Interdependency analysis of port calls and ship routes for cascading delay analysis between interconnected ports

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Abstract.

The resilience of the maritime infrastructure network is of major importance, since delays such as prolonged road congestion in specific ports may often initiate major cascading delays in ship routes that block transportation and/or disrupt services of other infrastructures over wide areas. Existing AIS maritime flow analysis methods lack the ability to understand the cascading effect of port delays and unavailability nor how to improve overall resilience in a network of ports interconnected by ship routes. Dependency risk graphs have been proposed as a tool for analyzing such cascading failures using infrastructure dependency chains. In this paper, we propose a risk-based interdependency analysis methodology capable to detect large-scale port call congestion and ship delays between interconnected ports of the maritime network and provide mitigation solutions to increase flow resilience. Dependency risk chains of ports provide important information about which ports are affected when other major ports are congested in the maritime transportation network. Targeted mitigation mechanisms for ship congestion and delays can be proposed and the causes of bottlenecks can be analyzed to introduce rerouting of ships with the best possible results in relieving delays. In this article, we demonstrate the proposed methodology on sample AIS data collected by a major company that records and analyzes historical ship data. Currently, our tool can analyze a simulated Mediterranean port network using port entry and exit calls along with route times, and detect n-order port routes dependencies and automatically proposed mitigation solutions to increase the overall congestion resilience of the maritime network.

Keywords: Port, Ship routes, traffic congestion mitigation, graph analysis, risk assessment, Maritime

1. INTRODUCTION

The U.S. department of Homeland security identifies the Maritime Transportation System as one of the seven key subsectors of the Transportation Systems Sector [dhs]. Efficient use of existing maritime network systems can result in reduced traffic congestion, cost and route delays. Congestion and flow prediction models can help both maritime users and transportation authorities improve port traffic resilience, alleviate congestion or reduce traffic incidences in advance, by predicting the future states of traffic flow [Hoogendoorn and Bovy 2001]. Dependency modeling, simulation and analysis of infrastructures have been studied extensively by researchers. Several methodologies and tools that focus on dependency analysis, estimate the impact [Franchina et al. 2011], [Robert 2004] or the risk derived from the dependencies within a critical infrastructure or among interdependent infrastructures [Kjølle et al. 2012], [Kotzanikolaou et al. 2013b], [Utne et al. 2011]. The risk usually depends on two factors; the likelihood (or probability) of a negative event occurring and the impact (consequences) of that negative event. Such impact usually results in a complete non-operation or a partial malfunction in an infrastructure due to dependencies in infrastructure networks, usually called a failure.

1.1 Contribution

In this paper we utilize a previous time-based dependency analysis methodology for Critical Infrastructure dependency modeling [Kotzanikolaou et al. 2013a], [Kotzanikolaou et al. 2013b], to analyze maritime port network traffic flows. We currently apply the proposed methodology in a dataset with ship routes, journey time flows provided by a major company that records and analyzes million vessel positions and port related events on a monthly basis.

The dataset includes entry and exit calls for cargo ships in all ports that connect cargo ships, including journey times, anchor and port entry and exit calls along with traffic flows over a 3-year period. Our two major contributions are:

1. A methodology able to model maritime networks as dependency graphs and calculates the dependency risk between interconnected ports using assessment of traffic flow data. The methodology is able to assess the risk of congestion in ports and calculate risk dependency paths (i.e. how congestion in one port affects other connected ports through ship routes). Ports are represented as graph vertices, with ship routes linking one port to another as edges between the vertices. The methodology uses the min-max algorithm and statistical dynamic averages to calculate likelihood and impact of congestion.

2. An analysis of historical ship data for entry and exit calls in ports of the maritime network, detecting n-order port dependencies and automatically proposing ports for specific mitigation solutions that increase the overall resilience of the entire network. The overall risk of cascading congestions was computed, which indicates the probability of impact transmission in a path through the connected edges. Specific ports that initiate cascading congestions were detected and simulation results indicated that applying traffic control or redirecting ships in different routes may increase overall traffic flow resilience in wider areas while decrease risk of congestions. This is an ongoing research and, currently, we cross-reference results with reports to check their validity.

2. Dependency analysis methodology

Dependency analysis assesses the risk of nth-order dependencies by applying results of organization-level risk assessments performed by critical infrastructure owners and operators. A dependency can be defined as a "one-directional reliance of an asset, system, network or collection thereof (within or across sectors) on an input, interaction or other requirement from other sources in order to function properly" [Treasury 2011]. The dependencies are modeled using a directional graph G = (N; E) where N is a set of nodes and E is a set of edges. In this work, N is the set of the components of the modeled infrastructure (i.e., the ports of maritime network) and E is the set of the links among the components (i.e., the ship routes among the ports). The graph is directional to represent dependencies from one component to other components within the critical infrastructure. An edge from a node Ni to node N_j, i.e., $N_i \rightarrow N_j$, depicts the dependency relationship between them. The disruption transferred through this dependency can be described by the values impact $I_{i;j}$ and likelihood $L_{i;j}$. The combination of these two values indicates the dependency risk $R_{i;j}$ to component Ni due to its dependence on component N_j, which is denoted by the edge Ni $\rightarrow N_j$. The dependency risk is quantified as an integer scaled [0...5], with 0 representing no risk and 5 severe risk. This value as associated with each edge, refers to the level of cascade derived risk for the receiver due to the dependency. The results of congestion analysis are used as input to this method. If $CI_{Y0} \rightarrow CI_{Y1} \rightarrow \ldots \rightarrow CI_{Yn}$ is a chain of dependencies, $L_{Y0\ldots Yn}$ is the likelihood of the nth-order cascading effect and $I_{Yn1,\, Yn}$ is the impact of the $CI_{Yn1} \rightarrow CI_{Yn}$ dependency, then the cascading risk exhibited by CI_{Yn} due to the nthorder dependency is computed as:

$$R_{Y_0,\ldots\ldots,Y_n} = L_{Y_0,\ldots\ldots,Y_n} \cdot I_{Y_{n-1},Y_n} \equiv \prod_{i=0}^{n-1} L_{Y_i,Y_{i+1}} \cdot I_{Y_{n-1},Y_n} \quad (1)$$

The cumulative dependency risk considers the overall risk exhibited by all the critical infrastructures in the sub-chains of the *n* th-order dependency. Let $CI_{Y0} \rightarrow CI_{Y1} \rightarrow \ldots \rightarrow CI_{Yn}$ be a chain of dependencies of length *n* . The cumulative dependency risk, denoted as $DR_{Y0,Y1,\ldots,Yn}$, is defined as the overall risk produced by an *n*th-order dependency:

$$DR_{Y_0,\ldots,Y_n} = \sum_{i=1}^{n} R_{Y_0,\ldots,Y_i} \equiv \sum_{i=1}^{n} \left(\prod_{j=1}^{i} L_{Y_{j-1},Y_j} \right) \cdot I_{Y_{i-1},Y_i} \quad (2)$$

Eq. (2) computes the overall dependency risk as the sum of the dependency risks of the affected nodes in the chain due to a failure realized in the source node of the dependency chain. The risk computation employs a risk matrix that combines the likelihood and incoming impact values of each vertex in the chain. Interested readers are referred to [Stergiopoulos 2016, Stergiopoulos 2014, Kotzanikolaou 2013] for additional details about dependency risk estimation.

In many instances, the likelihood values are difficult to estimate or may not be available. This means that, while a dependency can be identified between two nodes, the probability of a failure to propagate between the two nodes is either unknown or certain (likelihood=1). In both cases, the following simplified version of Eq. (2), which follows the assumption that if a node fails, then the dependent nodes will also fail (likelihood=1), is used:

$$DR_{Y_0,\ldots,Y_n} = \sum_{i=1}^{n} R_{Y_0,\ldots,Y_i} \equiv \sum_{i=1}^{n} I_{Y_{i-1},Yi} \quad (3)$$

The *n*th-order dependency risk is then calculated as the cumulative impacts on the affected nodes in the dependency chain.

2.1 The "Likelihood of Congestion" formal metric for anticipating congestion

Each relationship is assigned with a likelihood value, which declares, how likely the port described by the current relationship is, to be congested. Intuitively, this value is a probability, based on which we can make predictions about each port's state, at different times. In order for this to be calculated, we firstly need to check whether each relationship is proportionally fair to the other relationships describing the same port. Generally, when talking about proportional fairness, we are referring to a system, in which two or more competitive entities are battling for resource control, and how we can maintain balance between them [Kelly et al. 1998]. For example, in a computer network, our goal is to maximize the total throughput while at the same time allowing all the users to experience at least a minimal level of service. The above is calculated according to [Kelly et al. 1998] as follows:

A vector or rates X_r is proportionally fair if it is feasible, that is $X_r \geq 0$, and if for any other feasible vector X^*_r, the aggregate of proportional changes is zero or negative:

$$\sum_{r \in R} \frac{x_r^* - x_r}{x_r} \leq 0 \qquad (3)$$

In our case, X_r is the flow of the currently examined relationship, and X^*_r is the vector containing all the flow values for all other relationships referring to the same port as X_r. We mark each of our relationships as "good" iff they satisfy (3), and "bad" otherwise. Note that he do not have to check for feasibility, since both vectors contain traffic flow values, which are always positive.

After marking all the relationships as either "good" or "bad", the likelihood value for a relationship R is calculated as follows:

$$L_R = \frac{\text{Number of times R appears marked as "bad"}}{\text{Total number of times R appears}} \qquad (4)$$

In order to calculate average wait time flows for ship routes in corresponding ports, we calculate each port flow from port A to port B using Little's Law [Little 2008]:

Under steady state conditions, the average number of ships in a queuing system equals the average rate at which ships arrive multiplied by the average time that a ship spends in port at a given time t. Letting:

L(t) = average number of items in the queuing system,
W(t) = average waiting time in the system for an item, and
λ(t) = average number of items arriving per unit time, the law is
L(t)= λ(t) * W(t)

L(t) is equal to the initial state of the port along with the number of Entry and Exit calls at time t. λ(t) on the other hand is the average number of ships arriving at the port at t, which equals to the average number of Entry Calls for a given time t. With these in mind, Little's law can be heuristically written as follows to calculate the average waiting time of a ship in a port, for a given time t:

$$\mathrm{W(t)} = \frac{L(t)}{\lambda(t)} = \frac{PortCapacity + PortCalls}{Entry\ Calls} = \frac{(PortSize - ShipsInPort) + (Entry\ Calls - Exit\ Calls)}{Entry\ Calls}$$

Considering the above average wait time as an indication of port status, we can now utilize min-max fairness on our network to calculate "good" and "bad" links per unit time.

New advancements in signal setting optimization are recently obtained by considering Network Fundamental Diagrams (NFD) for analyzing dependencies between link density and link flow in a defined time slice (Musolino, 2014).

Following (Musolino 2014), by moving from the link to the maritime network, the idea is to consider the Average Flow (AF) instead of link flow and the Average Density (AD) instead of the link density in a time slice of analysis T, defined as follows:

$$\mathrm{AF} = \frac{\sum_i f_i * l_i}{\sum_i l_i} = \frac{\sum_i f_i * l_i}{L} \qquad \text{(ships/time) (6)}$$

$$\mathrm{AD} = \frac{\sum_i k_i * l_i}{\sum_i l_i} = \frac{\sum_i k_i * l_i}{L} \qquad \text{(ships/length) (7)}$$

With: i link of the network, li, length of link i, fi, traffic flow on link i, ki, density on link i; L = 6i li, total length of the network.

AF is the product between flow and length ((vehicles/time) * length) with respect to the total length (1/ length) of the network. AD is the product between density and length ((vehicles/length) * length) respect to the total length (1/length) of the network.

$$\mathrm{w(p)} = \frac{\text{Num of Entry Calls/hour}}{\text{Num of Exit Calls/hour}}, \quad \text{weight}$$

2.2 The "Impact" metric for congested ship routes

Aside from the likelihood value, each relationship is assigned with an Impact value as well. As the name suggests, this metric declares how severe a possible congestion will be on that edge. Impact thresholds are calculated based on averages of best and worst case data entries. The metric is described in levels, ranging from 1 to 5, with 5 being the highest. The impact level for each relationship of a port is calculated as follows:

1. We create a [1; 5] scale from our domain of flows (flow values for a port).
2. For each relationship, we rescale its flow value into the correct impact level in the range [1; 5].

We used the well-known linear scaling algorithm to achieve the above. Its result depicts the number of units of the original interval which are equal to 1 unit of the new interval.

The approach described above is a dynamic one. There is no common scale for all the ports. This happens, because in order to calculate the impact level for each port, we rescale based on its own maximum and minimum flow, so each produced impact level describes how impactful a flow value is for the currently examined port only. Thus, for each port, the scale describing its impact levels adapts to its own characteristics (its min and max flow values).

3. Critical Infrastructure Dependency Analysis (CIDA) tool

CIDA [Stergiopoulos et al. 2014] is a Critical Infrastructure Dependency Analysis tool that uses the Neo4j graph database [neo]. According to recent empirical [Batra and Tyagi 2012][Jouili and Vansteenberghe 2013] studies, Neo4j outperforms other similar systems in load time. CIDA supports decision makers to analyze and assess dependency risk paths for complex and large-scale scenarios of interdependent CIs. CIDA takes as input the nodes and edges of a graph. This ongoing project utilizes a variation of the CIDA tool along with the Neo4J library, to model and analyze cascading congestion dependencies between ports and ship routes.

Empirical research [Van Eeten et al. 2011] has revealed that cascading effects beyond fifth-order dependencies rarely affect infrastructures. To this end, the fifth-order was the upper limit on the port dependencies that were evaluated. Also, no cyclical paths were allowed as our purpose was modeling and examination of discrete, driver-intended real-world routes.

3.1 Historical data and data validation

The dataset containing all historical data about ship routes and port entry and exit calls is provided by a major company that provides shipping data analytics using AIS data. Although the provided dataset can be considered partially biased, still a bias in the dataset is not as relevant in our case as e.g. in image classifiers. The dataset is comprised of real historical data spanning 2 full years for all cargo ship routes. Potential imbalance of classes is a real world representation and should not be tampered with. Also, the amount of data big enough to exclude unrealistic biases.

An issue we encountered was the need to extrapolate tuples, for all nodes to have measurements corresponding to the same ships and route time intervals.

4. Example Case-Study

To demonstrate the applicability of our framework in analyzing port and ship route congestions and trends, we provide an example scenario or port connections of cascading effects. Although our tests are based on a real model, the impact, likelihood and time-related input assigned to each dependency do not rely on actual metric results, since this is an ongoing research and the provided example is simply for exhibition purposes.

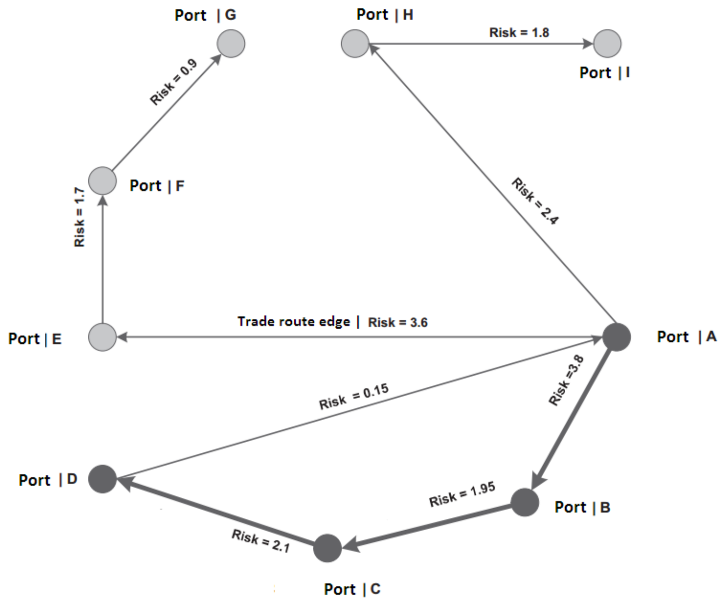

Figure 1. Example output model of CIDA for interconnected ports within ship routes.

The initiating event in this scenario is a congestion at Port A (see figure below). This event triggered the following 1st-order dependencies: Delay to ship routes leading to port B (node B), delay to other ship routes (node E) and problems in the delivery of cargo to nodes H and I. Also, delays to node B further impacted the delivery of cargo to D and back to node A (feedback loop), through ports C and D.

Table 1. Example dependency risk chains of interconnected ports.

NODE	ROUTE (EDGE RISK)	NODE	ROUTE (EDGE RISK)	NODE	ROUTE (EDGE RISK)	NODE	ROUTE (EDGE RISK)	NODE	ROUTE (EDGE RISK)	NODE	TOTAL RISK
PORT_B-B	[3.9004]	PORT_C-C	[2.729]	PORT_D-D	[0.20475]	PORT_A-A	[0.3276]	PORT_H-H	[0.24843]	PORT_I-I	**7.41**
PORT_B-B	[3.9004]	PORT_C-C	[2.729]	PORT_D-D	[0.20475]	PORT_A-A	[0.4914]	PORT_E-E	[0.215]	PORT_F-F	**7.54**
PORT_A-A	[4.8001]	PORT_H-H	[3.64]	PORT_I-I							**8.44**
PORT_A-A	[7.2]	PORT_E-E	[3.15]	PORT_F-F							**10.35**
PORT_A-A	[7.2]	PORT_B-B	[3.51]	PORT_C-C							**10.71**
PORT_A-A	[7.2]	PORT_E-E	[3.15]	PORT_F-F	[1.26]	PORT_G-G					**11.61**
PORT_A-A	[7.2]	PORT_B-B	[3.51]	PORT_C-C	[2.457]	PORT_D-D					**13.17**
PORT_A-A	[7.2]	PORT_B-B	[3.51]	PORT_C-C	[2.457]	PORT_D-D	[0.184275]	PORT_A-A	[0.29484]	PORT_H-H	**13.65**
PORT_A-A	[7.2]	PORT_B-B	[3.51]	PORT_C-C	[2.457]	PORT_D-D	[0.184275]	PORT_A-A	[0.44226]	PORT_E-E	**13.79**

A second result of the analysis is that, although path (A-B-C-D) exhibits the highest risk for almost all examined time frames, still we can see from the graph that path (A-E-F) is the most critical path concerning shorter ship destinations. This is due to the fact that although both dependencies A-B and A-E have a fast growth, the second dependency is expected to have the fastest convergence to its maximum impact (or is more likely prone to frequent delays in entry calls). Recall that our methodology can model different time points Tij and density Dij for each dependency.

Another result can be derived by comparing the evolution of sub-paths exhibiting high risk. For example, note that although the path (A-B-C-D) is the highest risk path, its sub-path (A-B-C) already may exhibit impact higher than the threshold within 1 hour of the port reaching 90% of its capacity. Thus it is necessary to implement mitigation controls at the first or second order dependency (port B).

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