# Supplementary I: Literature review of studies on interdependent critical infrastructures

Means of the abbreviations and acronyms in Table S1:

* Temporal scale: ST = short-term; LT = long-term
* Types of impacts: T = Technical; O = organizational; E = economic; S = societal.
* Granularities of measurement of infrastructure performance (MIP): B = binary; Ca = categorial; C = continuous
* Methods: IIM = inoperability input-output method; ER = empirical research; ABM = agent-based model; SD = system dynamics, BN = Bayesian network; OT = operational techniques
* Interdependency: L = logical; P = physical; G = geographical; C = cyber

Table S1. Recent research on interdependent critical infrastructures

| **No.** | **Sources** | **Year** | **Interdependent infrastructures** | **Background events** | **Oriented process** | **Abstraction Level** | **Temporal scale** | **Spatial scale** | **Types of impacts** | **Measurement of infrastructure performance** | **Granularities of MIP** | **Ultimate Outcomes** | **Case** | **Methods** | **Interdependency** |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 1 | Goldbeck *et al*. (2019) | 2019 | Metro Electricity power | Flood | Ex-post | MESO | ST | City | T | Demand and Supply | C | Resilience | R | Network | P |
| 2 | Loggins *et al*. (2019) | 2019 | Civil infrastructures Social infrastructures | General | Ex-post | MACRO | Static | County | T | Node, link, network related indicators | B | Restoration | R | OT  Network | P |
| 3 | Fang & Zio (2019) | 2019 | Power  Gas | Typhoon | Ex-ante Ex-post | MESO | Static | Region | T | Node, link, network related indicators | B | Resilience | R | OT  Network | P |
| 4 | Almoghathawi & Barker (2019) | 2019 | Power  Water | General | Ex-ante Ex-post | MESO | Static | N/A | T | Node, link, network related indicators | B | Resilience | V | Network | P |
| 5 | Mohamed (2019) | 2019 | Power Grid  ICT Network  E-Mobility | General | Ex-ante | MESO | Static | N/A | T | Node, link, network related indicators | B | General Failure | V | Network | P |
| 6 | Beyza *et al*. (2019) | 2019 | Power  Gas | General | Ex-ante | MESO | Static | N/A | T | Node, link, network related indicators | B | Resilience | V | Network | P |
| 7 | Kong *et al*. (2019) | 2019 | Electric  Gas  Oil | Hurricane Flood | Ex-ante Ex-post | MESO | Static | Region | T | Node, link, network related indicators | B | Resilience | R | Network | P |
| 8 | Klein & Klein (2019) | 2019 | 11 CIs | General | Ex-ante Ex-post | MICRO | ST | N/A | E | Sectors’ outputs | C | Operability | V | IIM\* | L |
| 9 | Almoghathawi *et al*. (2019) | 2019 | Power Water | General | Ex-ante Ex-post | MESO | Static | N/A | T | Node, link, network related indicators | B | Resilience | V | Network | P |
| 10 | Zhou *et al*. (2018) | 2019 | Water Power Gas | General | Ex-ante | MESO | Static | City | T | Node status-based network characteristics | B | Robustness | R | Network | F, G |
| 11 | Yang *et al*. (2019) | 2019 | Drainage pipe Transit | Rainfall | Ex-ante | MACRO | ST | Community | T | Drainage pipe capacity Traffic speed  …… | C | Vulnerability\* | R | PBM | G |
| 12 | Thompson *et al*. (2019) | 2019 | Power Water | Climate  Change | Ex-ante | MESO | LT | Region | T | Unmet demand Cost …… | C | Capacity | V | ABM | P |
| 13 | Khalid & Ali (2019) | 2019 | 23 CIs | Flooding | Ex-post | MICRO | ST | Nation | E | Sector inoperability | C | Operability\* | R | IIM | E |
| 14 | Tariverdi *et al*. (2019) | 2019 | Health Care Network Power Water Transportation | General | Ex-ante Ex-post | MESO | ST | City | T, O | Patients served Capacity of power water and transportation | C | Resilience | V | OT | F, G |
| 15 | Danziger *et al*. (2019) | 2019 | Power grid Telecommunication | General | Ex-ante | MESO | Static | N/A | T | Nodes remained or removed | B | Robustness | V | Network | P G |
| 16 | Attary *et al*. (2019) | 2019 | Power Building | Hurricane | Ex-ante | MESO | ST | Community | T, S | Power loss Buildings have power or not | Ca | Damage | R | ER | P |
| 17 | Lin *et al*. (2019) | 2019 | Telecommunication  Electricity | General | Ex-ante | MICRO MESO | ST | City | T, E | Failed node in telecommunication network and electrical grid | B | Loss | R | IIM Network | L, P |
| 18 | Applegate & Tien (2019) | 2019 | Power Water supply | General | Ex-ante | MESO | Static | City | T | Node status Failure probability Network Minimum Link Set | C, B | Vulnerability | R | Bayesian network | P G |
| 19 | Monsalve & Carlos de la Llera (2019) | 2019 | Gas Power Water | Earthquake | Ex-post | MICRO | ST | Nation | T | Capacity of each system | C | Restoration | R | ER | General |
| 20 | Dong *et al*. (2019) | 2019 | General | General | Ex-ante | MESO | Static | N/A | T | Node status | B | Vulnerability | V | Network | P G |
| 21 | Wang *et al*. (2018) | 2018 | Power Gas | General | Ex-ante | MESO | Static | City | T | Node status Node capacity (e.g., betweenness) | B | Vulnerability | R | Network | P |
| 22 | Zeraati *et al*. (2018) | 2018 | Power Cyber | General | Ex-ante | MACRO | Static | N/A | T | The delayed response of the disconnected components …… | C | Vulnerability | R | OT | P, C, G |
| 23 | Galbusera *et al*. (2018) | 2018 | Electricity Port | Earthquake | Ex-ante Ex-post | MESO | LT | Community | T | Node status with threshold | B | Resilience Recovery Serviceability | R | Network | P |
| 24 | Alinizzi *et al*. (2018) | 2018 | Pavement Underground utilities | General | Ex-ante | MESO | LT | N/A | T | Cost Treatment service Life | C | Preparedness | V | OT | G |
| 25 | He *et al*. (2018) | 2018 | Power Gas | General | Ex-ante | MACRO | ST | N/A | T | Gas consumption  Electric energy consumption | C | Vulnerability | V | OT | P |
| 26 | Dong *et al*. (2018) | 2018 | General | General | Ex-ante | MESO | Static | N/A | T | Node status | B | Vulnerability | V | Network | General |
| 27 | Zhao *et al*. (2018) | 2018 | Water supply Electric power Natural gas  Oil transportation Telecommunication | General | Ex-ante | MESO | Static | City | T | Node degree Flow Page rank | B | Criticality | R | Network | P |
| 28 | Xian & Jeong (2018) | 2018 | Electricity Water Telecommunication | Hurricane | Ex-ante Ex-post | MESO | LT | City | T, E | Node, link, network related indicators | C | Damage Recovery | R | IIM Network | P, L |
| 29 | Seppanen *et al*. (2018) | 2018 | General | Winter Storm | Ex-ante | MICRO | Static | N/A | G | N.A. | B | Vulnerability | V | ER | General |
| 30 | Lam & Tai (2018) | 2018 | 8 CIs | General | Ex-ante | MICRO | Static | N/A | T | System status with fuzzy | B | Vulnerability | V | Network | General |
| 31 | Hempel *et al*. (2018) | 2018 | Power Transportation | Blackout | Ex-ante Ex-post | MESO | ST, LT | General | T, O | Node, link, network related indicators | B | Criticality | V | ER | General |
| 32 | Rueda *et al*. (2018) | 2018 | Power | General | Ex-ante | MESO | Static | N/A | T | Node, link, network related indicators | B, C | Robustness | V | Network | P G |
| 33 | Mo *et al*. (2018) | 2018 | Water Energy | Future  Changes | Ex-ante | MESO | LT | City | S | Demands and supply | C | Resilience Sustainability | V | ABM SD | L |
| 34 | Mao & Li (2018) | 2018 | Electric power Telecommunication Water supply | Typhoon | Ex-ante | MESO | Static | City | T | Node, link, network related indicators | B | Impact  Resilience | R | Network | P |
| 35 | Tsavdaroglou *et al*. (2018) | 2018 | 7 CIs | Extreme Climatic Events | Ex-ante Ex-post | MESO | Static | Nation | T, O | Time to recover Exposure to hazard | C | Risk Vulnerability | R | ER | P |
| 36 | Zhang *et al*. (2018b) | 2018 | Electricity Water | General | Ex-post | MESO | ST | N/A | T | Node, link, network related indicators | B, C | Restoration | V | Network | P |
| 37 | Antenucci & Sansavini (2018) | 2018 | Electric Gas | Demand surge | Ex-ante | MESO | Static | N/A | T | Node, link, network related indicators | B, C | Adequacy Security | V | Network | P |
| 38 | Lu *et al*. (2018) | 2018 | Water Electricity | General | Ex-ante | MESO | Static | Community | T | Water capacity Electricity capacity | C | Vulnerability | R | Network | P |
| 39 | Rocco *et al*. (2018) | 2018 | Community  Electric power | General | Ex-post | MESO | ST | N/A | T | Node status | B, C | Recovery | V | OT Network | P |
| 40 | Liu *et al*. (2018) | 2018 | General | General | Ex-ante | MESO | Static | N/A | T | Node status preserved with the probability | B, C | Percolation | V | Network | General |
| 41 | Zhang *et al*. (2018a) | 2018 | General | General | Ex-post | MICRO | ST | Nation | E | Inoperability Restoration capacity Amount of resources  …… | C | Restoration | R | IIM | L |
| 42 | Duan *et al*. (2018) | 2018 | Communications Power | General | Ex-post | MESO | ST | N/A | T | Node, link, network related indicators | B, C | Reliability | V | Network | P, C |
| 43 | Chen *et al*. (2018) | 2018 | Communications Power | General | Ex-ante | MESO | Static | N/A | T | Node, link, network related indicators | B, C | Robustness Redundancy | V | Network | P |
| 44 | Banerjee *et al*. (2018) | 2018 | Power  Communication | General | Ex-ante | MESO | Static | Nation | T | Node, link, network related indicators | B | Robustness | R | Network | P |
| 45 | Johansen & Tien (2018) | 2018 | Power  Water Gas | General | Ex-ante Ex-post | MESO | Static | County | T | Failure probabilities for each component | B | Repair. | R | Bayesian network | G |
| 46 | Korkali *et al*. (2017) | 2017 | Communications Smart grid | General | Ex-ante | MESO | Static | Nation | T | Node status | B, C | Risk | R | Network | P |
| 47 | Zimmerman *et al*. (2017) | 2017 | Electric Power  Transportation Water Supply | Extreme Weather | Ex-ante Ex-post | MESO | ST | Nation | G | Infrastructure capacity Demands  Supplies | C | Resilience | R | ER | P, G, L |
| 48 | Portante *et al*. (2017) | 2017 | Electricity  Gas | Pipe Breaks | Ex-ante | MESO | Static | Nation | T | Node, link, network related indicators Total supply  Total demand | B, C | Interdependency | R | ER | P |
| 49 | Bloomfield *et al*. (2017) | 2017 | Electricity Telecommunication | General | Ex-ante | MESO | ST | City | T | Node, link, network related indicators | C | Risk | R | Network | P |
| 50 | Heracleous *et al*. (2017) | 2017 | Water Telecommunication Power | General | Ex-ante | MACRO | ST | N/A | T | Water capacity | B, Ca, C | Interdependency | V | PBM | P, C, L |
| 51 | Faust *et al*. (2017) | 2017 | Portable water Wastewater Stormwater | Urban Decline | Ex-ante | MICRO | LT | City | O, S | Water demand  Utility revenues  …… | C | Preparedness | V | SD ABM | P |
| 52 | Alirezaei *et al*. (2017) | 2017 | Road Economy | Climate Change | Ex-ante | MICRO | LT | Global | S, T | Air temperature Infrastructure condition Ocean temperature | Ca, C | Interdependency | R | Sd | L |
| 53 | Cheng (2017) | 2017 | General | Geo-Disasters | Ex-ante | MICRO | Static | City | G | Node, link, network related indicators | Ca | Interdependency | V | ER | P |
| 54 | Nan & Sansavini (2017) | 2017 | Sub-system in power | General | Ex-ante Ex-post | MESO | ST | Nation | T | Power demand and served  …… | B, C | Resilience | R | PBM | P |
| 55 | Dong & Frangopol (2017) | 2017 | Healthcare  Bridge | Earthquake | Ex-ante | MESO | ST | Region | T | Hospital functional level | Ca, C | Damage Functionality | R | Indicator-based metrics | G |
| 56 | Min (2017) | 2017 | General | General | Ex-ante Ex-post | MESO | Static | N/A | T | Node, link, network related indicators | B | Resilience | V | Network | P |
| 57 | Tian *et al*. (2017) | 2017 | General | General | Ex-ante | MESO | Static | N/A | T | Node, link, network related indicators | B | Cascading Failures | V | Network | P |
| 58 | Hong *et al*. (2017) | 2017 | General | General | Ex-post | MESO | Static | N/A | T | Node, link, network related indicators | B | Recovery | V | Network | P, G |
| 59 | Yan *et al*. (2017) | 2017 | General | General | Ex-ante | MESO | Static | N/A | T | Node, link, network related indicators | B | Vulnerability | V | Network | P |
| 60 | Yuan *et al*. (2017) | 2017 | General | General | Ex-ante | MESO | Static | N/A | T | Node, link, network related indicators | B | Cascading Failures | V | Network | P |
| 61 | Korkali *et al*. (2017) | 2017 | Electricity Telecommunication | General failures | Ex-ante | MESO | Static | N/A | T | Node, link, network related indicators | B | Cascading Failures | V | Network | P |
| 62 | Rueda & Calle (2017) | 2017 | Power  Telecommunication | Targeted attacks | Ex-ante | MESO | Static | N/A | T | Node, link, network related indicators | B | Reliability | V | Network | P |
| 63 | Peng & Poudineh (2016) | 2016 | Electricity  Gas | General | Ex-ante | MICRO | LT | Nation | T, S | Gas power supply Gas production | C | Capacity | R | SD | L |
| 64 | Krishnamurthy *et al*. (2016) | 2016 | Power Telecommunication | Earthquake | Ex-post | MICRO | ST | City | G | Power outages Mobile outages | C | Restoration | R | ER | P |
| 65 | Kelly *et al*. (2016) | 2016 | 9 CIs | General | Ex-ante | MICRO | LT | UK | E | Sector output | C | Vulnerability | R | IIM | L |
| 66 | Reed *et al*. (2016) | 2016 | Power  Telecommunication | Weather-Related Hazards | Ex-post | MICRO | ST | N/A | T, S | Customers affected | C | Resilience | R | ER | P |
| 67 | Rahnamay-Naeini & Hayat (2016) | 2016 | Electric Cyber | General | Ex-ante | MESO | ST | N/A | G | Number of failures Probability | C | Risk | V | ER | P |
| 68 | Omega *et al*. (2016) | 2016 | General | Supply change | Ex-ante | MESO | Static | Community | E | Sector output | C | Risk | R | IIM | L |
| 69 | Yazdani & Azizi (2016) | 2016 | Water supply Gas Drainage Electricity  Telecommunication Transportation | General | Ex-post | MICRO | ST | Community | T | Pattern description | B | Restoration | R | ER | P, G |
| 70 | Sharkey *et al*. (2016) | 2016 | General | Hurricane | Ex-post | MICRO | ST | Region | S, O, T | Pattern description | B | Restoration | R | ER | P, G |
| 71 | Haraguchi & Kim (2016) | 2016 | Electricity Transportation Health care Building  …… | Hurricane | Ex-ante | MICRO | ST | City | T | Pattern description | B | Damage | R | ER | G |
| 72 | Tri-Dung *et al*. (2016) | 2016 | Water supply Biomass production Refineries | General | Ex-ante Ex-post | MICRO | LT | N/A | T | Long-term functionality | C | Resiliency Sustainability | V | ER Indicator-based metrics | P |
| 73 | MacKenzie *et al*. (2016) | 2016 | Tourism Real estate Petro | Oil leakage | Ex-post | MICRO | ST | Nation | E | Sector output | C | Recovery | V | OT | L |
| 74 | Liu *et al*. (2016) | 2016 | General | General | Ex-ante | MESO | Static | N/A | T | Node, link, network related indicators | B | Redundancy | V | Network | P |
| 75 | Ouyang (2016) | 2016 | Power  Gas | Spatially localized attacks | Ex-ante | MESO | Static | Harris County | T | Node, link, network related indicators | B | Performance Metrics | R | Network | P, G |
| 76 | L.Zhang *et al*. (2016) | 2016 | Power  Transportation | General | Ex-ante | MESO | Static | N/A | T | Node, link, network related indicators | B | Reliability | V | Network | P, G |
| 77 | Hong *et al*. (2016) | 2016 | General | General | Ex-post | MESO | Static | N/A | T | Node, link, network related indicators | B | Failure Restoration | V | Network | P, G |
| 78 | Gonzalez *et al*. (2016) | 2016 | Gas  Water | Earthquake | Ex-post | MESO | Static | County | T | Node, link, network related indicators | B | Restoration | R | Network | P, G |
| 79 | Y. Zhang *et al*. (2016) | 2016 | Power  Water | General | Ex-ante | MESO | Static | N/A | T | Node, link, network related indicators | B | Vulnerability | V | Network | P |
| 80 | Wu *et al*. (2016) | 2016 | Power  Oil | Terrorist attacks | Ex-ante | MESO | Static | County | T | Node, link, network related indicators | B | Failures | R | Network | P, G |
| 81 | Pant *et al*. (2016) | 2016 | Railway Electricity Telecommunication Natural Gas Liquid/Solid fuels Water | Random component failures | Ex-ante | MESO | Static | Nation | T | Node, link, network related indicators | B | Vulnerability | R | Network | P |
| 82 | Loggins & Wallace (2015) | 2015 | Power Water Hospital Fire  …… | Hurricane | Ex-ante | MESO | Static | County | T | Power outage Water outage Waste outage  …… | B, Ca | Damage | R | ER | P |
| 83 | Yang *et al*. (2015) | 2015 | Gas Power | General | Ex-ante | MICRO | LT | Nation | E | Power transmission limits  Gas pipeline flow  …… | C | Effects | V | ER | L |
| 84 | Chopra & Khanna (2015) | 2015 | General | General | Ex-ante | MICRO | ST | Nation | E | Inoperability | C | Preparedness | R | ER IIM | L |
| 85 | Thomas *et al*. (2015) | 2015 | Power  Telecommunication Transportation  Wastewater | General | Ex-post | MESO | Static | County | T | Supply Nodes Demand Nodes | B, C | Restoration | V | Network | P, G |
| 86 | Ntalampiras *et al*. (2015) | 2015 | Power  Telecommunication | General | Ex-post | MESO | ST | N/A | T | Voltage …… | B, C | Diagnosis | V | Hmm | P |
| 87 | Xu *et al*. (2015) | 2015 | Transportation Gas | General | Ex-post | MICRO | LT | Nation | E | Sector output | C | Restoration | V | IIM | L |
| 88 | Hwang *et al*. (2015) | 2015 | General | Earthquake | Ex-post | MICRO | LT | City | S, E | Damage ratio Shortage of transport service  …… | C | Recovery | R | SD | P, L |
| 89 | Shekhtman *et al*. (2015) | 2015 | Electricity, Telecommunication | General | Ex-ante Ex-post | MESO | Static | N/A | T | Node, link, network related indicators | B | Resilience | R | Network | P |
| 90 | Hong *et al*. (2015) | 2015 | General | General | Ex-ante | MESO | Static | N/A | T | Node, link, network related indicators | B | Failure Cascade | V | Network | G |
| 91 | Chen *et al*. (2015) | 2015 | General | Extreme events | Ex-ante | MESO | Static | N/A | T | Node, link, network related indicators | B | Failures | V | Network | G |
| 92 | Z. Dong *et al*. (2015) | 2015 | General | General | Ex-ante | MESO | Static | N/A | T | Node, link, network related indicators | B | Robustness | V | Network | G |
| 93 | Chen *et al*. (2015) | 2015 | General | General | Ex-ante | MESO | Static | N/A | T | Node, link, network related indicators | B | Control | V | Network | G |
| 94 | R. Li *et al*. (2015) | 2015 | General | General | Ex-ante | MESO | Static | N/A | T | Node, link, network related indicators | B | Vulnerability | V | Network | P |
| 95 | Ouyang & Wang (2015) | 2015 | Electricity Gas | Hurricane | Ex-post | MESO | Static | N/A | T | Node, link, network related indicators | B | Restoration | V | Network | P |
| 96 | Sharkey *et al*. (2015) | 2015 | Power  Telecommunication  Transportation  Wastewater | General | Ex-post | MESO | Static | County | T | Node, link, network related indicators | B, C | Restoration | V | Network | P, G |
| 97 | G. Dong *et al*. (2015) | 2015 | General | General | Ex-ante | MESO | Static | N/A | T | Node, link, network related indicators | B | Robustness | V | Network | G |

# Supplementary II: Literature review of studies on integrating data-driven and physics-based approaches

As the 31 publications have specific scenarios, it is arduous to compare the pros and cons of DDMs and PBMs, but general motivations on why these researchers integrate DDMs and PBMs could be summarized. The motivations can be divided into two categories, namely “reasons for improvements” (RI) and “reasons for necessities” (RN). More specifically, they include (i) RI-1: to improve the efficiency and performance in order to save time and cost. For example, physics-based methods are high cost dramatically with the increase of system complexity; the process of data collection also may be too time-consuming to be abandoned. (ii) RI-2: to improve the accuracy and reliability through the ensemble of two types of methods, For example, data-driven methods are usually complained due to that it lack mature theory as the foundation to provide results with enough reliability; cross-validation of the results from the two categories of methods could enhance the overall reliability. (iii) RN-1: to make up the lack of data. Available and accessible data is so-limited compared with the complex infrastructure system in real world, but data-driven methods normally demands huge data with enough information density. (iv) RN-2: to make up the lack of physical knowledge. Although great efforts have been paid to investigate the physical operations of critical infrastructures, there are not all infrastructures’ failure mechanisms fully understood, and exiting physical knowledge cannot effectively simulate their failure processes.

According to the reasons, there are several typical ways to realize the integration of these DDMs and PBMs including: (i) I-1: Data-driven methods generate parameters for physics-based methods, corresponding to RI-1 or RN-2; (ii) I-2: Utilizing results from physics-based methods to training Data-driven methods, corresponding to RN-1; (iii) I-3: Compare/Validate the results of data-driven methods and physics-based methods from each other, corresponding to RI-2; (iv) I-4: Applying DDM or PBM respectively for different infrastructure systems or sub-systems, mainly corresponding to RN-1 and RN-2. The former three integration ways (i.e., I-1, I-2, and I-3) focus on a single system, but the last one (i.e. I-4) is at a system of system level, which is also the integration type in our proposed framework.

Table S2. Existing literature on integrating data-driven methods and physics-based approaches

| **No** | **Authors** | **Field** | **Ways of integration** | | | | **Reasons** | | | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  |  |  | | | | **For improvement** | | | **For**  **necessities** | |
|  |  |  | **I-1** | **I-2** | **I-3** | **I-4** | **RI-1** | **RI-2** | | **RI-3** | **RI-4** |
| 1 | Liang *et al*. (2019) | Water Quantity and Quality |  | ✓ |  |  |  | | ✓ |  |  |
| 2 | Hanachi *et al*. (2019) | Tool wear prediction |  |  | ✓ |  | ✓ | |  |  |  |
| 3 | Ren *et al*. (2019) | Petroleum industry | ✓ |  |  |  | ✓ | |  |  |  |
| 4 | Wang *et al*. (2019) | Manufacturing |  | ✓ |  |  |  | |  | ✓ |  |
| 5 | Zhou *et al*. (2019) | Interdependent infrastructure (Water & Transport) |  |  |  | ✓ |  | |  | ✓ | ✓ |
| 6 | Koponen *et al*. (2018) | Electricity Power |  | ✓ | ✓ |  |  | | ✓ |  |  |
| 7 | Rahman *et al*. (2018) | Computing(Incompressible Flow Solvers) | ✓ | ✓ |  |  |  | | ✓ |  |  |
| 8 | Giha *et al*. (2018) | Hydrology | ✓ |  |  |  |  | | ✓ |  |  |
| 9 | Subramaniyan *et al*. (2018) | Environment (PV Module Degradation) | ✓ | ✓ |  |  |  | | ✓ | ✓ |  |
| 10 | Kaneko *et al*. (2018) | Petroleum industry (Offshore drilling) |  | ✓ | ✓ |  | ✓ | | ✓ | ✓ |  |
| 11 | He (2018) | Electricity Power(Battery) | ✓ |  |  |  |  | | ✓ |  |  |
| 12 | Das & Samuel (2018) | General | ✓ |  |  |  | ✓ | |  |  |  |
| 13 | Guo *et al*. (2017) | Petroleum industry (Waterflooding) | ✓ |  |  |  |  | |  |  |  |
| 14 | Zhou *et al*. (2017) | Building (HAVC Systems) | ✓ |  |  |  |  | | ✓ |  |  |
| 15 | Hegde *et al*. (2017) | Petroleum industry (drilling, rate of penetration) | ✓ |  |  |  | ✓ | | ✓ |  |  |
| 16 | Mount *et al*. (2017) | Hydrology |  |  |  |  |  | | ✓ | ✓ |  |
| 17 | Mahdi *et al*. (2017) | Hydrology | ✓ |  |  |  |  | | ✓ |  |  |
| 18 | Byram *et al*. (2017) | Computing(image reconstruction) | ✓ |  |  |  | ✓ | |  |  |  |
| 19 | Christelis & Mantoglou (2017) | Petroleum industry | ✓ |  |  |  | ✓ | | ✓ |  |  |
| 20 | Artun (2017) | Petroleum industry (waterflooded reservoirs) | ✓ |  |  |  |  | | ✓ |  |  |
| 21 | Vaghefi *et al*. (2016) | Building (HAVC Systems) |  |  | ✓ |  |  | | ✓ |  |  |
| 22 | Shahidi (2016) | Building (structure) | ✓ |  |  |  |  | | ✓ |  |  |
| 23 | An *et al*. (2015) | General (Condition based maintenance) | ✓ |  |  |  |  | | ✓ |  |  |
| 24 | Klie (2015) | General (Industry Production) | ✓ |  |  |  |  | | ✓ |  |  |
| 25 | X. Li *et al*. (2015) | Manufacturing (Predict condition of components) |  |  |  |  |  | |  |  |  |
| 26 | Chen *et al*. (2014) | Electricity Power | ✓ |  |  |  |  | | ✓ |  |  |
| 27 | Hofleitner (2013) | Transportation | ✓ |  |  |  |  | | ✓ |  |  |
| 28 | Xie *et al*. (2012) | Electricity Power | ✓ | ✓ |  |  | ✓ | | ✓ |  |  |
| 29 | Ji *et al*. (2012) | Hydrology (Flood) | ✓ |  |  |  |  | | ✓ | ✓ |  |
| 30 | Pendse *et al*. (2012) | Weather (Rainfall) |  | ✓ |  |  |  | | ✓ |  |  |
| 31 | Ki Ooi *et al*. (2005) | Agriculture (Irrigation channels) | ✓ |  | ✓ |  |  | |  |  | ✓ |

# Supplementary III: Detailed text-mining process of extracting the failure pattern of water pipe bursts in Hong Kong

**(i) Data collection**

Using ‘water pipe burst’ and ‘water main burst’ as the keywords for searching, 2,731 news articles reporting water pipe bursts between 01.01. 2000 and 31.12.2018 were retrieved from Wise News – the largest news repository in Great China containing almost all newspapers published in Hong Kong. Information embedded in these news articles can be used as raw empirical records to monitor the development and performance of a city’s urban infrastructures (Bigger *et al*., 2009; Chang *et al*., 2009; Luiijf *et al*., 2009; McDaniels *et al*., 2007; McDaniels *et al*., 2015; Sharkey *et al*., 2015; Van Eeten *et al*., 2011). They additionally play an unseen filtration role in ignoring insignificant issues and focusing on key events.

**(ii) Data cleansing**

The collected news articles need to be cleansed for subsequent analysis. In this study, the articles were cleansed by following the principles of ‘Authority’, ‘Accuracy’, and ‘Uniqueness’ (Chapman, 2005). ‘Accuracy’ mainly refers to amending garbled texts and removing items with missing values; the resulted texts were encoded with UTF-8 scheme and 69 null items were ruled out. ‘Authority’ means that only trusted and authoritative newspapers were included as our data sources; there were only 16 of the 31 newspapers included, leading to that 47 news articles were excluded. ‘Uniqueness’ refers to deleting repeating news articles; this resulted in 152 news articles being removed. ‘Uniqueness’ also includes combining news reports on the same event. To do this, the degrees of similarity of the news were calculated with the TF-IDF algorithm and SimHash algorithm. After applying these principles in the data cleansing step, 1028 cleaned news sets – regarded as 1028 water pipe bursts – were obtained for further data mining.

**(iii) Domain knowledge preparation**

General natural language processing (NLP) tools for livelihood scenarios cannot be applied directly to extract infrastructure interdependency and failure patterns from cleansed news articles. In order to apply the tools to a vertical field users need to prepare domain knowledge components first, such as ‘keywords for searching’ (Kryvasheyeu *et al*., 2016), ‘index words’ (Yuan & Liu, 2018) or ‘trigger words’ (Li *et al*., 2018). In our current research, four domain knowledge components are prepared to help derive target infrastructure insights. Corresponding to the target information, hotspot areas, high-incidence time, and potential consequences of water pipe bursts, the components are listed in Table S3 consisting of: (i) Hong Kong Location Dictionary containing more than 5000 roads covering the whole city, which is collected from Commercial Map API; (ii) Regular expression of time, such as ‘a certain number’+‘o'clock’+‘today/yesterday’; (iii) Trigger words of pipe bursts, such as ‘burst’, ‘erupt’, ‘happen’, ‘explode’, and ‘break’; and (iv) Damage words regarding the consequences, such as ‘close’, ‘wade’, ‘sunk’, ‘collapse’, ‘subside’, ‘congestion’, ‘jam’, and ‘slow’ suggested by Yuan and Liu (2018). The basic rules are determined based on existing research and expertise, and they are iteratively updated according to the performance in step v (i.e., verification).

Table S3. Domain knowledge components prepared and target information extracted

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **No.** | **Target feature**  **information** | **Domain knowledge components** | **Target information extracted** | **Mining rules** |
| 1 | Hot areas | Hong Kong location dictionary | Location of water pipe bursts | * Could be null * One news normally has one affected road. When it happened in interaction, both roads will be regarded as affected roads. * Location in the title are prior to the location in the text * Location closer to the article beginning has higher priority |
| 2 | High-incidence time | Regular expression of time  &  Trigger words | Time of water pipe bursts | * Could be null * Time and trigger words should appear in a short sentence. For example, in the sentence that ‘a water pipe burst *happened* (trigger words) at *eight o'clock yesterday morning* (time)’, ‘happened’ is a trigger word, and ‘eight o'clock yesterday morning’ is the time, then this time will be regarded as the bursting time of the water pipe failure. * Time closer to the article beginning has higher priority |
| 3 | Potential consequences on road transport system | Affected infrastructures  &Corresponding damage word list | Consequences of water pipe bursts | * Could be null * Could have more than one impact * Using road transport as an example, the Affected infrastructures words include ‘road’, ‘vehicles’, ‘streets’ and so on; damage words include ‘closure’, ‘wade’, ‘collapsed’. |

Note: Specific contents of domain knowledge components are accessible in Table S5.

**(iv) Feature selection and extraction**

Three categories of target information are automatically extracted from the news. To realize the automatic process, a Python application was developed using the cross-platform integrated development environment PyCharm from JetBrains. The program was written based on a series of open libraries, including the *Scrapy* for web-crawler, *Jieba* and *NLTK* for keyword extraction, *NumPy* for scientific calculation, *OpenCC* for mixed language processing, and *pyExcelerator* and *PyMySQL* for data storage. The Python source code of the application together with a series of dependent packages has been uploaded to GitHub repository; all researchers can check out the source code for academic use and further enhancement.

**(v) Verification of extracted information**

To test the completeness and correctness of information extracted, ‘Accuracy’ is introduced to check the performance of the domain knowledge components (Yuan & Liu, 2018); it is defined as the ratio of the number of news from which information is correctly extracted to the total number of sample news articles. In current study, 100 out of the 1,028 news sets (at a 90% confidence level) were randomly selected; the selected news sets were manually labeled with the incidents’ location, time, and consequence for comparison with the results extracted automatically. For this study, the text-mining accuracy of burst location, burst time, and consequence are respectively 92%, 90%, and 95%, which confirm the effectiveness of the domain knowledge components and mining rules prepared. Should the accuracy be unsatisfactory, it is necessary to adjust the domain knowledge components according to the errors occurred in the sample news articles. The information extracted (i.e. burst location, burst time, and consequence ) in each news set as well as the verification details are presented in next Appendix.

Table S4: Raw data, intermediate products, and results of the text-mining approach

|  |  |  |
| --- | --- | --- |
| **Associated steps of the text-mining in Appendix III** | **Name of Sheets in the Excel** | **Description of the contents** |
| (i) Data collection | 1. News collected | * 2731 News articles on water pipe bursts * Title * Contents * News Date * Newspapers * Is the content null? * Hash value of the contents. * Is the newspaper source authoritative? * …… |
| (ii) Data cleansing | 2. News cleansed | * 2454 remained news and corresponding 1028 news sets reporting the pipe burst incidents |
| (iii) Domain knowledge preparation | 3.Domain knowledge components | * Streets/Roads * Regular expression for automatically extracting pipe burst time * Trigger words of burst time * consequences on road transport system * Trigger words of road transport system |
| (iv) Information extraction | 4.All information extracted | * Affected roads in each news articles * Bursting time * Consequence on road transport system |
| (v) Verification of extracted information | 5.Verification | * Are the ‘Locations’ identified true or false? * Are the ‘Burst time’ identified true or false? * Are the ‘consequences’ identified true or false? |
| Text-mining Results | 6.Results\_burst location | * Statistical data of bursting locations for ArcGIS visualization |
| 6. Results\_ burst time | * Statistical data of bursting time for ArcGIS visualization |
| 6. Results\_ consequence | * Statistical data of consequences observed on road transport system for |

The Excel file is accessible in “https://github.com/0AnonymousSite0/A-System-of-Systems-Framework-for-Characterizing-Interdependent-Infrastructure-Failures”. Here, Table S4 is Specification of the contents contained in the Excel file.

# Supplementary IV: Detailed traffic flow simulation process of extracting the failure pattern of water pipe bursts in Hong Kong

**(i) Identify physical objects, their attributes & operations**

In ‘traffic flow theory’, the basic objects in the road transport system include vehicles and roads. The generalization of cars includes trucks and cars, and roads aggregates road lanes, traffic lights, traffic signs, and so on. As shown in Figure 7, each object has some physical attributes and operations. For instance, the operation of vehicles follows the basic physical laws, including ‘*s=v\*t*’, ‘*a=△v/△t*’ and so on (‘*s*’ is distance, ‘*v*’ is velocity, ‘*t*’ is time, ‘*a*’ is acceleration); the roads have attributes, like road number, road name, road status, traffic volume, road topology, etc. The attribute values under normal conditions, such as traffic volumes, average speeds, and percentage of cars and trucks, are obtained from statistical data provided by Hong Kong Transport Department (Transport Department, 2018), and other attributes (e.g. roads’ directions, number of lanes, and phases of traffic lights) are investigated by our field trip and Google Street View.



Figure S1. Basic objects and corresponding attributes & operations

**(ii) Set specific simulation scenarios**

In accordance with the interface designed, one of the most likely places of the water pipe burst, Jaffe Road (Figure 8), is chosen as the affected road in PBM; the time of the scenario is set as morning rush hour; possible statuses of affected road, including ‘the affected roads are open but flooded with surface water’ and ‘the affected roads are closed’, will be simulated. Since the depth of inundated water affects the vehicle speeds, this former road status is furtherly divided into three scenarios (Nos. 2, 3 and 4 in Table 2 in the main context) with different flooded water depths; the functional relationship between surface water depths and vehicle speeds is from Yang *et al*. (2019). The road will be closed when the water is out of the depth of road curb (i.e. 15cm in Hong Kong) or the road structure has been destroyed, according to the safety operation procedures of the government department responding to water pipe bursts.

**(iii) Realize the physical model**

The road transport system is simulated with PTV VISSIM. It is one of the most widely applied traffic flow simulation platforms. The spatial scope of the road transport network is limited to Wan Chai district for two reasons. On the one hand, affected degree becomes lower along with the longer distance to bursting location (Pan *et al*., 2013), so we could do the simulation in a relative-small district; on the other hand, it is admitted that we do not have powerful enough computing facilities with the capacities to perform large-scale (e.g. the whole city) traffic flow simulation for observing extremely slight impacts’ propagation.

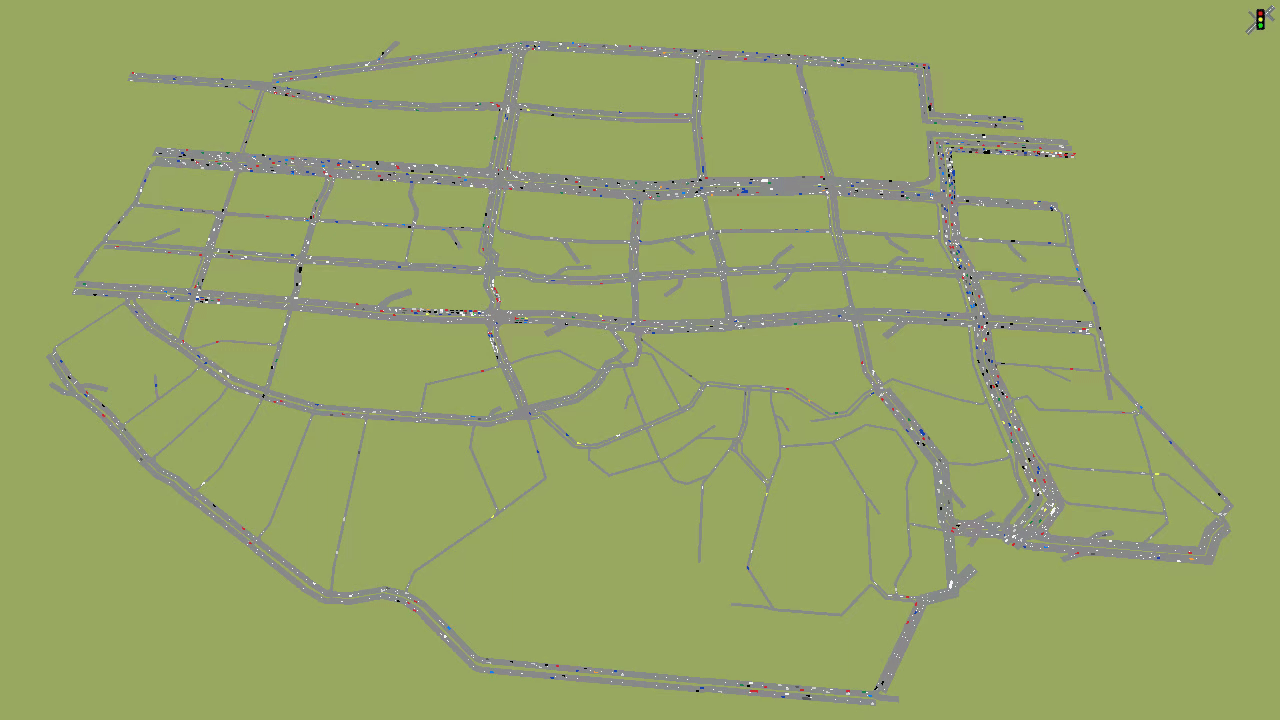


Figure S2. Simulation in VISSIM PTV software

Table S5: Raw data, intermediate products, and results of the traffic flow simulation

|  |  |  |
| --- | --- | --- |
| **Five scenarios in Table 3 in the manuscript** | **Name of Sheets in the Excel** | **Description of the contents** |
| Scenario 1 | Scenario1\_Node | * Time Interval * Movement * Queue Length * Max Queue Length * Vehicles * Average Vehicle Delay * Average Stopped Delay * Stops |
| Scenario1\_Link | * Time Interval * Link evaluation segment * density * speed * volume * Time Lost Relative |
| Scenario1\_Network | * Time Interval * Average Delay * Average Stops * Average Speed * Average Delay Stopped |
| Scenario 2 | Scenario2\_Node | * The contents are as the same as Scenario1\_Node |
| Scenario2\_Link | * The contents are as the same as Scenario1\_ Link |
| Scenario2\_Network | * The contents are as the same as Scenario1\_ Network |
| Scenario 3 | Scenario3\_Node | * The contents are as the same as Scenario1\_Node |
| Scenario3\_Link | * The contents are as the same as Scenario1\_ Link |
| Scenario3\_Network | * The contents are as the same as Scenario1\_ Network |
| Scenario 4 | Scenario4\_Node | * The contents are as the same as Scenario1\_Node |
| Scenario4\_Link | * The contents are as the same as Scenario1\_ Link |
| Scenario4\_Network | * The contents are as the same as Scenario1\_ Network |
| Scenario 5 | Scenario5\_Node | * The contents are as the same as Scenario1\_Node |
| Scenario5\_Link | * The contents are as the same as Scenario1\_ Link |
| Scenario5\_Network | * The contents are as the same as Scenario1\_ Network |

The Excel file is accessible in “https://github.com/0AnonymousSite0/A-System-of-Systems-Framework-for-Characterizing-Interdependent-Infrastructure-Failures”. Here, Table S5 is Specification of the contents contained in the Excel file.

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