Modeling Dynamics of Disruptive Events for Impact Analysis in Networked Critical Infrastructures

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ABSTRACT

Governments have strongly recognized that the proper functioning of critical infrastructures (CIs) highly determines the societal welfare. If a failed infrastructure is unable to deliver services and products to the others, disruptive effects can cascade into the larger system of CIs. In turn, decision-makers need to understand causal interdependencies and nonlinear feedback behaviors underlying the entire CIs network toward more effective crisis response plans.

This paper proposes a novel block building modeling approach based on System Dynamics (SD) to capture complex dynamics of CIs disruptions. We develop a SD model and apply it to hypothetical scenarios for simulation-based impact analysis of single and multiple disruptive events. With a special focus on temporal aspects of system resilience, we also demonstrate how the model can be used for dynamic resilience assessment. The model supports crisis managers in understanding scenarios of disruptions and forecasting their impacts to improve strategic planning in Critical Infrastructure Protection (CIP).

Keywords

Critical infrastructures, disruptions, impact analysis, resilience, System Dynamics modeling.

INTRODUCTION

Despite there is no universal definition for the evolving concept of Critical Infrastructure (CI), it has been widely recognized by governments that critical infrastructures play crucial roles in underpinning our economy, security and societal welfare. The proper functioning of energy, transportation, water plants, telecommunication, financial and other services, is vital for all communities and countries.

These "lifeline systems" are interdependent primarily by virtue of physical proximity and operational interaction (O'Rourke, 2007). For instance, after the Hurricane Katrina an electric power outage at the pumping stations of the major transmission pipelines led to serious interruptions in the crude oil and refined petroleum supplies.

Besides natural hazards, human-caused disasters represent a major threat to CIs and the underway cyber warfare is the overwhelming evidence. Think of the Stuxnet attack to PLCs and SCADA control systems of the Iranian industrial plant to damage gas centrifuges for uranium enrichment (Langner, 2013), just to mention one of the numerous cyber threats over the years. Modern infrastructures have become more and more interconnected especially due to the increasing reliance on IT for business operations, and this increases potential risks that even minor disruptions in a single CI can lead to catastrophic cascade of failures in CIs networks.

In turn, risk managers continuously call for new conceptual frameworks and extended analytical tools to support delicate crisis management processes taking place daily for protecting CIs from vulnerabilities and threats. On this note, Johannes de Nijs, NATO Branch Head Operational Analysis at HQ SACT argues: “decision makers need understanding, not just answers” (de Nijs, 2010). When CIs are challenged, authorities must be able to steer between heterogeneity, multiple and inconsistent boundaries, resilience building, knowledge transfer and other problems that limit the effectiveness of response policies (Hernantes, Rich, Laugé, Labaka, & Sarriegi, 2013).

This research paper applies a novel block building approach based on System Dynamics (SD) modeling to the still immature - but rapidly growing - research field of CI interdependencies with the aim to support crisis managers in understanding, assessing hypothetical scenarios of disruptions and forecasting their impacts toward more resilient system designs and effective recovery strategies. Questions that can be addressed with our SD model are, e.g., how to reduce cascading effects among CIs if a CI is down for a certain period of time, how to optimize CIs’ capabilities in order to increase system resilience, how to mitigate risks of CIs failures in case of increased demands.

For the purpose of impact analysis, a special emphasis is given to concepts of resilience and its relevant metrics (Hosseini, Barker, & Ramirez-Marquez, 2016). Our work focuses on “dynamic resilience” (Pant, Barker, & Zobel, 2014), which considers time-dependent aspects of system recovery capabilities. Accordingly, we refer to the following conceptualization of resilience based on system performance given by (Bruneau et al., 2003): “Resilience can be understood as the ability of the system to reduce the chance of a shock, to absorb a shock if it occurs (abrupt reduction of performance) and to recover quickly after a shock (reestablish normal performance)”.

Inspired by epidemics modeling of diffusion and recovery dynamics, we develop a SD model adopting a block building approach to get a better understanding of disruptions’ impacts over time in networked CIs. Unlike most of the previous works in modeling and simulations of CIs (Ouyang, 2014), we account for both dynamics within and across CIs while investigating two relevant dimensions of system resilience: operational state and service level (Sterbenz et al., 2013).

The paper is organized as follows. After a brief overview of existing approaches to CIs interdependency modeling, we explain our research method together with a detailed description of the SD model we have developed through block building. Next, we apply our model to hypothetical scenarios to demonstrate how it can be used for simulation-based impact analysis and dynamics resilience assessment. We compare level of services and operational dynamics of CIs over time to show different effects of single and multiple disruptions on recovery times as first step to support a resilience building process in CIs networks that covers the whole Crisis Management process (Labaka, Hernantes, Laugé, & Sarriegi, 2013).

LITERATURE REVIEW

In the early 21st century, (Rinaldi, Peerenboom, & Kelly, 2001) made the initial step toward the CI interdependencies research proposing a taxonomy that frames in six “dimensions” the major aspects of interdependencies.,Their pioneering work pointed to new research questions that have been partially answered in the last decade, while more and more unsolved questions are being raised in between.

In the wake of the Rinaldi, most of the later works have been focusing on qualitative aspects of the interdependency problem (e.g. (Popescu & Simion, 2012)), probably also due to the lack of data and publicly available information about CIs. Nevertheless, research efforts also focused on “the next step” of proposing metrics and frameworks to quantify impacts of cascades among CIs (Zimmerman & Restrepo, 2006).

More recently, the understanding of CIs as “system of systems” (Eusgeld, Nan, & Dietz, 2011) and the “network of networks” approach (Gao, Li, & Havlin, 2014) led to deeper investigations of dependencies within a CI and interdependencies across CIs. However, complexity of interdependency modeling often binds researchers to consider only a single infrastructure (Eusgeld, Kröger, Sansavini, Schläpfer, & Zio, 2009) or a few of them (O’Reilly, Jrad, Kelic, & Leclaire, 2007).

From a methodological perspective, a recent review of modeling and simulations approaches to interdependent infrastructure systems is (Ouyang, 2014).

Relevant to mention is a visionary project for building a very detailed simulator of all US critical infrastructures under development at the National Infrastructures Simulation and Analysis Centre (NISAC) (Brown, 2007), but most of NISAC activities are not publicly available.

Conversely, we argue it is essential the identification of those dimensions which are relevant to dynamic impact analysis rather than building in-depth models of all CI components that often lead to intractable complexity. This is the rationale behind our modeling approach that integrates interdependent dynamics of CIs.

As studying one specific infrastructure as an isolated and independent system is a concept now obsolete, we consider the larger system of networked CIs to understand dynamics of a single CI. Similarly to network flow modeling principles (e.g. (Holden, Val, Burkhard, & Nodwell, 2013)), we assume every infrastructure produces commodities to satisfy the demand while needs products and services from other CIs in order to operate normally.

In this direction, (Oh, Deshmukh, & Hastak, 2010) propose a disaster impact analysis based on two measurement factors: level of service and level of inter-relationship. The first assesses the damage of the disrupted infrastructure; the latter identifies how industries depend on adjacent infrastructure for sustaining their activities. Our model also accounts for the service level of each CI, but differently we distinguish between operational and service levels by introducing the demand factor. This is to say that even though some CI operations are damaged, the CI may still be able to provide services that meet the demand.

Concerning the demand factor, it is remarkable how input-output flow models connect the inability of CIs to produce as planned (i.e. inoperability) with demand perturbations (e.g. (Y. Y. Haimes et al., 2005)). However, they are unable to capture nonlinear feedback loops because of their formulation as a system of linear equations that only describes flows of commodities among CIs.

Here, we use SD modeling to replicate nonlinearities of the system over time with a set of differential equations. SD has been already used in the context of CIP (Vugrin & Camphouse, 2011), but mainly for policy evaluation and infrastructure design (Karaca, Raven, Machell, & Camci, 2015). To our best knowledge, none of previous works on CIs interdependencies uses embedded epidemic models as backbone of the dynamic modeling structure.

Furthermore, existing modeling and simulation approaches for CIP are mainly carried out at discrete time and a few do not consider the time-dependence (e.g. Leontief input-output economic models (Y. Haimes & Jiang, 2001)). Emphasizing the relevance of timing in dynamic environments such as crises, SD provides continuous-time simulations that allow easily testing and evaluating dynamic behaviors.

BLOCK BUILDING MODELING

System Dynamics (SD) modeling tools are used for framing, understanding, and capturing complex behavior of real-world systems over time in terms of stocks and flows, internal feedback loops and delays. Different to others simulation approaches such as Agent-Based or Discrete-Event, SD abstracts from single events and entities and takes an aggregate view concentrating on policies (Borshchev & Filippov, 2004). This means that the modeler has to think in terms of global structural dependencies, especially when adopting high levels of abstraction to understand complex dynamics of CIs systems like in our case.

There are different ways to develop SD models, our particular modeling approach consists in a block building process that simplifies and structures the development of the final SD model. The rationale behind is to focus on relevant dynamics underlying complex systems and model them in different steps. This allows breaking the overall complexity down into building blocks of models, which are then assembled together during the modeling.

More precisely, we develop a series of simple blocks of models replicating the dynamics of: a disruptive event, a single critical infrastructure, and interdependencies between infrastructures. These basic blocks are iteratively combined together and extended to build our final SD model and generate scenarios of disruption in interdependent CIs. We first define which infrastructures to consider in our networked system; then, a causal loop diagram can be used to identify causal links (edges) across such CIs (nodes) and respective SD blocks are integrated accordingly. Finally, disruptive events in one or more CIs are embedded to generate different scenarios of crisis with the purpose of impact analysis.

Below, we present building blocks we developed to capture different aspects characterizing disruptive events in networked CIs. Models and simulation results are obtained using Vensim PLE software package (Vensim PLE Version 6.2, Copyright 1988-2013 Ventana Systems, Inc.).

For additional details on System Dynamics theory, we refer the reader to the seminal book of (Sterman, 2000).

Block 1 - Modeling Disruptive Events

The aim of this building block is to define a function, $d(t)$, that replicates a general disruptive event according to characteristics that are relevant for risk assessment. Similar to our previous work (Canzani & Lechner, 2014), we use the function PULSE in Vensim software package to model the disruption. The PULSE function provides a pulse of height 1.0 starting at time t_d (i.e. 'disruption time') and lasting after ΔT_d time units (i.e. 'disruption duration'). As disruptive events can have different effects depending on their nature, we assume that disruptions have a certain magnitude ('disruption magnitude', m_d) varying between 0 (no disruption) and 10 (entire infrastructure breakdown). Thus, we define the disruption function as its magnitude factor m_d multiplied by the PULSE function, i.e.

$$d(t) := m_d \cdot PULSE(t_d, \Delta T_d).$$

Block 2 - Modeling Dynamics of a Single Critical Infrastructure

Before dealing with dynamic interdependencies between CIs, it is essential to understand the dynamics of a single infrastructure. This building block captures operational dynamics of a CI affected by a disruption using concepts from epidemics modeling.

Although CIs are not independent systems, every CI has its own dynamics determined by operations and internal processes that may be compromised and disrupted during situations of crisis. However, a deep analysis of all CI components is often costly and prohibitive due to the lack of available information and also out of the scope of this paper. We rather believe a more effective modeling way is to consider the CI dynamics as a function of the operational state of the system (i.e. running, down, and recovered operations over time).

Inspired by our previous investigation in epidemics modeling literature (Canzani & Lechner, 2015) to understand complex phenomena of propagation and recovery dynamics, we refer here to the Susceptible-Infected-Recovered-Susceptible (SIRS) compartmental epidemic model. Compartments represent the epidemiological categories in which individuals are divided when a pathogen appears in the community. For mathematical details on compartmental epidemic models, see (Brauer & Van den Driessche, 2008).

Adapting the SIRS model to our research domain, we consider the CI operational state changing through "compartments" due to disruptive events. At time t, we name running, down, and recovered operations respectively $OP_{run}(t)$, $OP_{down}(t)$, and $OP_{rec}(t)$. Ideally all CI operations are available and running, but system capabilities may change when a disruption occurs. This means that OP_{run} can break with a certain rate α due to the disruption and become out of service (i.e. OP_{down}). In this case, CI operators must intervene to repair down operations, so that OP_{down} move to OP_{rec} with rate β. Once recovered, OP_{rec} are finally restored back to function (i.e. OP_{run}) with rate γ.

Let n_{OP} the total number of operations, $OP_{run}(t) + OP_{down}(t) + OP_{rec}(t) = n_{OP}$ at any time t. In accordance with the set of differential equations describing the SIRS epidemic, our nonlinear model is formulated as follows.

$$\begin{cases} \dfrac{d}{dt}OP_{run}(t) = -\alpha(t)\left(\dfrac{OP_{run}(t)}{n_{OP}}\right) + \gamma OP_{rec}(t) \\ \dfrac{d}{dt}OP_{down}(t) = \alpha(t)\left(\dfrac{OP_{run}(t)}{n_{OP}}\right) - \beta OP_{down}(t) \\ \dfrac{d}{dt}OP_{rec}(t) = \beta OP_{down}(t) - \gamma OP_{rec}(t) \end{cases}$$

Clearly, the epidemic-likely dynamic behavior starts in the moment of time in which the disruption occurs. For this reason, this paper mainly focuses on the breakdown rate $\alpha(t)$ (while assuming constant average rates for β and γ). Considering the bigger system of networked CIs, the infrastructure breakdown depends both on eventual disruptions directly affecting the CI (Block 1) and cascading effects due to interdependencies with other CIs (Block 3, below).

Block 3 - Modeling Dynamics of Interdependent Critical Infrastructures

With the purpose of analyzing disruption impacts across CIs, the third building block serves to replicate dynamics of cascading effects occurring in interdependent CIs when one or several of them are disrupted. At the structural level, we define our system as a directed graph in which each node is a CI and links represent causal relationship between them.

Given a network of n CIs, we use i (with $i = 1 \dots n$) to denote a general CI as well to index variables that belong to the infrastructure i. For simplicity and context reasons, we replace n_{OP}, previously defined to describe the epidemic-likely dynamics of CI operations, with the maximum CI capability, C^i_{Max}. The rationale behind is trivial, as the maximum capability of a system is determined by its total number of operations. In particular, the CI is able to work at maximum capability at time t if and only if all operations are available to run, i.e. $OP^i_{run}(t) = C^i_{Max}$. We say in this case the CI is in its "normal operational state".

Block 3 models the entire system as network of SIRS epidemics models that accounts for both dynamics within and across CIs by embedding building blocks replicating operational dynamics of each node (Block 2) in case of disruptions (Block 1). We consider now also the level of service provided by each infrastructure. In simple words, a CI can fully provide service only if its current capabilities are able to provide an amount of services that (at least) meet the demand. Note that with the term "service" we mean also products, commodities, and all needs CIs provide one another.

We define a new control variable, $S^i(t)$, which assesses over time the 'service provided' by infrastructure i with respect to its current capability, $C^i(t)$, and the 'average demand', D^i_{Av}, for the service from other CIs. $S^i(t)$ varies over time between 0 (no service provided) and 1 (when the current capability is bigger or equal to the demand). In formula,

$$S^i(t) := \begin{cases} 1, & C^i(t) \geq D^i_{Av} \\ \frac{C^i(t)}{D^i_{Av}}, & otherwise \end{cases},$$

where the current infrastructure capability, $C^i(t)$, is defined by the ratio between the stock of 'running operations' OP^i_{run}, and the 'max capability' of the CI, C^i_{Max}. That is,

$$C^i(t) := \frac{OP^i_{run}(t)}{C^i_{Max}}.$$

Then, interdependencies among CIs are modeled as function of services they are able or unable to provide to each other.

Let J be the set of infrastructures j that have to provide services to infrastructure i for its correct functioning, then the nonlinear breakdown rate $\alpha^i(t)$ is determined by services $S^j(t)$ for $j \in J$. This means that inadequate levels of service $S^j(t)$ may trigger disruptive dynamics of operations in i. In formula,

$$\alpha^i(t) := \sum_{j \in J} \frac{e_{ij}\left(1 - S^j(t)\right)}{|J|},$$

where the cardinality of J serves as normalization and each weight $0 \leq e_{ij} \leq e_{max}$ assesses the effect of a failed infrastructure j on i, as services provided to a CI are not all equally "vital" for its functioning. Considering the directed network of interdependent CIs, we define the connection matrix $E = \{e_{ij}\}$ s.t. E is asymmetric. In particular, $e_{ij} = 0$ means the link $j \rightarrow i$ does not exist (accordingly $j \notin J$ by definition of J), but it may exist the viceversa ($i \rightarrow j$). Note also that $e_{ij} \neq 0$ if $j \in J$, therefore $e_{ij}\left(1 - S^j(t)\right) = 0$ if and only if the infrastructure j is able to fully provide service, i.e. $S^j(t) = 1$.

Summarizing, we say a disruption (Block 1) occurring in a CI is the trigger event that influences the breakdown rate of the target CI (Block 2) and consequently may provoke disruptive dynamics in other CIs due to their interdependencies (Block 3).

We remark that disruptions can be modeled independently in more than one infrastructure occurring at the same or different times. Then, cascading effects are mutually assessed by the weighted connection matrix E, and their magnitudes dynamically change according to the breakdown rate $\alpha^i(t)$ defined above for a general infrastructure i. In particular, CIs' breakdown rates in the model depend on the ability of CIs to provide critical services to each other over time. Assuming that infrastructure i is also directly affected by a disruption, the function $d(t)$ describing the disruptive event (Block 1) will be an additive term of $\alpha^i(t)$.

After the analytical description of building blocks, Figure 1 illustrates how they have been integrated one another in SD stock and flow model of two generic infrastructures i and j s.t. j is disrupted and i depends on services provided by j (i.e. $j \rightarrow i$).

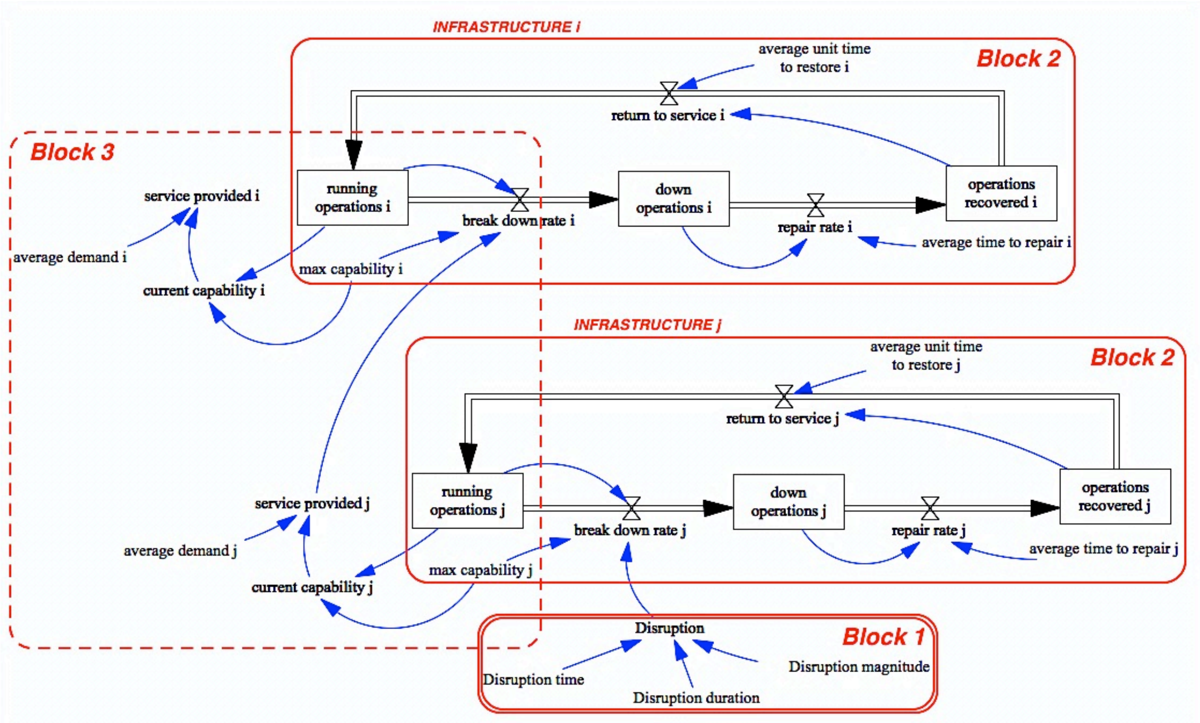


Figure 1. Integrated Building Blocks.

SIMULATIONS AND IMPACT ANALYSIS

In this section we build and simulate different scenarios of disruptions to demonstrate how our model can support risk assessment and management processes. Arguments for the use of scenario-generation methods to forecast possible futures in decision-making contexts are discussed in (Banuls & Turoff, 2011). The authors integrate Delphi method and Cross Impact Analysis to describe possible scenarios of interdependent events. Here, we use data gathered from experts in (Laugé, Hernantes, & Sarriegi, 2015) as input parameters for our model and consider hypothetical scenarios with the purpose of illustrating model applications to dynamic impact analysis based now on System Dynamics simulations.

General Scenario Description and Setting

We refer here to the relatively simple system of five CIs in Figure 2. Note that this particular setting does not limit further applications of our modeling approach to other scenarios.

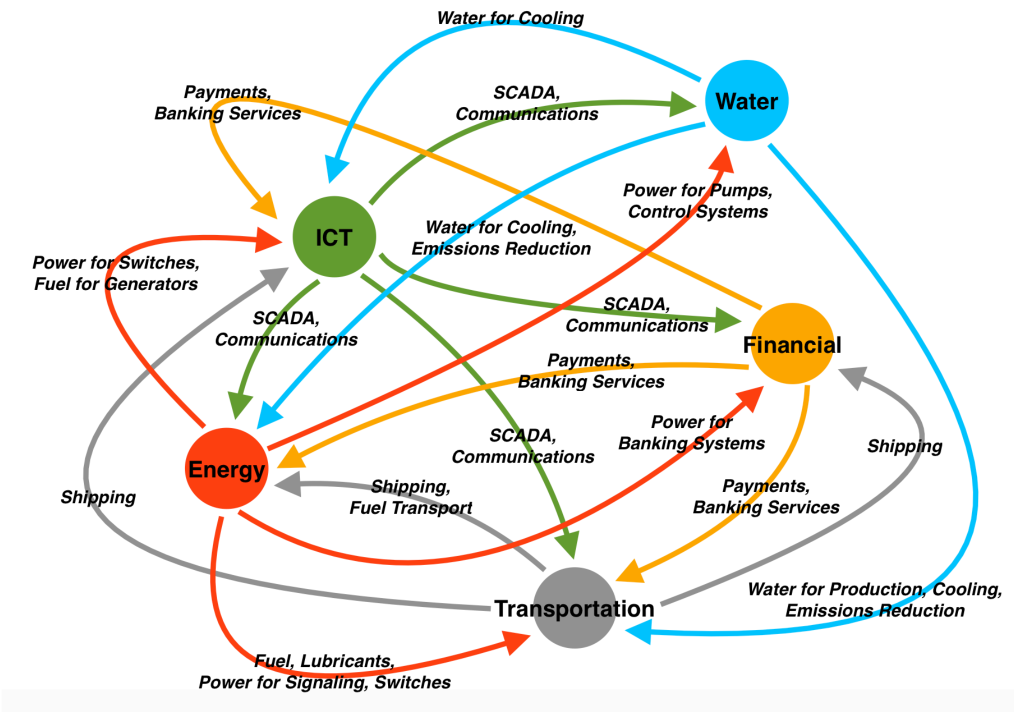


Figure 2. Qualitative Scenario Representation.

Figure 2 depicts causal links across CIs with respect to services they provide to each other. This qualitative characterization of CIs interdependencies is based on (Rinaldi et al., 2001).

The quantitative assessment of interdependencies is based on the results of a latest survey of CIs experts from several countries conducted by (Laugé et al., 2015). The experts were asked to quantify on a scale of 0 to 5 the magnitude of effects on each CI if another CI would be non-operational for less than two hours (Table 1).

	e_{ij}	*Effect on i*				
		Energy	ICT	Water	Financial	Transport
Failed j	Energy	-	0.86	1.33	2.67	2.40
	ICT	2.67	-	1.00	2.33	2.40
	Water	0.83	0.57	-	0.00	0.20
	Financial	0.17	0.71	0.00	-	0.60
	Transport	1.17	1.00	0.00	1.00	-

Table 1. Quantitative Assessments of CI interdependencies. Adapted From (Laugé et al., 2015)**.**

Our model takes data in Table 1 as input to set values of the connection matrix $E = \{e_{ij}\}, 0 \leq e_{ij} \leq 5$, that exactly aim to estimate the level of effects of eventual failures in infrastructure j on infrastructure i (Block 3).

We remark that E serves only to mutually assess interdependent effects between CIs. This means that input data must fit our simulations' time scale (Hours) but it does not limit the analysis to disruption durations accounted by the survey (Laugé et al., 2015). In our model, magnitudes of interdependencies will change over time within feedback loops that determine system behaviors accounting for nonlinear dynamics of disruptions (Block 1), CIs operations (Block 2), and services (Block 3).

For convenience, we assume each CI has max capability $C^i_{Max} = 100\ operations$. By definition of 'normal operational state' (Block 2), $OP^i_{run}(t) = C^i_{Max}$ per $0 \leq t < t_d$, (i.e. before to stress the system with a disruptive event). The average demands for services, D^i_{Av}, is then assumed being 90% of C^i_{Max}, as in real-world situations infrastructures do not usually work at the maximum of their capabilities for being able to meet the demand. Again, assumptions only serve to run simulations with the purpose of demonstrating applicability of our original modeling approach; therefore they do not limit further model application to different scenarios.

Starting from this model setting, we carry out a simulation-based impact analysis by comparing different scenarios of disruptions. For each infrastructure i, we analyze interdependent dynamics of

- 'Running Operations', $0 \leq OP^i_{run}(t) \leq 100$, which indicates the operational state of single CIs (graphs on right);
- 'Service Provided', $0 \leq S^i(t) \leq 1$, determining if disruption impacts make a CI unable to provide adequate services to other CIs and so damage effects are cascading among them (graphs on left).

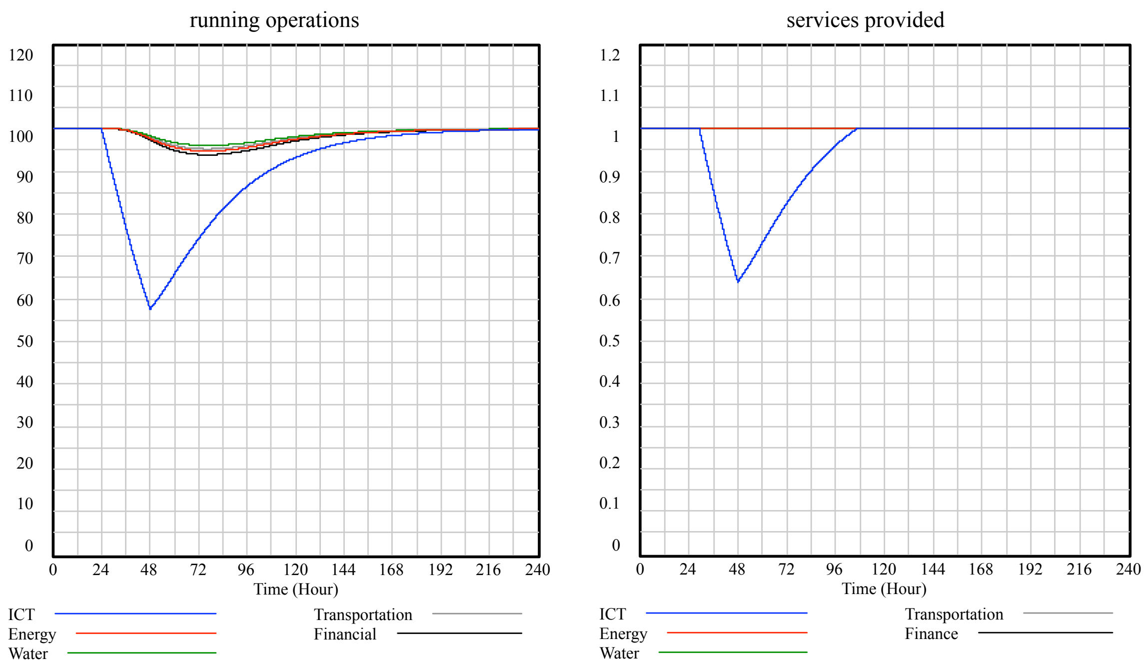
Note that simulations were launched over 2 weeks period with an hourly time scale (i.e. $INITIAL\ TIME = 0$ and $FINAL\ TIME = 336\ hours$).

Scenario 1 - Single Disruption

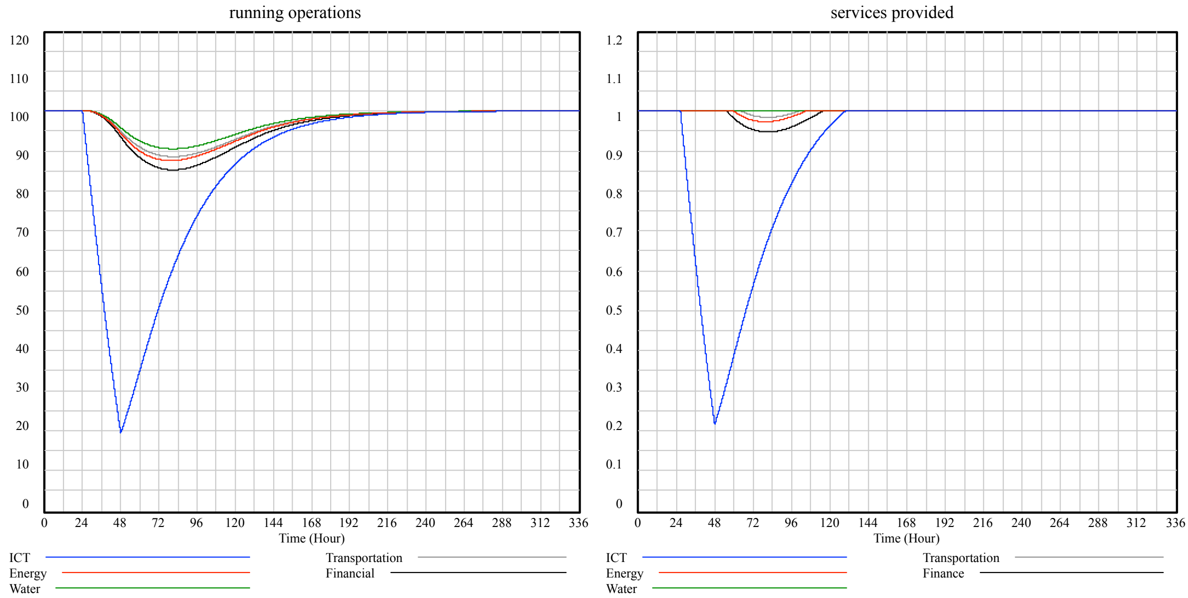
We simulate a disruption in the Information Communication Technology (ICT) infrastructure occurring at simulation time $t_{d'} = 48\ hours$ with duration $\Delta T_{d'} = 24\ hours$. It can be a cyber attack aiming to manipulate SCADA control and communication systems today used by any CI to regulate operations, and affecting the ICT for 1 day before detection and mitigation responses to perform.

As different damages caused by this kind of disruption depend on motivations, resources, and skills of the cyber activist (e.g. Stuxnet (Langner, 2013)), we conduct an impact analysis by varying the disruption magnitude factor $m_{d'}$, $0 \leq m_{d'} \leq 10$ (block 1).

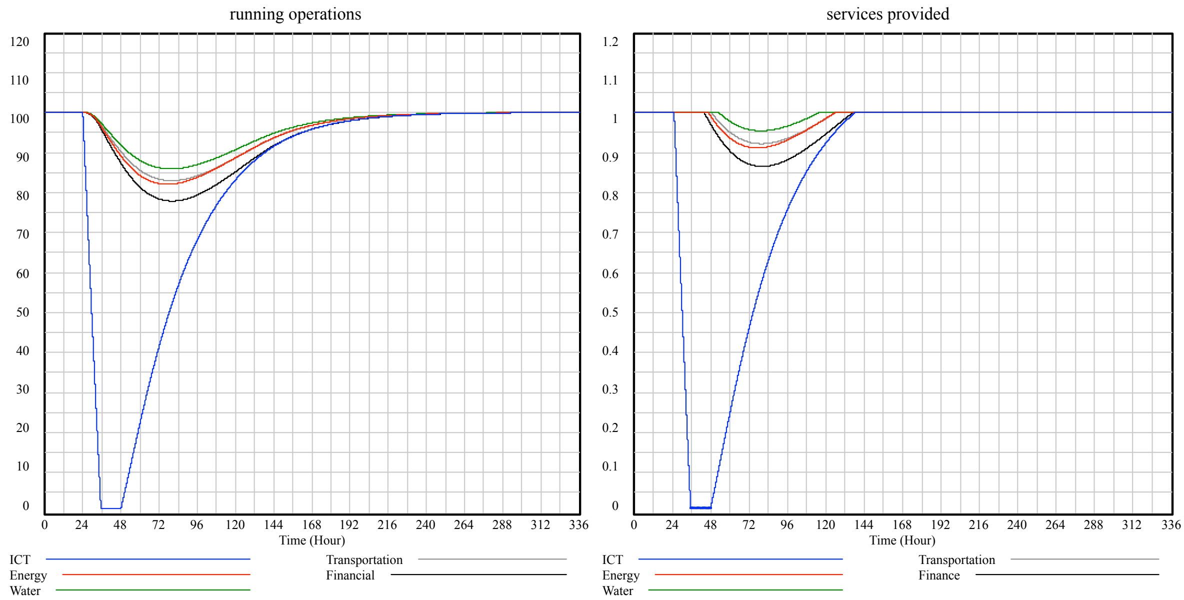
- $m_{d'} = 2$ (*Small Disruption*): the cyber activist succeeds to partially take over the control of ICT operations so that the ICT infrastructure loses about 35% of service capabilities out. Nevertheless, the bigger system is able to absorb the disruption so that it does not cascade into other CIs. Energy, Water, Transportation, and Financial infrastructures can still fully satisfy the services' demands although their operations get partially damaged.



- $m_{d'} = 4$ (*Medium Disruption*): since growing capabilities of cyber attackers may lead to increased damages in the target infrastructure, 80% of ICT operations go down and the consequent high loss of ICT services causes operational disruptions into all other CIs. With the exception of the Water infrastructure, disruption impacts also provoke service interruptions to the other infrastructures.



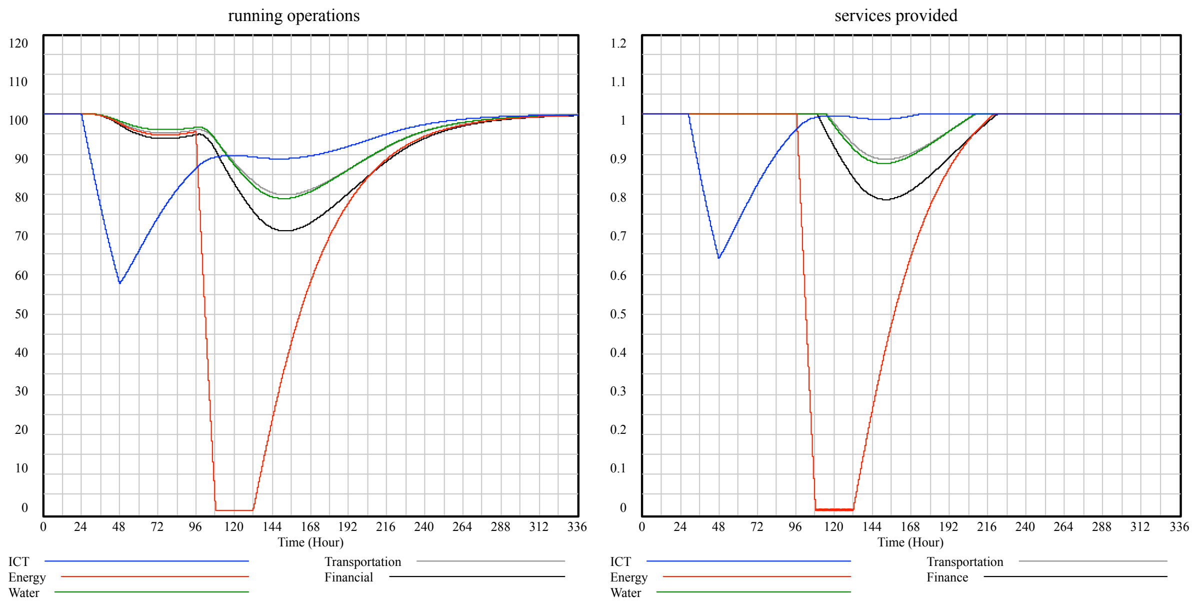
- $m_{d'} = 9$ (*Big Disruption*): ICT operations and services are completely down for 12 hours. In this case the system is not enough resilient and effects of the cyber disruption cascade into all other infrastructures due to strong CIs dependences on SCADA technologies. CIs can deliver adequate services only after 4 days the ICT disruption occurred, while 10 days are needed before all CIs operations return to normal state (fully available).



Scenario 2 - Multiple Disruptions

Let us assume now that a disruption in the Energy infrastructure occurs after the cyber attack to the ICT infrastructure with low magnitude factor $m_{d'} = 2$ (*Small Disruption* in Scenario 1). It may be an electric power outage occurring at simulation time $t_{d''} = 96\ hours$ and affecting the Energy CI for 1,5 days ($\Delta T_{d''} = 36\ hours$) with high magnitude factor $m_{d''} = 8$.

Of our interest is to demonstrate how coupled dynamics of disruptive events impact on system performances at operational and service levels. Although Scenario 1 shows that relatively small disruptions in the ICT do not cascade into the bigger system, we observe that the impacts can be catastrophic if a power outage occurs while the ICT infrastructure is recovering from that "small" cyber crisis. Inability of the Energy to provide services influences the ICT operations' recovery due to nonlinear feedback dynamics captured by our model.



Comparing the charts above with the single *Small Disruption* (Scenario 1), we note ICT (blue line) needs longer to restore internal operations. This is a reasonable system behavior, as electric power is essential to carry out mitigation and recovery actions in SCADA and telecommunications systems.

We can also observe that even though the Financial CI (black line) is not directly affected by disruptions, it has the longest recovery because financial operations strongly rely on services provided by ICT and Energy (both directly affected by independent disruptive events).

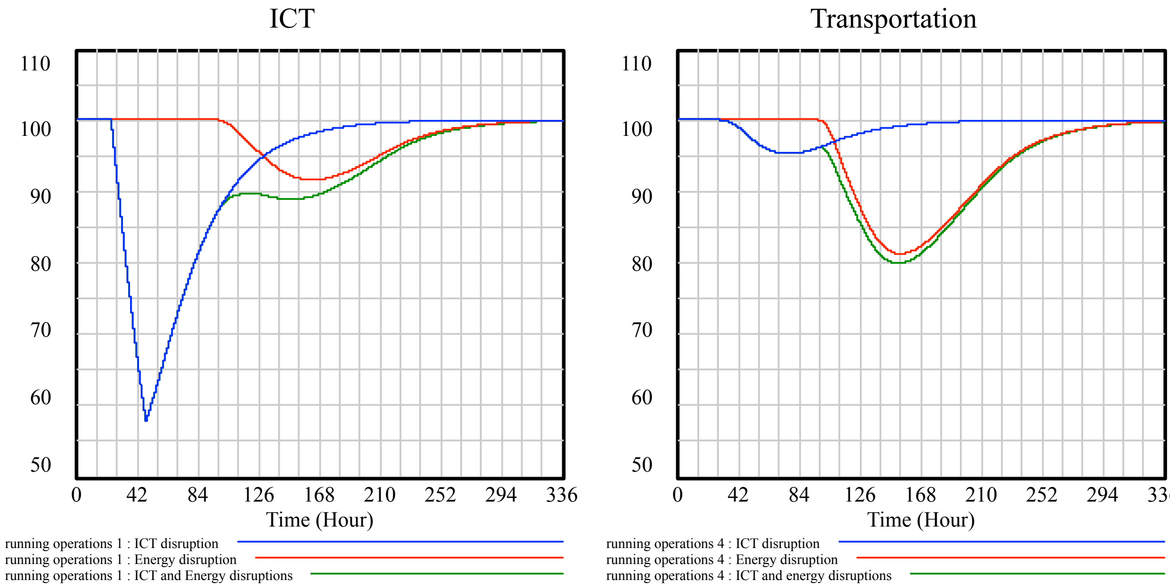
DYNAMIC RESILIENCE ASSESSMENT

On the basis of the dynamic impact analysis proposed in this paper, time-dependent resilience evaluation is straightforward. In this section we briefly introduce our SD model as potential instrument toward dynamic resilience assessment. For such a purpose, we primarily understand "dynamic resilience" in the context of system recovery speed: a more resilient system is the one able to recover faster from a crisis situation (Pant et al., 2014). In addition to recoverability, resilience can be quantified according to other capacities such as absorptive capacity and adaptive capacity (Francis & Bekera, 2014). These three characteristics enable to describe system resilience in terms of proportions of initial system performance (i.e. normal state).

Accordingly, our model provides simulation-based insights for dynamic resilience assessment by capturing CI operational dynamics over time due to disruptions. In fact, we can compare the stock of running operations, $OP^{i}_{run}(t)$, under different disruption scenarios to measure CI performances.

Simulation outputs below illustrate this concept for two infrastructures: one in which the disruption occurs (ICT) and another (Transportation) that is not directly disrupted, but gets damaged due to cascading effects.

The blue line refers to the ICT small disruption of Scenario 1, the green line to ICT and Energy disruptions of Scenario 2, and the red line replicates only the Energy disruption (i.e. Scenario 2 without ICT disruption).



These results demonstrate how changes in recovery times strongly depend on different disruptions occurring over time. Furthermore, losses of resilience can be easily calculated as function of operational performances between the disruption time and the time of recovery (i.e. time in which the system return to a normal operational state after the disruptions). For instance, by measuring the triangle areas in the graphs above according to the largely used resilience framework proposed by (Bruneau et al., 2003).

Considering CI performances at operational and service levels over time, our modeling approach suits a wide range of other existing metrics for resilience analysis; e.g. (Francis & Bekera, 2014; Hosseini et al., 2016; Sterbenz et al., 2013).

Given the relevance of recognizing interdependencies among CIs in planning for operations, we propose a tool that accounts for both micro (single CI) and macro (across CIs) dynamics of such complex systems. This also means that resilience components of every infrastructure are evaluated with respect to the bigger system thanks to the model's ability of capturing dynamics of single CIs through causal relationships and feedback loops between them.

CONCLUSION AND FUTURE WORK

This research work proposes a novel modeling approach to capture complex dynamics of disruptive events in CIs networks. We adopt a block building process based on SD methods to get a better understanding of interdependent dynamics within and across CIs. Primarily inspired by epidemics modeling, we develop blocks of models to capture different dynamic aspects characterizing the system behavior. We demonstrate how these blocks can be used to build scenarios for simulation-based impact analysis and dynamic resilience assessment.

We seek in this way to provide insights for potential users of the SD model, such as crisis managers that continuously attempt to forecast scenarios and assess risks of failures in interdependent CIs. Policies can be easily evaluated by changing model parameters; e.g. different values of CIs' capabilities may increase system resilience. Testing effectiveness of prevention and mitigation strategies with our model is definitely a target topic for next publications.

Flexibility and potentials of our approach allow to a number of other applications. We focus on networked CIs, but the choice of the abstraction level is up to users' interest and domain. Dynamics of each node can refer to a single process or component of an organization, and dynamic interdependencies among networked processes can be studied to finally get insights on organization's performances.

Moreover, the model can be easily extended thanks to the block building approach. As our particular interest is to explore the field of cyber security, we are currently developing a further block that models cyber attackdefense dynamics in CIs through the use of Game Theory.

Future work also aims to test model capabilities by considering structured demands for specific CI services. Perturbations and different demand patterns will highlight interesting disruption dynamics. E.g. energy blackouts during daylight or in the night can have different impacts on other CIs.

The practical relevance of our modeling relies on the fact that dynamic simulations and graphical outputs are particularly suitable for decision-makers who may not have mathematical background. Moreover, it allows to get a specific understanding of complex system dynamics during crises without huge amounts of data required. Nevertheless, limitations may concern unavailable real-world information to validate CI scenarios and model parameters as we did by using survey data in (Laugé et al., 2015). On this note, it would be interesting to support and compare our model with scenario-generation methods such as the CIA-ISM approach that particularly suits with SD tools (Banuls & Turoff, 2011).

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