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Vulnerability Assessment and Re-Routing of Freight Trains under Disruptions: A Coal Supply Chain Network Application

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Abstract

In this paper, we present a two-stage mixed integer programming (MIP) interdiction model in which an interdictor chooses a limited amount of elements to attack first on a given network, and then an operator dispatches trains through the residual network. Our MIP model explicitly incorporates discrete unit flows of trains on the rail network with time-variant capacities. A real coal rail transportation network is used in order to generate scenarios to provide tactical and operational level vulnerability assessment analysis including rerouting decisions, travel and delay costs analysis, and the frequency of interdictions of facilities for the dynamic rail system.

1. Introduction

Today, our society depends on its transportation systems more than ever. A large percentage of the products we consume are transported long distances by road, rail, air, or a combination of modes. In addition, many people travel on roads to go to work every day. One of the main risks embedded in transportation systems is the failure of infrastructure elements such as bridges, tunnels, and facilities (ports, rail yards, warehouses etc.). These elements can fail due to natural disasters, terrorist attacks, or just because they are in bad condition. The impact of these failures includes loss of life, economic loss, increased travel costs and congestion due to rerouting.

Rail transportation is an important and growing component of freight transportation in the United States. The benefits of rail transportation are that it is cheaper and produces less carbon

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emissions than road transportation. It is also easier to transport heavy loads on rail than on truck. Leaders in transportation are trying to increase the volume of goods transported by rail to alleviate loads on the road network and reduce carbon emissions. Large freight companies also are moving more of their transportation to a combination of rail and road.

There are several aspects of rail transportation that make it different than other transportation modes. First, the operations of a railroad are more centrally controlled than in the road network. That is, train operators have less autonomy to choose their own routes and schedules. Second, compared to road transportation, there is not as much excess capacity in rail transportation. Thus, it is important to consider capacity when routing and scheduling.

Disruptions have a large impact on rail transportation because there are less alternate routes available when a disruption occurs. There are several reason for the lack of alternate routes. First, rail is not as ubiquitous as roads. Second, much of the track in the United States is single line track. Thus, only one train can be on the track at a time in either direction. This makes it more difficult to reroute trains after a disruption. Third, the operation of a railyard can be complex and therefore it is difficult for a railyard to accommodate excess capacity. Again, this must be taken into consideration when rerouting.

In this paper, we present a mathematical model for estimating the consequence of a disruption to a rail transportation network in which an interdictor optimally chooses a set of infrastructure elements to attack in order to maximize the total disruption to the network. As a response, after the disruptions, an operator reschedules and re-optimizes trains in such a way that all demands and capacity restrictions are satisfied. In addition to modeling the threat of an interdictor, this model is also used to determine critical elements of the network by identifying the set of elements of the rail network whose unavailability causes the largest consequence. The consequence estimation of disruptions are also taken into account in a unit train transportation system by modeling trains as discrete demand units that stay intact from origin to destination. The model captures the movement of trains in time and space over a finite time horizon. Tracks and railyards in the network have strict capacity constraints for discrete time periods. Given these properties, the proposed mathematical model can be utilized to solve any problem that requires multi-period transportation scheduling under disruptions. Thus, the application is not limited to rail transportation.

Several events in the last 30 years illustrate that the freight rail transportation system in the United States is vulnerable to disruptions. In 1993, flooding of the Mississippi and Missouri rivers

caused several railroads to experience delays and cancellations. The estimated total cost of the disruption was \$ 182 million (Haefner et al., 1996). In 1996, a merger between Union Pacific and Southern Pacific railroads led to delays for many of Union Pacific's customers (Quillen, 1997). In 2005, a derailment on a main line in Wyoming near the Powder River Basin led to a shortage of coal in many parts of the United States as well as price increases (Bleizeffer, 2005). Finally, after the death of Osama Bin Laden, it was revealed that Al-Qaeda was planning an attack on the rail infrastructure in the United States (Boyd, 2011).

Jespersen-Groth et al. (2009) demonstrates that there are 22 disruptions related to railway infrastructure failure in the Dutch railway network in a day due to technical problems, weather, third parties and other causes, and on average, a single disruption lasts 1.7 hours. Preventive maintenance is the first stage of mitigating the risks associated with any type of railway infrastructure failure. It first assesses risks that might cause any damage to regular operations and then proposes maintenance activities to minimize the total destruction. In order to identify the risks embedded in railway infrastructure (usually tracks between two nodes), Åhrén and Parida (2009) develop maintenance performance indicators via benchmarking for railway infrastructures in Norway and Sweden. Different types of reliability functions are used in order to represent the reliability distribution of the railway infrastructure components (see Chen et al. (2013), Podofillini et al. (2006) for a case study in Norway) or to incorporate the potential delays/congestions due to infrastructure breakdown (see Higgins (1998) for a case study in Australia).

The remainder of the paper is organized as follows. Section 2 summarizes basic properties of coal transportation by rail. Then, Section 3 highlights the most relevant studies in the literature focusing on disruptions in rail transportation networks. A formal problem description, the proposed two-stage mathematical model formulation and our solution methodology are presented in Section 4. Section 5 demonstrates the analysis of the computational results obtained by using a real coal supply chain network. Finally, conclusions and future work are described in Section 6 .

2. Coal transportation by rail

In this study, we consider rail transportation of bulk commodities such as coal, grain, and scrap metal since they make up a large percentage of the volume transported on rail. In bulk transportation, demand is in terms of entire trains; therefore, there is no need to switch cars at intermediate classification yards. The demand for these commodities is also smoother than the

demand for lower volume items. For example, several power plants in the southern United States place a fixed-quantity order every month.

Coal combustion has been commonly used to generate electricity and provide power for many kinds of operations in the United States. In 2008, it was announced that 48.2% of the electricity consumed in the US was produced by the combustion of coal in coal power plants (U.S. Energy Information Administration, 2010). The electricity generated in these plants is being used in many areas such as: hospital operations, vaccine storage, security and surveillance systems, as well as water treatment. Hence, in order to keep this source of electricity safe for such important services in case of a disruption or disaster, operations in the coal supply chain must be secured. Moreover, coal transportation is a good representative of bulk transportation by rail, and therefore a good source of data to test the proposed model, since 70% of coal was transported by rail throughout the U.S. in 2010 (U.S. Energy Information Administration, 2012).

After the coal is mined, it is sent to a processing facility where the coal pieces are crushed into more manageable chunks. The trains typically consist of 125 to 150 cars loaded with between 110-120 tons of coal in each rail car. These trains are dispatched on their routes towards specific power plants. Even though the primary objective in the coal supply chain is to meet electricity demand, reducing the transportation and storage costs of coal as much as possible is also a major consideration. Moreover, optimizing coal inventory control policies in plants might help reduce the risk of electricity shortages, but that is not in the scope of this paper. We only aim to meet the dynamic discrete demands of coal plants under disruptions. In this sense, the current approach can be seen as a just-in-time approach.

Most power plants are designed in such a way that they can only use a single type of coal in order to generate electricity. Hence, there could be serious results of a disruption or a disaster that occurs in the coal supply chain, especially for the areas of the country that rely heavily on electricity generated from the coal mined in Wyoming's Powder River Basin (PRB). In this case study, the sub-bituminous coal transportation network is used. Sub-bituminous is the most common type of coal mined in PRB. The PRB accounts for about 40 % of all consumption within the US (U.S. Energy Information Administration, 2012). This particular coal type has significantly lower SO_2 emissions and cannot produce high energy output. However, many energy companies are automatically attracted by the low emissions level and the abundance of supply of this type of coal.

While transporting coal from mines to power plants, many important constraints are observed

in the coal supply chain. The amount of coal that can be carried by a train is restricted by the size of the trains used in the system. Also, depending on the sizes of these trains, some trains can only travel on special tracks. The availability of coal in different time periods for loading/unloading operations requires extra planning. Hence, there could be serious results of a disruption or a disaster that occurs in the coal supply chain, especially for the areas of the country that rely heavily on electricity generated from the coal mined in the PRB.

3. Modelling disruptions in rail transportation systems

Assad (1980); Ahuja et al. (2005); Nemani and Ahuja (2011) demonstrate variety of modeling techniques that have been developed for the rail transportation systems. Crainic (2000) surveys the research on freight transportation. He discusses three planning levels: strategic, tactical, and operational. In the strategic level, long-term decisions are made such as where to locate yards and where to build rail lines. At the tactical level, medium-term decisions are made such as the routing of trains and aggregate scheduling. The operational level includes shorter-term decisions such as crew scheduling and locomotive scheduling.

There are two types of rail transportation: merchandise trains and unit trains. Merchandise trains are composed of cars with different destinations. Therefore, consolidation, or blocking, is a crucial part of merchandise train operations. Partly due to the challenging problems associated with the blocking process, most of the research on rail transportation from an operations research perspective has considered merchandise trains (see Nemani and Ahuja (2011)). Unit trains are composed of cars with the same destination; thus, blocking is no longer needed. There is not as much research on unit train transportation. Lawley et al. (2008) present a time-space routing and scheduling model for unit trains. Their model accounts for both loaded and empty trains. The second stage of our formulation is similar to this model except that we do not account for empty trains.

In this study, we provide decision makers with the tool they need to prepare a course of action after disruptions occur. It determines the most vulnerable elements of the network and re-optimizes the train movements on the network with available nodes and arcs. This is different from the problem of optimizing the response to a particular disruption. Because of the prevalence of disruptions in transportation networks, there has been a significant amount of work on managing the recovery from a disruption. Applications include machine scheduling (Qi et al., 2006), production-inventory

systems (Xia et al., 2004), supply chains (Qi et al., 2004), passenger air transportation (Kohl et al., 2007), passenger rail transportation (Jespersen-Groth et al., 2009), and project scheduling (Zhu et al., 2005).

One way to study the vulnerability of a network is to identify the critical nodes and edges of the network. Interdiction models identify critical nodes and edges by modeling a game between an adversary and the operator of the network, who routes flow through the network after the adversary makes his attack. Fulkerson and Harding (1977) are among the first to study how to interdict arcs in a network to maximally increase the length of the shortest path; they are followed by others (Israeli and Wood, 2002). Wollmer (1964) is among the first to provide a model for interdicting a maximum-flow network. Others have extended this problem to consider probabilistically successful attacks (Cormican et al., 1998; Janjarassuk and Linderoth, 2008) and multiple objectives (Royset and Wood, 2007; Rocco et al., 2009, 2010). Researchers have also considered other objectives such as minimizing the maximum reliability path (Pan and Morton, 2008) and minimizing the maximum profit (Lim and Smith, 2007). Further, Church et al. (2004) present models for interdicting a set of facilities.

Researchers have also begun to study the vulnerability of freight rail networks. Burdett and Kozan (2014) propose an approach to prepare a robust train timetable that is capable of detecting the critical operations and their impacts on others in case of any delay. In another study (Burdett and Kozan, 2009), they propose techniques that can be used to schedule extra train services given the existing schedule is left unchanged or re-scheduled. Peterson and Church (2008) describe models for the impact of a disruption to the United States freight transportation network. They present an uncapacitated model that is a modification of the shortest path problem. They also present a continuous multicommodity network flow model that has line capacities. Babick (2009) models the allocation of security resources to the rail network in the state of California as a defender-attacker-operator problem, represented by a bi-level mixed-integer programming formulation. Both studies treat the rail transportation as a continuous network flow problem with time invariant capacities. In our work, we model the rail transportation system as a *discrete dynamic network flow problem*.

As mentioned above, there have been many studies on how to reduce network risks that can be applied to transportation networks. However, the mathematical models employed in these studies do not have enough detail to be applied directly to rail networks where disruptions are allowed. For instance, existing models mostly model goods as continuous (divisible quantities). However, in

most settings trains can only be realistically modelled using discrete units of flow. Moreover, the flow of entities in current models is usually assumed to be static or time invariant, meaning that the flow from origin to destination takes place iinstantaneously. Although real flows are almost never static, modeling flows as static is appropriate for uncapacitated networks or networks in which there are capacity constraints over long time periods (e.g., a month) but there are not strict capacity constraints for shorter time intervals (e.g., day or hour). Even though static flow models are also appropriate for strategic level decisions, they do not provide enough resolution to identify the impacts of disruptions on rail networks with short term capacities on railyards and tracks.

Thus, this paper differs from previous studies in that it explicitly incorporates disruptions and discrete unit flows of trains on rail networks with discrete time varying capacities. The factors considered in our model result in realistic scenarios that lead to tactical and operational level vulnerability assessment analyses including rerouting decisions, travel and delay costs analysis, and the frequency of interdictions of facilities for a rail transportation system. Furthermore, decision makers can utilize the proposed web-based decision support tool to monitor the changes in the rail network.

4. Mathematical model development

In this section, we model the problem of identifying critical elements as a two-stage mathematical programming model. An *interdictor* acts first and incapacitates a set of nodes and arcs. Once an infrastructure is incapacitated, we assume that it will remain incapacitated in the entire planning horizon. An operator follows the interdictor and chooses routes and schedules for trains given network elements that have not failed. Routing and scheduling of trains is done given a network with available nodes and arcs after disruption. Therefore, our second stage integer programming (IP) model aims to satisfy the demands of plants with minimum cost and without eliminating the capacity restrictions of network elements while dispatching trains from mines to plants through predetermined routes. A time-indexed formulation captures the true capacity limitations of nodes and arcs in any given period. The flexibility of being able to arrange the length of the planning period provides great control on the scale of the problem as well. For the sake of simplicity, we only consider the flow of identical unit trains that carry the same amount of coal regardless of the origin destination pair they are assigned to. The model selects the cheapest route first and then schedules trains according to capacity and demand requirements.

Table 1 introduces the sets, parameters and decision variables that are used in the two-stage integer-programming model.

Let y be a vector of interdiction variables in which y_i is 1 if node i is destroyed and 0 otherwise. Let f_i be the cost of interdicting node i. The interdictor has a budget of b to spend on interdicting nodes. Let Y be the feasible region of y defined by constraints (1b) and(1c). We propose the following bi-level capacity-interdiction and routing model:

$$\max \ell(y) \tag{1a}$$

$$\text{s.t.} \quad y_i \in \{0,1\} \quad \forall i \in \mathcal{N} \tag{1b}$$

$$\sum_{i \in \mathcal{N}} f_i y_i \leq b \tag{1c}$$

$$\text{where } \ell(y) = \quad \min_{y \in Y} \quad \sum_{r \in R} \sum_{t \in T} g_r X_{rt} + \sum_{r \in R} \sum_{t \in T} q l_t O_{rt} \tag{2a}$$

$$\text{s.t.} \quad O_{rt} + X_{rt} \geq O_{r,t-\triangle} \qquad \forall r \in \mathcal{R}, t = \triangle, \triangle+1, \ldots, T \tag{2b}$$

$$\sum_{t \in T(d)} \sum_{r | i \in RN(r)} X_{r,t-\tau_{ri}} \leq TC_{id}(1 - y_i) \qquad \forall d \in \mathcal{D}, i \in \mathcal{N} \tag{2c}$$

$$\sum_{t \in T(d)} \sum_{r | a \in RT(r)} X_{r,t-\tau_{ra}} \leq TC_{ad} \qquad \forall d \in \mathcal{D}, a \in \mathcal{A} \tag{2d}$$

$$\sum_{t \in T} \sum_{r | i = h(r)} X_{rt} \geq h_i \qquad \forall i \in \mathcal{P} \tag{2e}$$

$$\sum_{r \in \mathcal{R}} (X_{rt} + O_{rt}) \leq n \quad \forall t \in \mathcal{T} \tag{2f}$$

$$X_{rt}, O_{rt} \in \mathbb{Z}^+ \qquad \forall r \in \mathcal{R}, t \in \mathcal{T}. \tag{2g}$$

The objective function (2a) seeks to minimize the total cost incurred by 1) the total distance traveled and 2) the total delay incurred when trains have to wait at their origin stations. Note that the maximization problem $\ell(y)$ is a function of the interdiction variables. The interdictor's objective function (1a) is to maximize the same total cost that is attempted to be minimized by the operator. Constraints (2b) balance flow at the origin station of route r. For each planning period ($\triangle$) and route (r), the number of trains waiting at the origin node and departing the origin node to travel on route r at time period t must be greater than number of trains available at the origin node Δ time units before, at time period ($t - \triangle$). Constraints (2c) and (2d) guarantee that the flow

Table 1: Notation

Sets	
N	set of all loading/unloading stations (nodes)
$M \subseteq N$	set of mines
$P \subseteq N$	set of plants
A	set of all track segments
R	set of feasible routes between all O–D pairs for all trains
$RT(r) \subseteq A$	set of track segments included in the route of O–D pair $r \in R$
$RN(r) \subseteq N$	set of nodes included in the route of O–D pair $r \in R$
T	set of all time periods $\{\triangle, 2\triangle, \ldots, \lvert T\rvert\}$
D	set of days making up the planning horizon
$T(d)$	set of time periods in day $d \in D$
Parameters	
$\triangle \in Z^+$	duration of time period
K	number of planning periods in planning horizon
$o(r) \subseteq M$	origin station of route $r \in R$
$h(r) \subseteq P$	destination station of route $r \in R$ (Plants)
TC_{at}	track capacity of segment $a \in A$ at time $t \in T$
TC_{it}	track capacity of node $i \in N$ at time $t \in T$
τ_r	total travel time of route $r \in R$ in multiples of $\triangle$
τ_{ra}	travel time on route $r \in R$ to reach track segment $a \in RT(r)$ in multiples of $\triangle$
τ_{ri}	travel time on route $r \in R$ to reach node $i \in RN(r)$ in multiples of $\triangle$
d_r	distance of route $r \in R$
c	cost per unit distance, which includes fixed costs (labor, equipment cost, etc.) and variable costs (fuel, maintenance cost, etc.)
g_r	cost of moving one unit train on route $r \in R$
h_i	demand of station i over the planning horizon
l_t	length of the time period of $t \in T$
q	cost incurred when 1 train is delayed one time unit
CR	q/c
Decision variables	
X_{rt}	number of trains departing from $o(r)$ on route $r \in R$ in time period $t \in T$
O_{rt}	number of trains waiting (or being loaded/unloaded) at $o(r)$ of route $r \in R$ in time period $t \in T$

of trains moving each day does not exceed the daily track segment and node capacity, respectively. Moreover, the right hand side of constraints (2c) forces an interdicted node to have zero capacity. Constraints (2e) state that the demand of each plant should be satisfied. Finally, constraints (2f) ensure that the number of trains waiting at the origin node and departing that node must be less than or equal to n, the number of trains, for each route and time period. The next section discusses the solution methodology developed to solve this version of the bi-level interdiction model.

Our second stage routing problem is inspired by the train scheduling model in Lawley et al. (2008). In their formulation (and ours), train movements (i.e. journey at intermediate locations) are captured in similar manners. Decision variables (X_{rt} and O_{rt}) keep track of the train movements at intermediate locations with the help of parameters τ_{ri} (travel time on route r to reach node i) and τ_{ra} (travel time on route r to reach track segment a). Thus, the model has the power to estimate the congestion levels on any given nodes and arcs. Accordingly, constraints (2c) and (2d) limit the daily train movements for each node and arc, respectively. Even though we consider broad time periods in our experiments, the model has the capability of representing operational and tactical level plans for train movements with the help of time related sets (T and D) and parameter $\triangle$.

4.1. Reformulation

The bi-level problem (2) is a max-min problem and therefore cannot be solved by standard commercial solvers. In our approach, we take the dual of the inner minimization problem in order to reformulate the model as a single level maximization problem. This conversion trick is a standard approach in bi-level optimization. However, if we leave the second stage to be a pure integer problem, the dual of the pure integer inner problem is not guaranteed to have a duality gap of zero. In other words, Slater's condition (sufficient condition for strong duality) does not hold. Furthermore, Caprara et al. (2002) proves that the Train Timetabling Problem (TTP) that "considers a single, one-way track linking two major stations, with a number of intermediate stations in between" is NP-hard. Lawley et al. (2008) also shows that the complexity (the number of decision variables and constraints) of the time-space train scheduling model such as (2) depends on the number of tracks, routes between O-D pairs, plants, mines, intermediate railyards and user defined parameters such as T, D and $\triangle$. We note that the number of decision variables and constraints in (2) increases exponentially as these input parameters increase. As a consequence, in order to be able to satisfy the sufficient condition for strong duality (which also makes transition from max-min to single level max possible) and reduce the impact of the complexity by obtaining bounds via linear relaxation,

we solve the problem using the following approach. We first fix the y variables and relax the integrality restriction on the X and O variables. Then, the dual of the inner minimization is taken. Since both levels are then maximization after taking the inner dual, the bi-level problem reduces to a single level mixed-integer program (MIP).

Step 1: We relax the inner minimization problem:

$$\max_{y\in Y} \tilde{\ell}(y) = \quad \min \quad \sum_{r\in R}\sum_{t\in T} g_r X_{rt} + \sum_{r\in R}\sum_{t\in T} ql_t O_{rt} \qquad \text{[duals]} \tag{3a}$$

$$\text{s.t.} \quad O_{rt} + X_{rt} \geq O_{r,t-\triangle} \qquad \forall r \in \mathcal{R}, t = \triangle, \ldots, |T| \qquad [\alpha_{rt}] \tag{3b}$$

$$\sum_{r|i\in\mathcal{N}(r)} \sum_{\substack{t \in \mathcal{T}(d) \\ t \geq \tau_{ri}}} X_{r,t-\tau_{ri}} \leq TC_{id}(1-y_i) \qquad \forall i \in \mathcal{N}, d \in \mathcal{D} \qquad [\beta_{id}] \tag{3c}$$

$$\sum_{r|a\in\mathcal{A}(r)} \sum_{\substack{t \in \mathcal{T}(d) \\ t \geq \tau_{ra}}} X_{r,t-\tau_{ra}} \leq TC_{ad} \qquad \forall a \in \mathcal{A}, d \in \mathcal{D} \qquad [\gamma_{ad}] \tag{3d}$$

$$\sum_{t\in T}\sum_{r|i=h(r)} X_{rt} \geq h_i \qquad \forall i \in \mathcal{P} \qquad [\zeta_i] \tag{3e}$$

$$\sum_{r\in\mathcal{R}} (X_{rt} + O_{rt}) \leq n \quad \forall t \in \mathcal{T} \qquad [\phi_t] \tag{3f}$$

$$X_{rt}, O_{rt} \geq 0 \qquad \forall r \in \mathcal{R}, t \in \mathcal{T} \quad [\delta_{rt}, \eta_{rt}] \tag{3g}$$

Step 2: We now take the dual of the inner minimization. The resulting model is then:

$$\begin{aligned}
\max_{y\in Y} \quad & \sum_{i\in\mathcal{N}}\sum_{d\in\mathcal{D}} TC_{id}(1-y_i)\beta_{id} + \sum_{a\in\mathcal{A}}\sum_{d\in\mathcal{D}} TC_{ad}\gamma_{ad} \\
& + \sum_{i\in\mathcal{P}} h_i\zeta_i + \sum_{t\in\mathcal{T}} n\phi_t && \text{(4a)} \\
\text{s.t.} \quad & \sum_{i\in\mathcal{N}(r)} \mathbb{I}\left\{\beta_{i,d(0+\tau_{ri})}\right\} + \sum_{a\in\mathcal{A}(r)} \mathbb{I}\left\{\gamma_{a,d(0+\tau_{ra})}\right\} \\
& + \zeta_{h(r)} + \phi_0 + \delta_{r0} \le g_r \quad \forall r\in\mathcal{R} && \text{(4b)} \\
& \alpha_{rt} + \sum_{i\in\mathcal{N}(r)} \mathbb{I}\left\{\beta_{i,d(t+\tau_{ri})}\right\} + \sum_{a\in\mathcal{A}(r)} \mathbb{I}\left\{\gamma_{a,d(t+\tau_{ra})}\right\} \\
& + \zeta_{h(r)} + \phi_t + \delta_{rt} \le g_r \quad \forall r\in\mathcal{R}, t=\triangle,\ldots,|T| && \text{(4c)} \\
& -\alpha_{r,1} + \phi_0 + \eta_{r0} \le ql_0 \quad \forall r\in\mathcal{R} && \text{(4d)} \\
& \alpha_{rt} - \alpha_{r,t+\Delta} + \phi_t + \eta_{rt} \le ql_t \quad \forall r\in\mathcal{R}, t=\triangle,\ldots,|T|-1 && \text{(4e)} \\
& \alpha_{r|T|} + \phi_{|T|} + \eta_{r|T|} \le ql_{|T|} \quad \forall r\in\mathcal{R} && \text{(4f)} \\
& \alpha_{rt} \le 0 \quad \forall r\in\mathcal{R}, t=\triangle,\ldots,|T| && \text{(4g)} \\
& \beta_{id} \le 0 \quad \forall i\in\mathcal{N}, d\in\mathcal{D} && \text{(4h)} \\
& \gamma_{ad} \le 0 \quad \forall d\in\mathcal{D}, a\in\mathcal{A} && \text{(4i)} \\
& \zeta_i \ge 0 \quad \forall i\in\mathcal{P} && \text{(4j)} \\
& \phi_t \le 0 \quad \forall t\in\mathcal{T} && \text{(4k)} \\
& \delta_{rt}, \eta_{rt} \ge 0 \quad \forall r\in\mathcal{R}, t\in\mathcal{T} && \text{(4l)}
\end{aligned}$$

where $d(t)$ is the day of time period t, $|T|$ is the last time period, $\mathbb{I}\left\{\beta_{i,d(t+\tau_{ri})}\right\} = \beta_{i,d(t+\tau_{ri})}$ if $t+\tau_{ri} \le T$ and 0 otherwise, and $\mathbb{I}\left\{\gamma_{a,d(t+\tau_{ra})}\right\} = \gamma_{a,d(t+\tau_{ra})}$ if $t+\tau_{ra} \le T$ and 0 otherwise.

Notice that when we take the dual of the inner minimization problem, it changes the inner minimization problem to a maximization problem. Eliminating the maximization sign for the inner problem yields a single-level maximization model.

Also notice that our single-level model has now nonlinear terms $y_i\beta_{id}$. Since these nonlinear terms are a product of a binary variable and a continuous variable, we can linearize them by applying a technique described by Sherali and Alameddine (1992). First, substitute the non-negative variable

$\kappa_{id} = y_i \beta_{id}$. Then, add the constraints:

$$\kappa_{id} - \underline{\beta}_{id} y_i \geq 0 \quad \forall i \in \mathcal{N}, d \in \mathcal{D} \tag{5a}$$

$$\kappa_{id} - \beta_{id} \geq 0 \quad \forall i \in \mathcal{N}, d \in \mathcal{D} \tag{5b}$$

with $\underline{\beta}_{id}$ denoting a lower bound of β_{id}.

This results in the following single-level MIP:

$$\begin{aligned} \max\nolimits_{y \in Y} \quad & \sum_{i \in \mathcal{N}} \sum_{d \in \mathcal{D}} (TC_{id}\beta_{id} - TC_{id}\kappa_{id}) + \sum_{a \in \mathcal{A}} \sum_{d \in \mathcal{D}} TC_{ad}\gamma_{ad} \\ & + \sum_{i \in \mathcal{P}} h_i \zeta_i + \sum_{t \in \mathcal{T}} n\phi_t \qquad (6a) \\ \text{s.t.} \quad & \text{(4b)–(4l)} \\ & \text{(5a)–(5b).} \end{aligned}$$

5. Computational results

Note that we first relaxed the X and O decision variables of the second stage problem and then took the dual of it to obtain a MIP formulation. In practice, it is possible that the solution of the MIP can have fractional decision variables. However, our analysis shows that for our problems the proportion of fractional X and O variables is observed to be no greater than 0.2% and 1%, respectively.

In the following subsections, we first illustrate the basic properties of the networks used in model (6). Then, we demonstrate how these different networks impact the interdictor's and operator's decisions. Our two-stage interdiction program is solved by using IBM ILOG CPLEX 12.1 on a single node (with two Intel six-core Xeon X5670 2.93 GHz processors and 24GB of memory) of a high performance supercomputer (HPC). Alternatively, a standard desktop computer with 16GB of memory can solve the model without any memory problems.

5.1. Network and data construction process

The North American railroad system provided by The Center for Transportation Analysis (CTA) in the Oak Ridge National Laboratory (The Center for Transportation Analysis) is used to represent

the U.S. rail network. In addition, the coal plants and coal mines are retrieved from the United States Coal Activity (USCA) Map project (U.S. Coal Activity Map). Through focusing on large suppliers and consumers of coal, the refined network provides an initial representative model of the entire coal supply chain. There are 792 mines and 526 plants in the original USCA Map. The average consumption rate for each mine is approximately 2,000K tons/year, while the average production rate over all of the plants is 1,400K tons/year. There were a great number of mines and plants to consider based upon these averages. Therefore, the number of mines and plants is reduced by using the constraint that the average production and consumption rate at each mine or plant has to be greater than 5,000K tons/year. This value is chosen as a threshold for network reduction. There were 39 mines and 49 plants that fit the constraint. Then the mines and plants are found in which sub-bituminous coal is being mined and burned, respectively.

Based on the rail network data obtained through the steps described above, we label 8 sub-bituminous coal mines, 23 sub-bituminous coal plants and 37 rail yards as primary nodes. While generating routes between each mine-plant pair, we observe that there are 135,655 nodes (mines, plants, rail yards, tunnels, bridges and other connection points) and 172,888 arcs in the original network. Thus, it is too difficult to enumerate all possible routes between every O-D pairs. Even if all routes between all O-D pairs are known, the problem would be intractable due to the extensive number of decision variables and constraints. Hence, in order to generate a manageable rail network based on this dataset, we developed a trimming algorithm (see Algorithm Appendix A.1) which explores K-shortest paths (Yen, 1971) between any combinations of mines and plants with $K = 3$ and $K = 10$ to obtain different sets of routes with sizes $|R| = 552$ and $|R| = 1840$, respectively. By using this procedure, we produced a connected graph (every destination is reachable from every origin) with 456 nodes which includes 8 mines, 23 plants, 37 yards, 388 critical elements (tunnels, bridges, etc.) and 36,935 arcs. Using this route selection strategy, multiple routes (shortest paths) between coal plants and mines are generated to be used as input routes for the model (6).

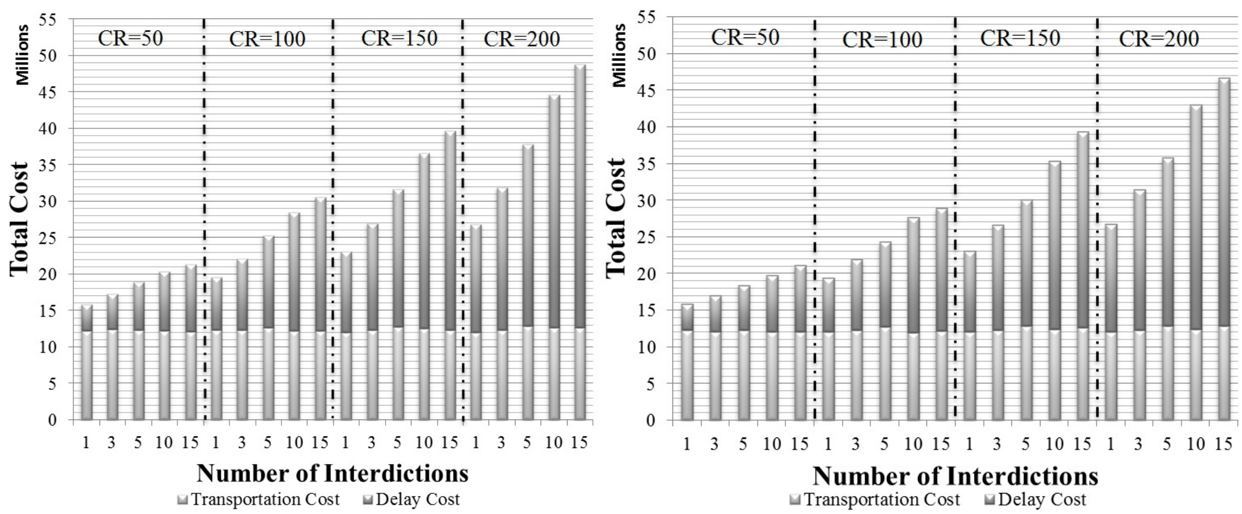
There are several studies that have developed approaches to assess railway capacity (see Kozan and Burdett (2005); Burdett and Kozan (2006); Mattsson (2007); Abril et al. (2008)). Gorman (1998) defines the link (track) capacity to be less than a fixed number of trains over some time period without slowing the traffic due to excessive train movements on a track. Thus, we assign a numerical value to represent the capacity of a track segment. Using smaller capacities might increase the congestion whereas larger capacities might have no impact on train scheduling. In our

experiments, we assume that railyards and tracks have the same discrete unit train capacity for each time period in the planning horizon.

5.2. Impacts of network size and budget level

In this section, we assess the impacts of an interdiction budget (b), network size ($|R|$) and the ratio of the cost of delaying a train for a single time period to the cost of operating a train per unit distance (CR).

Note that there are three main costs included in the objective function of model 6. These cost items are total transportation (operation), total delay, and total interdiction costs. f_i gives us the flexibility to model the cost of interdicting infrastructure i. However, regardless of which node is interdicted, it is counted as one interdiction ($f_i = 1$) in this current setting. Hence, the total cost incurred by transporting coal from mines to plants and the total cost due to delays are the two main costs that the defender wants to minimize, while the interdictor wants to maximize them.



(a) $|R|$=552 (b) $|R|$=1840

Figure 1: Cost components v.s. number of interdictions

Figures 1a and 1b demonstrate total transportation and delay costs on four different networks where the total number of routes in the network ($|R|$) is 552 and 1840, respectively. Changes in these cost terms are also observed by running model (6) for different cost ratios (CR) and interdictor's budget levels (b). It is commonly seen in Figure 1 that for each CR level, total transportation

costs do not change significantly as the number of interdicted nodes in the network is increased. *However, delay costs increase dramatically compared to the total transportation cost as more nodes are interdicted.* This implies that as the interdictor manages to disable more routes and nodes in the network, it yields extra delays but train transportation can be handled at similar cost levels in each scenario. Similarly, total transportation cost remains almost at the same level despite varying CR and b parameters. One expects to see similar transportation costs with different CR values since CR is changed only by varying the cost of delaying a train for an hour not the cost of operating a route. However, based on the cost terms in Figure 1, we can see that neither higher budget levels nor larger CR values resulted in a significant increase of total transportation costs in different networks. Model (6) finds similar minimum transportation costs regardless of which/how many nodes are interdicted for different CR values. The main reason behind this phenomenon is that if an element on a route is interdicted, other alternative routes are made available with similar costs by the K-shortest path algorithm. Even though the cost of operating trains on several routes remains nearly the same, disruptions cause significant increases in delay costs as b and CR increase.

Table 2: Interdicted nodes with varying CR when $|R|$=552

b	CR=50	CR=100
1	74	74
3	72-74-80	73-81-187
5	70-72-74-79-81	70-72-74-80-187
10	69-70-72-74-78-80-86-88-91-187	68-70-72-74-78-80-86-88-103-187
15	51-69-70-72-74-78-80-82-84-86-88-91-93-103-187	51-68-70-72-74-78-80-83-84-86-88-91-93-102-187
b	**CR=150**	**CR=200**
1	80	80
3	72-80-187	72-81-187
5	70-72-74-80-187	70-72-74-81-187
10	68-70-72-74-78-80-86-88-103-187	68-70-72-74-78-80-86-88-103-187
15	51-68-70-72-74-78-80-83-84-86-88-91-92-103-187	51-68-70-72-74-78-80-83-84-86-89-91-92-103-187

Tables 2 and 3 list the nodes that are interdicted in the scenarios provided in Figure 1. Most of the nodes interdicted with smaller budget levels are also attacked when the budget levels are increased. For instance, in Table 2, nodes 72, 74, and 80 are attacked when $CR = 50$ and $b = 3$. These three nodes are also taken out from the network when $CR = 50$ and $b = 10$, or 15. For the scenario with $b = 5$, two of these nodes (72, 74) are disabled by the interdictor. Similarly, the frequency of interdicting a single or combinations of network elements in different networks with different values of b and CR is reported. Based on the interdiction frequency levels in Tables 2 and 3, the decision makers can assess how vulnerable the network elements are under several input

parameters.

Table 3: Interdicted nodes with varying CR when R=1840

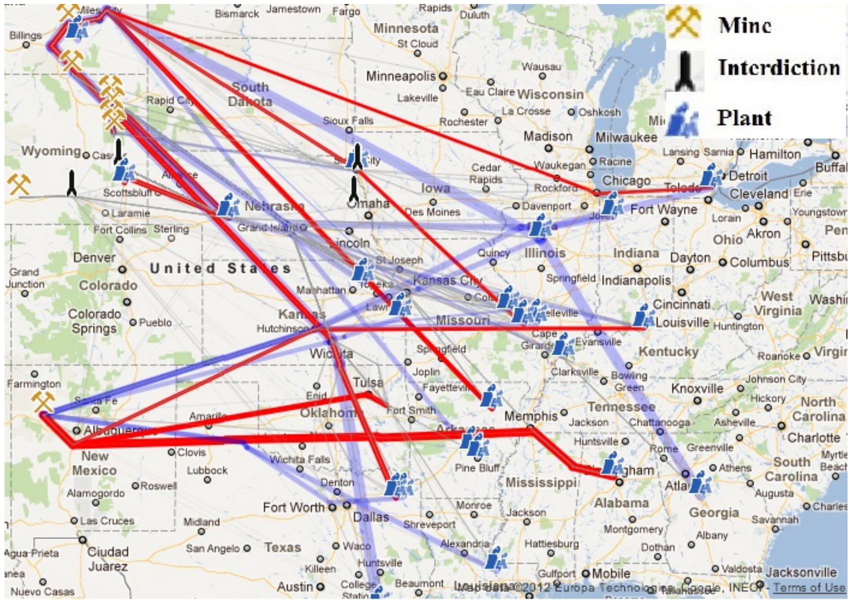
b	CR=50	CR=100
1	74	80
3	72-80-187	72-81-187
5	70-72-74-81-187	70-72-74-81-187
10	47-69-70-72-74-79-80-187-311-312	47-69-70-72-74-78-80-103-187-312
15	47-51-69-70-72-74-78-80-86-88-91-92-96-187-312	47-51-69-70-72-74-78-80-86-88-91-93-96-187-312

b	CR=150	CR=200
1	81	80
3	72-80-187	72-80-187
5	70-72-74-80-187	70-72-74-81-187
10	47-68-70-72-74-78-80-103-187-312	47-68-70-72-74-78-80-103-187-312
15	47-51-68-70-72-74-78-80-86-88-91-93-187-311-312	47-51-68-70-72-74-78-80-86-88-91-92-187-311-313

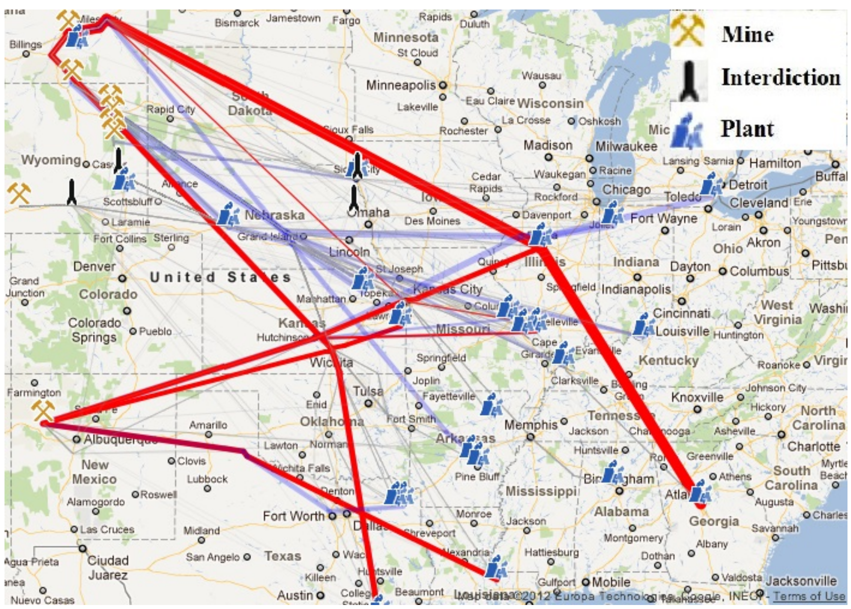
Model (6) shows that similar network elements are interdicted under comparable b levels even though the number of routes in the network ($|R|$) or cost ratios (CR) are different (i.e. see Tables 2 and 3). Even though solution times increase gradually as the interdictor's budget (b) and the number of routes ($|R|$) increase, our two stage model is solved to optimality within less than 6.3 seconds for the instance with $|R| = 1840$ and $b = 15$.

5.3. Rerouting decisions after disruption(s)

In the previous section, we demonstrated how total transportation and delay costs respond to varying b, CR, and $|R|$. In this section, we introduce a Google Maps-based tool that displays the routes along which the unit trains are moving (X_{rt}) and waiting (O_{rt}) at different time periods $\triangle$. Figure 2 shows mines, plants, and interdicted nodes, as well as the routes along which the trains are dispatched and delays occurred due to interdictions at a specific time period ($\triangle$). In order to display the delays and movements of trains clearly, straight lines represent the routes between mines and plants. However, in reality, those straight lines stand for shortest paths between selected origin and destination nodes. Moreover, the more frequently a route is being used, the thicker the"red" straight line becomes to represent the intensity of the route. Similarly, the more frequently delays occur on a route, the thicker the "blue" straight line is drawn to highlight the intensity of the delays on that route. It can be seen that some of the delayed trains represented by blue lines in Figure 2a at $\triangle = 5$ are dispatched along the routes they have been waiting on at $\triangle = 10$ in Figure 2b and therefore the color for those routes is changed to red. Finally, grey routes represent the routes that are not being used or there is no delay being incurred on at that time period.



(a) Monitoring delayed and moving trains on routes at $\triangle = 5$



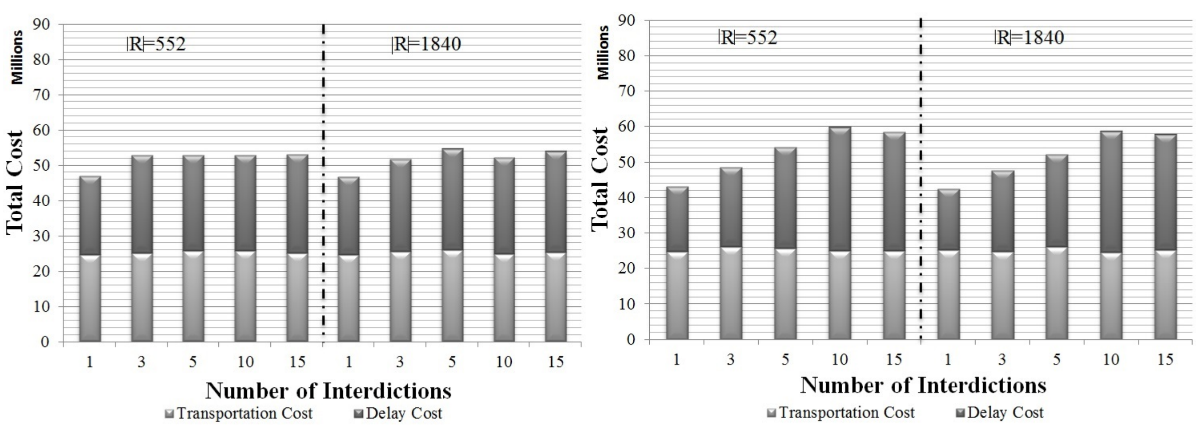
(b) Monitoring delayed and moving trains on routes at $\triangle = 10$

Figure 2: $|R| = 552$, $b = 5$ and CR=100

5.4. Impacts of capacity and demand levels

In Section 5.2, it was observed that the impact of an interdictor's budget (b) has a negligible impact on the total transportation cost. On the other hand, significant increases are observed in total delay cost as the budget increases in all scenarios even within the same CR zones (see Figures 1a and 1b). Being able to measure the capacity of each arc and node enables us to assess the impacts of interdictions more precisely. Note that arc and node capacity constraints (3c) and (3d) are already able to assess the capacity of nodes and arcs in terms of unit trains for a given specific amount of time. For this case study, it is assumed that once a node is interdicted, then the capacity of incoming and outgoing arcs is also set to zero as well as the capacity of the node itself. On the other hand, in some situations, it is possible that the same interdiction might affect the capacity of other non-interdicted nodes and arcs as well (huge explosion, flood etc.). Such capacity adjustments can be made easily with the help of constraints (3c) and (3d). Moreover, the same capacity reduction technique can be employed when other trains use the same tracks and rail yards. In such circumstances, the capacity constraints should be adjusted so that the impacts of congestion can be reflected in the model.

In order to account for the scenarios mentioned above, Figure 3 illustrates the impacts of interdictions under different demand and node capacity levels for different network sizes when $CR = 100$.



(a) Increasing the demands of all plants by 100 %

(b) Increasing both the demands of all plants and node capacities by 100 % and 50%, respectively

Figure 3: Transportation and delay cost when $CR = 100$

Figures 3a and 3b illustrate the total transportation and delay costs with respect to the inter-

dictor's budget level when demands of all plant nodes are increased by 100 %. In addition, all node capacities are raised by 50 % to reflect the changes in cost terms in Figure 3b. The effect of budget level on total transportation cost is at the minimum level in Figures 3a and 3b. However, increases in demand levels lead to a proportional increase in transportation costs since the number of unit trains needs to be transported between origin destination pairs is increased.

Due to the increase in demand levels, delay costs also increase due to the congestion at rail yards and tracks. Moreover, demand increases result in larger delay costs in such a way that the delay costs for larger and smaller budget levels are brought close together as evidenced in Figure 3a. In addition to the 100 % increase in demand levels, increasing all node capacities by 50 % reduces the delay costs for the cases when the interdictor's budget is small (i.e. 1, 3) as shown in Figure 3b. However, an increase in delay cost is observed when the budget level is high (≥ 5). This is because increasing demands and/or node capacities enables an interdictor to interdict different rail elements. Such differences can be seen in Tables A.1 and A.2.

6. Conclusions

This study aims to identify the impacts of vulnerable infrastructure elements in a real rail transportation network. We describe the problem elements and boundaries and discuss the commonly encountered model formulations in the literature where the vulnerability of the network is the point of interest. Then, we introduce a new model that is dynamic, discrete, capacitated, and time varying, as opposed to previous models that are static, continuous, uncapacitated, and time invariant. The required reformulation to reduce the bi-level max-min problem into a single level max problem in case of disruptions to the real coal case transportation network is explained. Finally, we analyze the results of the computational experiments.

One of the main contributions of this paper to the literature is that the proposed mathematical model captures the movement of unit trains in time and space over a finite time horizon and identifies the critical nodes in the network whose unavailability causes the largest destruction in terms of total transportation and delay costs. For instance, Tables 2, 3, A.1 and A.2 list which nodes are interdicted in different scenarios and therefore we can assess the vulnerability of nodes based on these interdiction frequencies. The impacts of disruptions on objectives for different scenarios are demonstrated and rerouting decisions are illustrated via a web-based tool which provides useful insights for decision makers in planning further activities on the same rail transportation network.

For each scenario, we are able to demonstrate the number of trains waiting for departure for route r in time period t (O_{rt}) and the number of trains moving on route r in time period t (X_{rt}) on a map.

Another significant contribution is that our results point out that increasing the number of disruptions has almost no impact on transportation cost whereas, the delay cost due to congestions in rerouting unit trains dramatically escalates. This is because, the usage of the K-shortest path algorithm to construct the initial set of routes provides almost identical paths between each origin and destination pairs in terms of total distance. However, having multiple good alternative routes is not enough to prevent the delays of unit trains as the number of interdiction increases. Our study actually assesses the advantages of having multiple good alternative routes on the rail transportation network to minimize not only the transportation cost but also the delay cost caused by disruptions.

There are several directions that should be considered as next steps in modeling the impacts of disruptions on the rail network. First, we would like to incorporate the flow of unit trains in the reverse direction (plants to mines) as well while considering the routing decisions. In the current problem formulation, empty train flows from plants to mines are not considered. This is because, in case of disruptions, the operator's immediate objective is set to re-route the trains to plants with minimum transportation and congestion cost. After the trains safely arrive in plants, it would be more reasonable to send them back to the mines with some sort of infrastructure recovery process models on the network that are not in the scope of this study but will be considered as an extension to our work.

The second direction is to incorporate the uncertainty associated with the occurrence of disruptions using a stochastic programming framework.

Appendix A. Appendix

Appendix A.1. Trimming Algorithm

Initially, we labeled 8 sub-bituminous coal mines and 23 sub-bituminous coal plants together with 37 rail yards as *primary nodes.* The idea behind the trimming algorithm Appendix A.1 is to label the physical infrastructure (tunnels, bridges etc.) elements as primary nodes. If there is an infrastructure facility in between O-D pairs, the trimming algorithm makes sure that they are represented in the set of enumerated routes with start node, end node and the distance in between these two. Then, all primary components of the network (i.e. tunnels, bridges, plants, mines)

included in the K-shortest path algorithm are added to the reduced network that is used to test the two stage interdiction model.

Note that all adjectives (i.e. primary, elementary etc.) before “nodes/arcs” are just used to differentiate between physical infrastructure elements and mines/plants, railyards on the network. All nodes and arcs mentioned in this section exist on the network. The following notation describes some definitions of the terms used in trimming algorithm Appendix A.1.

- Y =set of railyards
- $\mathcal{N}$ =set of nodes ”primary nodes”
- B =set of elementary edges without infrastructure element
- $\mathcal{Q}$ =set of edges that connect two nodes
- n_{ij}^k= set of elementary nodes on the kth shortest path between i and j
- a_{ij}^k= set of elementary edges on the kth shortest path between i and j
- m_{ij} =the number of paths between i and j
- δ_{ij}^k =the length of the kth shortest path between$i$ and j
- d_{ij} = length of edge (i, j)

The first two steps connect each primary node to its closest primary node. In the first step, the algorithm checks if any two primary nodes are connected without any other primary node in between. If so, the edge connecting that pair of primary node is added to the edge set $\mathbb{E}$ (step 1) and for each member of this set, a dummy path is created (step 2). In step 3, If there is no other primary node found in between, then the original path is preserved with its original components (rail line distances, nodes etc.).

After step 2, the primary nodes become connected to one another. However, actual distances and nodes in between primary nodes are still unknown. In the remaining steps, the algorithm generates the K-th shortest paths for each O-D pairs connected by arcs in edge set $\mathbb{E}$. During this stage, infrastructure elements are embedded in the paths $\in \mathbb{E}$. This is performed in the following way. Let (m, n) be an infrastructure element with m as beginning node and n as end node between

primary node i and j. Then we create and add edges (i, m), (m, n) and (n, j) to $\mathcal{Q}$. Nodes defining the primary element (m and n), are also added to $\mathcal{N}$ as well.

We use start and end node to represent an infrastructure node. This is because we want to make sure that the nodes connected by links from both end and start nodes are also used to generate K-shortest paths. At first, representing an infrastructure (bridge, tunnel etc.) by two nodes might seem to have an impact on the best solution. However, our model makes sure that the interdictor will never choose to interdict both of them since eliminating one of them is enough to make the infrastructure not usable.

Algorithm Appendix A.1 Procedure for constructing a connected network from USCA data

```
Set 𝒩 = M ∪ P ∪ Y
Let 𝔼 = ∅ be an empty set of edges.
1. Connect each node to its closest nodes
    for each node pair (i, j) ∈ 𝒩 such that i ≠ j
        IF n_ij^1 does not contain a node in the set 𝒩, THEN add (i, j) to 𝔼
2. Add dummy paths
    for each arc (i, j) ∈ 𝔼
        add a dummy path from i to j that is composed of the single edge (i, j)
        set a_ij^(m_ij+1) = (i, j)
        set δ_ij^k to a large number
3. Add alternates for routes that have vulnerable elementary arcs
    for each arc (i, j) ∈ 𝔼
       Set k = 1
       Set interdictionCost=0
       while k ≤ m_ij+1
           for each (ℓ, p) ∈ a_ij^k ∩ B
             interdictionCost+=f_ℓm
           IF a_ij^k ∩ B ≠ ∅ and interdictionCost≤ b
             for each (ℓ, m) ∈ a_ij^k ∩ B
               add (i, ℓ), (ℓ, p), and (p, j) to 𝒬
               add ℓ and p to 𝒩
               set d_iℓ = δ_iℓ^1, d_ℓp = δ_ℓp^1, and d_pj = δ_pj^1
           ELSE
             add (i, j) to 𝒬
             set d_ij = δ_ij^k
             break from while loop
         k = k + 1
4. Compute capacity of arcs
    for each arc (i, j) ∈ 𝒬
RETURN the graph defined by nodes 𝒩, edges 𝒬, and distances (d_ij)_(i,j)
```

Table A.1: Interdicted nodes when CR=100 and demands of all plants are increased by 100 %

b	$\lvert R\rvert$=552	$\lvert R\rvert$=1840
1	80	81
3	70-72-80	70-72-74
5	70-72-74-80-187	70-72-74-80-187
10	70-71-72-73-74-75-80-81-186-187	63-68-70-72-74-78-80-103-187-312
15	68-69-70-71-72-73-74-75-78-79-80-81-102-186-187	47-68-69-70-71-72-73-74-75-78-79-80-81-180-186

Table A.2: Interdicted nodes when CR=100 and demands of all plants and node capacities are increased by 100 % and 50%, respectively

b	$\lvert R\rvert$=552	$\lvert R\rvert$=1840
1	73	73
3	70-72-74	72-80-187
5	70-72-74-80-187	70-72-74-81-187
10	69-70-72-74-78-80-86-88-103-187	47-68-70-72-74-78-80-103-187-312
15	51-69-70-72-74-78-80-83-84-86-88-91-93-102-187	47-51-68-70-72-74-78-80-86-88-91-92-96-187-312

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