An Updated System Dynamics Model for Analysing the Cascading Effects of Critical Infrastructure Failures

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ABSTRACT

Aiming at examining the cascading effects of the failure of Critical Infrastructure (CI), this work-in-progress research introduces an improved System Dynamics model. We represent an improvement over the previous models aimed at studying CIs interdependencies and their cascading effects. Our model builds on earlier models and corrects their flaws. In addition to introducing structural enhancements, the improvements include using unpublished data, a fresh look at a previously collected dataset and employing a new data processing to address and resolve some longstanding issues. The dataset was fed to an optimisation model to produce a new dataset used in our model. The structure of our SD model, its dataset and the data processing techniques we employed to create this dataset are all described in the study. Although the model has passed the fundamental validation criteria, more validation testing and scenario exploration are yet to be conducted.

Keywords

Critical Infrastructure, Cascading failures, System Dynamics, Modelling and simulation, Decision-Making.

INTRODUCTION

Background

Systems and resources required for society's basic needs, like energy, water, transportation, communication, healthcare, etc., are called Critical Infrastructure (CI). The economy, public safety, and public health might suffer significantly if one of these CIs fails. Such failure may, in some circumstances, have a domino effect on other CI systems. The breakdown of CIs systems might significantly impact modern society. Both natural and man-made risks can cause CIs failure. A CI failure can have devastating effects, leading to significant financial losses, fatalities, and damage to CI systems (U.S. Cybersecurity and Infrastructure Security Agency 2020).

Hurricane Katrina's massive power outages in 2005 resulted in substantial financial losses, with projected damages to the energy infrastructure alone totalling $3.5 billion (Casey et al. 2020). Furthermore, almost 225,000 consumers lost power due to the 2015 cyberattack on Ukraine's power infrastructure, and much more severe effects may have ensued (Polityuk et al. 2017). Accordingly, it is crucial to improve the resilience of CIs to reduce the risk of failure and possible cascade effects. This entails, among other measures, investing in CIs modernisation and enhancing cybersecurity to protect against online attacks and other potential threats. To reduce the risk of loss and mitigate the effect of any failure, it is crucial to ensure that CIs are well-planned, maintained, and updated. Ongoing research, CIs investments, collaborative strategies among stakeholders, and identifying the most vulnerable CIs are all crucial in managing and reducing the risks of CI failures.

Purpose and objectives

This ongoing research paper's primary goal is to present an updated and improved System Dynamics (SD) model for investigating the cascading impacts of CI failures. By correctly representing CI activities and utilising actual data to support the model's assumptions, the proposed model responds to critiques of earlier models. The model's capability to simulate the possible cascading consequences of failures in one CI on all others can aid stakeholders in making well-informed decisions about risk management and disaster response. The article describes the structure of the model, the data used to construct and validate it, and some preliminary validation tests that the model has successfully undergone to achieve this objective.

A secondary goal of the model is to provide a framework for future research on the impact of CI failures. The model may be used to simulate various situations, including the results of targeted attacks on a specific CI or simultaneous failures in several CIs. The creation of risk management techniques can be influenced by such scenarios, which can assist in identifying possible weaknesses in CI systems. The model's adaptability makes it a helpful tool for ongoing study since it enables the integration of new data as it becomes available.

SD in the context of CI

Several techniques are available for modelling CIs failure cascading effects, including SD (Eusgeld and Kröger 2008; Ouyang 2014). SD is a simulation modelling methodology with applications in multiple domains, including CI modelling. It is particularly suited for representing intricate systems with feedback loops and dynamic interrelationships between components (Forrester 1961; Sterman 2000). In the context of CI modelling, SD can aid in comprehending the impact of disturbances to one system component on the entire system, leading to adverse events or cascading effects. One significant benefit of the SD methodology is its ability to demonstrate the causality between variables in an easily understandable manner.

In a comparative analysis of nine methods for modelling and simulating CIs' interdependencies, Eusgeld and Kröger (2008) concluded that SD modelling was the most suited approach for interdependency analysis and system modelling, with low data requirements. SD is flexible enough to model physical and cyber interdependencies and can handle confined and cascading failures. Furthermore, SD modelling is highly effective in monitoring and analysing failure events and information.

In order to gather a broad selection of relevant literature, a search was performed on www.semanticscholar.org using the search string: *"Critical Infrastructure" AND "Cascading Failures" AND "System Dynamics"*. The results were sorted in descending order of relevance and limited to the past ten years. To ensure thoroughness, the results were reviewed until no further relevant studies were identified. Numerous papers have addressed the CI failure cascading effects in the last decade.

Armenia et al. (2014, 2018) and Cavallini et al. (2014) presented an approach for modelling the effects of CI failures due to unexpected events. The CIs of Transport, Energy and Telecommunications were modelled using SD. The model was developed as a component of a European Commission-funded project focused on developing a tool to evaluate the impacts of critical events. The project's ultimate objective was to provide decision-makers with a sophisticated tool to help them mitigate adverse effects in emergencies.

Laugé's doctoral research (2014) and Laugé et al. (2015) focused on a set of eleven CIs based on the European Commission's (2005) definition. These CIs were Energy, ICT, Water, Food, Health, Financial, Public and legal order and safety, Civil administration, Transport, Chemical and nuclear industry, and Space and research. In Laugé et al. (2013) and Laugé's doctoral thesis (2014), they developed an SD model that concentrated on the CIs of Energy, Food, and Transport. The model served as an example of a tool that allows managers to simulate various scenarios with both short- and long-term perspectives and analyse the effects of different management policies. The model aims to provide managers with a better understanding of the dependencies among CIs and how their effects evolve. According to Laugé's findings, the model could serve as a training tool to enhance the understanding of crisis and CI managers regarding the complexity of existing dependencies among CIs and the consequent impacts of their failures.

Canzani (2016), Canzani et al. (2016) and her doctoral research (2017) employed an SD model to investigate the cascading effects of failures in the CIs of Energy, ICT, Water, Financial, and Transport due to a cyber-attack or disruption in ICT. The model is based on the Susceptible, Infectious, and Recovered (SIR) model from epidemiology (Sterman 2000), where the Susceptible, Infected, and Recovered represent the Running, Down, and Recovered operations in a CI, respectively. Canzani extracted a table of constants from Laugé et al. (2015) to prepare a matrix of constants, representing the effect of failure in one CI resulting from a less than two hours failure in another. This matrix was incorporated into Canzani's model to regulate the failing CIs' breakdown rates. Canzani used the same SD approach in Canzani et al. (2017) and Canzani and Pickl (2016).

Farstad, in his master's research (2018), critiqued the analogy of Canzani's model to the SIR model and argued that the less than two hours failure matrix is not applicable for all disruption durations. As a result, Farstad developed an enhanced SD model with only Running and Down compartments, applied to the same five CIs as Canzani's (2016) model. Farstad also incorporated three different matrices from Laugé (2014) research for disruption durations of less than two hours, less than 24 hours, and more than one week in CI according to the scenario to be tested.

A new SD model that enhanced Farstad and Canzani's was introduced by Abdelgawad et al. (2019), as they extended the CIs understudy from five to all eleven CIs studied by Laugé (2014) and Laugé et al. (2015). Additionally, instead of using one table or more extracted from Laugé (2014) as a matrix of constants controlling the CIs' breakdown rates as done by Farstad and Canzani, they chronologically sorted and joined all the 11×11 tables created by Laugé ("less than two hours", "less than six hours", "less than 12 hours", "less than 24 hours", "more than 24 hours" and "more than one week") into a cube. This cube was split into 110 different time series, each portraying the failure effect of one particular CI on another particular CI over disruption time. Accordingly, a dynamic failure fraction based on these time series was used instead of a constant value to control the CI breakdown rate throughout a disruption scenario simulation.

This new SD model was used to test and discuss the cascading effects of a cyber-attack and how an intelligent attacker could exploit existing knowledge on cascading impacts to plan for perfidiously timed cyber-attacks requiring low resources that would achieve a significant disruption of CIs. The model allowed analysing cascading effects impacts and checking the robustness of a CI towards a series of disruptions, whether arising by chance or planned by an attacker if they timed and targeted at the weakest links dynamically, as the cascading effects propagate. Abdelgawad and Gonzalez (2019) added a new structure to the same SD model of Abdelgawad et al. (2019) to calculate the aggregate effects of cascading failures in CIs and compare them with the direct cascading failures estimated by experts. The research found that the aggregate effects become more significant than the direct the longer the duration of the disruption becomes. The paper concluded that such an SD model could improve desktop-based exercises as it highlights effects beyond experts' judgmental assessments.

Ryu and Park (2018) presented another SD model to describe the causal relationships between Water and Energy CIs. Their model aimed at suggesting management policies to increase the resilience of the water supply system. The model was simulated under disruptive scenarios to analyse systemic behaviour. The simulation result showed that enhancing the resilience of the water supply system improved the recovery capacity of the water supply system and the energy supply system.

Trucco et al. (2018) presented a multilevel simulation modelling approach that combined Discrete Event Simulation and SD to evaluate the economic impact of CI disruptions on key resource supply chains such as food and pharmaceuticals. These supply chains rely heavily on CIs, making them vulnerable to any disruptions in CIs. The approach was demonstrated through a case study that analysed the vulnerability and resilience of the Italian fast-moving consumer goods supply chain against disruptions in its underlying CIs. The simulation results provided valuable insights into the interdependence between key resource supply chains and CIs. They also could help supply chain managers identify and prioritise resilience strategies.

Instead of focusing on sudden failures or attacks on CIs like the previously reviewed literature, Frydenlund et al. (2016) used an SD approach to model degradation and infrastructure investment in three CIs (Transport, Public utilities, and Communications). The model combined traditional physical and cyber approaches to model CIs with a human factors component to quantify the degradation of interdependent CIs. The model showed some of the dangerous feedback cycles of degradation between CIs when investment and social resiliency are insufficient. This paper aimed to develop a method to incorporate social systems into interdependent infrastructure research that can be built into a tool to aid policymakers in understanding and addressing investment linkages between CIs.

All surveyed SD models were small models. There are veracious benefits to using smaller models instead of focusing on detailed models (Ghaffarzadegan et al. 2011). They are easy to comprehend, focus on critical elements, and only ask for a few characteristics with direct relationships between them. The evaluation of these linkages is indeed based on professional judgment. In general, SD offers an effective method for simulating cascading effects and investigating tactics to improve the resilience of complex systems. It enables researchers to model the behaviour of complex systems under various circumstances and capture the interdependencies between different system components. This makes it a perfect method for comprehending the possibility of cascading consequences and for investigating mitigation techniques.

SYSTEM DYNAMICS MODEL

Data collection and processing

The present paper introduces an SD model that addresses critical issues in the model developed by Abdelgawad et al. (2019). Using the expert estimates tables published in Laugé's doctoral thesis (2014) or Laugé et al.'s paper (2015) is problematic for two reasons. Firstly, Laugé used averages with Likert scale data. Although widely used with the Likert scale, the average is unsuitable for ordinal data. The median in such a case is an appropriate measure of central tendency (Law and Pascoe 2012). Secondly, based on the questionnaire administered by Laugé (see Figure 1), its scale, and how to answer it explanation (see Figure 2), it is clear that it describes the status of the non-working operations CI level more than the breakdown rate as used by Canzani (2016), Farstad (2018), and Abdelgawad et al. (2019).

26. Which effect would your CI have if the following CIs are down for…

	…less than 2 hours	…less than 6 hours	…less than 12 hours	…less than 24 hours	…more than 24 hours	…more than 1 week
Energy						
Information and Communication Technologies						
Water						
Food						
Health						
Financial						
Public & Legal Order and Safety						
Civil Administration						
Transport						
Chemical and Nuclear Industry						
Space and Research						

Figure 1. Extracted from page 166 (Question 26 of Ana Laugé's questionnaire to CI representatives/managers) © Laugé

Critical Infrastructures' dependency degree

Note: In the following questions do not fill in answers for your CI. For example, if you are an energy expert fill in answers for the other 10 CIs but leave the Energy gaps blank.

Think about the degree of effects on your CI if any other CI fails due to its dependency on the failed CI. We would like you to answer to the following questions considering this scale:

0 --> No effect: My CI can operate as usual

1 --> Very low effect: My CI can operate deploying few extra resources

2 --> Low effect: My CI can operate deploying huge amount of extra resources

3 --> Medium effect: My CI can only deliver critical services deploying few extra resources

4 --> High effect: My CI can only deliver critical services deploying huge amount of extra resources

5 --> Very high effect: My CI cannot continue operating

Figure 2. Extracted from page 165 (How to answer explanation of question 26 of Ana Laugé's questionnaire to CI representatives/managers) © Laugé

Furthermore, Abdelgawad et al. (2019) followed Canzani (2016) and Farstad (2018) in assuming the same arbitrary constant repair and restoration time for all CIs. However, this assumption poses another problem as the repair and restoration times vary among different CIs, as could be noted from Laugé (2014); The recovery time was obtained through her questionnaire to the CIs representatives and managers. On page 51, Laugé (2014) stated that "[f]urthermore, experts were asked to answer about their recovery time when the affected CI is repaired, in order to know if their recovery is immediate or needs some time", and also "[f]igure 3.3 2nd section of the questionnaire: CI dependencies evidences" shows this part of the questionnaire (see Figure 3). Laugé (2014) did not include any values for the CIs' repair and restoration times in her published data.

It was possible to contact Laugé and obtain the original data files, which, in addition to the disaggregate Likert results, contain the unpublished answers to the repair and restoration time question she collected during her doctoral research. We have reprocessed the original data and extracted two new datasets as follows:

1) The Likert Scale Data

Instead of the average values Laugé calculated, have calculated the median of the data collected on the Likert scale for the severity of cascading effects on one CI caused by a disruption of "less than two hours", "less than six hours", "less than 12 hours", "less than 24 hours", "more than 24 hours" and "more than one week" in another CI. We came up with six 11×11 tables corresponding to the six disruption periods. Similar to (2019), we converted these successive matrices into 110 time series (e.g. Figure 4 to the left). As mentioned earlier, each time series portrays the behaviour of one CI out-of-service operations level after and during a disruption in another CI. Accordingly, we added one value to each time series equal to Zero at time Zero to express that the CI was working at its capacity immediately before the disruption. We have also repeated the last value of each time series and put it at a time equal to the final time of our new model to express that the behaviour stays at this value as indicated by the questionnaire ("more than a week", see Figure 1). Each new time series was multiplied by 20, so five means total out-of-service or 100% ("very high effect: my CI cannot continue operating", see Figure 2).

Think about a natural disaster that has not affected your CI but others. We would like you to describe the evidences which make your CI dependent on other CIs. Please indicate the most important dependencies (up to 3). Furthermore, when the affected CI is repaired, will your recovery be immediate or delayed?

a) Which are the detailed consequences on your CI if CI X is down for more than 48 hours?
b) Now thinking about the time for recovery. When CI X is repaired or restored, how much time will you need time to recover your CI normal activity?
   - ☐ Less than 1h.
   - ☐ Less than 6h.
   - ☐ More than 6h.
   - ☐ Other (Please specify):

Figure 3. Extracted "Figure 3.3 2nd section of the questionnaire: CI dependencies evidences" © Laugé

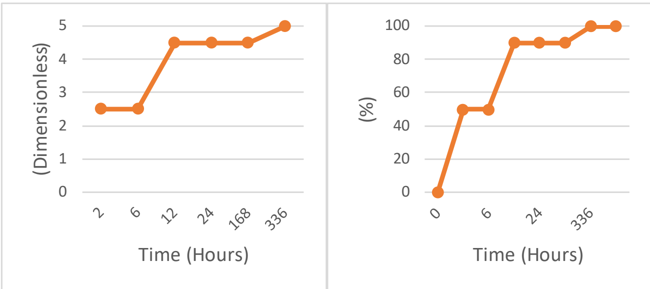

Figure 4: Example of the median time series portraying the effect of Energy CI failure on Chemical and Nuclear Industry CI (median time series to the left/generated CI out-of-service operations level)

2) The Repair and Restore Time

The time durations options collected by Laugé, as shown in Figure 3, are "Less than 1h", "Less than 6h", "More than 6h", and "Others (please specify)". To calculate an average CI repair and restore time for each CI, we had to find some way to convert these periods into time points. It was intuitive to convert all answers of "Less than 1h" duration to half an hour, the average between zero and one hour. We used the same way for "Less than 6h", which is between one hour and six hours. However, for "More than 6h" and "Others", we arbitrarily put it as the average between six hours and the highest answer collected for this specific CI. Then we averaged the individual respondent's answers to create one value of repair and restore time for each CI. This way, we could construct a zero-diagonal 11×11 matrix with elements expressing the CI repair and restore time after a disruption caused by another CI. The matrix was saved in an Excel file and subsequently loaded into the model by the SD simulation software Vensim DSS 7.2 (Ventana Systems, Inc. 2017) during runtime.

Model structure

The stock-and-flow diagram of our model is shown in Figure 5. The model has two stocks/levels for each CI. "CIi In-Service Operations" and "CIi Out-of-Service Operations". We have used the small letter "i" beside the CI in the names of these two levels and other model variables to denote and distinguish the affected variables "CIi" from the affecting variables "CIj". The two levels, "CIi In-Service Operations" and "CIi Out-of-Service Operations", hold 100% and 0% at the simulation's initial time, denoting CI's normal functioning. In mathematical form, equations 1 and 2, respectively.

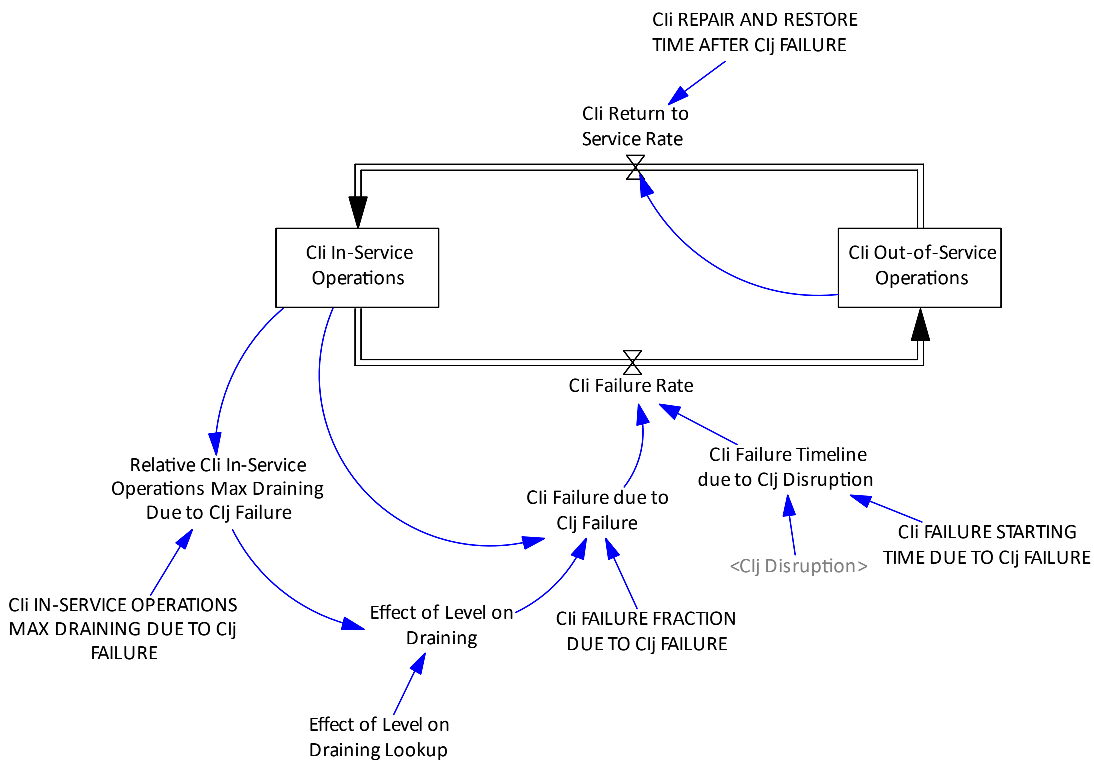

Figure 5: Model structure

$$CISO_i = 100 + \int_{T_0}^{T} (CRS_i - CFR_i)\, dt \tag{1}$$

Where:

$CISO_i$: CI_i In-Service Operations

CRS_i: CI_i Return to Service Rate

CFR_i: CI_i Failure Rate

$$COS_i = 0 + \int_{t_0}^{t} (CFR_i - CRS_i)\, dt \tag{2}$$

Where:

COS_i: CI_i Out-of-Service Operations

CRS_i: CI_i Return to Service Rate

CFR_i: CI_i Failure Rate

Although not orthodox, we would like to start with the flow/rate "CIi Return to Service Rate" because its related SD structure is more straightforward than the structure related to the "CIi Failure Rate". Equation 6 mathematically expresses the "CIi Return to Service Rate" shown in Figure 5. This is a regular "decay" molecule equation (Hines 2005), in which the level value is divided by the time to drain until it is totally depleted. A Piecewise function is used to prevent division by zero. As mentioned in the last subsection, the "CIi Repair and Restore Time after CIj Failure" is a matrix of parameters expressing the CI repair and restore time after a disruption caused by another CI, as mentioned in the last subsection. This matrix is loaded to the model by Vensim DSS via an Excel file during runtime.

$$CRS_i = \begin{cases} \dfrac{COS_i}{\max\limits_j CR_{i,j}} & \max\limits_j CR_{i,j} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

Where:

CRS_i: CI_i Return to Service Rate

COS_i: CI_i Out-of-Service Operations

$CR_{i,j}$: CI_i Repair and Restore Time after CI_j Failure

$|i|$: Cardinality of vector i, i.e. number of its elements which is 11 for our model case

On the other side, the "CIi Failure Rate" (see equations 4 and 5) is the maximum value of the matrix "CIi Failure due to CIj Failure" if and only if any of the "CIi Failure Timeline due to CIj Disruption" disruption timelines have value. The disruption timeline concept was introduced by Abdelgawad et al. in (2019) (See Figure 6). The idea is to start a new timeline for each CI disruption; this timeline differs from the simulation timeline and any other CI disruption timeline. In our model, we have chosen to model the timeline as a Vensim Macro so that it behaves as a function called DTIMELINE, as in equation 5. According to the median data extracted from Laugé (2014), there are cases where the disruption effect of a certain CIj does not immediately affect another CIi. The "CIi Failure Starting Time due to CIj Failure" is a matrix of parameters with elements depicting the time CIi fails after CIj disruption starts. This matrix is loaded to the model by Vensim DSS via an Excel file during runtime.

$$CFR_i = \begin{cases} \max\limits_j CF_{i,j} & \sum_j CFT_{i,j} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

Where:

CFR_i: CI_i Failure Rate

$CF_{i,j}$: CI_i Failure Rate due to CI_j Failure

$CFT_{i,j}$: CI_i Failure Timeline due to CI_j Disruption

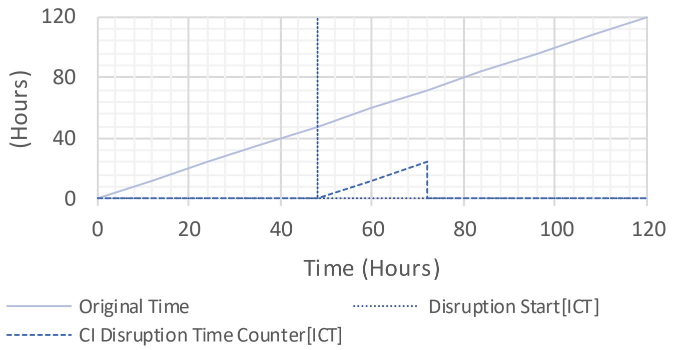

Figure 6: Extracted "Original and Generated Simulation Timelines (Disruption Starts at Hour 48)" © Abdelgawad et al.

$$CFT_{i,j} = \text{DTIMELINE}\left(AICF_i, CFS_{i,j}\right) \tag{5}$$

Where:

$CFT_{i,j}$: CI_i Failure Timeline due to CI_j Disruption

$AICF_i$: CI_j Disruptions

$CFS_{i,j}$: CI_i Failure Starting Time due to CI_j Failure

DTIMELINE: Disruption Timeline Macro

Equations 6, 7, and 8 together express a "level protected by level" molecule equation, in which "the actual outflow is the product of the desired draining and a function that shuts off the outflow as the level approaches zero" (Hines 2005). The elements of the matrix "CIi Failure due to CIj Failure" are the valves that control the "CIi Failure Rate", assuming that the "CIi In-Service Operations" level is not fully depleted.

The "CIi Failure Fraction due to CIj Failure" and "CIi In-Service Operations Max Draining due to CIj Failure" are two parameter matrices loaded to the model by Vensim DSS via the same Excel file mentioned earlier during runtime. The values of "CIi Failure Fraction due to CIj Failure" were produced through an optimisation process, as explained in the following subsection, while the values of "CIi In-Service Operations Max Draining due to CIj Failure" are the maximum value of the median time series for the pair CIi and CIj we have created in the last subsection.

$$CF_{i,j} = CISO_i \cdot CFF_{i,j} \cdot ELOD_{i,j} \tag{6}$$

Where:

$CF_{i,j}$: CI_i Failure due to CI_j Failure

$CISO_i$: CI_i In-Service Operations

$CFF_{i,j}$: CI_i Failure Fraction due to CI_j Failure

$ELOD_{i,j}$: Effect of level on draining

$$ELOD_{i,j} = \mathrm{ELODL}\left(RCIMD_{i,j}\right) \tag{7}$$

Where:

$ELODL_{i,j}$: Effect of Level on Draining Lookup

$$RCIMD_{i,j} = \frac{\left(CISO_i - CIMD_{i,j}\right)}{100} \tag{8}$$

Where:

$RCIMD_{i,j}$: Relative CI_i In-Service Operations Max Draining Due to CI_j Failure

$CISO_i$: CI_i In-Service Operations

$CIMD_{i,j}$: CI_i In-Service Operations Max Draining due to CI_j Failure

Two types of CI disruptions can occur during the simulation of this model. We have coined them as "Induced" and "Autonomous". "Induced" disruption is generated as a pulse signal or a train of pulses to simulate a disruption/attack or a series of disruptions/attacks in a particular CI. "Autonomous" disruption, on the other hand, simulates the failure of a particular CI due to the cascading effect of a failure in another CI. Both types affect "CIi Failure Rate" through "CIj disruptions". "CIj disruptions" is set to the greater of "Induced" or "Autonomous"; it could also be set to their sum as far as this sum does not exceed one. (see Equation 9).

Figure 7 shows how both CI disruption types are generated in the model. Equation 10 shows that "Autonomous" disruption happens if the value of each of the "CIi In-Service Operations" levels does not exceed its "CIi Minimum Demand", while Equation 11 expresses the "Induced" disruption as a pulse or train of pulses, as mentioned earlier.

$$AICF_i = \begin{cases} ACF_i & ACF_i > CID_j \\ CID_j & \text{otherwise} \end{cases} \tag{9}$$

Where:

$AICF_i$: CI_j disruptions

ACF_i: CI_j Autonomous Disruption

CID_j: CI_j Induced Disruption

$$ACF_i = \begin{cases} \dfrac{CISO_i}{CMD_i} & CISO_i < CMD_i \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

Where:

ACF_i: CI_j Autonomous Disruption

$CISO_i$: CI_i In-Service Operations

CMD_i: CI_i Minimum Demand

$$CID_j = \begin{cases} CIM_j & CIS_j+(n-1)\cdot\left(CIDD_j+TCID_j\right) \le t < CIS_j+(n-1)\cdot CIDD_j + TCID_j \\ 0 & \text{otherwise} \\ 0 & t \le CIF_j \end{cases} \quad (11)$$

Where: $n = \left\lfloor \frac{t-CIS_j}{CIDD_j+TCID_j} \right\rfloor + 1$, and

CID_j: CI_j Induced Disruption

CIM_j: CI_j Induced Disruption Magnitude

CIS_j: CI_j Induced Disruption Starting Time

$TCID_j$: Time between CI_j Induced Disruption Durations

$CIDD_j$: CI_j Induced Disruption Duration

CIF_j: CI_j Induced Disruption Durations Final Time

$\left\lfloor \frac{t-CIS_j}{CIDD_j+TCID_j} \right\rfloor$: Floor of the value $\frac{t-CIS_j}{CIDD_j+TCID_j}$

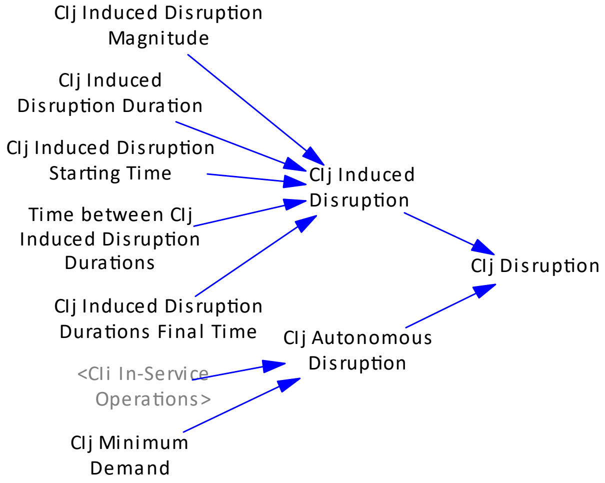

Figure 7: CI Disruption

Parameters estimation through an optimisation model

As mentioned in the previous subsection, “CI_i Failure Starting Time due to CI_j Failure”, “CIi In-Service Operations Max Draining due to CIj Failure”, and “CIi Failure Fraction due to CIj Failure” are three parameters’ matrices loaded to the model by Vensim DSS through an Excel file during runtime. It was also mentioned that the values of “CI_i Failure Starting Time due to CI_j Failure” and “CIi In-Service Operations Max Draining due to CIj Failure” were calculated based on Laugé’s data while “CIi Failure Fraction due to CIj Failure” had been produced through an optimisation process.

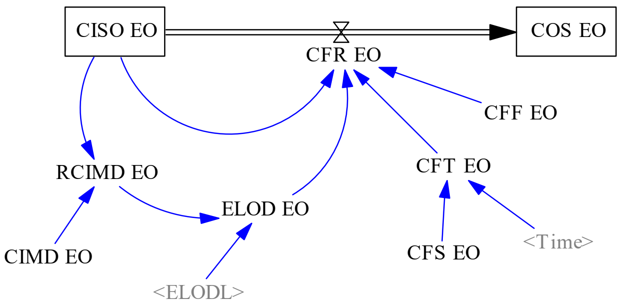

Figure 8: An example of the optimisation model structure (E: $CI_{Eneregy}$ and O: CI_{Food})

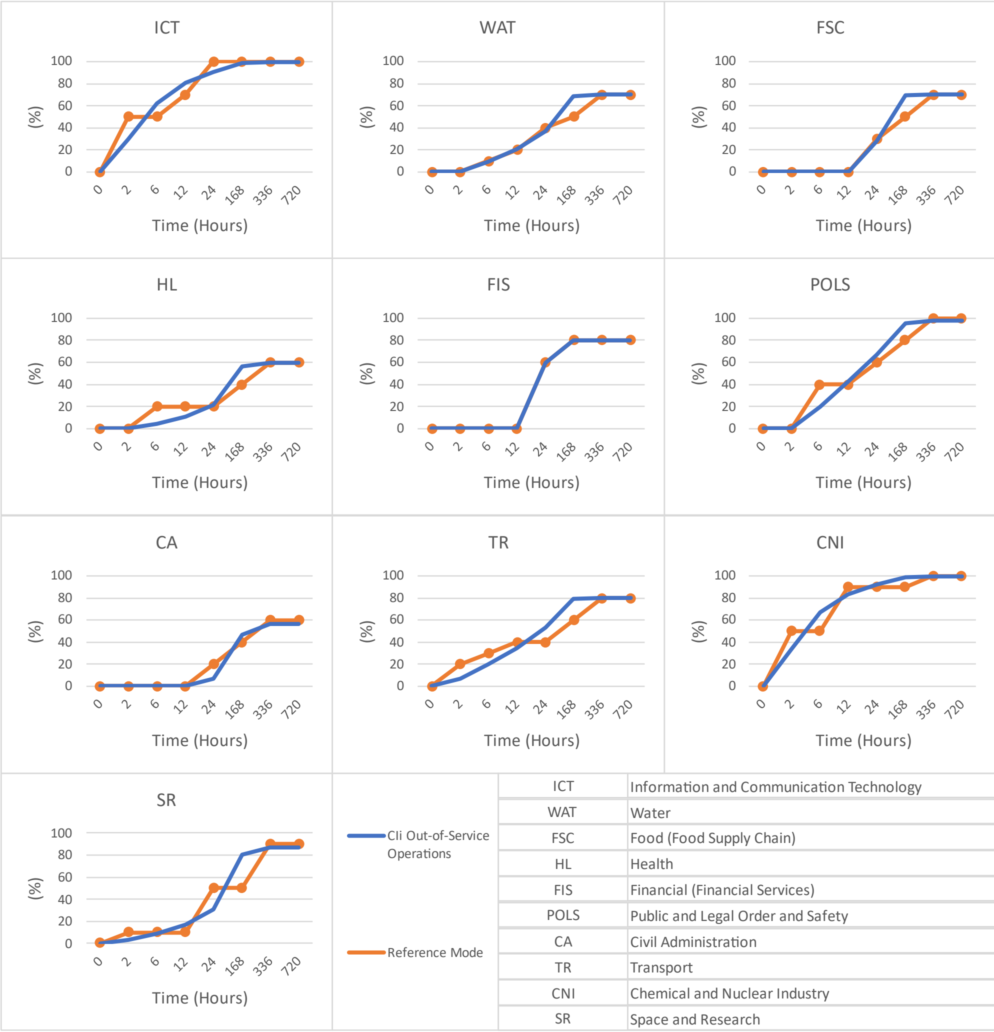

Figure 9: Part of the results of the optimisation process (Out-of-service of all CIs due to Energy CI failure)

In order to calculate the "CIi Failure Fraction due to CIj Failure", a simplified version of the CI Failure Rate with both "CI In-Service Operations" and "CI Out-of-Service Operations" levels for each pair of CIs was extracted from our model. Figure 8 illustrates this structure for disruption of Energy CI on Food CI. Another 109 comparable structures were constructed in one Vensim model to account for every possible pair of CIs in the original model. Building such a model is a tedious and error-prone process; therefore, we used a Python script to produce it. Additionally, since this new model was built for optimisation using Vensim DSS optimisation functionality, the Python script produced all other files required for the optimisation process (the payoff definition file, the optimisation control file, and the reference mode dataset).

The optimisation process was done using Powell optimiser and involved adjusting the "CIi Failure Fraction due to CIj Failure" (CFF EO in Figure 8) to match the simulation results of "CI Out-of-Service Operations" (COS EO in Figure 8) with its respective median data calculated based on Laugé's data. The optimisation was constrained by the values of "CIi Failure Starting Time due to CIj Failure" and "CIi In-Service Operations Max Draining due to CIj Failure" (CFS EO and CIMD EO in Figure 8, respectively). Figure 9 displays a portion of the optimisation process results, specifically the "Out-of-service operations" of all CIs caused by the failure of the Energy CI.

RESULTS

Results of the simulation model

Figure 10 illustrates the behaviour of our model in three distinct simulation scenarios. The sub-charts are arranged in three columns (1 to 3) corresponding to scenarios 1 to 3, respectively. Rows depict the behaviour over time of the following variables: CIj Induced Disruption, CIj Autonomous Disruption, CIi In-Service Operations at 90%

CIj Minimum Demand, and CIi In-Service Operations at 100% CIj Minimum Demand. Table 1 describes the "Induced" disruption ("CI_{Energy} Induced Disruption") sent to the model regarding disruption starting time, duration, and magnitude in the three simulation scenarios.

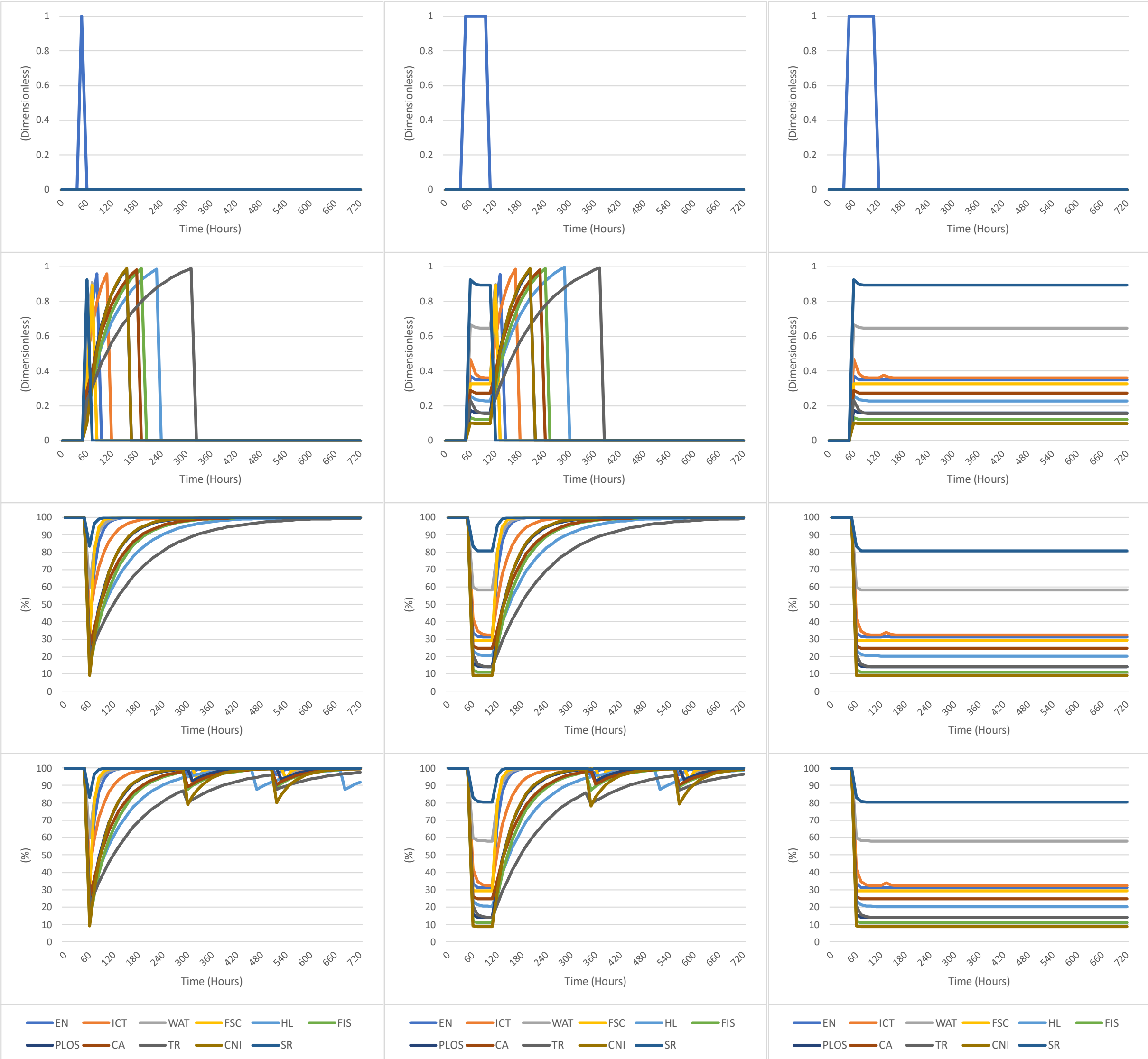

Figure 10: Model Behaviour; Sub-charts are arranged in three columns (1 to 3) corresponding to scenarios 1 to 3, respectively. Rows represent the behaviour over time of the following: CIj Induced Disruption, CIj Autonomous Disruption, CIi In-Service Operations at 90% CIj Minimum Demand, and CIi In-Service Operations at 100% CIj Minimum Demand

Table 1. Descriptions of simulation scenarios

	CI_{Energy} Induced Disruption Starting Time	**CI_{Energy} Induced Disruption Duration**	**CI_{Energy} Induced Disruption Magnitude**
Scenario 1	48 h	12 h	1
Scenario 2	48 h	60 h	1
Scenario 3	48 h	72 h	1

In all three scenarios, the Energy CI experiences an "Induced" disruption/attack of the highest magnitude (severity level = 1) at hour 48 of the simulation. In the first scenario, the disruption period lasts for 12 hours. When CIj Minimum Demand is 90%, the CIi In-Service Operations of all CIs drop to varying degrees and recover at different times. By the end of the simulation, the CIi In-Service Operations for all CIs stabilise again. When CIj Minimum

Demand is 100%, the CIi In-Service Operations of all CIs recover considerably but never fully stabilise, as they oscillate between 80% and 100%.

In the second scenario, despite the extended disruption period (two days and a half), the behaviour pattern is similar to that of the first scenario but with more extended recovery periods. In the third scenario, when the "Induced" disruption duration reaches three days, the "CIi In-Service Operations" of all CIs never recover over the simulation period, neither at 90% nor 100% of "CIj Minimum Demand".

This is still work-in-progress research. However, the results' severity has significant implications for policymakers and CI managers. Policymakers and CI managers should take note of the potential impact of "Induced" disruptions/attacks on CIs and their cascading effects on the "In-Service Operations" of all CIs. They must consider implementing appropriate measures to protect against such attacks, such as maintaining minimum demand levels and developing more robust systems for detecting and responding to disruptions/attacks within each CI. They should consider investing in alternative sources less vulnerable to such attacks and developing contingency plans to mitigate the effects of any potential disruptions/attacks.

Validation and testing

At this research stage, our SD model has undergone only the basic validation tests Sterman (2000) outlined. These tests include the Integration Error test, in which we conducted simulations using different integration time steps and numerical integration methods, and the model yielded the expected results. Additionally, we performed the Dimensional Consistency test by assigning units of measurement to all model variables and verifying their consistency using the Vensim DSS unit testing functionality. Finally, we conducted the Extreme Conditions test by subjecting the model inputs to extreme values and ensuring that the resulting model simulations met our expectations.

Limitations and future research directions

Tests like sensitivity analysis, boundary adequacy, and structure assessment are still required (Sterman 2000). In addition, our testing was limited to basic scenarios, as presented in the previous sections; therefore, conducting tests using more complex scenarios is imperative. It is also crucial to examine scenarios proposed in earlier studies by Abdelgawad et al. (2019), Abdelgawad and Gonzalez (2019), Canzani (2016), and Farstad (2018) and compare the results. However, considering the absence of a reference model, such scenarios' outcomes will necessitate field experts' input.

CONCLUSION

The cascading effects of Critical Infrastructure (CI) failures are an increasingly critical issue in our interconnected world. These failures can have severe consequences on other CIs and the overall economy. To study the cascading effects of such failures, several System Dynamics (SD) models have been developed, some building on the work of previous models and attempting to improve on their limitations.

The data collection effort by Ana Laugé (2014) was an essential step in understanding the interconnectedness of CI systems. However, her use of averages on Likert scale data is not the best choice. A more suitable measure of "central tendency", such as the median, should be used. Furthermore, the scale used in the questionnaire is more relevant to the status of the non-working operations level than the breakdown rate as done in the previous models.

The SD model built by Elisa Canzani (2016), based on Laugé's data, was criticised for using an epidemic diffusion model, which may not accurately reflect CI operations (Farstad 2018). Abdelgawad et al. (2019) presented a new model that addressed that and extended the analysis to include all 11 surveyed CIs. The model of Abdelgawad et al. represents a significant improvement over the previous models. Their use of a time series dataset that shows the failure effect of any of the eleven CIs on any other CIs provides a more accurate representation of the interconnectedness of CI systems. However, the arbitrary assumption of a constant average repair and restoration time for all CIs after failure is inaccurate.

The SD model developed in this paper builds on the work of Abdelgawad et al. (2019) and introduces several improvements. The most significant improvement is using an updated dataset that corrects some of the flaws in previous data processing techniques. Additionally, our model's structure and data processing techniques are described in detail, allowing for easier replication and validation.

Although our model has passed basic SD model validation criteria, more validation testing and scenario exploration are needed. Future research should focus on refining the dataset, validating the model structure and behaviour with field experts, and exploring more complex and realistic scenarios.

The SD model presented in this paper, the modelling process, the data collection tools created earlier by Laugé, and our data processing methodology compile a framework for modelling CIs failure cascading effects. This approach offers a structured method for understanding the complex interdependencies and feedback loops that can lead to the spread of failures across interconnected CIs. Using this SD model, analysts can develop insights into the potential impacts of CI failures, which can inform decision-making and risk-management efforts. Therefore, using the SD model and its associated modelling process can enhance our ability to anticipate, prepare for, and respond to cascading failures in critical CIs.

In conclusion, the study of CI interdependencies and the cascading effects of their failures is a critical issue that requires continuous research and modelling efforts. The SD model presented in this paper represents another step in understanding these complex systems. However, much work must be done to ensure we can effectively prevent and manage CI failures and their cascading effects.

ACKNOWLEDGMENTS

The author would like to express their gratitude to Dr Ana Laugé for generously providing the raw data from her doctoral research, which was essential to this study. Additionally, the author would like to thank Dr Leire Labaka from the University of Navarra for her invaluable assistance in facilitating communication with Dr Laugé and retrieving the data.

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