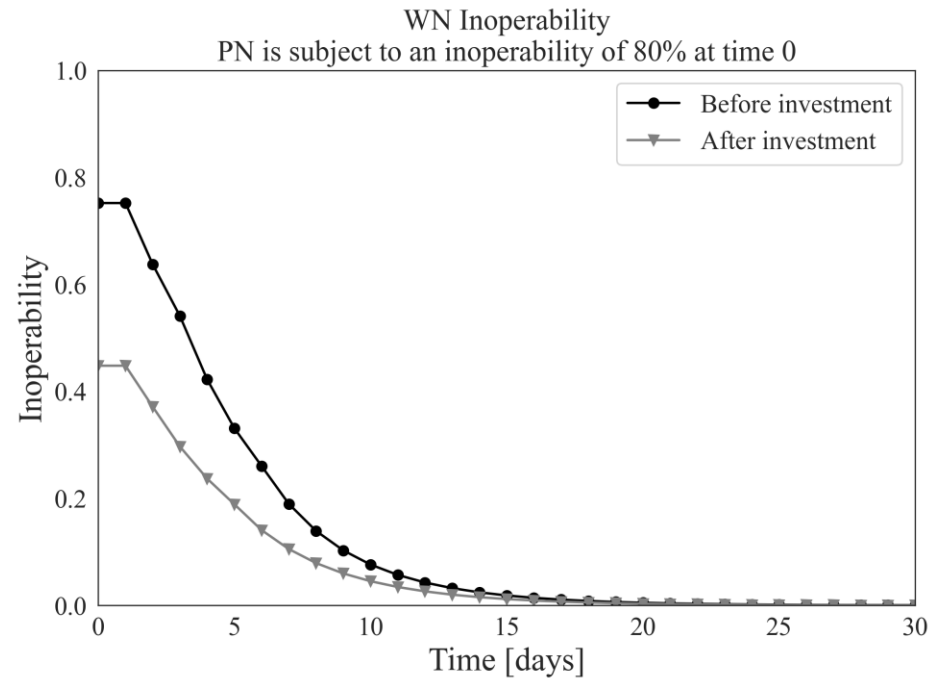
### 2.2 Graph Theory-based Model



[1]

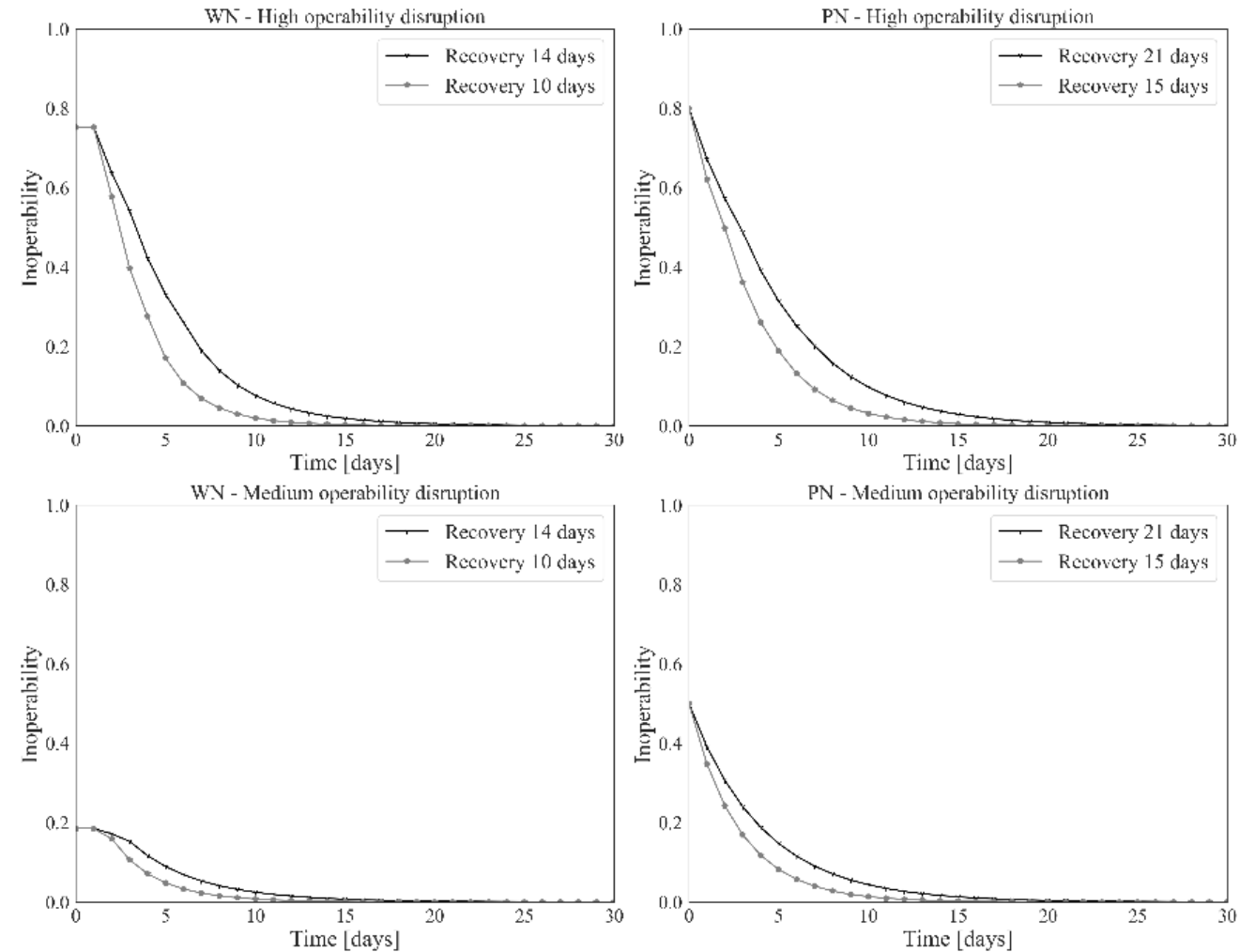
## 2. Hybrid Approach to Model Interdependencies

### 2.2 Graph Theory-based Model



## 2. Hybrid Approach to Model Interdependencies

### 2.2 Graph Theory-based Model



[1]

## 2. Hybrid Approach to Model Interdependencies

### 2.2 Graph Theory-based Model



Input-Output model



Network theory





## 2. Hybrid Approach to Model Interdependencies

### 2.2 Graph Theory-based Model - References

- [1] Clavijo-Mesa, M. V., Di Maio, F., & Zio, E. (2024). “unpublished” Dynamic Inoperability Input-Output modeling of a system of systems made of multi-state interdependent critical infrastructures. Reliability Engineering and System Safety.

#### Dynamic Inoperability Input-Output Modeling of a System of Systems Made of Multi-State Interdependent Critical Infrastructures

Maria Valentina Clavijo Mesa<sup>a</sup>, Francesco Di Maio<sup>a,\*</sup>, Enrico Zio<sup>b,a</sup>

<sup>a</sup>Energy Department, Politecnico di Milano, Milan, Italy

<sup>b</sup>MINES Paris-PSL University, Centre de Recherche sur les Risques et les Crises (CRC), Sophia Antipolis, France

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#### Abstract

Critical Infrastructures (CIs) are fundamental for the operation of societies. They function interdependently in a system-of-systems configuration. Interdependencies are unveiled also when CIs become inoperable or only partially operable due to disruptions. The state of partial or full inoperability of a disrupted CI can cascade to the interdependent CIs connected to it in the system of systems, causing various degrees of inoperability. This paper presents a novel approach for modeling the disruption cascade dynamics in multi-state interdependent CIs. A Dynamic Inoperability Input-output Model (DIIM) is proposed to describe the multi-state transition dynamics of the CIs. A case study is worked out to show the application of the proposed approach to a system of systems formed by interdependent power and water networks.

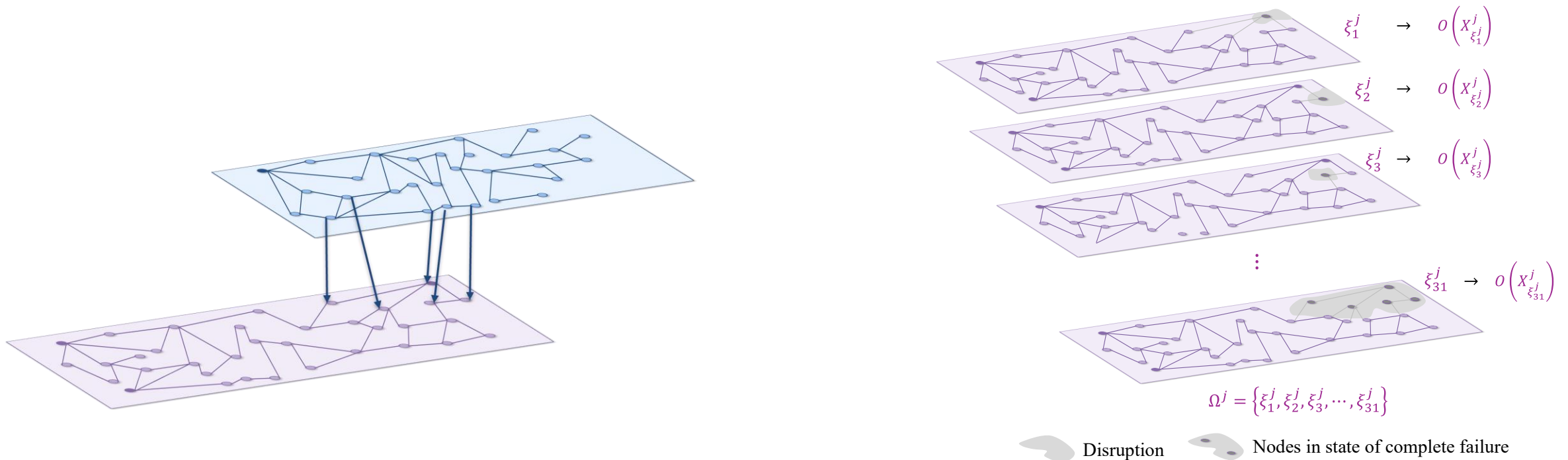
**Keywords:** Critical infrastructures, System of Systems, Interdependencies, Multiple states, Dynamic Inoperability Input-output Model (DIIM), Network theory, Simulation, Power grid, Water network.

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Email address: [francesco.dimaio@polimi.it](mailto:francesco.dimaio@polimi.it)

## 2.3 Application Example: Random Failures



## 2. Hybrid Approach to Model Interdependencies

### 2.3 Application Example: Random Failures

#### *Dynamic Input-output Inoperability Model (DIIM)*

Fundamental equation of **DIIM** (discrete time steps of one arbitrary unit of time)

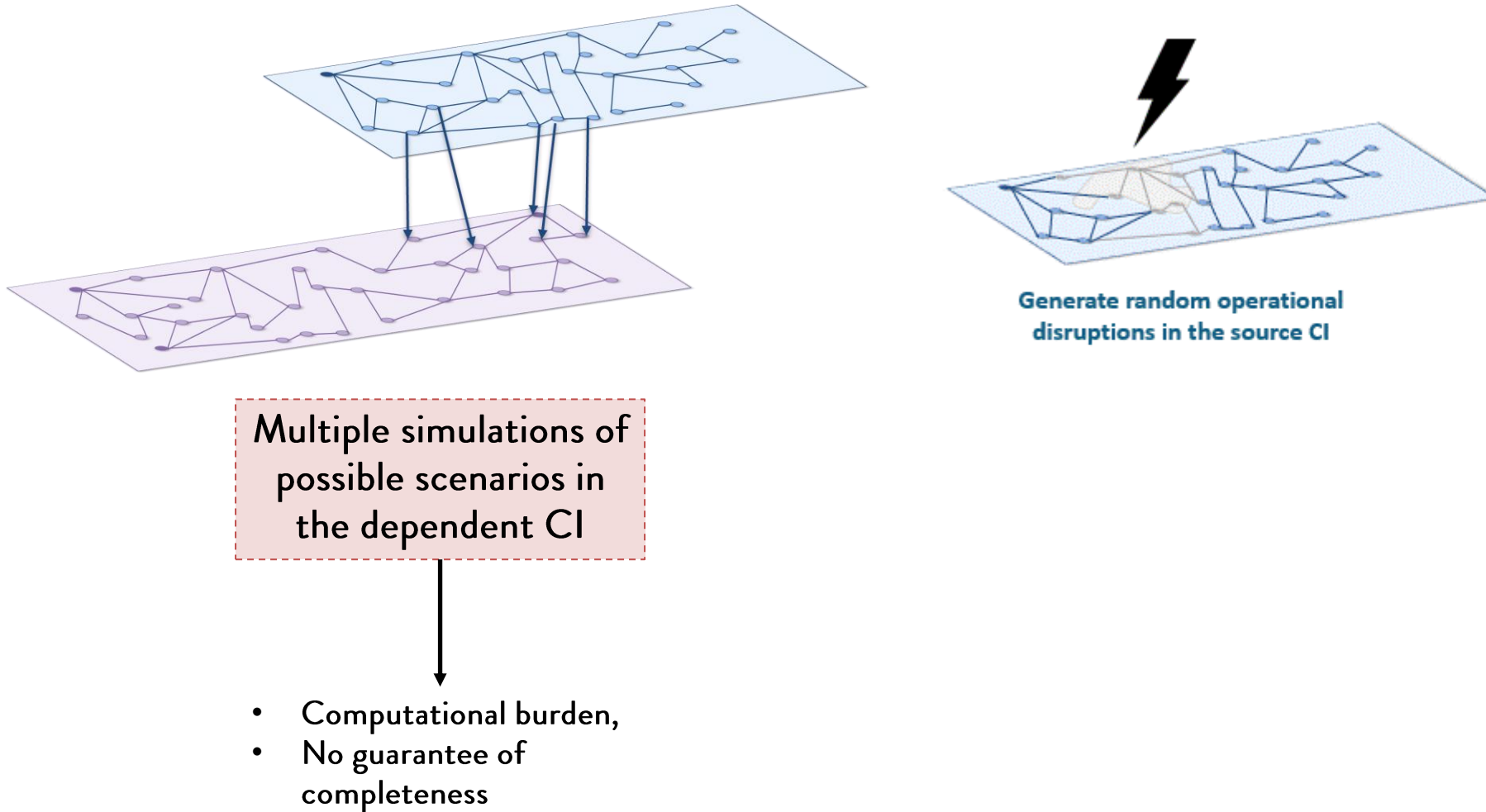
$$\bar{q}(t + 1) = \bar{q}(t) - \bar{\bar{K}}\bar{q}(t) + \bar{\bar{K}}\bar{\bar{A}}\bar{q}(t) + \bar{\bar{K}}\bar{c}(t)$$

↑  
*Interdependency* matrix ( $a_{ji}$  = interdependency coefficient describing the inoperability contributed by the  $i$ -th inoperable CI ( $q_i = 1$ ) to the  $j$ -th CI

Multiple failure scenarios must be considered to estimate interdependency coefficients in the **DIIM**

## 2. Hybrid Approach to Model Interdependencies

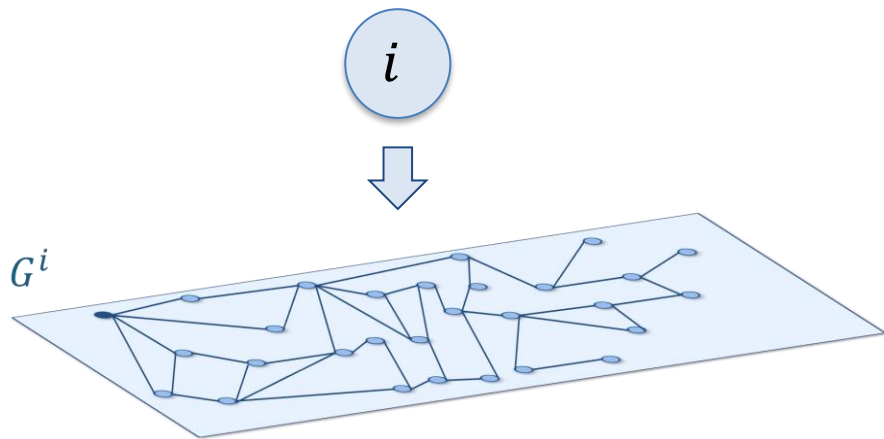
### 2.3 Application Example: Random Failures



## 2. Hybrid Approach to Model Interdependencies

### 2.3 Application Example: Random Failures

#### 1. Characterization of the CIs topology and operational attributes



Each node in the CI

$$n_z^i \in N^i \rightarrow \bar{x}^{n_z^i} = \begin{cases} x_1^{n_z^i} & \text{Fully functioning} \\ \vdots \\ x_{K_{n_z^i}}^{n_z^i} & \text{Complete failure} \end{cases}$$

The state of the CI is a function of the states of its nodes

$$\bar{X}^i = \begin{bmatrix} X_1^i \\ X_2^i \\ \vdots \\ X_L^i \end{bmatrix} \therefore X_l^i = \phi(\bar{x}^{n_1^i}, \dots, \bar{x}^{n_z^i})$$

Using demand satisfaction as a proxy for the overall operational state of the the  $i$ -th CI...

$$O(X_l^i) = 1 - \frac{D(X_l^i)}{D(X_1^i)}$$



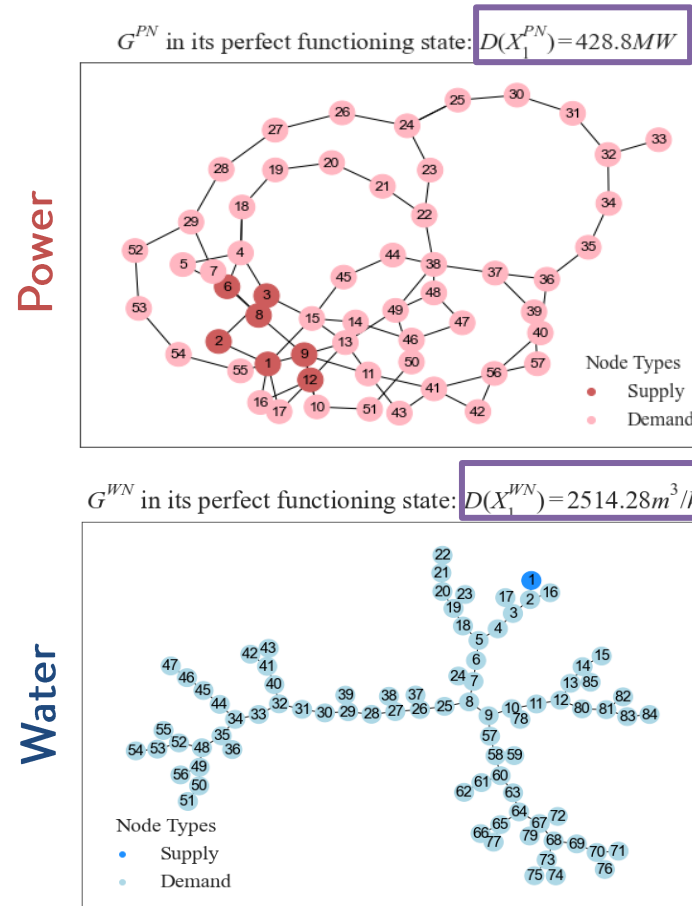
The nominal demand for the  $i$ -th CI is estimated when all nodes are in **perfect state**

**$D(X_1^i)$**

## 2. Hybrid Approach to Model Interdependencies

### 2.3 Application Example: Random Failures

#### 1. Characterization of the CIs topology and operational attributes



$$n_z^i \in N_S^i \rightarrow \bar{x}^{n_z^i} = \begin{bmatrix} x_1^{n_z^i} \\ x_2^{n_z^i} \\ x_3^{n_z^i} \\ x_4^{n_z^i} \end{bmatrix} \begin{matrix} \text{Operational} \\ \text{Disconnected} \\ \text{Overloaded} \\ \text{Inoperable} \end{matrix}$$

$$n_z^i \in N_D^i \rightarrow \bar{x}^{n_z^i} = \begin{bmatrix} x_1^{n_z^i} \\ x_2^{n_z^i} \\ x_3^{n_z^i} \end{bmatrix} \begin{matrix} \text{Operational} \\ \text{Disconnected} \\ \text{Inoperable} \end{matrix}$$

$$x_1^{n_z^i} = 1, \forall n_z^i \in N^i \rightarrow X_1^i$$

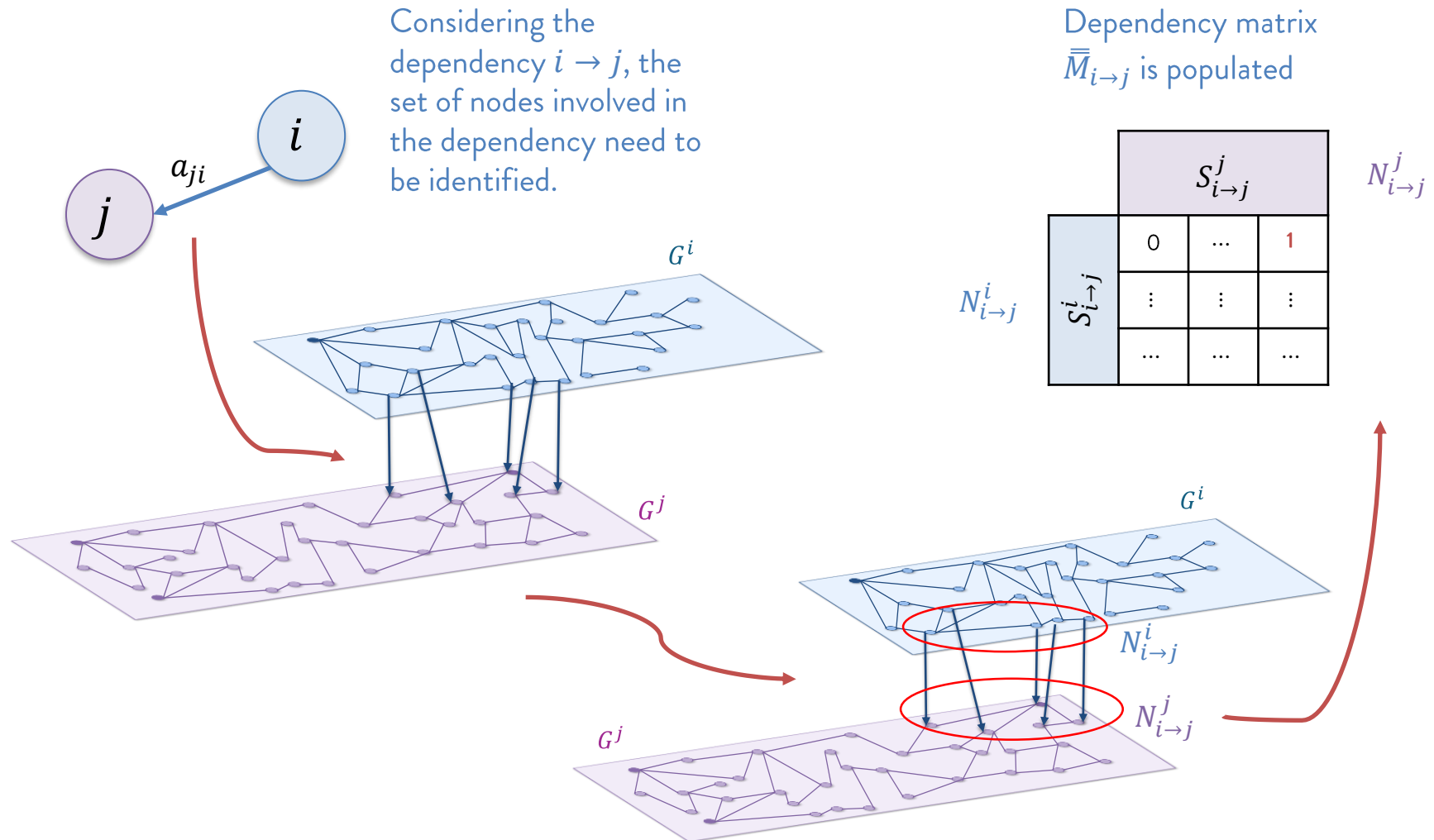


## 2. Hybrid Approach to Model Interdependencies

### 2.3 Application Example: Random Failures

1. Characterization of the CIs' topology and operational attributes

2. Characterization of the dependencies



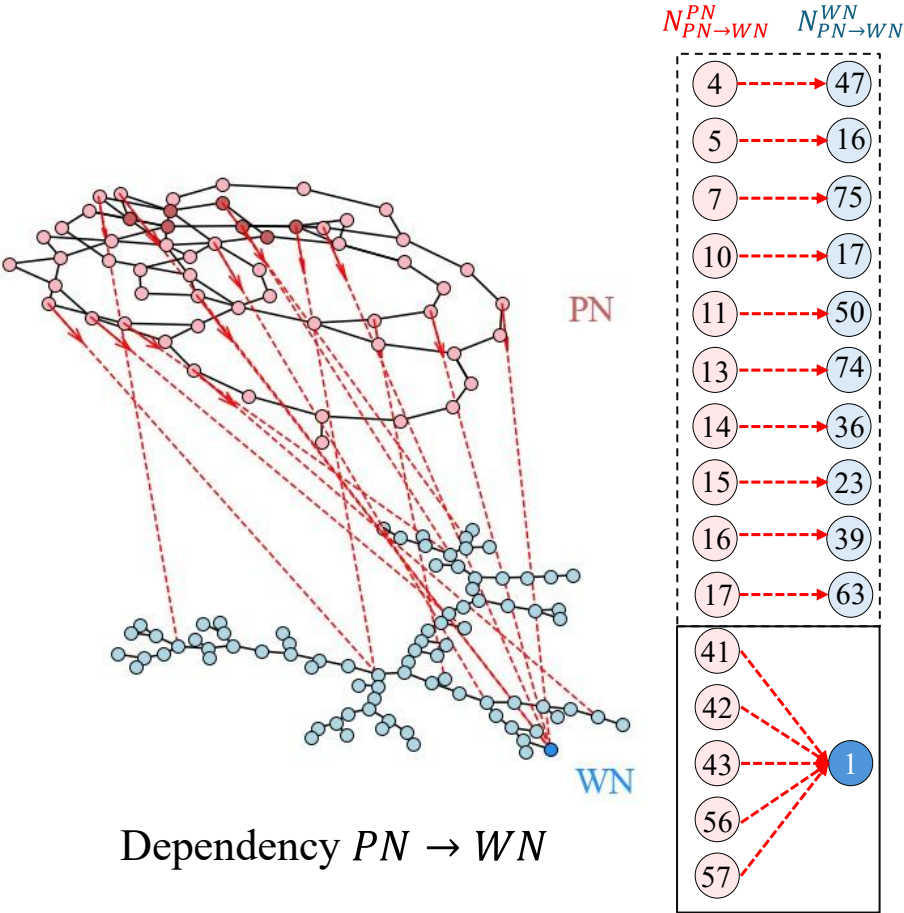
# 2. Hybrid Approach to Model Interdependencies

## 2.3 Application Example: Random Failures

1. Characterization of the CIs' topology and operational attributes

2. Characterization of the dependencies

	$S_{PN \rightarrow WN}^{WN}$		
$S_{PN \rightarrow WN}^{PN}$	...	...	...
	⋮	⋮	⋮
	...	...	...



If a node in  $N_{PN \rightarrow WN}^{PN}$  is not in operational state, the corresponding  $N_{PN \rightarrow WN}^{WN}$  becomes inoperable

The supplier node in  $N_{PN \rightarrow WN}^{WN}$  becomes inoperable only if ALL five supporting nodes are not in operational state

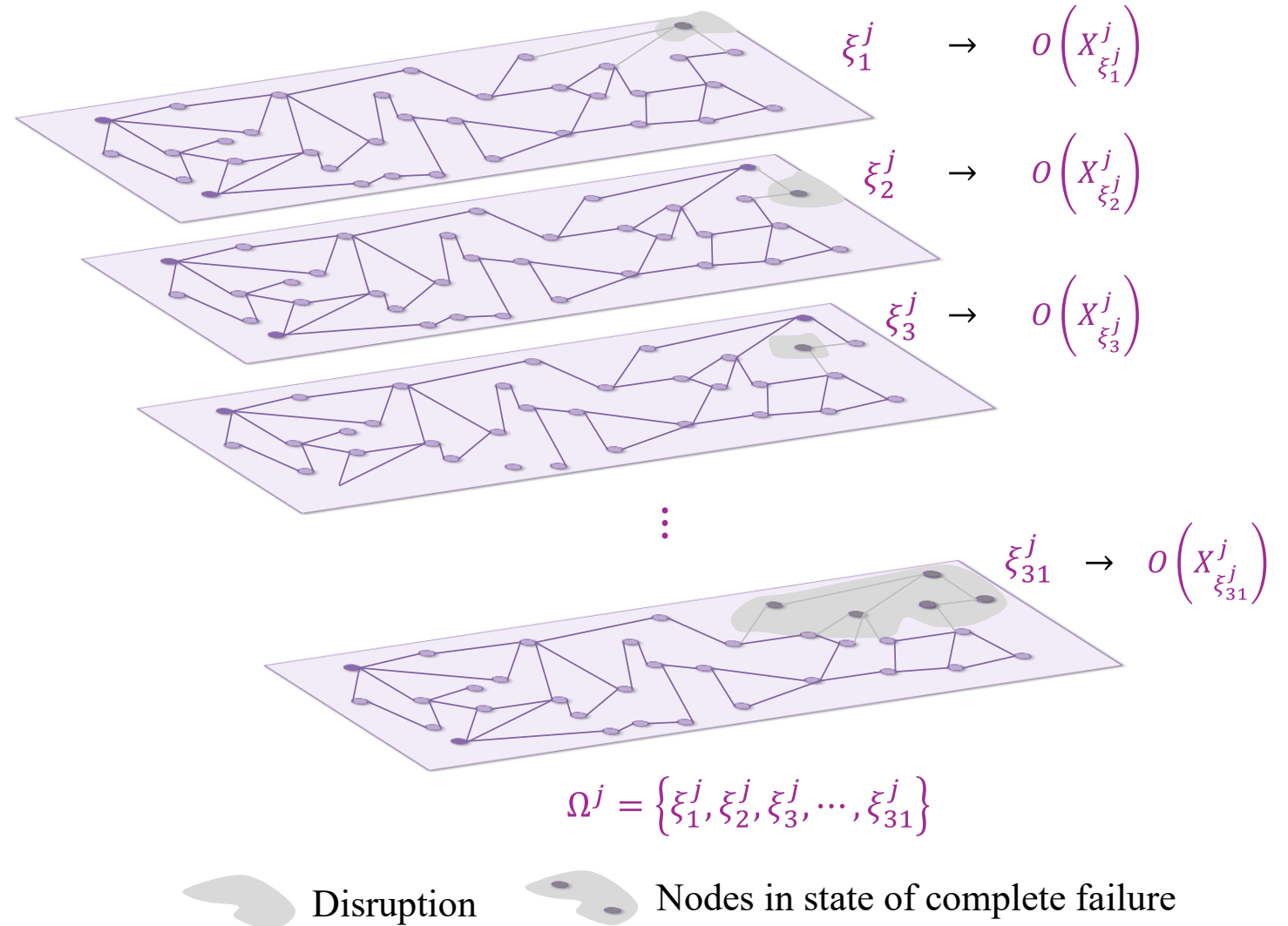
## 2. Hybrid Approach to Model Interdependencies

### 2.3 Application Example: Random Failures

1. Characterization of the CIs' topology and operational attributes

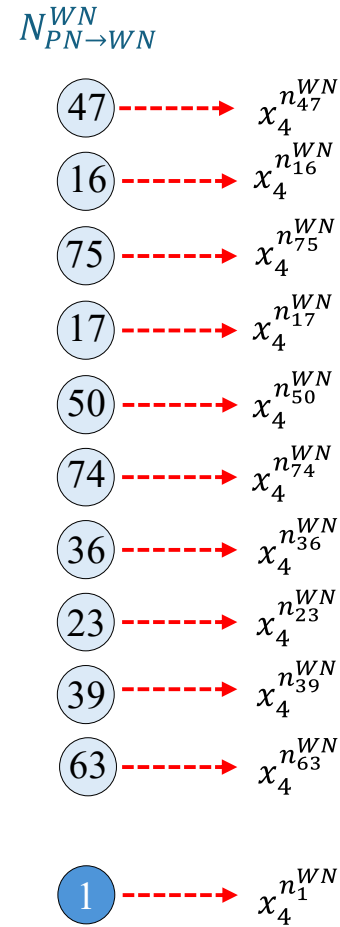
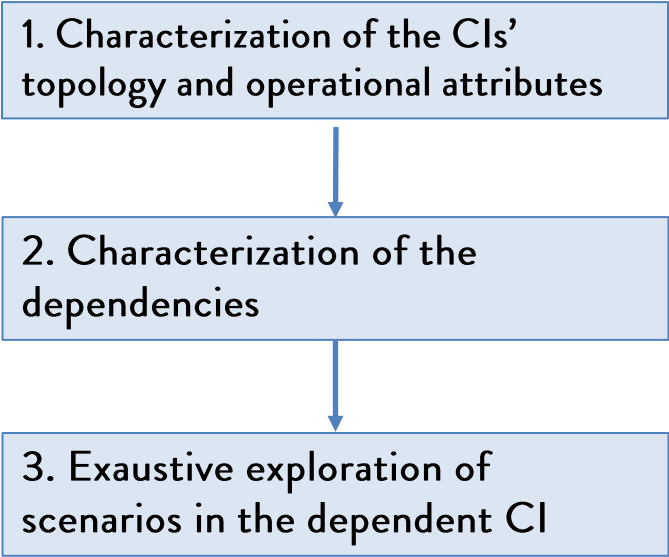
2. Characterization of the dependencies

3. Exhaustive exploration of scenarios in the dependent CI



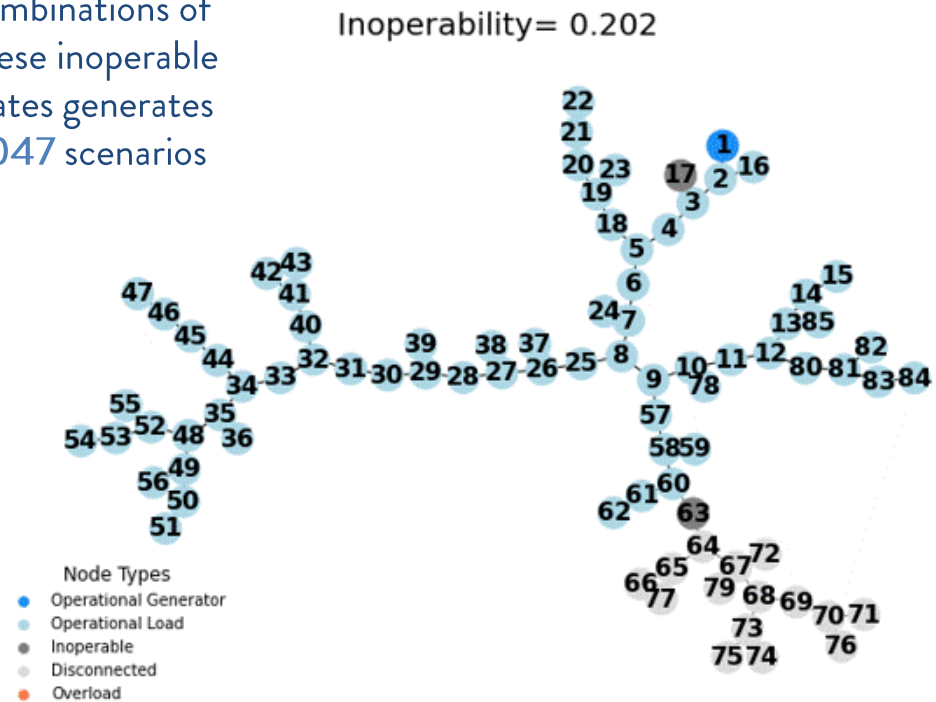
# 2. Hybrid Approach to Model Interdependencies

## 2.3 Application Example: Random Failures



Cascading effects in WN can result from the direct perturbation of 11 nodes

Exploring all combinations of these inoperable states generates 2047 scenarios



## 2. Hybrid Approach to Model Interdependencies

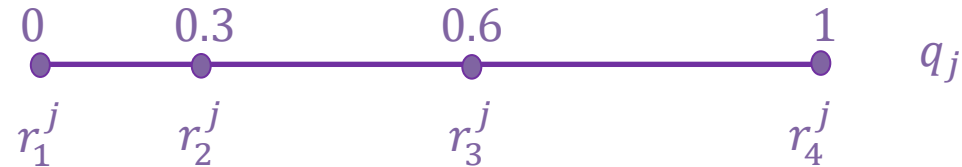
### 2.3 Application Example: Random Failures

1. Characterization of the CIs' topology and operational attributes

2. Characterization of the dependencies

3. Exhaustive exploration of scenarios in the dependent CI

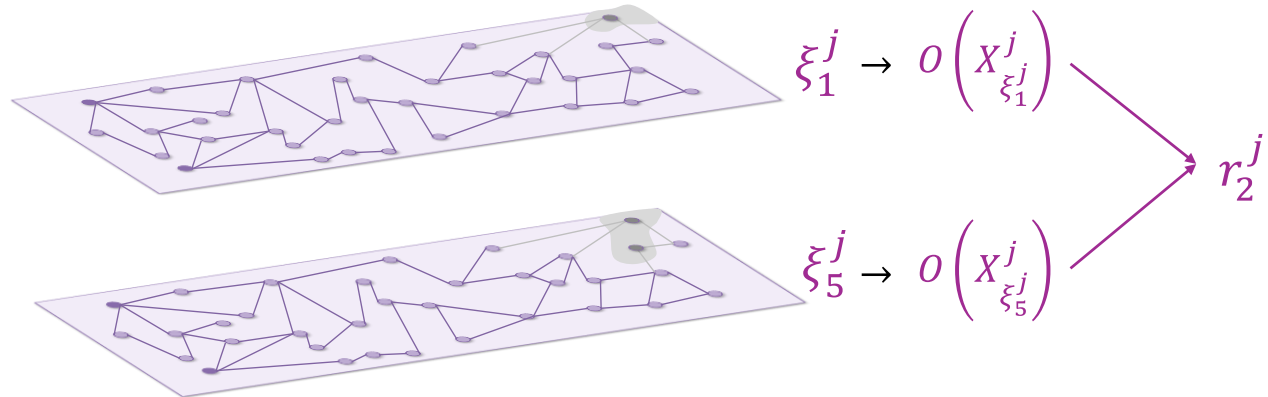
4. Identification of Minimal Inoperability Sets (MISs)



The inoperability domain  $[0, 1]$  of the dependent CI is discretized into intervals

$$r^j = \{[0], (0, 0.3], (0.3, 0.6], (0.6, 1]\}$$

An iterative algorithm is used to identify minimal combination of node states that lead to each inoperability interval



## 2. Hybrid Approach to Model Interdependencies

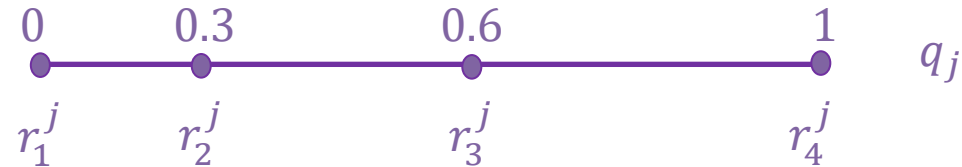
### 2.3 Application Example: Random Failures

1. Characterization of the CIs' topology and operational attributes

2. Characterization of the dependencies

3. Exhaustive exploration of scenarios in the dependent CI

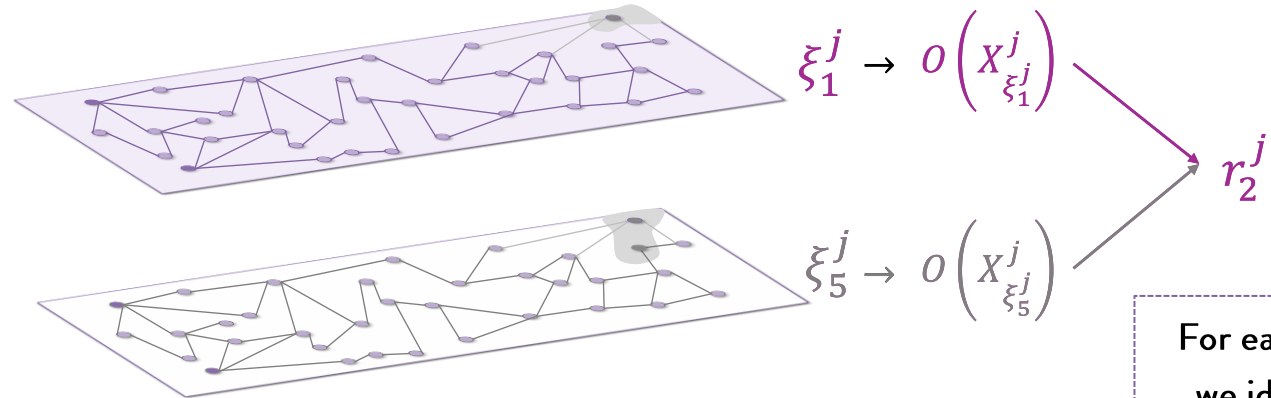
4. Identification of Minimal Inoperability Sets (MISs)



The inoperability domain  $[0, 1]$  of the dependent CI is discretized into intervals

$$r^j = \{[0], (0, 0.3], (0.3, 0.6], (0.6, 1]\}$$

For example...  $\xi_1^j$  is sufficient to achieve  $r_2^j$ , then  $\xi_1^j$  is a MIS



For each  $r_l^j \in r^j$ ,  
we identify  $\bar{M}_l^j$



## 2. Hybrid Approach to Model Interdependencies

### 2.3 Application Example: Random Failures

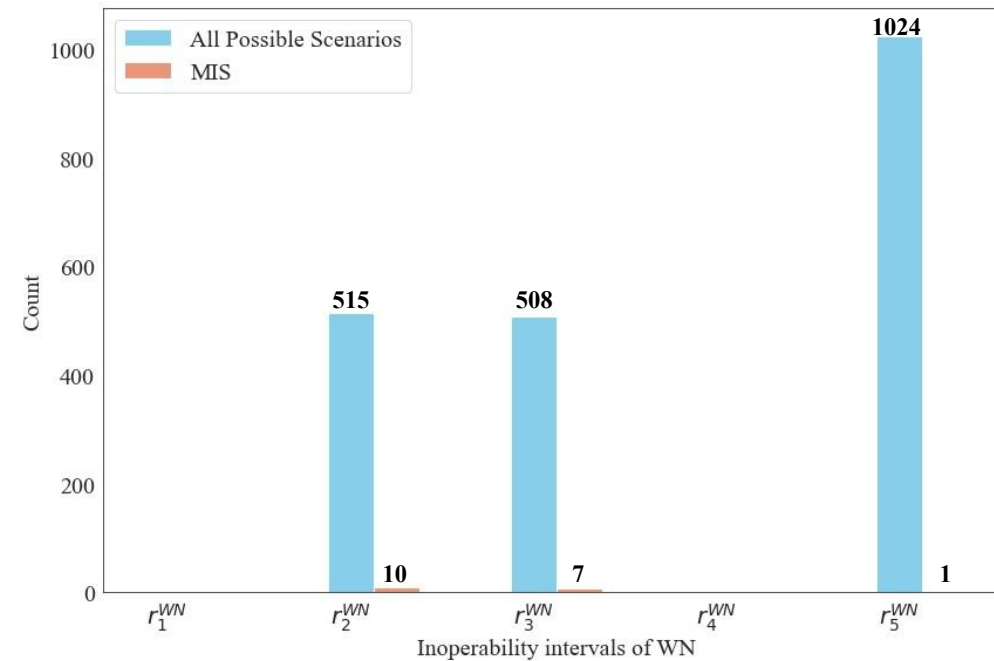
1. Characterization of the CIs' topology and operational attributes

2. Characterization of the dependencies

3. Exhaustive exploration of scenarios in the dependent CI

4. Identification of Minimal Inoperability Sets (MISs)

$$r^{WN} = \{r_1^{WN}, r_2^{WN}, r_3^{WN}, r_4^{WN}, r_5^{WN}\} = \{[0], (0, 0.2], (0.2, 0.6], (0.6, 0.8], (0.8, 1]\}$$



MISs focus the analysis on the **most impactful scenarios**, eliminating redundant or unnecessary ones that do not provide additional insights

## 2. Hybrid Approach to Model Interdependencies

### 2.3 Application Example: Random Failures

1. Characterization of the CIs' topology and operational attributes

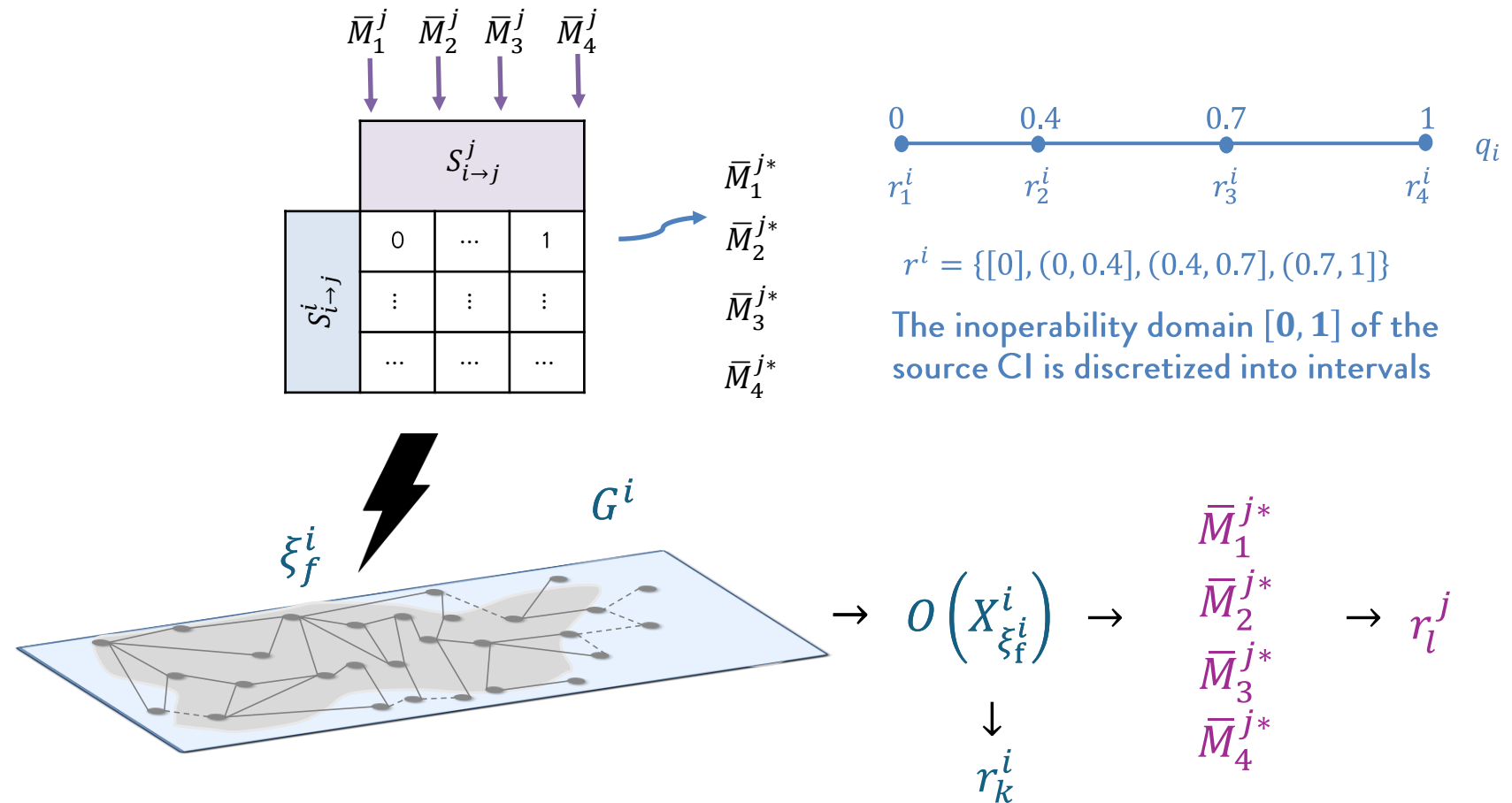
2. Characterization of the dependencies

3. Exhaustive exploration of scenarios in the dependent CI

4. Identification of Minimal Inoperability Sets (MISs)

5. Estimation of inoperability using DIIM

Using the dependency matrix  $\bar{M}_{i \rightarrow j}$ , MISs are correlated with state sets of the source CI



## 2. Hybrid Approach to Model Interdependencies

### 2.3 Application Example: Random Failures

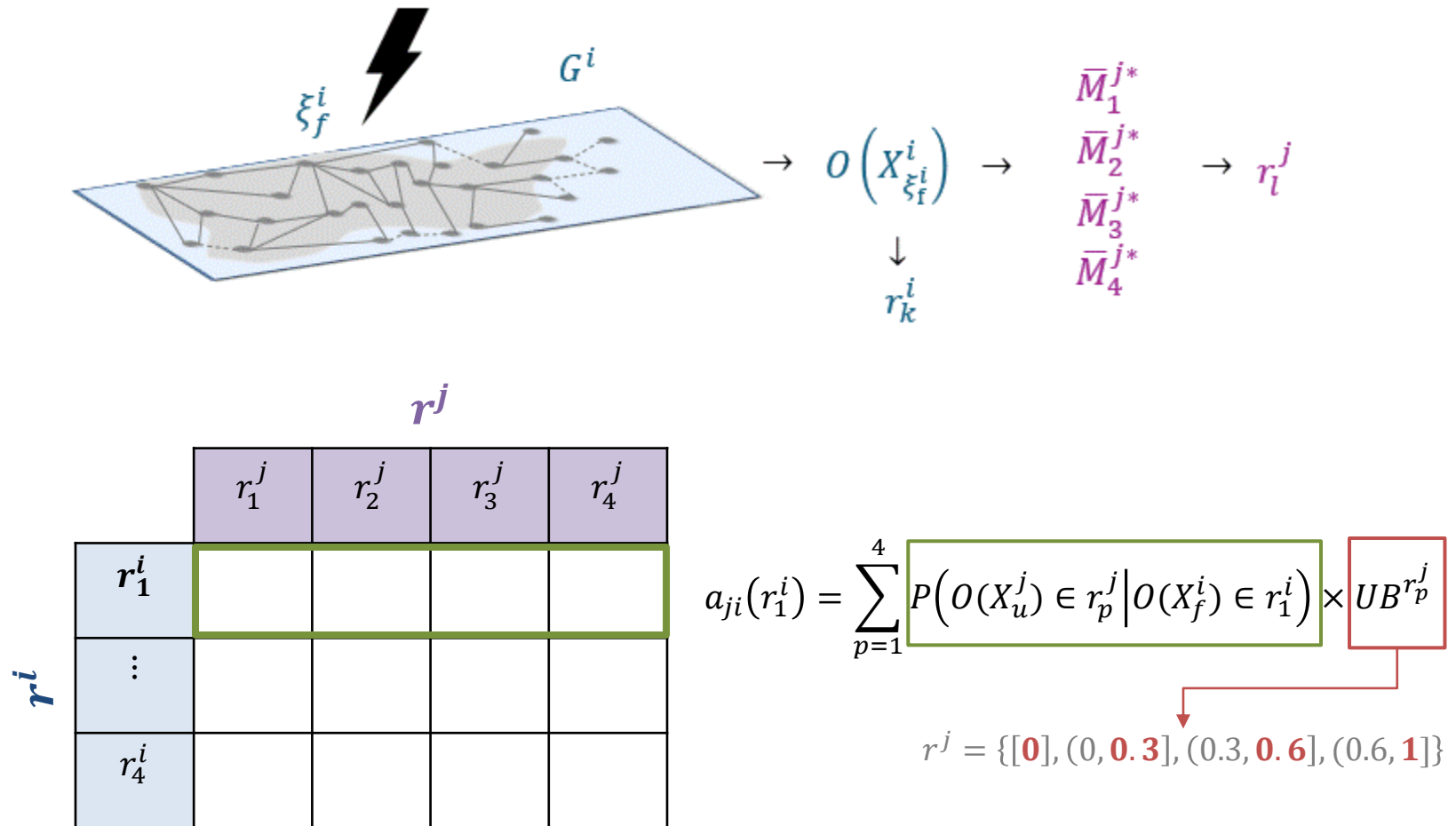
1. Characterization of the CIs' topology and operational attributes

2. Characterization of the dependencies

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4. Identification of Minimal Inoperability Sets (MISs)

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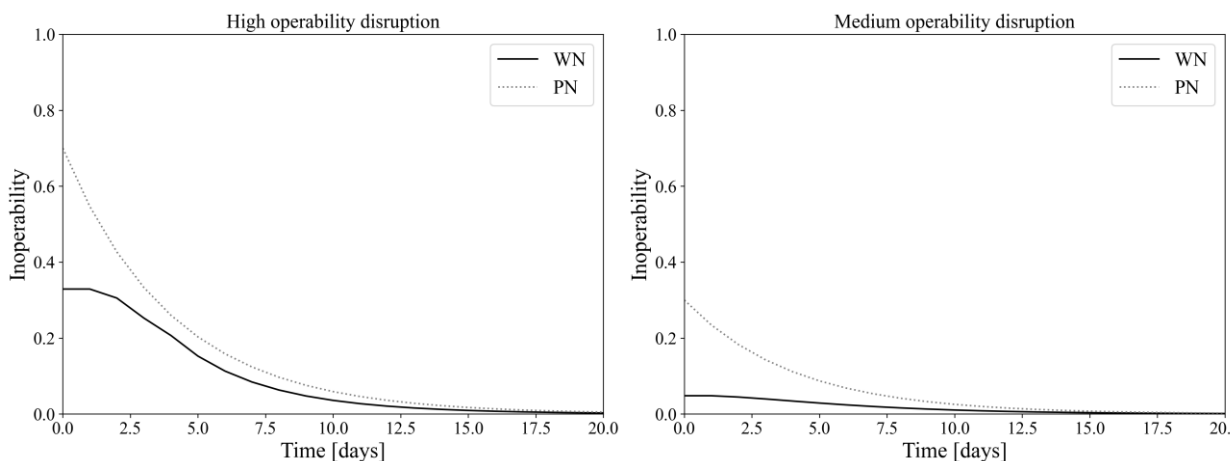
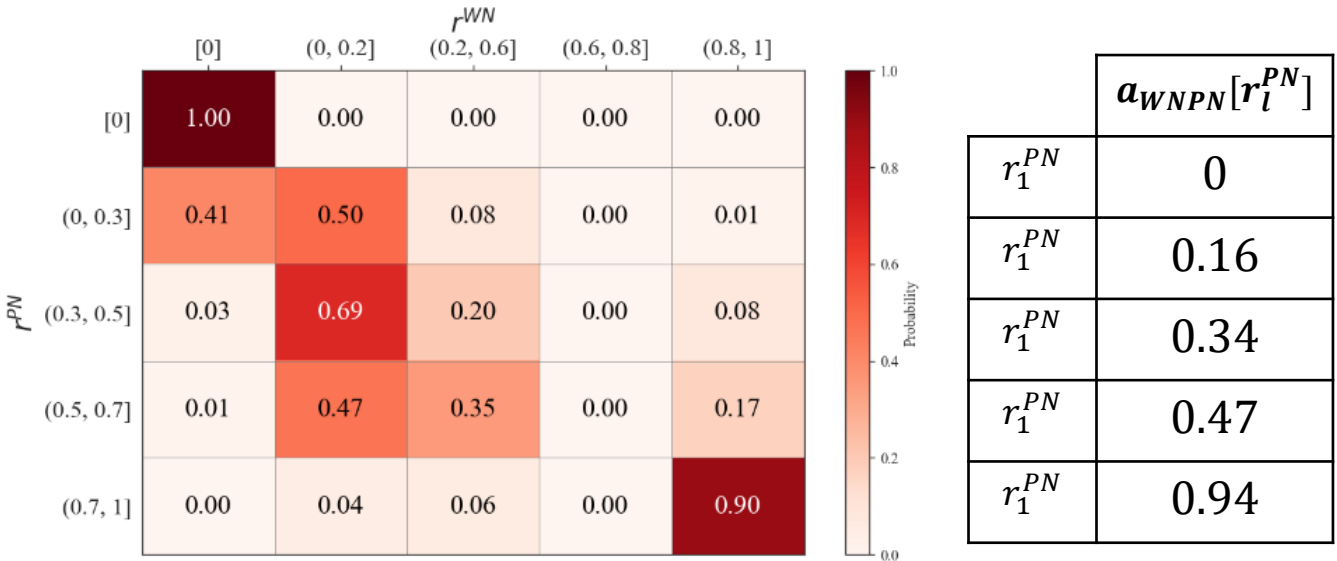
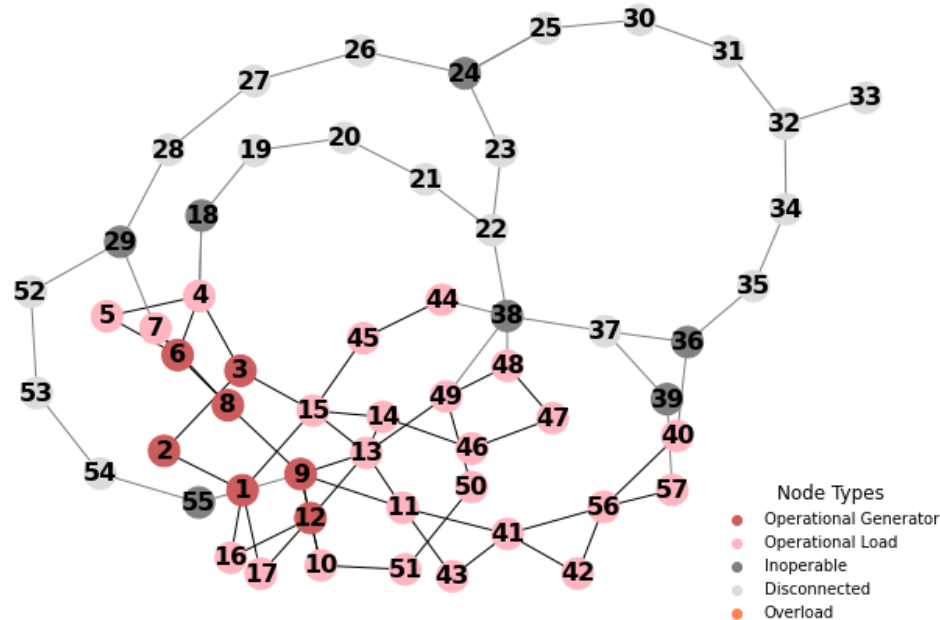


# 2. Hybrid Approach to Model Interdependencies

## 2.3 Application Example: Random Failures

$$r^{PN} = \{r_1^{PN}, r_2^{PN}, r_3^{PN}, r_4^{PN}, r_5^{PN}\}$$
$$r^{PN} = \{[0], (0, 0.3], (0.3, 0.5], (0.5, 0.7], (0.7, 1]\}$$

Inoperability= 0.520, No cascading effects in WN



# 2. Hybrid Approach to Model Interdependencies

## 2.3 Application Example: Random Failures

		without MISs	with MISs			
		$a_{WNPN}[r_k^{PN}]$	$a_{WNPN}[r_k^{PN}]$			
$r^{PN}$	[0]	0	0	Identification of the most frequent inoperability intervals of each CI	✓	✓
	(0, 0.3]	0.18	0.16	Ability to model the stochastic nature of dependency between CIs	✓	✓
	(0.3, 0.5]	0.37	0.34	For each inoperability interval in the dependent CI, MISs are identified	✗	✓
	(0.5, 0.7]	0.60	0.47	Computational time for 1000 disruption scenarios	92.82 seconds	61.10 seconds
	(0.7, 1]	0.94	0.94			

13.02 seconds to identify the MISs

48.08 seconds to estimate interdependency coefficients

## 2. Hybrid Approach to Model Interdependencies

### 2.3 Application Example: Random Failures

- *Inoperability assessment of interdependent CIs* requires to model cascading failures between CIs.
- *Minimal Inoperability Sets* analysis is originally introduced to identify the *minimal combination of node states* that guarantee *specified inoperability thresholds* in interdependent CIs.
- By *Minimal Inoperability Sets* analysis, the *most impactful failure scenarios are identified*, which can guide targeted resilience decisions.



## 2. Hybrid Approach to Model Interdependencies

### 2.3 Application Example: Random Failures



2024 the 8th International Conference on System Reliability and Safety

## Inoperability Assessment of Interdependent Critical Infrastructures by Minimal Inoperability Sets Analysis

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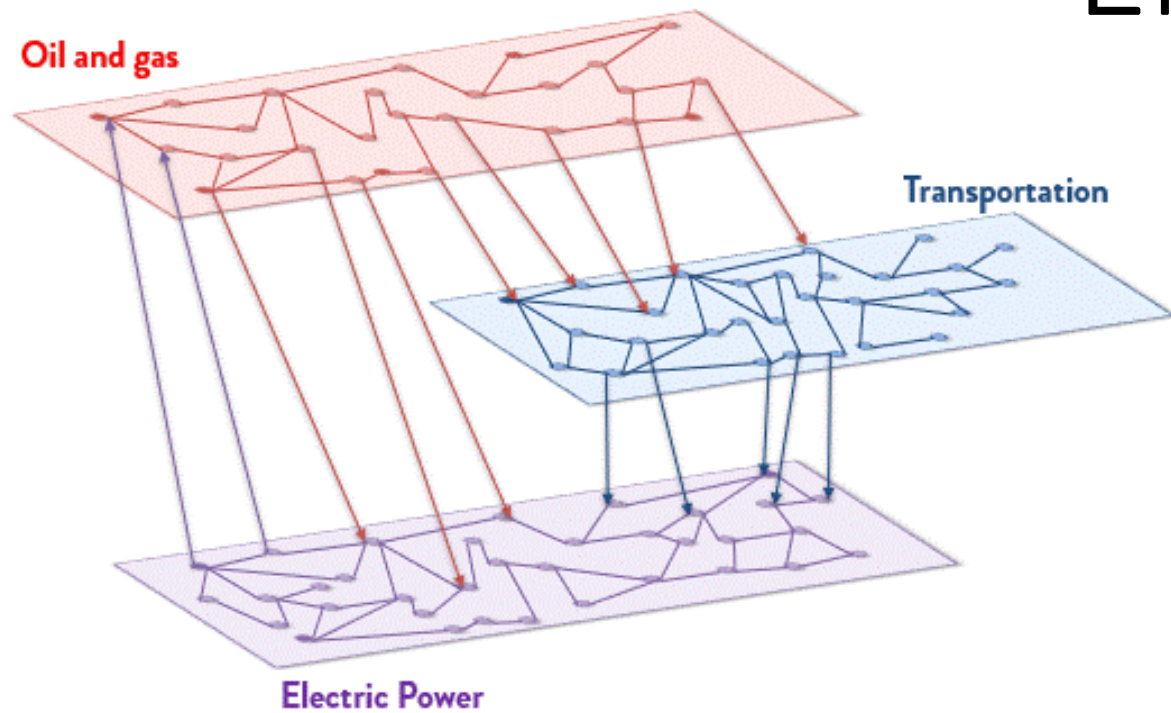
[4]

## 2. Hybrid Approach to Model Interdependencies

### 2.3 Application Example: Random Failures - References

- [1] 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. [https://doi.org/10.1061/\(asce\)1076-0342\(2005\)11:2\(67](https://doi.org/10.1061/(asce)1076-0342(2005)11:2(67)
- [2] Setola, R., Oliva, G., & Conte, F. (2012). Time-Varying Input-Output inoperability model. *Journal Of Infrastructure Systems*, 19(1), 47-57. [https://doi.org/10.1061/\(asce\)is.1943-555x.0000099](https://doi.org/10.1061/(asce)is.1943-555x.0000099)
- [3] Xu, W., Wang, Z., Hong, L., He, L., & Chen, X. (2013). The uncertainty recovery analysis for interdependent infrastructure systems using the dynamic inoperability input-output model. *International Journal Of Systems Science*, 46(7), 1299-1306. <https://doi.org/10.1080/00207721.2013.822121>
- [4] Clavijo-Mesa, M. V., Di Maio, F., & Zio, E. (2024b). Inoperability Assessment of Interdependent Critical Infrastructures by Minimal Inoperability Sets Analysis. 2024 8th International Conference On System Reliability And Safety (ICSRS), 291-295. <https://doi.org/10.1109/icsrs63046.2024.10927577>

## 2.4 Application Example: Natural Hazard Effects





## 2. Hybrid Approach to Model Interdependencies

### 2.4 Application Example: Natural Hazard Effects



A highway stands immersed in floodwaters from Hurricane Harvey, Texas on August 30<sup>th</sup>, 2017 [1]



A snow-covered town during the 2021 Texas winter storm [2]

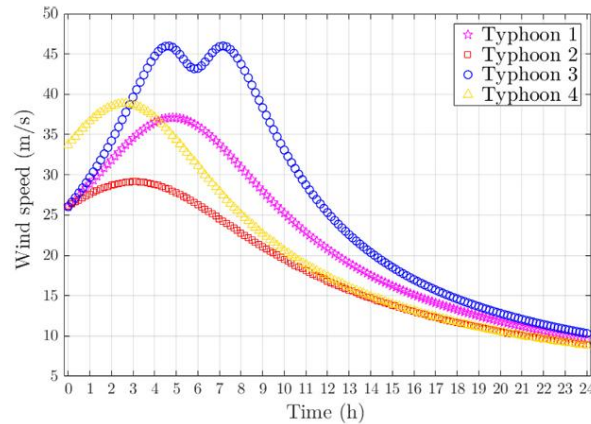


Widespread flooding in Southern Brazil after dam failures and storms in 2024 [3]

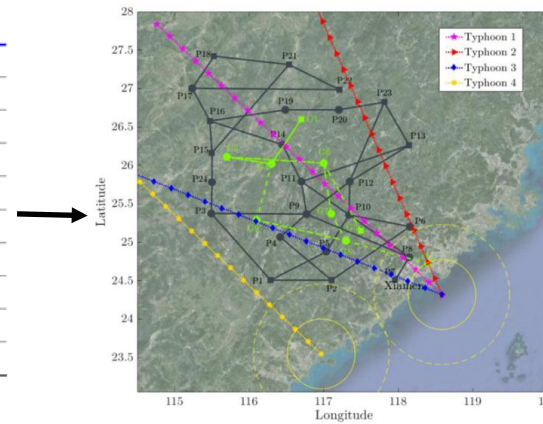
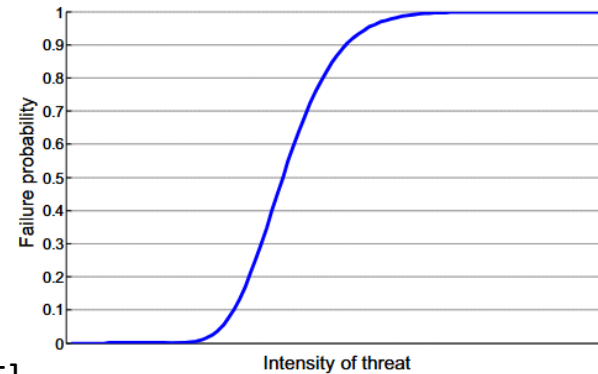
Although *terrorist attacks* initially motivated the study of *CIs protection*, *climate change* has made *extreme events* more plausible around the world

## 2. Hybrid Approach to Model Interdependencies

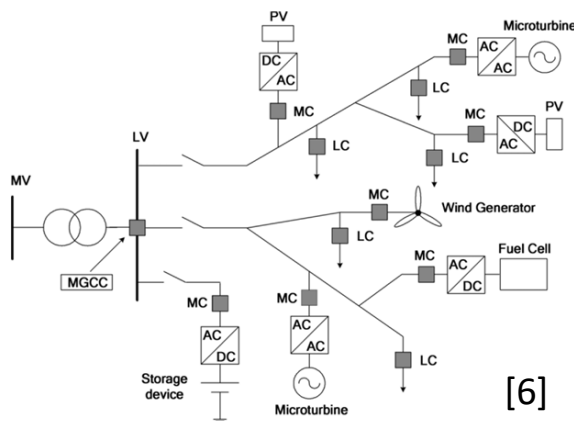
### 2.4 Application Example: Natural Hazard Effects



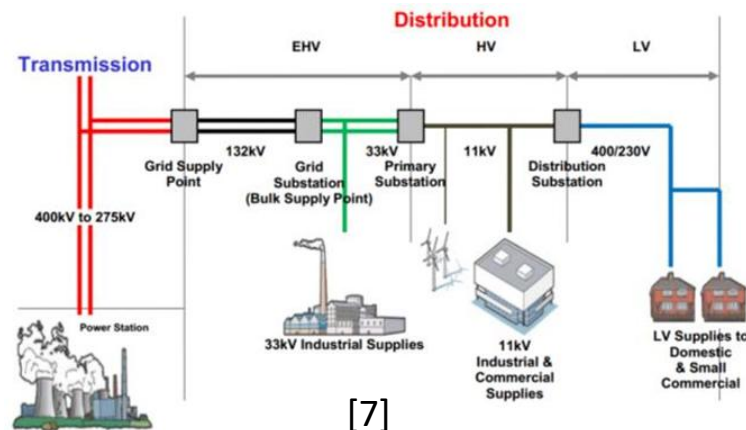
[4,5]



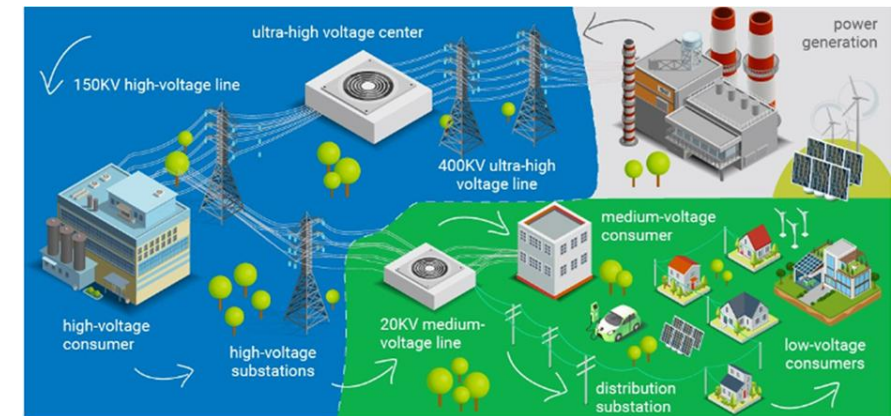
Many studies address *CI vulnerability*, but *overlook* the *spatial dependency* of natural hazards



[6]



[7]



[8]



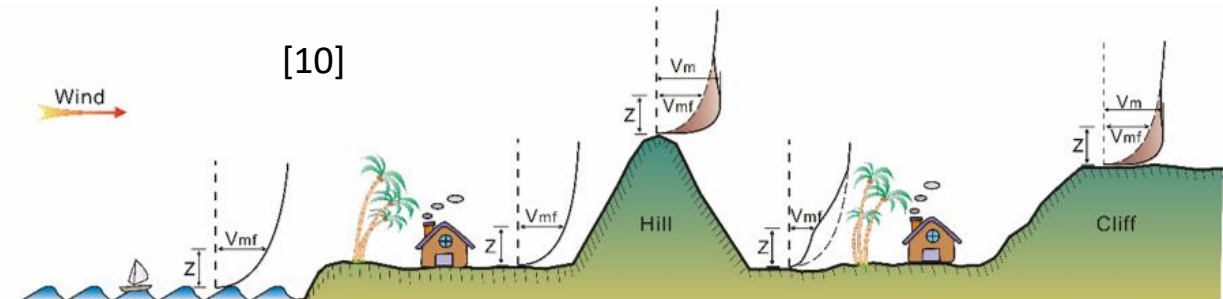
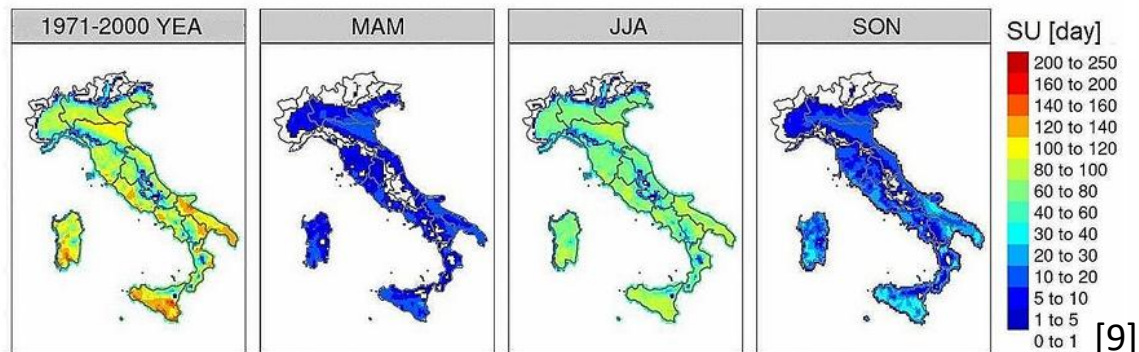
## 2. Hybrid Approach to Model Interdependencies

### 2.4 Application Example: Natural Hazard Effects

*Hazard spatial modeling* is advancing, but often remains *disconnected* from CI vulnerability and *cascading effects between interdependent CIs*



[11]

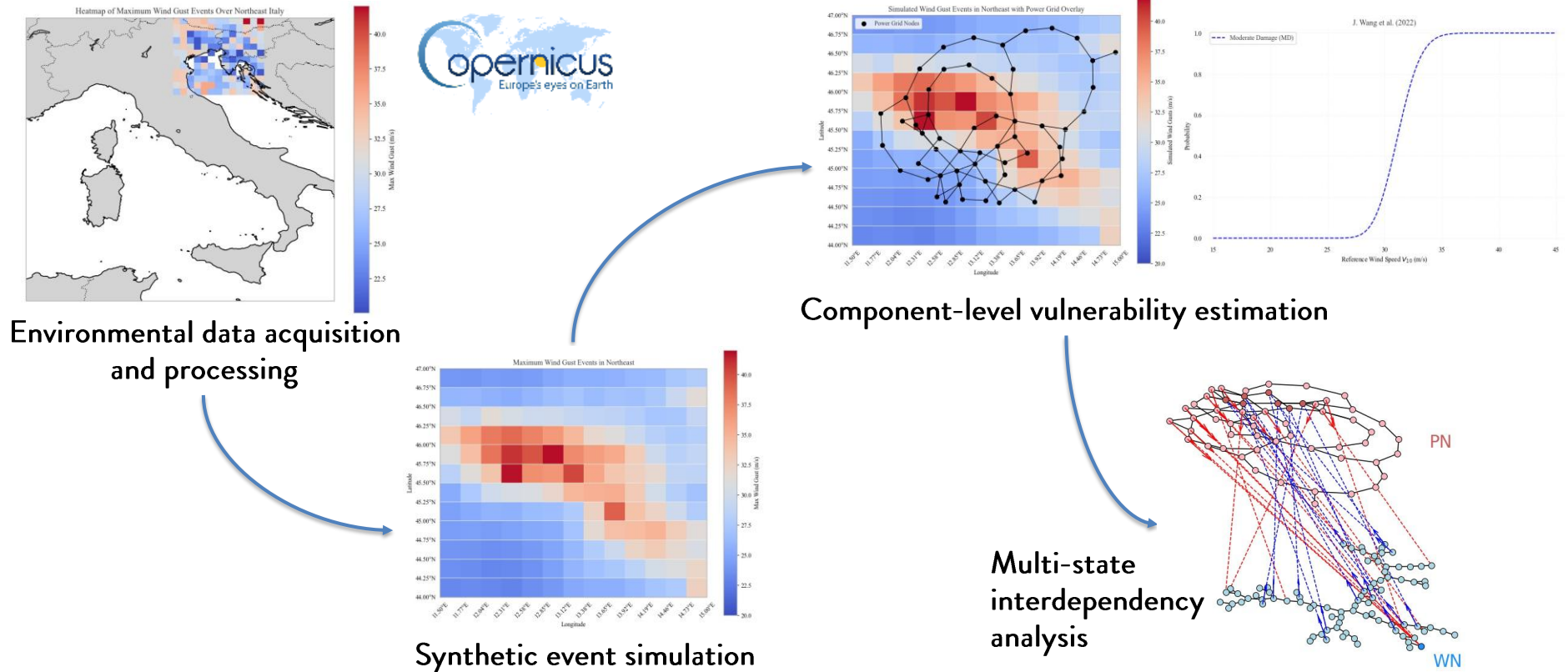




## 2. Hybrid Approach to Model Interdependencies

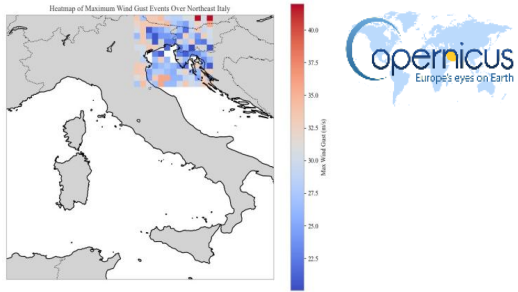
### 2.4 Application Example: Natural Hazard Effects

How can we model the *spatially correlated* and *cascading impacts* of natural hazards on *interdependent CIs*?



# 2. Hybrid Approach to Model Interdependencies

## 2.4 Application Example: Natural Hazard Effects

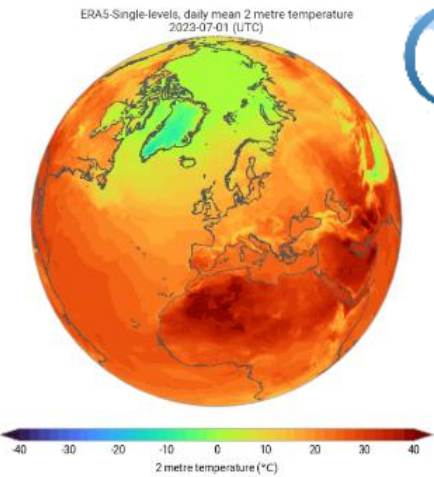


Environmental data acquisition and processing



Wind is a key hazard for power grids, causing transmission and distribution structures collapse, frequent faults, and widespread outages as wind speeds increase

[12, 13]

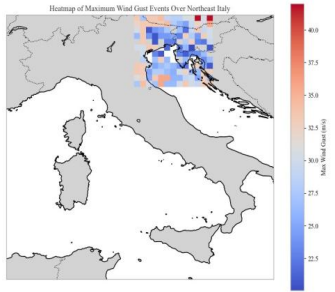


ERA5 is a dataset produced by the **European Centre for Medium-Range Weather Forecasts**, offering global climate data with high temporal and spatial resolution.

Description of dataset	
Dataset	ERA5 post-processed daily statistics on single levels from 1940 to present
Time Horizon	December 1994 – December 2021
Variables	10m U component of wind
	10m V component of wind
	Instantaneous 10m wind gust
Frequency	6 hourly
Area	North: 47°N West: 6°E South: 36°N East: 18°E → Italy

# 2. Hybrid Approach to Model Interdependencies

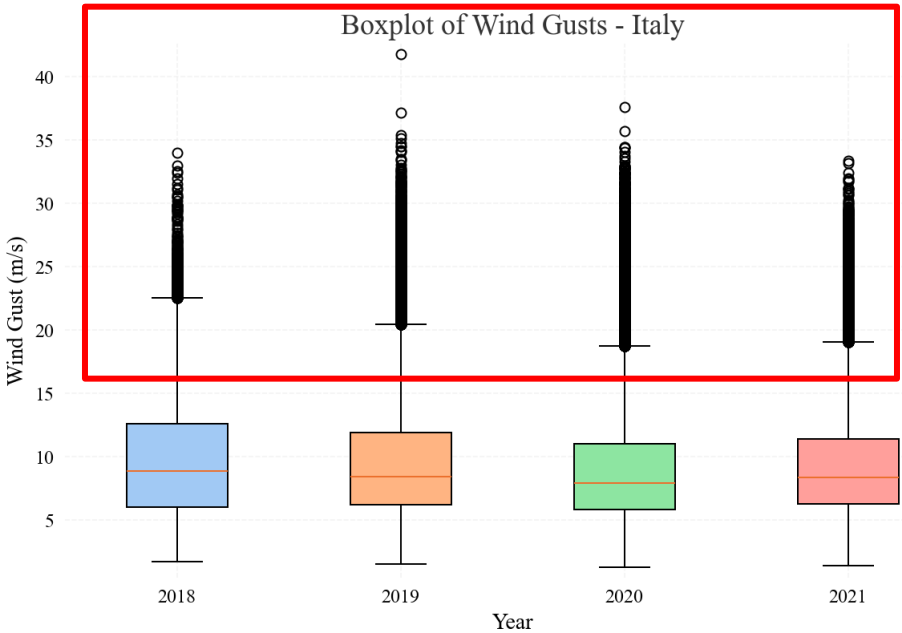
## 2.4 Application Example: Natural Hazard Effects



Environmental data acquisition and processing



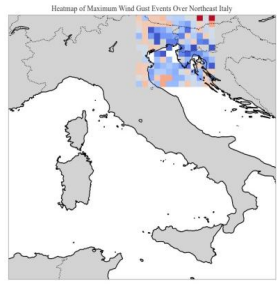
While maximum wind speeds show general trends, *instantaneous wind gusts capture peak short-duration* winds critical for structure fragility assessments [14]



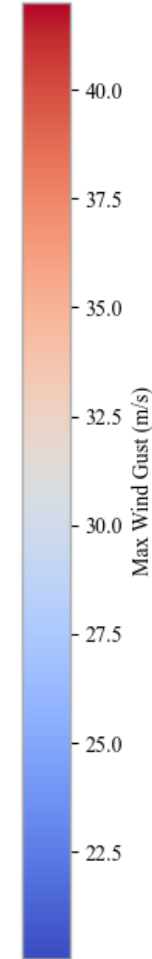
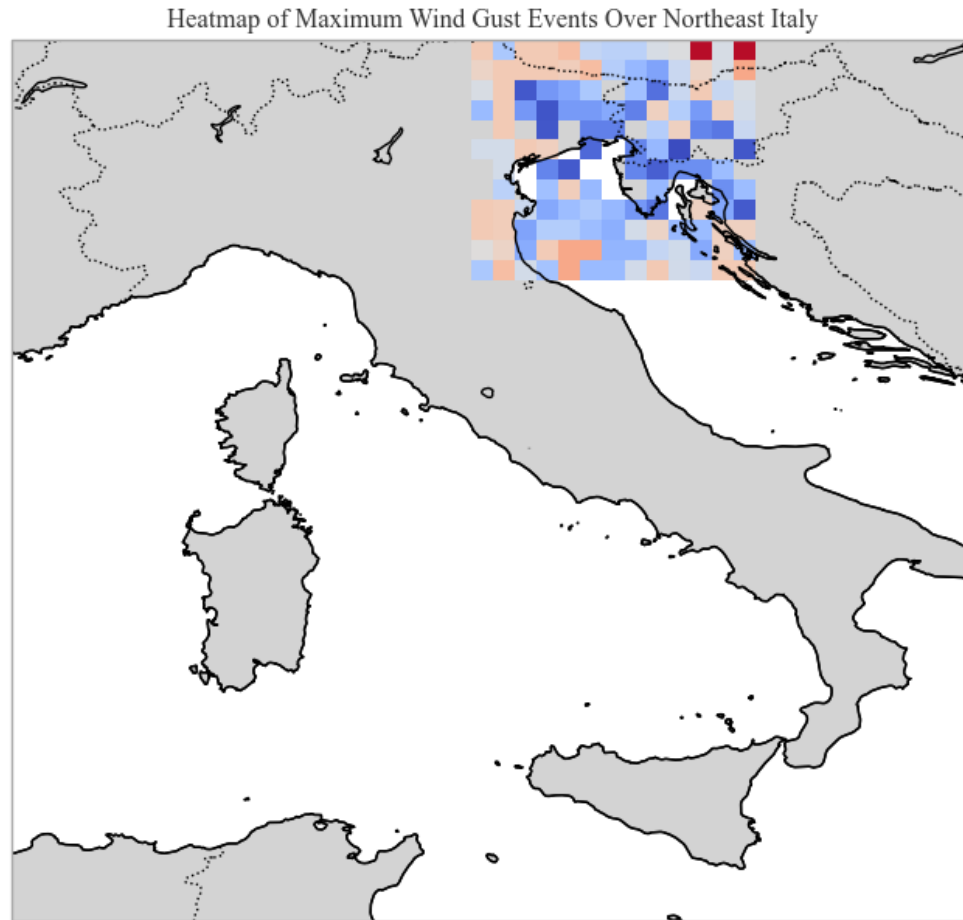
	Border/Offshore	Central	Islands	Northeast	Northwest	Southern
Mean	24.56	24.42	24.56	24.96	24.39	24.31
Standard deviation	3.58	3.37	3.58	3.66	3.43	3.35
Percentile 95	32.14	30.58	31.19	32.82	30.87	30.26

## 2. Hybrid Approach to Model Interdependencies

### 2.4 Application Example: Natural Hazard Effects



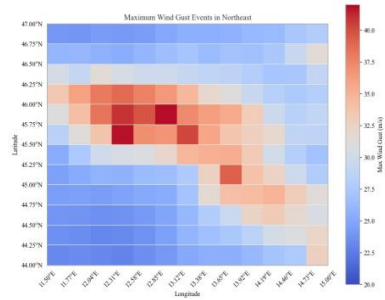
Environmental data acquisition  
and processing



Maximum 3 second wind **at 10 m height** collected on a horizontal resolution of  $0.25^\circ \times 0.25^\circ$ , this corresponds to approximately  $27.8 \text{ km} \times 27.8 \text{ km}$

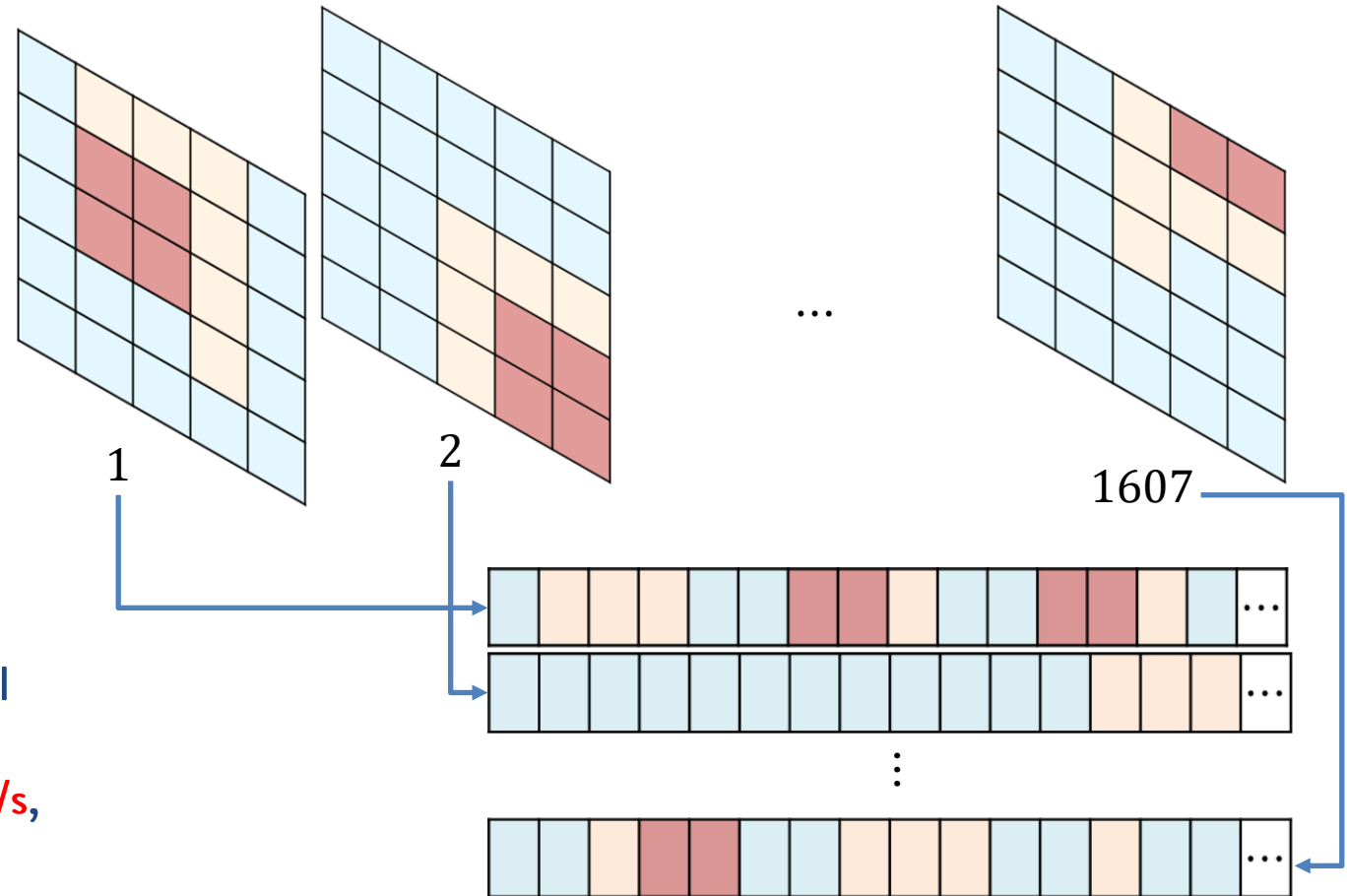
## 2. Hybrid Approach to Model Interdependencies

### 2.4 Application Example: Natural Hazard Effects



Synthetic event simulation

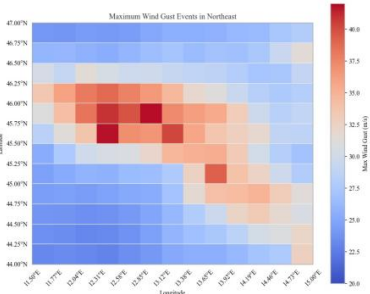
From 1994 to 2021, we identified all days in which at least one grid point recorded a wind gust exceeding **20 m/s**, resulting in a total of **1607** events





# 2. Hybrid Approach to Model Interdependencies

## 2.4 Application Example: Natural Hazard Effects

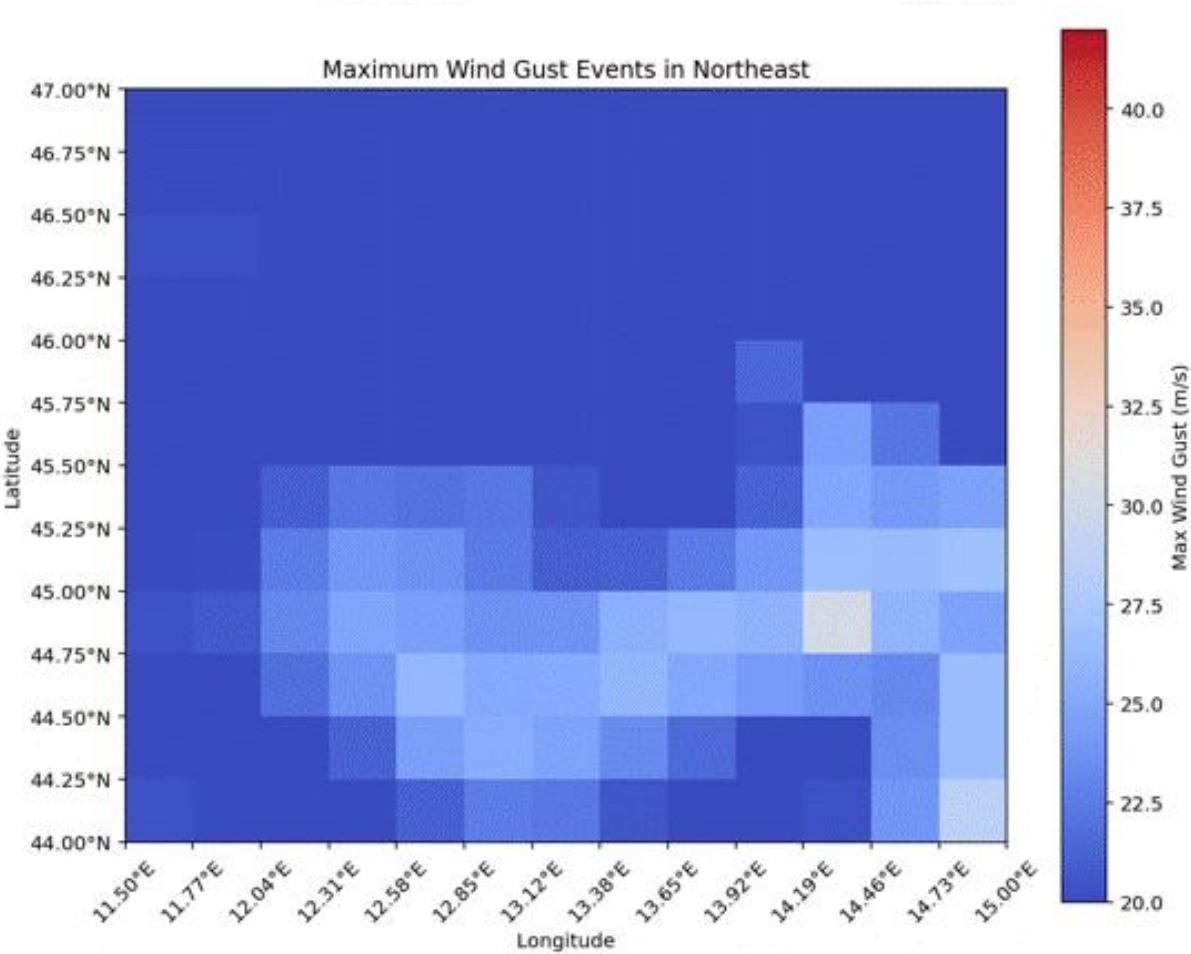


Synthetic event simulation



Gaussian Copula fitting failed due to a non-positive definite correlation matrix

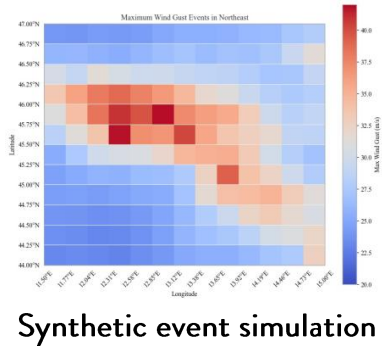
Criteria	C-Vine	D-Vine
Log-Likelihood (LL)	4.1457e+03	1.2865e+04
Akaike information criterion (AIC)	-8.2913e+03	-2.5730e+04
Bayesian information criterion (BIC)	-8.2913e+03	-2.5730e+04
Copula inference time	41.37 seconds	52.71 seconds
Time to generate 1000 disruption scenarios	7.62 seconds	9.65 seconds



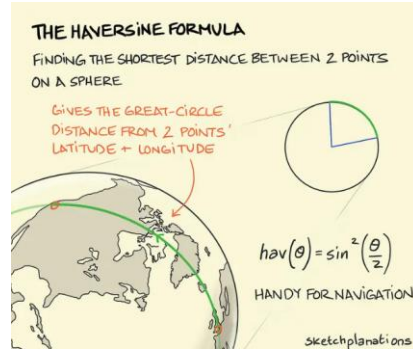


## 2. Hybrid Approach to Model Interdependencies

### 2.4 Application Example: Natural Hazard Effects



Synthetic event simulation

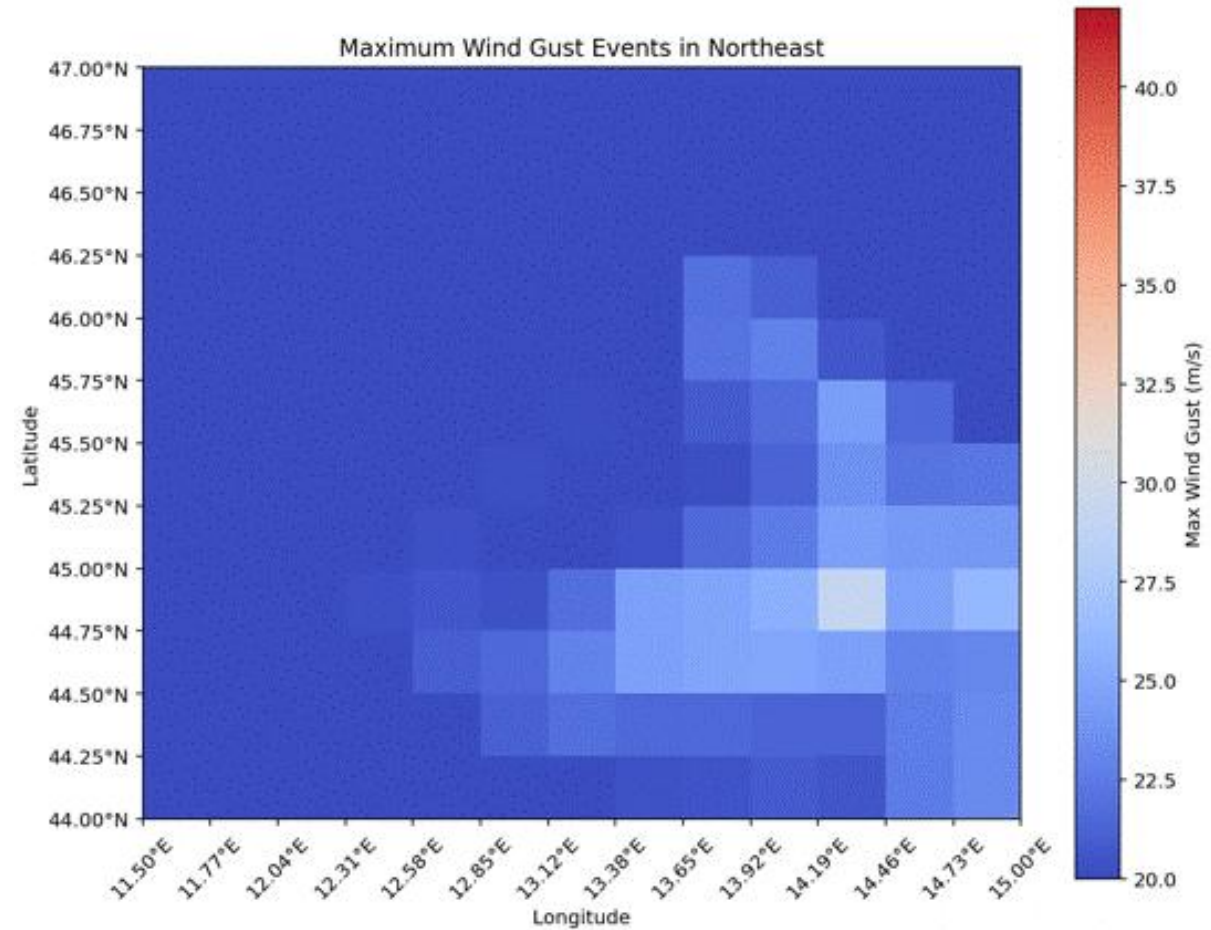


Using real latitude and longitude coordinates for point in the grid, distances are calculated with the Haversine formula

Empirical covariance

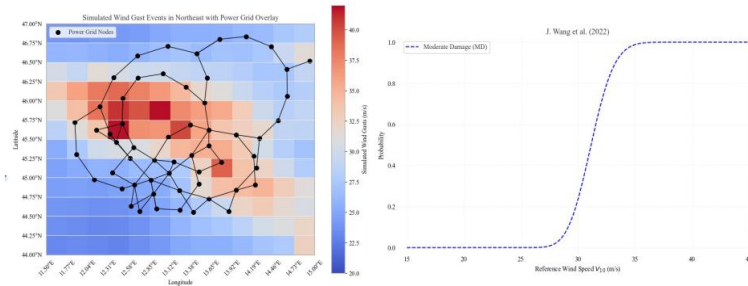
$$\text{Cov}(Z_i, Z_j) = \frac{1}{m-1} \sum_{k=1}^m (Z_i^{(k)} - \bar{Z}_i)(Z_j^{(k)} - \bar{Z}_j)$$

- $Z_i, Z_j$  wind gust values at grid points  $x_i, x_j$ , transformed to standard normal space,
- $m$  number of wind gust scenarios,
- $Z_i^{(k)}$  wind gust in standard normal space at point  $i$  during scenario  $k$ ,
- $\bar{Z}_i$  mean of the transformed values at point  $i$  across all scenarios

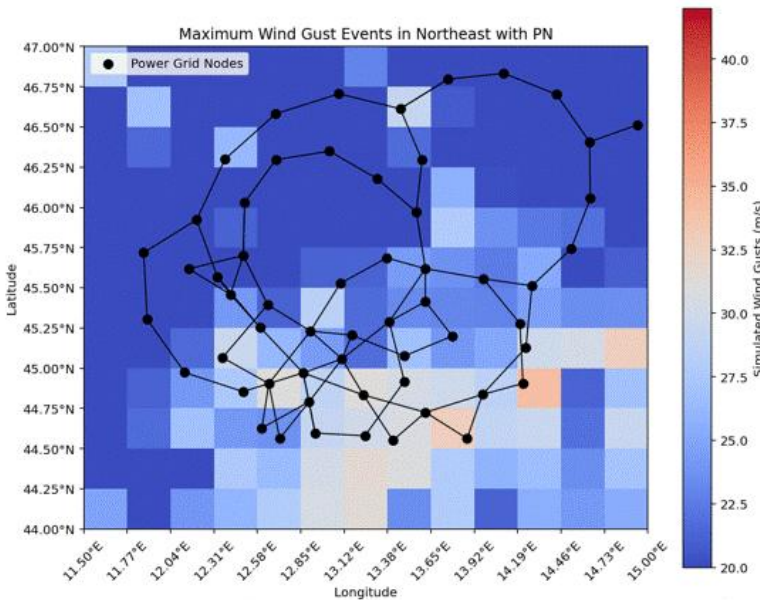


## 2. Hybrid Approach to Model Interdependencies

### 2.4 Application Example: Natural Hazard Effects



Component-level vulnerability estimation

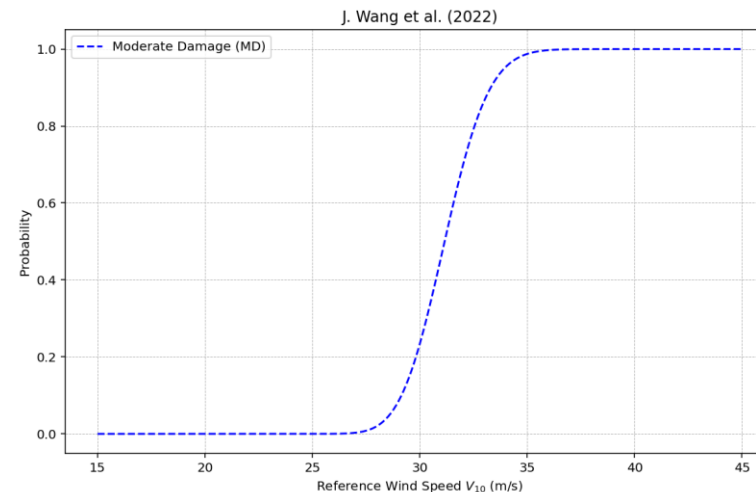


- Generate pseudo-scenarios of **wind gusts** at grid nodes on the **Northeast of Italy**



- Compute **edge exposure** as the **maximum wind gust** between the two connected nodes

- Estimate **failure probability** using the **Moderate Damage fragility curve** from [15]



$$P_f(w) = \Phi\left(\frac{\log(w) - m}{\beta}\right),$$

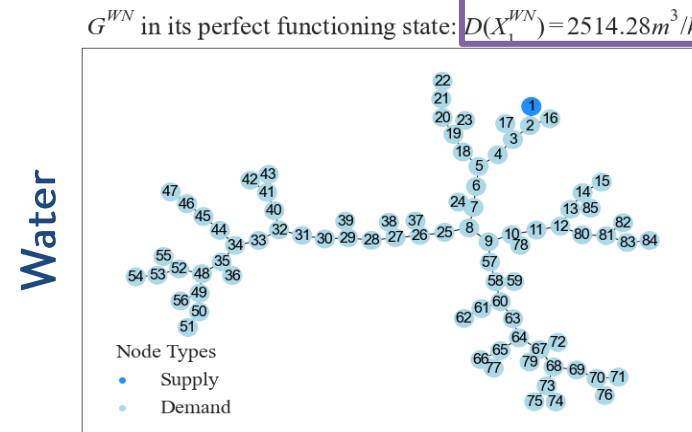
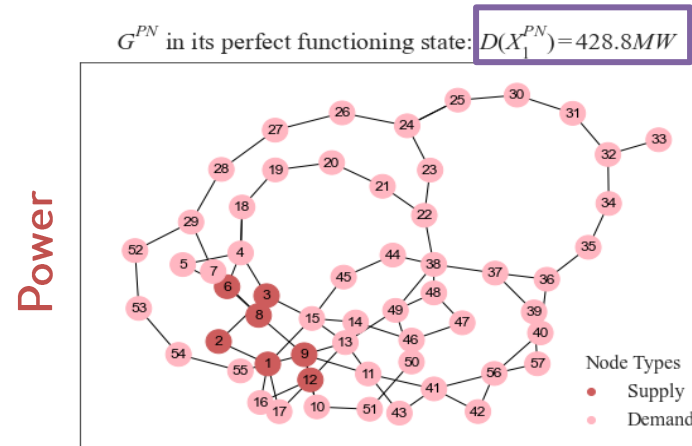
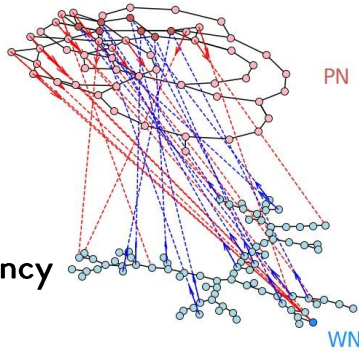
$$\therefore m = 3.439, \beta = 0.052$$

- Simulate **edge failure** by comparing a **random number**  $U \sim u(0, 1)$  to  $P_f$  (if  $U < P_f$ , the edge is removed from PN)

## 2. Hybrid Approach to Model Interdependencies

### 2.4 Application Example: Natural Hazard Effects

Multi-state  
interdependency  
analysis



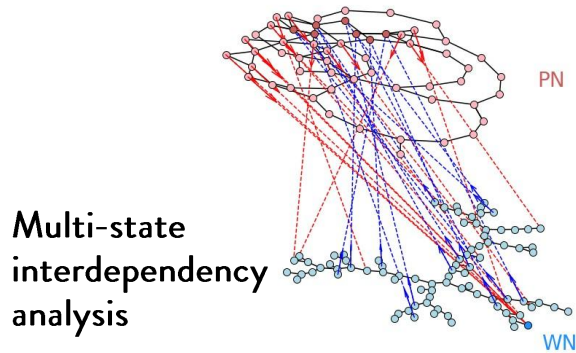
$$n_z^i \in N_S^i \rightarrow \bar{x}^{n_z^i} = \begin{bmatrix} x_1^{n_z^i} \\ x_2^{n_z^i} \\ x_3^{n_z^i} \\ x_4^{n_z^i} \end{bmatrix} \begin{matrix} \text{Operational} \\ \text{Disconnected} \\ \text{Overloaded} \\ \text{Inoperable} \end{matrix}$$

$$n_z^i \in N_D^i \rightarrow \bar{x}^{n_z^i} = \begin{bmatrix} x_1^{n_z^i} \\ x_2^{n_z^i} \\ x_3^{n_z^i} \end{bmatrix} \begin{matrix} \text{Operational} \\ \text{Disconnected} \\ \text{Inoperable} \end{matrix}$$

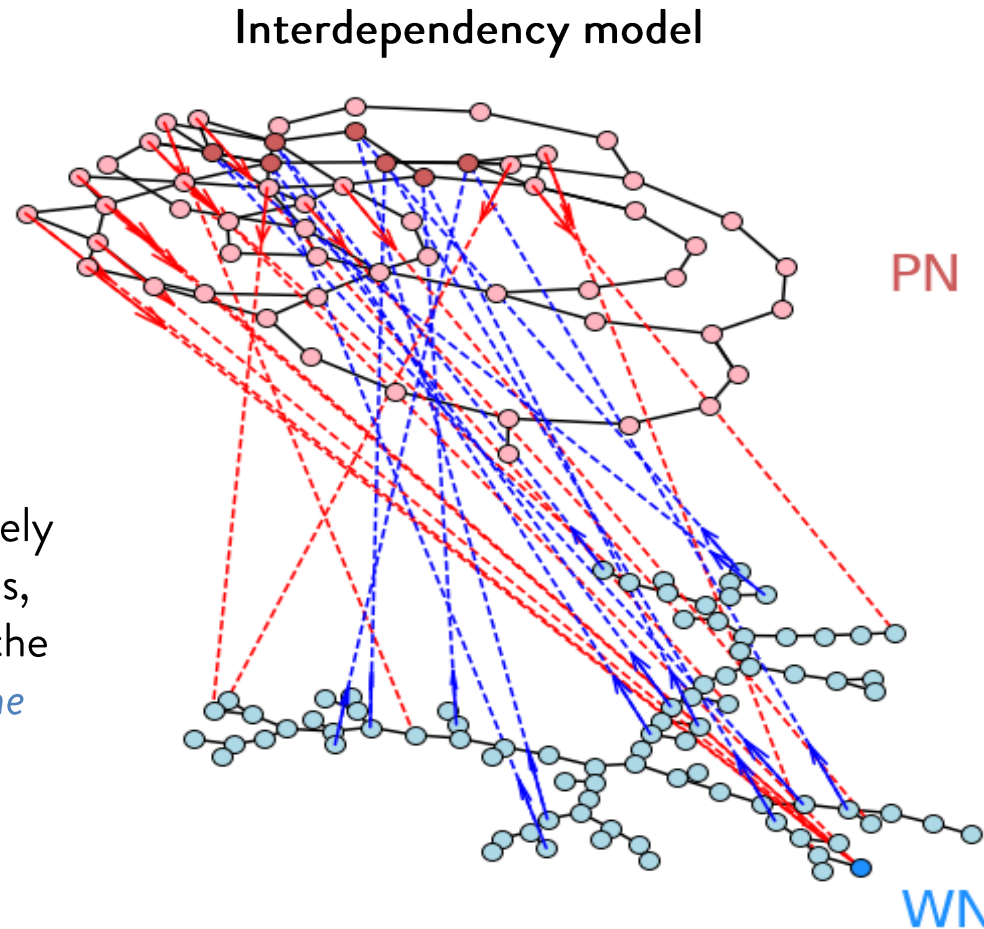
$$x_1^{n_z^i} = 1, \forall n_z^i \in N^i \rightarrow X_1^i$$

## 2. Hybrid Approach to Model Interdependencies

### 2.4 Application Example: Natural Hazard Effects



Water treatment and pumping nodes rely on electricity supplied by power nodes, while all power generators depend on the water network for cooling—*making the system of systems interdependent*



$$r^{PN} = \left\{ \begin{array}{l} [0, \\ (0, 0.3], \\ (0.3, 0.5], \\ (0.5, 0.7], \\ (0.7, 1] \end{array} \right\}$$

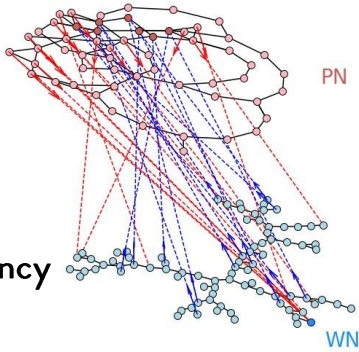
$$r^{WN} = \left\{ \begin{array}{l} [0, \\ (0, 0.2], \\ (0.2, 0.6], \\ (0.6, 0.8], \\ (0.8, 1] \end{array} \right\}$$



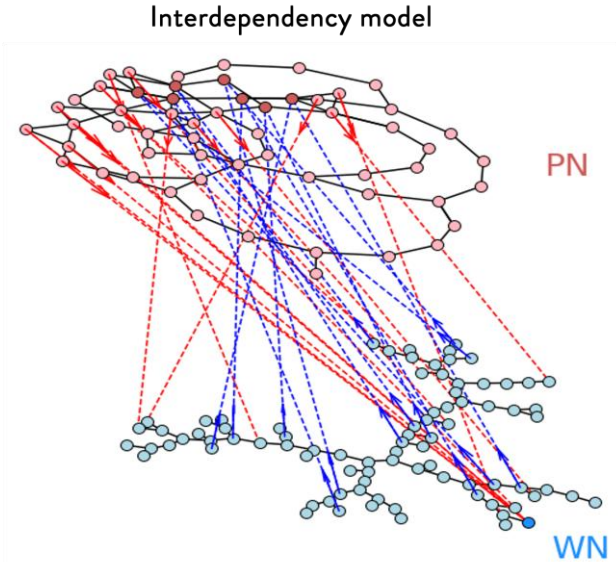
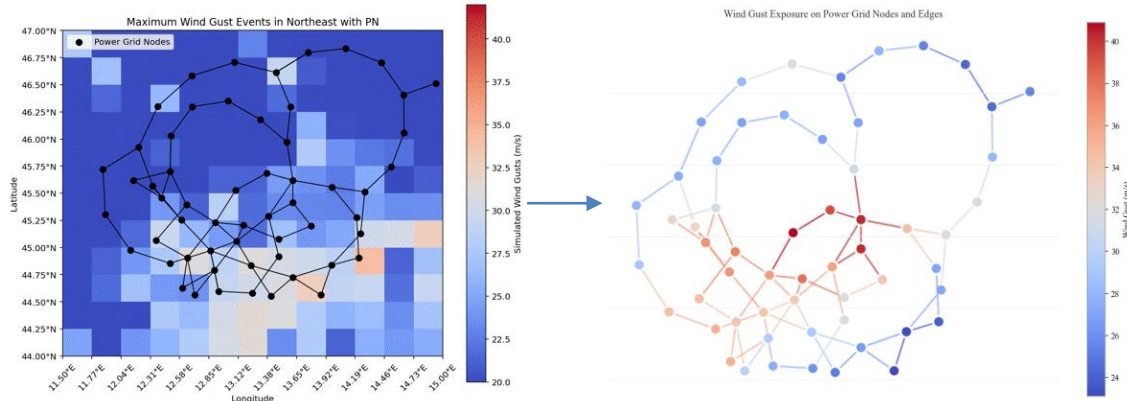
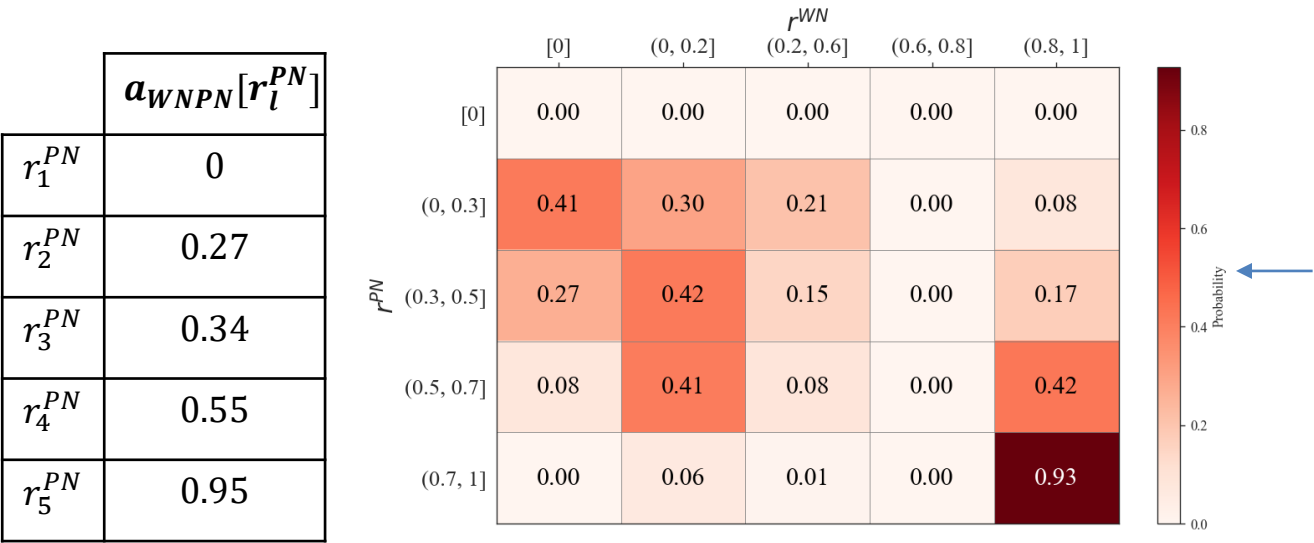
# 2. Hybrid Approach to Model Interdependencies

## 2.4 Application Example: Natural Hazard Effects

Multi-state interdependency analysis

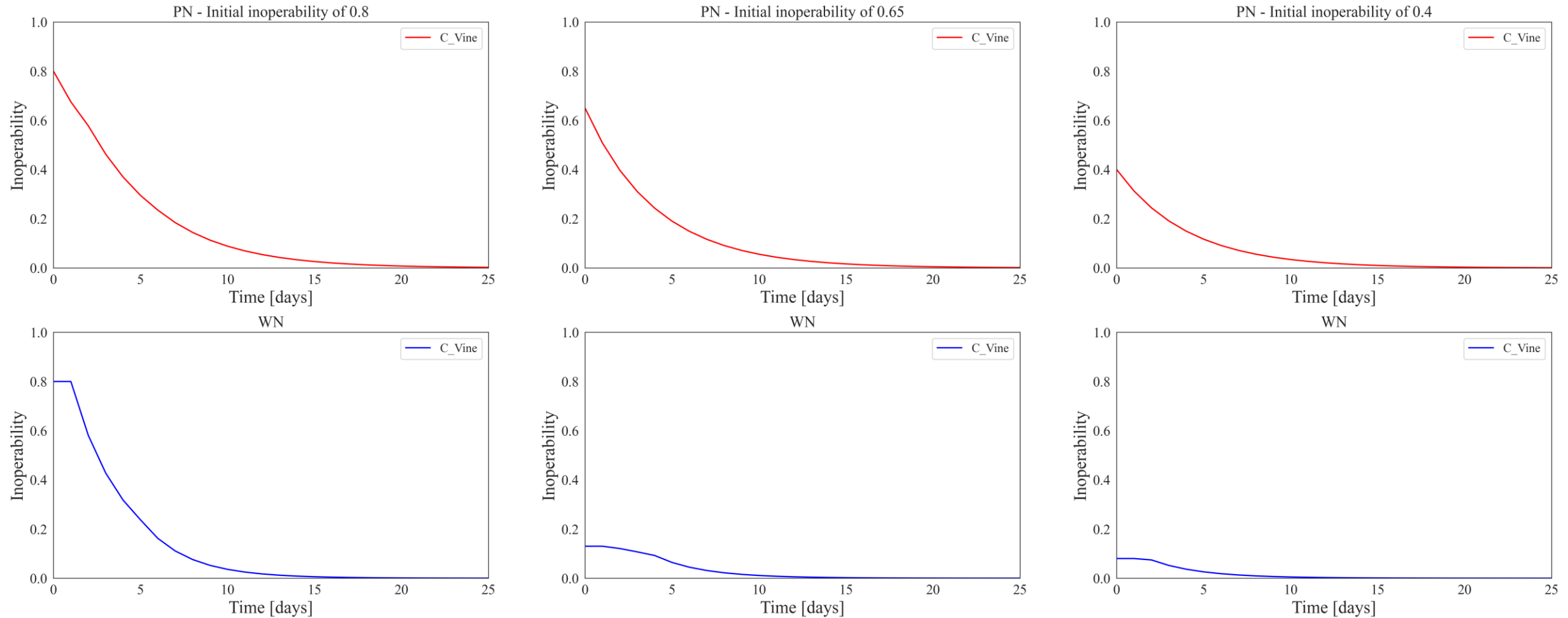


Edges were modelled using a *binary state*.  
A random number was compared to the fragility curve for **Moderate Damage** — if exceeded, the edge was *removed* from the network



## 2. Hybrid Approach to Model Interdependencies

### 2.4 Application Example: Natural Hazard Effects



## 2. Hybrid Approach to Model Interdependencies

### 2.4 Application Example: Natural Hazard Effects

#### Interdependent Critical Infrastructures Inoperability due to Spatially Dependent Natural Hazards Modelled by Copulas

Maria Valentina Clavijo Mesa<sup>a</sup>, Francesco Di Maio<sup>a,\*</sup>, Enrico Zio<sup>b,a</sup>

<sup>a</sup>Energy Department, Politecnico di Milano, Milan, Italy

<sup>b</sup>MINES Paris-PSL University, Centre de Recherche sur les Risques et les Crises (CRC),  
Sophia Antipolis, France

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#### Abstract

Exposure of Critical Infrastructures (CIs) to natural hazards is spatially dependent. Copulas can capture non-linear and asymmetric dependencies of natural hazard intensities across a spatial domain. In particular, C-Vine copulas offer a flexible modeling approach for complex dependencies, including tail effects due to extreme hazard events. The Copulas modeling solution is exemplified on an interdependent water and power network exposed to extreme wind in the Northeast of Italy. Inoperability is then evaluated by a Dynamic Inoperability Input-Output Model (DIIM).

**Keywords:** Natural hazards, Spatial dependence, Inoperability, Interdependent critical infrastructures, C-Vine Copula.

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#### A Natural Hazard Stochastic Field for the Assessment of the Inoperability of Interdependent Critical Infrastructures exposed to Climate Change

Maria Valentina Clavijo Mesa<sup>a</sup>, Francesco Di Maio<sup>a,\*</sup>, Enrico Zio<sup>b,a</sup>

<sup>a</sup>Energy Department, Politecnico di Milano, Milan, Italy

<sup>b</sup>MINES Paris-PSL University, Centre de Recherche sur les Risques et les Crises (CRC),  
Sophia Antipolis, France

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#### Abstract

Stochastic field is an effective solution for modeling natural hazards under climate change, especially when they expose large-scale multi-state interdependent critical infrastructures (CIs) to inoperability. Historical and climate projected natural hazards data on a vast geographical scale are to be manipulated to catch its spatial dependencies. With stochastic field historical data are used to characterize the marginal behavior of the hazard at each location, that using the Karhunen–Loève Expansion (KLE), simulates spatially coherent extreme event scenarios. The modeling solution is exemplified on a multi-state interdependent power and water network located in the North of Italy. The inoperability under the climate projected hazard stochastic field is evaluated using the Dynamic Inoperability Input-output Model (DIIM), that captures cascading and interdependent effects, under evolving climate and natural events conditions.

**Keywords:** Stochastic Field, Inoperability Assessment, Critical Infrastructures, Climate Change, Karhunen–Loève Expansion.

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## 2. Hybrid Approach to Model Interdependencies

### 2.4 Application Example: Natural Hazard Effects

#### Doctoral guidance



**lasar<sup>3</sup>**

Laboratory of Analysis of  
Systems for the  
Assessment of Reliability,  
Risk and Resilience



PhD, Assistant Professor

Research focus: *safety, security, risk, resilience assessment*

**Ibrahim Ahmed**



PhD, Full Professor

Research focus: *modelling, simulation and data analytics for PHM*

**Piero Baraldi**



PhD, Associate Professor

Research focus: *safety, security, risk, resilience assessment*

**Francesco Di Maio**



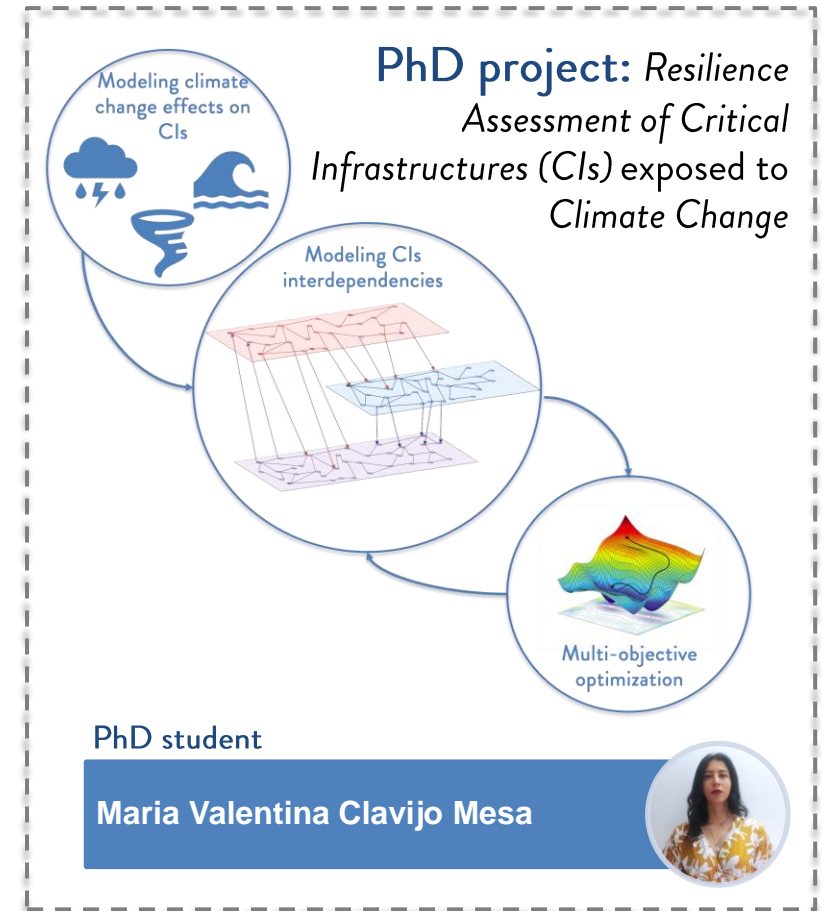
PhD, Full Professor

Scientific Director of  
research and  
development  
activities in LASAR

**Enrico Zio**

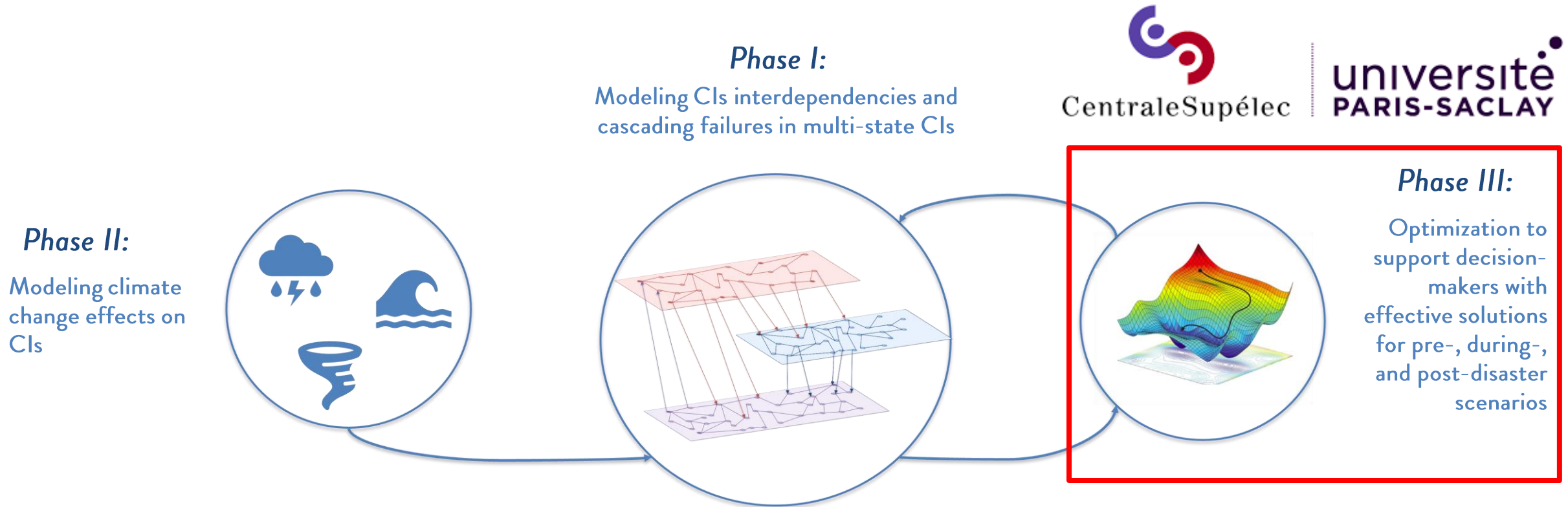


**Research Supervisors**



## 2. Hybrid Approach to Model Interdependencies

### 2.4 Application Example: Natural Hazard Effects



## 2. Hybrid Approach to Model Interdependencies

### 2.4 Application Example: Natural Hazard Effects: References

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**THANKS**

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