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Conceptual Development of a Probabilistic Graphical Framework for Assessing Port Resilience

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Abstract

Technological advances such as cyber physical systems and autonomous vehicles combined with increased disruptions including the Covid-19 pandemic and coastal natural disasters have heightened the importance of port risk analysis methodologies and frameworks that can accurately quantify and optimize resilience. This work presents the conceptual development of a novel combination of analysis methodologies linking a probabilistic graphic approach on a network of risk events with a functional dependency approach on a system network. Key advantages of these two methodologies are the ability to model and learn causal interactions rather than simply correlations and a high level of computational efficiency. This combination of robustness and flexibility offers the ability to quickly analyze multiple port configurations in order to invest in efforts that maximize the resilience-cost ratio. In addition, the methodology opens the door for real-time anomaly detection and causal analysis in order to enhance efforts in the protecting against attacks on infrastructure and in particular cyber physical systems.

Keywords: Ports; Risk analysis; Resilience; Probabilistic graphical models; Functional dependency analysis; Modeling and simulation

1. Introduction

Technological advances at ports worldwide continue to provide opportunities and challenges due to increasing applications of Industry 4.0 technologies including cyber physical systems, autonomous vehicles, and logistical strategies for multimodal transportation. Ports are a critical element in supply chains where asynchronous cargo streams converge from suppliers and subsequently diverge to their respective target consumers (Verschuur, Koks, & Hall, 2020). Given this criticality, it is imperative that risks are carefully quantified and appropriately balanced with efforts to improve resilience.

Recently, misestimations of consumer demand and raw material sourcing issues have been compounded by the COVID-19 pandemic and are expected to have lasting impacts for years to come (Domonoske, 2021; Wu & Mochizuki, 2021). In fact, a shift in culture and operation is emerging which centers optimization of resilience and improved quantification and understanding of risk at the forefront of maritime transport policy and procedure (United Nations, 2020). Prior to these unparalleled disruptions from the current pandemic, ports were planning for investments in modernization included broader implementation of cyber physical systems and preparation for autonomous vehicles (The Port of Virginia, 2016). Even under normal operating conditions, the implementation of innovative practices and technologies brings with it inherent risks.

Because the sustainability of port operations requires resilient practices (Justice, Bhaskar, Pateman, Cain, & Cahoon, 2016), it is imperative that future analysis methods provide the ability to not only quantify risk but determine the causal interactions between risk events and simulate the system response. In addition, methods should be computationally efficient enough to conduct analyses on various alternatives for resilience interventions as well as sensitivity analyses on assumptions to ensure that port managers can make the most informed decisions to optimize resilience. Recent literature has indicated that while neural networks have been extremely successful across a diverse array of problems, they have fallen short in applications where causal relationships need to be differentiated from correlations (Schölkopf et al., 2021). Probabilistic graphical models have been used to model the ripple effect in supply chains considering causal dependencies between disruptive events (Hosseini, Al Khaled, & Sarder, 2016). However, these networks are computationally expensive not only to train, but to also to simulate which limits their applicability to complex systems (Guo & Hsu, 2002). Maritime ports certainly qualify as complex systems as they embody an asynchronous convergence of multimodal transportation systems with increasing requirements to consider implementation of cyber physical systems and autonomous vehicles.

In this work, a framework is proposed and developed that allows for the combination of a probabilistic graphical model, in particular a dynamics Bayesian Networks, with a functional dependency model. Functional dependency models, for example System Operational Dependency Analysis (SODA), allow for lower computational costs and use parameters that have intuitive meaning with regard to the dependencies between subsystems and components (Guariniello & DeLaurentis, 2017). The proposed model uses dependency analysis methodology to model the systems itself while simultaneously using a Bayesian network to model risk events, their interdependencies, and their effect on system subsystems and components. Once system risks are characterized and disruptions are assessed, stakeholders can prioritize investments that will have the highest impact on resilience (Diaz, Smith, Acero, Longo, & Padovano, 2021).

The remainder of this paper is organized as follows. Section 2 summarizes previous contributions to modeling and analysis of risk and resilience in ports. Section 3 provides an overview of the model development including motivation for the choice of each of the combined methodologies. Section 4 will show the application of the model to a network abstraction designed based on The Port of Virginia. Finally, Section 5 will conclude the paper and provide recommendations for future work.

2. State of the art

To ground the current conceptual framework in the literature, this section provides an overview of applications, including those related to ports specifically and maritime in general, of the two methodologies that are combined to create the novel framework proposed by this work, namely, Bayesian networks and functional dependency analysis.

2.1. Bayesian Networks for System Risk and Resilience

Bayesian networks have been used to analyze the ripple effect of disruptions through complex systems, including supply chains (Hosseini & Ivanov, 2020) and quantify resilience (Hosseini et al., 2016). Bayesian networks are noted to have particular applicability to systems, such as ports, where the factors affecting resilience are qualitative rather than quantitative (Hosseini & Barker, 2016). One benefit of these models is that they provide a causal representation for networks. Additionally, initial network parameters and structure can be learned even from small data sets or subject matter expertise. These initial learned distributions can be incorporated as prior evidence and the model can update these distributions based on additional data as it becomes available resulting in an increase of model accuracy over time (Lauritzen & Spiegelhalter, 1988). One problem with these approaches is that both exact and approximate algorithms for forward post-learning inference are NP-hard which directly limits efforts to evaluate complex systems in real-time (Guo & Hsu, 2002).

2.2. Functional Dependency Analysis

The use of functional dependency analysis has been proposed or utilized in a number of fields to characterize dependencies and risks. These methods of analysis are rooted in Leontief's input-output models (Leontief, 1951). These models were more recently extended to conduct risk management analysis for infrastructures (Jiang & Haimes, 2004). Later, it was extended to model risk in complex systems, specifically risk management for capability portfolios (Garvey & Pinto, 2009). This more generalized implementation was further extended to include a more robust characterization of performance in complex systems, including aerospace systems (Guariniello & DeLaurentis, 2017). Recently, these methods have been proposed as useful for conceptual frameworks that assess risks in complex systems, such as supply chains, that are experiencing digital transformation (Diaz et al., 2021; Diaz, Smith, Landaeta, & Padovano, 2020).

3. Materials and Methods

Noting that current Bayesian network implementations for propagating risk in a supply chain network use discrete (usually binary) random variables for each node, this work proposes using Bayesian networks to model the risk events which naturally lend themselves to a binary implementation using states of disruption occurred or did not occur. On the other hand, the parameters used to quantify system performance are generally continuous variables. In order to preserve this higher level of detail, the system network will be modeled and analyzed using functional dependency analysis. This section will provide an overview of the implementation of a Bayesian network for the network of risk events, i.e., the risk network, and the implementation of a functional dependency analysis for the model of the port itself, i.e., the system network.

3.1. Risk Network

To establish the theoretical grounding of the risk network and its ability to establish dependencies between random variables, a probability space must be established. Generally, a probability space is a triple (Ω, E, P) where Ω is the sample space of all possible outcomes, E is a σ-algebra over Ω specifying how the sample space can be divided into a set of events, and P is a measure on (Ω, E) mapping events E to the set of real numbers. Each real number represents the probability of an event, E, occurring. Figure 1 shows a probability space with three risks. Note that Risk a can occur simultaneously with Risk b or Risk c, but all three cannot occur simultaneously.

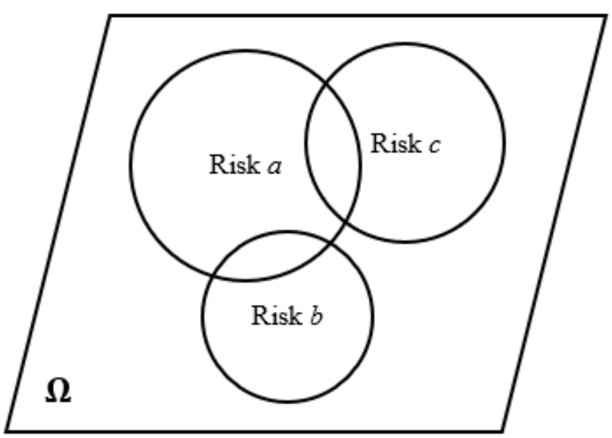

Figure 1. A probability space showing three risk events.

In order to relate these events in a probabilistic graphical model, random variables must be defined. The simplest random variable that is an indicator function defined as follows:

$$X_i = \begin{cases} 1 \; if \; event \; associated \; with \; Risk \; i \; occurs \\ 0 \; otherwise \end{cases} \quad (1)$$

For illustrative purposes, it will be assumed that Risk b is dependent on Risk a and Risk c is independent of both. This leads to the probabilistic graphical model show in Figure 2. The final two steps are to establish conditional probabilities for the risk events and then relate the nodes in the risk network to dependent nodes in the system network. Given data, the conditional probabilities can be learned for each random variable in a process similar to (Ghahramani, 1997). Since the internal health status of a node in the system network will be modeled as a random variable, these connections can be learned the same way or estimated by a subject matter expert. More details on the internal health random variables will be given in the next section.

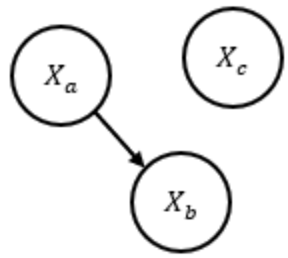

Figure 2. Simple probabilistic graphical model show dependence of three random variables.

3.2. System Network

Once the Bayesian network is learned, a method similar to System Operational Dependency Analysis (SODA) (Guariniello & DeLaurentis, 2017) will be applied with extra parameters incorporated to maintain the causal relationships, as needed. SODA, similar to its predecessor Functional Dependency Network Analysis (FDNA) (Garvey & Pinto, 2009), allows for the effects of dependent relationships to be analyzed using forward propagation on a network in the form of a directed acyclic graph. The level at which a given node functions, namely its operability, can be calculated as a piecewise, weighted, linear combination of the operability values for the dependent nodes and a parameter representing its own internal health, referred to here as e. Considering the example network shown in Figure 3, the operability of node 6 would be a function of the operability of the operabilities of nodes 3 and 4 and its own internal health parameters. The operability for nodes 1 and 2 would be equal to the values of their internal health parameters as neither has any dependencies. Calculating these piecewise linear relationships is much less computationally intensive than inference calculations using Bayesian networks. Though simple, these weights and parameters have intuitive meaning based on the relationships between the operability values of dependent nodes. By investigating these relationships once they are learned from the Bayesian network representation, additional parameters can be implemented with the specific goal of capturing the complexities of the causal relationships learned by the Bayesian network.

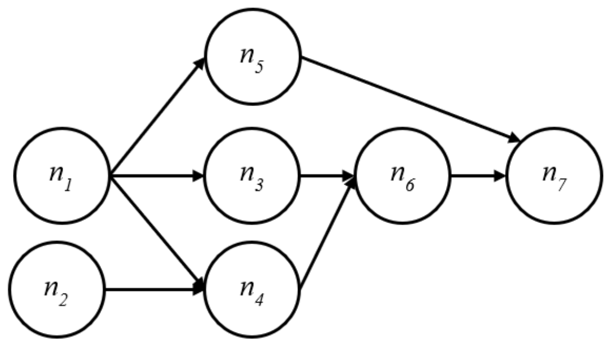

Figure 3. An example system network.

Other than the ability to add additional parameters to models more complex behavior, the main advantage of the current work over previous functional dependency methodologies is the ability to use the dynamic Bayesian network, i.e., the risk network, to inform the values of the internal health parameters in the systems network. In previous work, these were manipulated directly to create various failure scenarios. Additionally, these values were not considered dynamic with respect to time. Therefore, no considerations were made for the possibility of concurrent disruptive events. Here, the internal health parameter will incorporate three resilience capacities, i.e., adaptive, absorptive, and restorative (Henry & Ramirez-Marquez, 2012). Each internal health node will be in one of four states which are normal, absorptive, responsive, and recovery. Figure 4 shows these states along with their transitions and the overall dependence of the system node internal health on nodes in the risk network. The internal health behavior over time in each state is shown in Figure 5. In summary, a node effected by a disruptive event sees a decrease in its internal health over time. After some time has passed, the node is able to stabilize its internal health at a constant level. Eventually, the node is able to recover some or all of its lost internal health value and arrive at a new normal level of internal health. How the node moves between states is determined by the conditional probabilities relating the node to the dynamic Bayesian risk network.

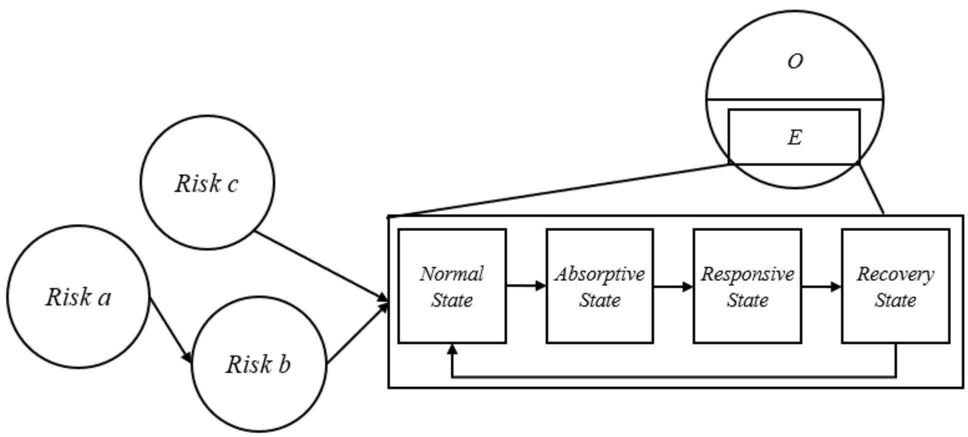

Figure 4. Depiction of states for system node internal health that are dependent on events in the risk network.

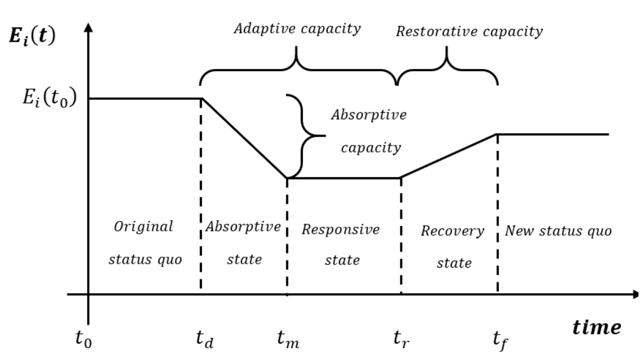

Figure 5. Relationship between internal node health and time as the node responds to a disruption (Adapted from (Hosseini, Ivanov, & Blackhurst, 2020)).

4. Results and Discussion

In order to provide an example and support discussion, this section will present an application of the framework presented to a model of the cyber physical systems at the Port of Virginia. The model presented is an abstraction from the Port of Virginia's "NIT South Animation" (The Port of Virginia, 2017). The risk and system networks are shown in Figure 6.

4.1. Application to Port of Virginia

For the purposes of clarity and explanation, several assumptions have been made in the construction of the abstract model used to illustrate the current framework. First the focus has been limited to on relevant key performance indicators such as handling time for various types of transport (ships, rail, and trucks), volume of containers handled, and overall cost and productivity, to allow key processes and entities involved in port operations to be identified for inclusion in the conceptual model (Nicoletti, Chiurco, Arango, & Diaz, 2014). These key processes and entities are represented as nodes in the system network shown in Figure 6. In particular, the boundary of the port is represented by entry and exit points for three different modalities of transportation, namely, truck, ship, and rail. The container stacks serve as the center for container processing, handling, and transfer between these transportation modalities. In between each modality bringing containers into the port and the container stacks, nodes are used to represent the various cyber physical systems with which the containers and vehicles carrying them interact. The result is an overall network topology for the system network in the Port of Virginia taking the form of a tree with the container stacks at the root node.

Additionally, only a subset of possible disturbances is shown to illustrate the core functionalities of the framework rather than attempting to encompass every possible scenario. In particular, disruptions have been chosen in an attempt to emphasize the types of events that can be modeled when this conceptual framework is implemented. For example, a cyberattack could breach any of the cyber physical systems that interact with the various forms of transportation and container stacks. However, the fact that all of these systems are vulnerable to cyberattack does not imply that they would all be attacked simultaneously or that they are equally vulnerable to attacks. The conditional probability tables relating the cyberattack risk to each dependent system node can be tailored to represent diverse levels of reaction. A more local disruption, such as a shipping route disturbance, could have only one dependent node. Even though one node may only be affected initially, the functional dependency analysis performed on the system network would allow for the assessment of affects that ripple through the system and reveal nodes that are vulnerable to a disturbance they may not be directly dependent on.

Additionally, the dynamic Bayesian network model that describes the behavior of the risk network allows dependencies to be captured between the risk events themselves. In the port model, natural disasters are shown to directly affect all three transportation modalities. Ports have a higher vulnerability to natural disaster than various other systems in the supply chain due to their coastal locations (Gong, Xiao, Jiang, Zheng, & Fu, 2020; Verschuur et al., 2020). For the Port of Virginia and its surrounding region, the probability of traffic disruptions increases and decreases with a direct dependency on conditions at the world's largest naval station just a few miles away (Dowell, Sigmon, & Livingston, 2012). As a result of this heightened dependence on both natural disasters and surrounding traffic conditions, understanding and modeling any dependent relationship between the two is critical.

While a full implementation is not conducted in the presentation of this conceptual framework, it is prudent to detail how such a task could be completed now that the intricacies of a particular model, including nodes and dependencies in both the risk and system networks, have been elucidated. Assuming that performance data is available for the system network nodes and likelihood of occurrence and quantification of impact is available for the risk network, parameter values can be learned that will allow for simulation of the network under given conditions. These learned parameters can be used to simulate internal health values for nodes affected by a disruption. Then, network dependency parameters allow forward propagation to be used to determine the operability of all nodes in the network.

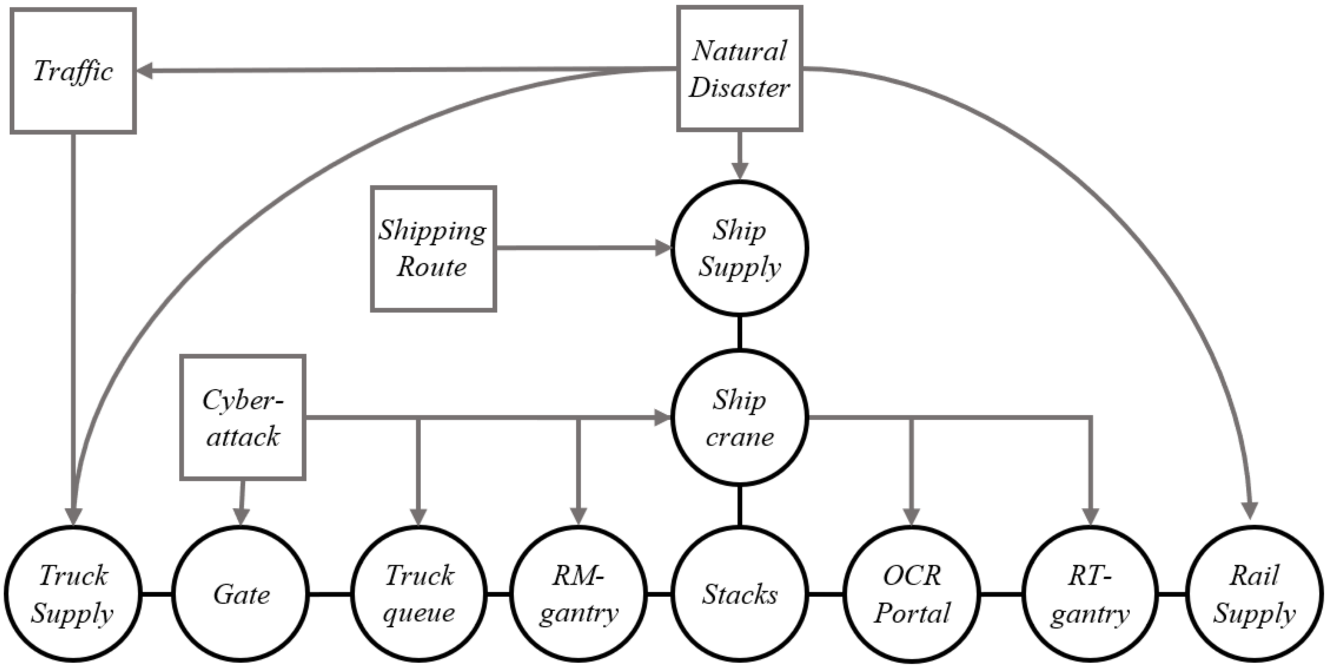

Figure 6. Combined risk (grey square nodes) and system (black circular nodes) networks for the Port of Virginia example.

4.2. Hypervulnerabilities

It is important to determine if specific characteristics of network topology or dependencies can result in some nodes being at a higher risk than others. These nodes that are at increased risk are said to be hypervulnerable. For example, nodes may be hypervulnerable when affected by a combination of vulnerabilities which are likely to occur together and whose effects may not combine linearly. In the port network shown, a natural disaster event affects all supply nodes, but since traffic is an additional dependency of this event the truck supply node will be affected differently than the others. A full analysis would allow analysts to not only quantify this increased level of vulnerability, but also to simulate various options for increasing resilience around the vulnerable node or set of nodes.

Another example of a hypervulnerability could result from an event which occurs with a frequency that is high enough that the system cannot recover between events. By allowing risk events to be modeled using random variables, the expected rate of occurrence can be weighed against the expected recovery time in order to ascertain whether there are any nodes that have not had sufficient time to recover prior to a subsequent occurrence of a disruptive event. These nodes would be classified as hypervulnerable and their resilience would likely decrease over time due to the compound effects of repeated events.

4.3. Topology of Disruptions

As the risk network and system network are modeled as two separate, but interacting, dependent networks, the topology of one can and will affect the topology of the other. Of specific interest are the topological characteristics of system nodes that are dependent on a given risk node. The simplest example is a global versus local disruption. While a global disruptive event would be expected to affect all nodes, local disruptive events would only affect a subset. Additionally, a disruptive event affecting more than one node could have varying events on these different nodes based on their topological characteristics within the two networks.

Another topological characteristic that could be used to characterize a disruption is the degree of a node. Risk nodes that support more connections, both to other risk nodes and to system nodes, would be expected to have a higher impact on the system. System nodes that are connected to a higher number of risk nodes may be hypervulnerable depending on when these risks occur and how their effects interact.

4.4. Resilience Assessment

Due to the low computational cost of learning system parameters for and conducting inference on the system network, analysts can rapidly assess alternative port configurations with respect to their resilience capacities under a variety of different disruptive events. Specific stochastic measures of resilience have been developed and related to a port's ability to recover its original level of operability (Pant, Barker, Ramirez-Marquez, & Rocco, 2014). This ability and associated metrics map directly to the post-disturbance reactive and responsive states from Figure 5. While it would be advantageous to numerically optimize resilience using the proposed metrics, the previous work has found that these measures can increase system cost (Hosseini, Ivanov, & Dolgui, 2019). The input-output models that functional dependency analysis is based on have been used to quickly assess the effect of actions aimed to increase resilience (Okuyama & Santos, 2014). In this case, increasing the computational efficiency with which the resilience metrics can be estimated allows for faster, automated comparison of various port configurations.

5. Conclusions

This work has presented a novel, conceptual framework for assessing port resilience. This framework leverages and combines dynamic Bayesian networks and functional dependency analysis to probabilistically model disruptive events and quickly forward propagate their resulting effects to quantify system resilience and open the door for its subsequent optimization. This approach aims to capitalize on the ability of Bayesian networks to capture causal relationships between risk event rather than just spurious correlations while simultaneously leveraging the computational efficiency of functional dependency analysis to support optimization of network structure with respect to resilience. An additional application where correct identification of causal relationships and computational efficiency are exceedingly important is real-time monitoring and detection of system anomalies. Correctly identifying the root cause of anomalies would allow port managers to differentiate between harmless variations and cyberattacks.

In the near future, the research team plans to implement this conceptual framework as a prototype system that can be used to model not only port systems, but other aspects of maritime supply chains as well. Extensions to the contained methodology include the ability to model bidirectional dependencies and optimize resilience over multiple system configurations.

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