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PROTECTING GLOBAL MARITIME-BASED INTERMODAL FREIGHT DISTRIBUTION SYSTEMS FROM THE IMPACTS OF CLIMATE CHANGE

Final Report

by

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EXECUTIVE SUMMARY

Ports are key elements of global supply chains, providing connection between land- and maritime-based transportation modes. They operate in cooperative, but competitive, *co-opetitive*, environments wherein individual port throughput is linked through an underlying transshipment network. Short-term port performance and long-term market share can be significantly impacted by a disaster event; thus, ports plan to invest in capacity expansion and protective measures to increase their reliability or resiliency in times of disruption. To account for the co-opetition among ports, a bi-level multiplayer game theoretic approach is used, wherein each individual port takes protective investment decisions while anticipating the response of the common market-clearing shipping assignment problem in the impacted network. This lower-level assignment is modeled as a cost minimization problem, which allows for consideration of gains and losses from other ports decisions through changes in port and service capacities and port cargo handling times. Linear properties of the lower-level formulation permit reformulation of the individual port bi-level optimization problems as single-level problems by replacing the common lower-level by its equivalent Karush Kuhn Tucker (KKT) conditions. Simultaneous consideration of individual port optimization problems creates a multi-leader, common-follower problem, i.e. an unrestricted game, that is modeled as an Equilibrium Problem with Equilibrium Constraints (EPEC). Equilibria solutions are sought by use of a diagonalization technique. Solutions of unrestricted, semi-restricted and restricted games are analyzed and compared for a hypothetical application from the literature involving ports in East Asia and Europe. The proposed co-opetitive approach was found to lead to increased served total demand, significantly increased market share for many ports and improved services for shippers.

1.0 INTRODUCTION

Maritime transport operating within Intermodal (IM) freight distribution systems remain the dominant mode for international trade (International Maritime Organization, https://business.un.org/en/entities/13). It plays a significant role in the U.S. and world economies, serving as the backbone to global trade and supply chain networks. Ports are critical components of these systems, providing key land-water connections. However, they are vulnerable to disruptive impacts from a range of anthropogenic and natural hazard causes, including tsunamis, earthquakes, meteorological events, terrorism, worker strikes and operational accidents. Moreover, damage, disruptions, backups, or physical, administrative or operational changes that arise in a single port can affect the performance of other ports, along with the overall system. Consider for example an event arising at a single port that impacts its throughput capacity. In addition to a shortage in berth space for incoming vessels, vessels will be delayed from moving to the next location, in turn creating queues and additional upstream backups and downstream delays. An initial disruption, thus, causes delays that ripple through the network, impacting other ports' operations and system-level productivity. This ripple effect in the maritime network is depicted in **Error! Reference source not found.** where a disruption in one port leads to delays at other ports along the shipping routes.

In this competitive environment, disruptions can lead to significant immediate losses in revenue and ultimate market share, as alternative competing ports can serve diverted traffic. This is especially problematic in transshipment operations, where interchange locations are replaceable, and traffic diversion can lead to a rebalancing of revenues across the port network. The disruptions, thus, affect the long-term competitive position of affected ports, potentially preventing them from regaining their pre-disaster market share even after capacity is completely restored (Chang 2000). If such disruptions occur frequently enough, whether or not due directly to events at a specific port, the delays will impact the ports' reliability and thus its reputation. Many shipping companies directly or indirectly account for potential delays and resulting losses in choosing their IM routes. Ports are, therefore, incentivized to make pre-disaster mitigative and preventative investments to reduce vulnerabilities for the purpose of maintaining and increasing their market share (Song & Panayides 2012). This is also important to manufacturers and suppliers that rely on the IM network to ship or receive their goods and materials. Companies relying on raw materials or parts will direct shippers to consider multiple alternative routes in case of port disruptions to avoid delays in manufacturing (Tang 2006).

An individual port authority can invest in its own facilities to protect its business from the threats of disruptions and more major disaster events. These investments may involve pre-event enhancements (e.g. reinforcing or raising a wharf or pier, raising roadway and railway elements, redesigning drainage systems, building coastal defenses, soil strengthening, seismic design, facility retrofit, installation of security systems,…), post-event repair, or improvements in equipment, insurance coverage, and personnel training. Pre-event preparedness is especially important where post-disaster actions may be inadequate for the disaster event category (Chang 2000). While such investments are important, they do not guarantee performance, because a port's fate is a function of its place within the larger shipping network. A disruption in one port node of this maritime network can affect the continuation/disruption or gains/losses at other network elements. Thus, protective investments must aim to guard against or enable adaptive action for both on-site events and events at interconnected facilities within the maritime network, and benefits may be derived from investing in others' facilities. The protective investment problem exists, thus, in a cooperative and simultaneously competitive, *co-opetitive*, environment wherein each port can anticipate its competitors' investment decisions and consider potential gains from collaboration. The term co-opetition was introduced by Nalebuff et al. (1996) in the context of business management.

The global maritime-port network involves a range of stakeholders from national, state and private sectors. Ports may be publically or privately owned, and may be operated by the same or different public or private parties (Brooks 2004). In this co-opetitive IM environment, each stakeholder is interested in not only the well-being of its own facilities, but also in other facilities within its maritime network. This complicates the process of analyzing and optimizing preventative or response-related investments to disruption events. A co-opetitive optimization scheme not previously considered in the literature in this context is proposed herein for this purpose. This scheme supports the development of decentralized, yet cooperative investment strategies.

This multi-stakeholder, protective investment problem for ports operating within a competitive but connected IM network is conceptualized as a multi-player, bi-level investment problem. Decisions by a player to invest in its own or other's facilities are taken individually at the upper level of the bi-level formulation while anticipating solution of a common liner shipping assignment at the lower level. The ports' objectives are to maximize their own throughput (i.e. profit) by protecting from impacts of disruption events across the port network. Given post-event route capacities and traversal times, the liner shipping problem assigns container shipping demand to the functioning routes; that is, it recalibrates market response to disrupted transport options.

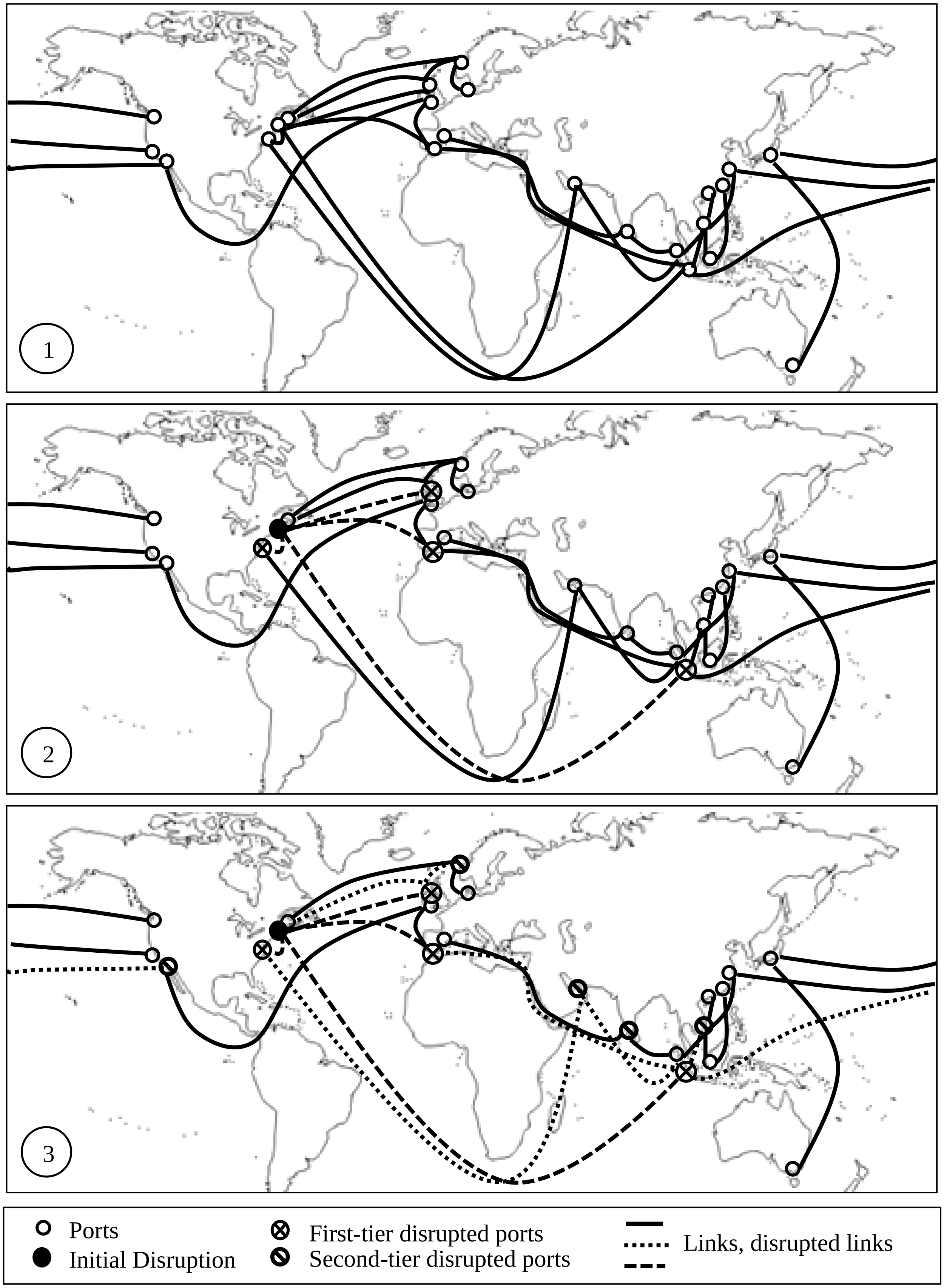
1
2
3
Ports
Initial Disruption
First-tier disrupted ports
Second-tier disrupted ports
Links, disrupted links

Figure 1: Cascading effects of perturbations in the liner shipping network

This bi-level problem can be transformed into a set of interrelated, single-level problems, one for each port, by adding identical Karush Kuhn Tucker (KKT) optimality conditions of the common lower-level shipping assignment problem to the upper level of each individual investment problem. This creates a set of Mathematical Programs with Equilibrium Constraints (MPECs) with one for each port. These individual optimization problems cannot be solved independently since they are influenced by the decisions of other ports involved in the common KKT conditions. This is equivalent to a single-level, multi-leader (multi-port), common follower (shipment assignment) problem or Equilibrium Program with Equilibrium Constraints (EPEC). Solution of this EPEC is reached at a multi-actor "Stackelberg equilibrium" in which each stakeholder seeks an investment strategy that given decisions taken by other stakeholders maximizes its own objective and, simultaneously, the response of the market in the lower-level (embedded within the KKT conditions) to investments. This formulation concept is presented in Section 3 and depicted in Figure 2.

To solve the resulting EPEC, the diagonalization technique presented in Gabriel et al. (2013) and summarized in Section 4 for the proposed protective investment problem was implemented within the ILOG-CPLEX software environment. This technique is considered to be a variant of the Gauss-Seidel method for numerical solution of simultaneous equations. Resulting investment decisions determine in which components and to what extent the different stakeholders should invest for their own benefit (i.e. profit, market share or other objective) while accounting for the impacts of their decisions within a common market. Before proceeding to description of the formulation and solution methodology, relevant literature is reviewed. In Section 4, the proposed solution framework is applied to a test application network and insights are gleaned.

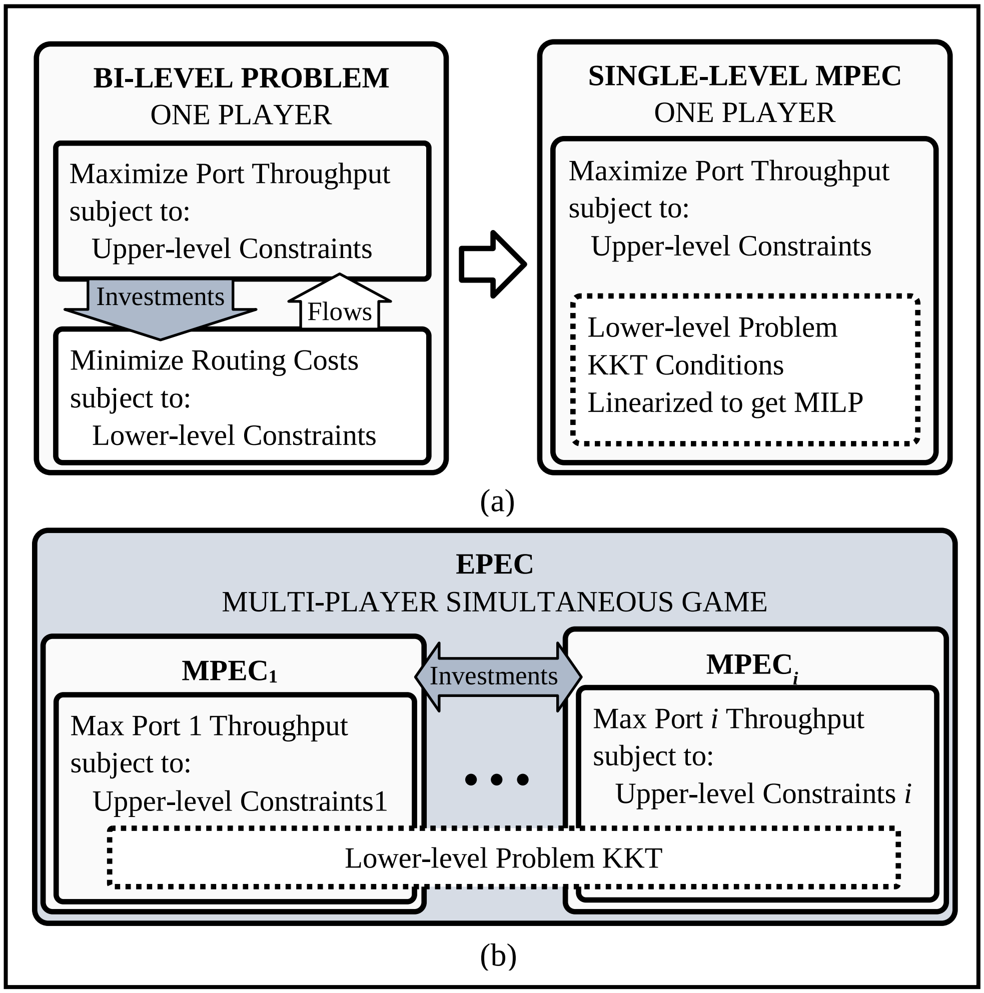

Figure 2: Overview of the EPEC evolution: (a) Transforming the bi-level problem into a single-level linear MPEC. (b) Construction of the EPEC from MPECs of all the ports.

2.0 BACKGROUND

Supply chain risk management has been extensively studied. In this context, risk is typically defined with respect to reoccurring (e.g. operational) or rarer catastrophic disruptions that impact some aspect of the supply chain. Only a few such works explicitly consider the role of transportation in supply chain risk. Ho et al. (2015), in their comprehensive review on supply chain risk management, list only one work (Hishamuddin et al., 2013) that accounts for transportation risks in supply chains. Hishamuddin et al. focus on recovery scheduling related to ordering and production; they do not investigate potential protective investments to reduce this transportation risk. Rienkhemaniyom and Ravindran (2014) mathematically modeled a multi-objective supply chain network design problem involving risks associated with disruptions at facilities and transportation links. Their model seeks decisions on the design of the supply chain, including decisions related to the selection of suppliers, manufacturing plants, and distribution centers, as well as plans for production and distribution. They propose the use of goal programming to seek optimal or satisficing design solutions in terms of network performance and risk attributes. Loh and Van Thai (2014) discuss the increasingly important role of ports in the global supply chain network. They note that very few works have focused on the management of port disruptions as part of the supply chain. Thus, this remains an open area.

Effective investment decision making for improved resiliency requires a deep understanding of the system-level impacts of port disruptions. Some works have sought to describe how disruptions cascade through the supply chain network. Wu et al. (2007) studied the propagation of disruptions in supply chains and their impacts on the network. They used a technique they termed Disruption Analysis Network for this purpose. This technique models the supply-chain interconnections using an underlying directed bipartite graph. Using this graph-based representation, the impact of simulated disruption events can be estimated with respect to important network attributes. Sokolov et al. (2016) proposed a two-model, multi-criteria approach for use in supply chain design that captures the ripple effects of disruptions. The model accounts for static structural properties of the supply chain through the use of graph theory concepts. The static model is extended to include time-dependent characteristics needed to understand the dynamic effects of disruptions. These effects are interpreted as an indicator of design robustness.

The use of "Systemigrams" is suggested in Mansouri et al. (2009) for studying the effects of disruptions in a multi-agent maritime transportation system of ships, ports, intermodal connections, waterways and users. This tool enables the various stakeholders of the supply chain, from the manufacturers to the retail stores, to create qualitative understanding of the perspectives, organizational requirements and strategies of other stakeholders. This tool is aimed at supporting a participatory environment by elucidating interdependencies. Rose and Wei (2013) studied direct and indirect effects of port disruptions on regional and national economies using an input-output (I-O) (demand-supply) macroscopic approach. Resiliency of the economy as a function of inventories, re-routing, overtime and extra shifts is incorporated.

The literature is replete with qualitative works and reviews that consider threats to ports, their resiliency, decision-making practices and their impacts on the global supply chain network. Becker et al. (2012) conducted a comprehensive survey of port authorities around the world. They investigated the current knowledge, perceptions and planning efforts among seaport administrators to address the impacts of climate change. The authors found that by and large the respondents did not plan for climate change. Moreover, they planned for a period of less than 10 years, despite that their infrastructure decisions may have century-long impacts. They noted that the respondents were in agreement about the importance of addressing the potential consequences of climate change, but felt uninformed. Shaw et al. (2016) explored the multi-level structure of port resilience planning, including government departments, port operators, importers, agents and logistic firms. They suggest that this complex system requires information sharing between stakeholders for preparation for disasters. Python and Wakeman (2016) review some of the lessons learned from post-super storm Sandy at the ports of New York and New Jersey. They concluded that ports must address the risks of climate change impacts. They argue that if ports are willing to overcome the competitiveness and share information during disruptions, they can increase their own resiliency, as well as ensure the resiliency of the supply chain.

Some works focus on resiliency modeling, quantification and optimization for an individual port. These works model detailed port operations. The output of their models can be used to create performance curves for scenario generation in this study. Nair et al. (2010) applied a resilience quantification and enhancement framework proposed in (Chen & Miller-Hooks 2012) to ports. They built a detailed network model of port operations for a port in Poland and used a throughput ratio based on satisfied demand as their resiliency measure. They considered five categories of hazard events for generating thousands of potential disruption scenarios and suggested a host of recovery actions for recapturing lost operational capacity under a multi-hazard stochastic framework. They measure resiliency in terms of both the inherent coping capacity and adaptability as a function of recovery action. Shafieezadeh and Ivey Burden (2014) introduced a framework for quantification of seismic resiliency of a seaport. They used the integral of post-disruption performance over time to measure network resiliency. Yang et al. (2015) used a fuzzy risk analysis approach to evaluate the economic impact of adaptation policies for port resiliency. Using fuzzy set theory, they combine linguistic data on climate change risk parameters (timeframe, likelihood, severity of consequences) to produce fuzzy safety score. They estimate the potential risk reduction and cost-effectiveness of considered adaptation strategies.

A few studies assessed the resiliency of a networked system of ports. Omer et al. (2012) studied the resiliency of maritime transportation systems using a proposed Networked Infrastructure Resiliency Assessment (NIRA) framework. They suggest three resiliency metrics: tonnage, time and cost resiliency. They quantified the impact of disruptions on two connected ports using a system dynamics model to account for the impact of a reduction in capacity of the receiving port on shipping times. They evaluated the benefits of alternative in-land connections on the resiliency metrics for the two ports. Achurra-Gonzalez et al. (2016) used a cost-based container flow assignment method (presented in Bell et al., 2013) to investigate the role of capacity reduction in ports in redistribution of cargo flows due to changing route costs. Angeloudis et al. (2007) examined the properties of the liner-container shipping network using concepts of graph theory. They found the network to be scale-free, wherein some nodes have exceptionally high degree compared to the majority of nodes, and detected the busiest nodes in the network. They examined the responsiveness of the network to events that impair network elements (nodes) through rerouting the container ships. They concluded that the critical nodes of the network are not necessarily the busiest ones, and the impacts on processing of shipments at other ports is highly variable. Peng et al. (2016) formulate a centralized version of the protective investment decision problem for the liner shipping network as a two-stage stochastic program given randomly arising disruption events. While related to this work, Peng et al.'s work presumes that a single authority can invest across the network using a common budget. Such a system-optimal, centralized investment strategy can provide a bound on network-wide performance under a social, shipping cost minimizing, objective.

Although a number of works have studied the reliability or resiliency of port networks, either from a graph theory viewpoint (Angeloudis et al. 2007) or by examining throughput before and after disruptions (Achurra-Gonzalez et al., 2016; Angeloudis et al., 2007; Peng et al., 2016; Omer et al., 2012), all considered protective investment decisions to be made centrally under a single, common budget. In reality, the ports are not managed centrally, and in fact are competing and cooperating to increase their own market shares.

A number of studies have modeled competition between two ports through setting of handling costs (port charges) for shippers, expansion and service-choice strategies, and sometimes by seeking to impact port-of-call decisions. Ishii et al. (2013) constructed a non-cooperative, two-player game for setting port charges given port capacity expansion plans and demand uncertainty. Asgari et al. (2013) model a game among two competing hub ports for setting port charges. Shipping companies, acting as the leader, choose the lowest cost option. They use a utility function to model the attractiveness of each hub port to the shipping companies and embed the utility function within an objective through which the ports respond to shipper decisions at the lower level. Song et al. (2016a) model a two-level game among two liner shipping companies. Similar to Asgari et al., Song et al. model port-call decisions by two competing shipping companies (the leaders) at the upper level and port charge settings by two ports (followers) in the lower level. Song et al. (2016b) for a similar problem propose a two-player (two-ports) game in which payoffs of the game are assessed through the benefits to a single ocean carrier choosing a port-of-call. They mathematically derived the equilibrium solution to this simplified game. Chen and Liu (2016) use a two-player game to model expansion investment decisions of two ports considering congestion and uncertain market demand. Zhuang et al. (2014) also present a two-player game for two ports considering service-choice decisions and derive the equilibrium solution mathematically for their specialized problem. Other works have multiplayer, bi- or tri-level structures also related to port charge decision (Lee et al., 2014; Lee et al., 2014a; Lee and Choo, 2016; Zhang et al., 2009). These works anticipate shipper routing decisions in the lower level response.

Other relevant works arise in the broader field of infrastructure investment that also apply a two- or more-player (game theoretic) approach. Reilly et al. (2015) model investment decision making for interdependent infrastructure networks as a game. They provide a general formulation that associates investments and payoffs for two players and compare solutions under a simultaneous game, sequential game, and social optimum. They discuss the application of the two-player game theory approach for flood protection investment planning. Of greater relevance to supply chains is work by Bakshi and Kleindorfer (2009). They used a Harsanyi-Selten-Nash bargaining framework to model mitigative investments of two participants in a supply chain. They study tradeoffs between pre-event mitigative investment sharing and post-event loss-sharing net of insurance payouts. Bakshi and Mohan (2015) studied mitigation of cascading disruptions in supply networks. They found that investments and payoffs of a firm are dependent on at most its tier-2 suppliers. Finally, Do et al. (2015) used a game theoretic approach to investigate competition between two ports in investing for expansion given uncertain demand. They estimated that profits enabled through expansion and ensuing increase in market share were highly dependent on the actions of other ports in the maritime network. These works are relevant here in their game-theoretic approaches, and their recognition of the importance of understanding the ramifications of a port's decisions given its place within an interconnected port network.

The few works that consider a multi-player scheme in the context of infrastructure resiliency and reliability (Bakshi and Kleindorfer, 2009; Reilly et al., 2015; Bakshi and Mohan, 2015; Do et al., 2015) are generic, using Nash games of only two investors under simplified investment strategies and payoff schemes.

The work herein offers a multi-leader, common-follower structure, i.e. an EPEC formulation, that enables a realistic representation of the co-opetitive environment in which multiple ports operating within a maritime network involving shippers must make their investment decisions.

3.0 MATHEMATICAL MODEL

The multi-stakeholder, protective port investment problem is formulated in this section. First, though, the single-player version, an MPEC, which takes the perspective of an individual port investing in isolation, is presented.

3.1 PROBLEM FROM A SINGLE PORT'S PERSPECTIVE

A single port can make pre-disaster investments with the aim of maintaining or quickly reclaiming capacity during or after a disruption event. In addition to retaining its current market share, the port, through its investments, may be poised to capture a larger portion of the shipping market. In this subsection, the protective investment problem is formulated taking this single-port perspective.

3.1.1 The bi-level investment decision making formulation for individual ports

The single-player protective investment problem is formulated as a bi-level problem in which a port (leader) makes protective investment decisions at the upper-level while anticipating the response of a lower-level problem. The lower-level problem corresponds to the market clearing shipping assignment problem. Throughput maximization is sought in the upper level, while shippers (the followers) seek lowest cost routes in the lower level. Solution is obtained at a Stackelberg equilibrium wherein investments are optimal for the given market response. This structure is presented in Figure 2(a).

1.1.1.1 Upper-level protective investment decisions

In the upper-level, investment decisions are made from the perspective of a port authority with the goal of mitigating the impacts of a disruption event and preventing the loss of business to competing, unaffected or better prepared ports. Notation used in formulating the upper level along with the upper-level formulation for two perspectives are given next. The response at the lower level is presented in the next subsection.

Table 1 Notation used in the upper-level problem, investment decision-making, formulation

Sets		Subsets		Indices	
A	Legs	A_p^+	Legs entering port p	a	Legs
O	Origin ports	A_p^-	Legs leaving port p	p, i	Ports
D	Destination ports			o	Origin ports
P	All ports			d	Destination ports

Parameters	
b_p	Budget of port p

Decision variables	
x_{ip}	Investments of port i in port p (parameters to the lower-level problem), $p \in P$
y_{ad}	Flow of containers on leg a en route to destination d, where a leg is a specific transit task between two ports
f_{od}	Flow of containers from origin o to destination d

Optimization from Port i's perspective:

$$Max \sum_{d \in D} \sum_{a \in A_i^+} y_{ad} + \sum_{d \in D} f_{id} - \beta \sum_{p \in P} x_{ip} \tag{1}$$

Subject to:

$$\sum_{p \in P} x_{ip} \leq b_i \tag{2}$$

$$x_{ip} \geq 0 \quad \forall p \in P \tag{3}$$

The objective as given by (1) seeks to maximize total container traffic, including inbound, outbound and transshipment traffic. To avoid double-counting, only inbound movements of the transshipments are counted. Added revenue generated through sea-to-land container handling can be included through an additional term if desired. The penalty term, $\beta \cdot \sum_{p \in P} x_{ip}$, is added to the objective to ensure that port i only invests when the investment leads to additional throughput. β must be smaller than the marginal value of processing one additional container. Budget limitations are given in Constraint (2). Investments by port i must be nonnegative (Constraints (3)). Flows along the legs (y_{ad} for $a \in A_i^+$ and A_i^-) are set in conjunction with solution of the lower-level problem described in the next subsection.

An alternative objective function that captures the trade-offs between protective investments and loss of shipping business might be considered:

$$Max \left(\sum_{d \in D} \sum_{a \in A_i^+} y_{ad} + \sum_{d \in D} f_{id} \right) c - \sum_{p \in P} x_{ip}, \tag{4}$$

where c converts port throughput to a monetary value. With such a profit-based objective, both the budget constraint (4) and the β term in (4) can be eliminated.

System perspective (maximize welfare)

Taking a centralized decision-making approach, the objective is given in terms of maximizing total port throughput in the maritime network wherein port investments, x_p, across the network are allocated from a common, pooled budget b for the benefit of social welfare. A centralized approach is commonly taken in the literature. While it may benefit the shippers, this may not be the case for the individual ports.

$$Max \sum_{p \in P} \left(\sum_{d \in D} \sum_{a \in A_p^+} y_{ad} + \sum_{d \in D} f_{pd} - \beta x_p \right) \tag{5}$$

Subject to:

$$\sum_{p \in P} x_p \leq b \tag{6}$$

$$x_p \geq 0 \quad \forall p \in P \tag{7}$$

1.1.1.2 Lower Level: Market Clearing (Shipment Assignment)

The decisions of port authorities to invest in mitigative actions are based on the anticipated response from the underlying shipping network reflected in the lower-level assignment problem. The impacts of a disaster scenario given protective, port-level investments determine the port/route capacities and processing/traversal times in the network. For the lower-level problem, a cost-based routing assignment formulation is adopted from Achurra-Gonzalez et al. (2016) (for a review on liner shipping and container routing optimization the reader is referred to Tran and Haasis, 2015). Where possible, notation follows that given in this earlier work.

A pre-defined set of services with associated links and legs model the liner-shipping network. Containers are assigned to legs such that costs of handling, renting and depreciation due to cargo transfer or dwell times are minimized. Note that each unit of shipment involves handling at the two ends of its trip; thus, Achurra-Gonzalez et al. assign higher handling costs to leg ends that occur at shipment origins and destinations. Legs representing movements between transshipment nodes are assumed to require modest handling costs at their end points. Any handling cost above this is considered extra. If the sum of extra handling costs for legs connecting origin-destination (o-d) pairs is equal to the sum of extra costs of handling for legs between origins and transshipment nodes and between transshipment nodes and destinations, as is the case in Achurra-Gonzalez et al. (2016), the total handling cost for each container would only depend on the number of legs used in its shipment, and the extra handling costs will be equal in any feasible combination of legs. Thus, leg types as used in their formulation are unnecessary and their formulation can be simplified without loss. This previous work considered only a single o-d pair; however, the proposed simplification is required in applications with multiple o-d pairs. This is because the leg type is defined for only one o-d pair, while containers in the same ship may have different origins and destinations.

Table 2 Notation for the lower level, route assignment problem

Sets		Subsets		Indices	
A	Legs	A_p^+	Legs entering port p	a	Legs
O	Origin ports	A_p^-	Legs leaving port p	o	Origin ports
D	Destination ports	A_r	Legs on route r	d	Destination ports
P	All ports	L_r	Links on route r	p	Ports
R	All routes	P_r	Ports on route r	r	Routes
L	All links			l	Links

Parameters	
t_a	Sailing time on leg a, including port loading and unloading times, without improvements from pre-disaster investments
$x_{pp'}$	Investments of port p in port p' for $p, p' \in P$
g_p	Capacity loss reduction due to disaster event per unit investment in port p
h_r	Capacity loss reduction due to disaster event per unit investment in any port on route r
s_a	Reduction in traversal time increase due to disaster event per unit investment in any port on leg a
q	Ratio of effectiveness of internal to external investment
CHC_r	Container handling cost per container for a leg on route r
RDC	Per container rental and depreciation cost (inventory cost) per unit time
TD_{od}	Containers to be transported from origin o to destination d
δ_{alr}	1 if leg a uses link l on route r, 0 otherwise
v_a	Frequency of sailing on leg a
RC_r	Post-disaster capacity of route r
k_p	Post-disaster maximum throughput capacity at port p
PC	Penalty cost for containers not transported

Decision variables	
f_{od}	Flow of containers from origin o to destination d
y_{ad}	Flow of containers on leg a en route to destination d

Dual variables
$\alpha_{pd}, \gamma_p, \eta_{rl}, \theta_{od}^{min}, \theta_{od}^{max}, \lambda_{ad}$

$$Min \sum_{r\in R}\sum_{a\in A_r}\left(CHC_r \sum_{d\in D} y_{ad}\right) + \sum_{o\in O}\sum_{d\in D}(TD_{od} - f_{od})PC + RDC\sum_{d\in D}\sum_{a\in A}\left(t_a - s_a \sum_{p\in\{p^{a-},p^{a+}\}} g_p\left(\sum_{p'\in P\setminus\{p\}} x_{p'p} + q x_{pp}\right) + \sum_{a\in A} 1/v_a\right) y_{ad} \quad (8)$$

Subject to:

$$\sum_{a\in A_p^+} y_{ad} - \sum_{a\in A_p^-} y_{ad} = \begin{cases} -f_{od} & for\ p = o \in O \\ \sum_{o\in O} f_{od} & for\ p = d \in D \\ 0 & otherwise \end{cases} \quad \forall d \in D \qquad : \alpha_{pd} \tag{9}$$

$$k_p + g_p\left(\sum_{p'\in P\setminus\{p\}} x_{p'p} + qx_{pp}\right) \geq \sum_{a\in A_p^+}\sum_{d\in D} y_{ad} + \sum_{a\in A_p^-}\sum_{d\in D} y_{ad} \quad \forall p \in P \qquad : \gamma_p \tag{10}$$

$$RC_r + h_r \sum_{p\in P_r} g_p\left(\sum_{p'\in P\setminus\{p\}} x_{p'p} + qx_{pp}\right) \geq \sum_{a\in A} \delta_{alr} \sum_{d\in D} y_{ad} \quad \forall l \in L_r, \forall r \in R \qquad : \eta_{rl} \tag{11}$$

$$0 \leq f_{od} \leq TD_{od} \quad \forall o \in O, \forall d \in D \qquad : \theta_{od}^{min}, \theta_{od}^{max} \tag{12}$$

$$y_{ad} \geq 0 \quad \forall a \in A, \forall d \in D \qquad : \lambda_{ad} \tag{13}$$

where p^{a-} and p^{a+} are starting and finish ports of leg a.

Objective function (8) seeks a minimum total handling, depreciation, rental and penalty cost solution. Rental and depreciation costs are a function of cargo travel and dwell times (given as the reciprocal of frequencies). In some instances, the capacities of the routes or ports may not be sufficient to satisfy all demand, and a penalty is incurred. The penalty encourages a solution with maximum network throughput. To capture the benefits of investment, the objective includes corresponding improvements in leg traversal times (including port handling times) due to investments, which may be gained even without disruption.

Conservation of flow at the ports is guaranteed through Constraints (9). Constraints (10) ensure that total inflow and outflow of containers in each port is not greater than the port's post-disaster throughput capacity. The post-disaster capacity is determined by upper-level investments and disaster impacts as realized. Route capacity constraints are enforced in (11) wherein for each route-specific link, aggregated flows along all constituent legs are included. During ordinary times, route capacities are derived from ship capacity and route service frequencies. Post-disaster, a reduction in capacities of routes that include the affected port(s) is taken. The effects of investments aimed at countering disaster impacts are also included. Together, Objective (8) and Constraints (10) and (11) model the reductions in port and route-level capacities and increased traversal/handling costs due to the disaster event, as well as the effectiveness of pre-event investment actions. Objective (8) and Constraints (10) and (11) can be revised to model investment benefits in traversal time and port and route capacities that are attained only in the event of disruption. Constraints (12) enforce the OD flows to be between 0 and a total fixed demand.

3.1.2 Single-level formulation of individual port optimization (MPEC)

The upper- and lower-level problems together create the bi-level investment optimization problem for a single port decision-maker operating within a larger maritime network. This can be summarized as the following mathematical problem:

Max (1)
subject to:
(2) and (3)
Min (8)
subject to:
(9)-(13)

To facilitate the reformulation of port i's investment problem in a single level, the lower-level problem, (8)-(13), can be replaced by its KKT conditions. Since the lower-level problem is linear, the KKT conditions are necessary and sufficient for optimality, and the problem reduces to a MPEC (Figure 2(a)) as given next.

MPEC for port i

$$Max \sum_{d\in D}\sum_{a\in A_i^+} y_{ad} + \sum_{d\in D} f_{id} - \beta \sum_{p\in P} x_{ip} \tag{1}$$

Subject to:

$$\sum_{p\in P} x_{ip} \le b_i \tag{2}$$

$$x_{ip} \ge 0 \quad \forall p \in P \tag{3}$$

$$\begin{aligned} \partial \mathcal{L}_i / \partial y_{ad} &= \alpha_{p^{a+}d} - \alpha_{p^{a-}d} + \gamma_{p^{a+}} + \gamma_{p^{a-}} - \sum_{a\in A} \delta_{alr} \sum_{d\in D} \eta_{rl} - \lambda_{ad} + CHC_{r^a} + RDC/v_a \\ &+ \left(t_a - s_a \sum_{p\in\{p^{a-},p^{a+}\}} g_p \left(\sum_{p'\in P\setminus\{p\}} x_{p'p} + q x_{pp} \right) \right) RDC = 0 \; \forall a \in A, \forall d \in D \end{aligned} \tag{14}$$

$$\partial \mathcal{L}_i / \partial f_{od} = \alpha_{od} - \alpha_{dd} - \theta_{od}^{min} + \theta_{od}^{max} - PC = 0 \quad \forall o \in O, \forall d \in D \tag{15}$$

$$\sum_{a\in A_p^+} y_{ad} - \sum_{a\in A_p^-} y_{ad} = \begin{cases} -f_{od} & for\ p = o \in O \\ \sum_{o\in O} f_{od} & for\ p = d \in D \\ 0 & otherwise \end{cases} \quad \forall d \in D \tag{9}$$

$$0 \le k_p + g_p \left(\sum_{p'\in P\setminus\{p\}} x_{p'p} + q x_{pp} \right) - \sum_{a\in A_p^+}\sum_{d\in D} y_{ad} - \sum_{a\in A_p^-}\sum_{d\in D} y_{ad} \perp \gamma_p \ge 0 \quad \forall p \in P \tag{16}$$

$$0 \le RC_r + h_r \sum_{p\in P_r} g_p \left(\sum_{p'\in P\setminus\{p\}} x_{p'p} + q x_{pp} \right) - \sum_{a\in A} \delta_{alr} \sum_{d\in D} y_{ad} \perp \eta_{rl} \ge 0 \quad \forall l \in L_r, r \in R \tag{17}$$

$$0 \le f_{od} \perp \theta_{od}^{min} \ge 0 \quad \forall o \in O, \forall d \in D \tag{18}$$

$$0 \le TD_{od} - f_{od} \perp \theta_{od}^{max} \ge 0 \quad \forall o \in O, \forall d \in D \tag{19}$$

$$0 \le y_{ad} \perp \lambda_{ad} \ge 0 \quad \forall a \in A, \forall d \in D \tag{20}$$

where r^a is service route of leg a.

Constraints (2) and (3) are upper-level constraints while (9) and (14)-(20) are lower-level KKT conditions including the equality, inequality, complementary slackness and non-negativity constraints. By way of example, the function $\perp$ with respect to constraint (19) operates as:

$0 \le TD_{od} - f_{od}$,	a lower-level inequality
$0 \le \theta_{od}^{max}$,	non-negativity of the dual variable

$$(TD_{od} - f_{od})\,\theta_{od}^{max} = 0, \qquad \text{complementarity slackness}$$

A disjunctive constraints approach (Fortuny-Amat & McCarl 1981) is applied in creating equivalent linear constraints for complementarity equations (16)-(20), resulting in reformulation of the MPEC as a Mixed Integer Program (MIP). As an example, for constraints (19):

$$0 \leq TD_{od} - f_{od},\ 0 \leq \theta_{od}^{max},\ TD_{od} - f_{od} \leq KM^1,\ \theta_{od}^{max} \leq (1-K)M^2,\ K \in \{0,1\},$$

where M^1 and M^2 are large values that place no restrictions on $(TD_{od} - f_{od})$ and θ_{od}^{max} when K is 1 or 0, respectively. On the other hand, if the Ms are set unnecessarily large, they will expand the feasibility region and significantly increase MIP solution time. For primal variables, the selection of these values can relate to the application. The setting of these values for the dual variables, however, is less intuitive and may require trial-and-error. In the context of this model, M^1 can be set within a small increment above the associated maximum o-d flow or port or route capacity. In some cases, the setting of M^2 can be guided by insights gleaned from the shadow prices of the lower-level problem. In all cases, they must be larger than (roughly equal to or slightly more than double) the value of the penalty cost, PC, applied within the KKT constraints associated with the lower-level objective function.

By employing this linear equivalent model, optimality of the individual MPECs is guaranteed. Moreover, this approach increases the speed of convergence of the proposed diagonalization method described in the next section.

3.2 SOLUTION UNDER SIMULTANEOUS, COMPETITIVE INVESTMENT (EPEC)

Simultaneous consideration of the MPECs associated with each of the ports creates a single EPEC which produces an equilibrium solution on the investment decisions (Figure 2(b)). To solve this EPEC, the well-known diagonalization technique (see Gabriel et al., 2013 for additional background) is employed here (**Error! Reference source not found.**Figure 3). This technique can be described in terms of the following main steps.

1- Initial investment decisions are selected. A multi-start technique is commonly implemented and will potentially produce multiple equilibria.

2- The individual port protective investment problem is solved assuming fixed investment decisions for all other ports, and investment decisions are updated before proceeding to solve the individual problem for the next port. This is repeated until all individual port problems are solved once.

3- Step 2 is repeated until the investment decisions converge. Convergence is achieved when the difference between the results of two consecutive iterations are less than a defined threshold.

For a network with p ports, r service routes, a legs, l links, od OD pairs and d destinations, the MPEC for one port is a MIP with $(3od + 2a \times d + l + p \times d + p^2)$ continuous variables, $(2od + a \times d + l + p)$ binary variables (for disjunctive constraints) and $(7od + 4a \times d + 3l + p \times d + p^2 + 2p)$ constraints. Solution times also depend on the big M settings. Note that the problem size does not depend on the characteristics of the considered disaster scenario. While convergence of the diagonalization technique for solving the larger

EPEC is not guaranteed, it was found to work well (generally achieved within three to six iterations of the whole process and 20 iterations in the worst case) in this application (Section 4).

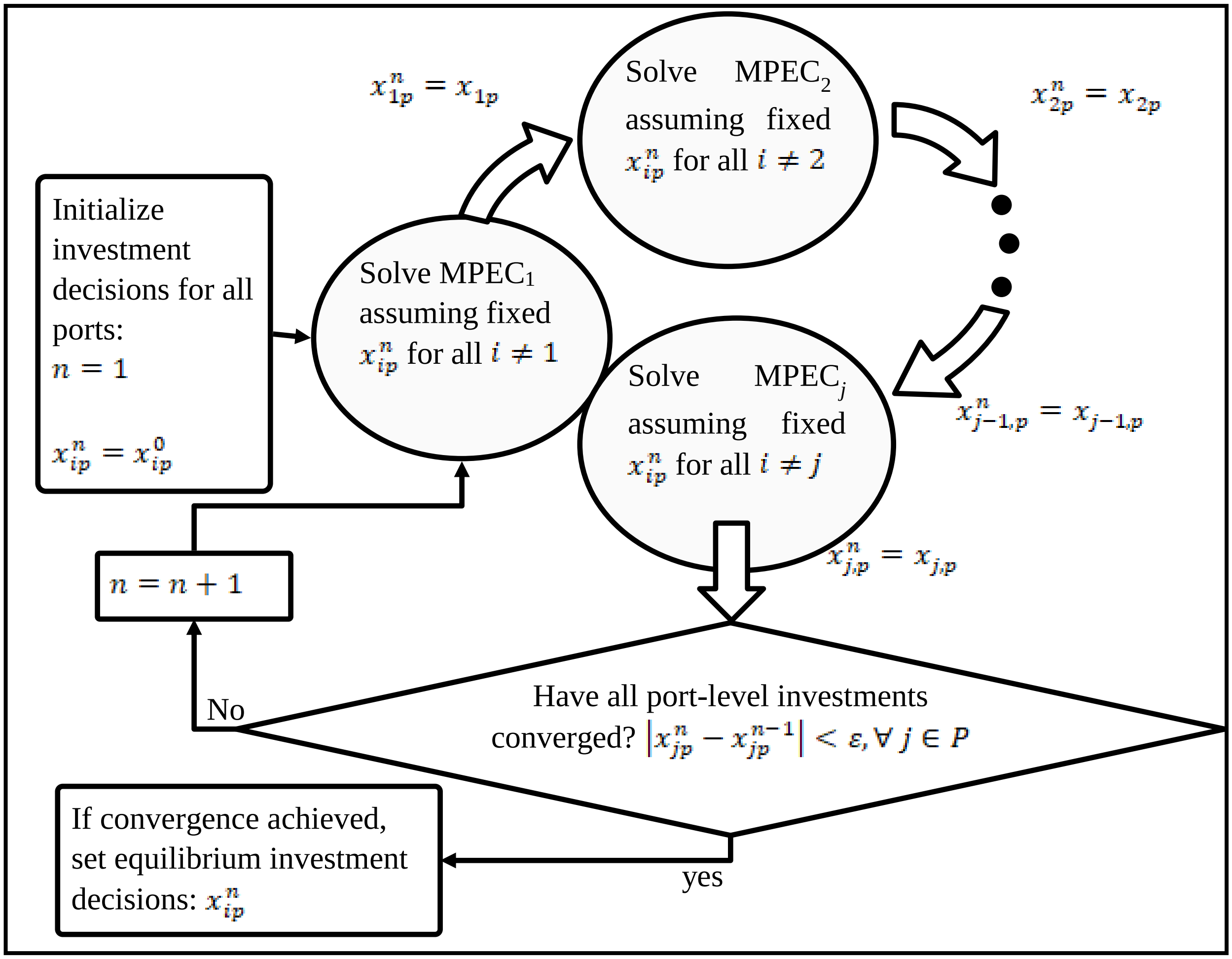

Figure 3 Solution of the EPEC through the Proposed Diagonalization Technique

One might solve this problem by constructing the EPEC through simultaneous consideration of the KKT conditions of all the individual MPECs in one grand problem. To achieve this, an equivalent single-level MPEC can be derived for each player by moving constraints of the lower level to the upper level and adding corresponding dual constraints and strong duality conditions to ensure that solutions meet primal-dual optimality. To solve the combined set of single-level MPECs, the KKT conditions of each MPEC can be incorporated within a single program. Solution of this grand problem is obtained at a multi-player equilibrium. This approach, however, requires convexity of each MPEC for KKT condition sufficiency, which was not present.

4.0 TEST APPLICATION

4.1 SETTINGS

The framework was tested on 6-node maritime network representation of ports presented in (Achurra-Gonzalez et al., 2016). Network nodes correspond to four East Asian ports and two clusters of ports at the centroids of Europe and Asia. As depicted in Figure 4, network nodes are connected through five service routes. Port and route capacities, route frequencies, port budgets, o-d demand and handling, rental, depreciation and penalty costs are all listed in Table 3.

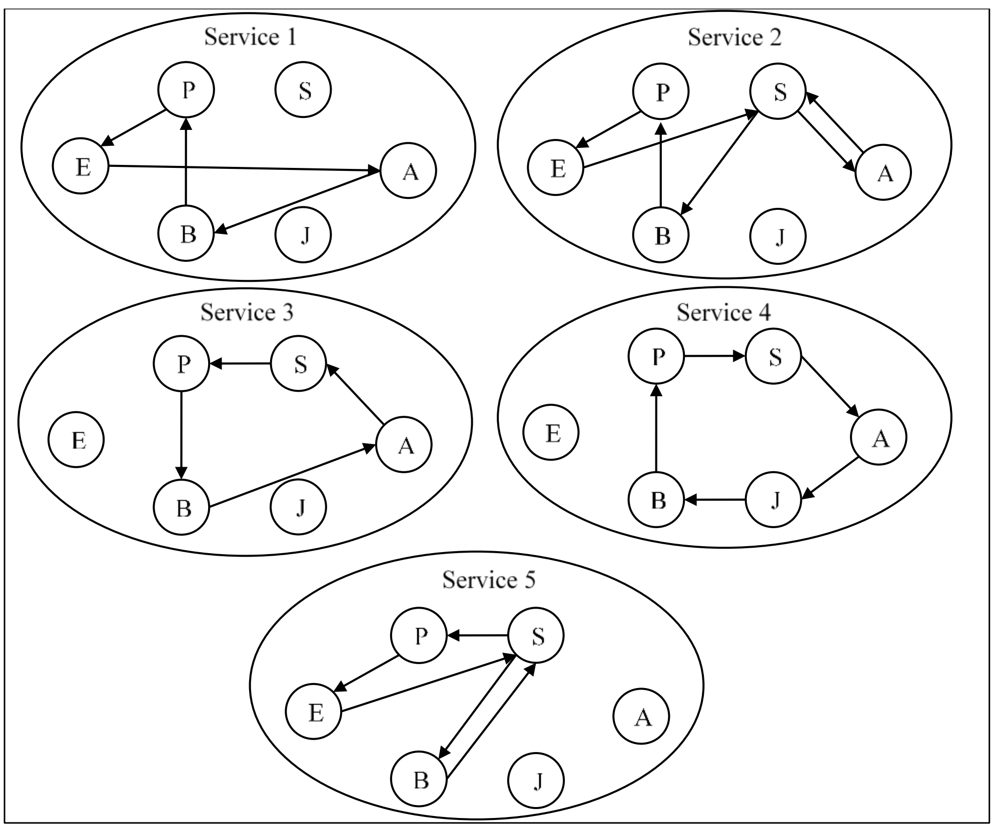

Figure 4 Services between Southeast Asia centroid (A), Singapore (S), Port Klang (P), Jakarta (J), Belawan (B), Europe centroid (E).

Table 3 Model Inputs and Parameters

Port, p	Port capacity, k_p^0(TEU)	Budget (units of capacity)	Service routes, r	Route capacity, RC_r(TEU)
Singapore	14500*	4000	1	8000*
Port Klang	7500*	4000	2	8000*
Jakarta	9000*	1000	3	4000*
Belawan	7500*	1900	4	4000*
Asia	30000*	1000	5	8000*
Europe	30000*	1000		

Origin, o	Destination, d	o-d Demand, TD_{od} (TEU)
Southeast Asia	Europe	18000*
Jakarta	Europe	2000
Singapore	Port Klang	3000
Belawan	Port Klang	2000

Handling, rental and depreciation costs	Unit Cost
Loading and unloading at transshipment port, CHC	\$300/TEU*
Rental and depreciation cost for container, RDC	\$24.5/TEU/day*
Penalty cost for not meeting the demand, PC	\$10,000/TEU*

* Values adopted from Achurra-Gonzalez et al. (2016)

Table 4 Summary of scenarios

ID	Scenario	Capacity Changes	Handling Time Changes
0	Base scenario, pristine conditions	None	None
1	Earthquake simultaneously impacting Jakarta and Belawan ports*	0% port capacity in J and B -17% capacity in Service 1 -16% capacity in Service 2 -70% capacity in Service 3 -56% capacity in Service 4 -18% capacity in Service 5	+300% handling times at Jakarta and Belawan ports
2	Flooding impacting Port Klang	10% port capacity in P -30% capacity in Service 1 -20% capacity in Service 2 -10% capacity in Service 3 -30% capacity in Service 4 -10% capacity in Service 5	+200% handling times at Port Klang

* Scenario adopted from Achurra-Gonzalez et al. (2016)

The impact of an earthquake or storm as described in each considered scenario is reflected through capacity reduction and increased handling times. Reductions in port and/or route capacities affect the number of TEUs that can enter and leave a port in a period of time. Increases in handling times between ports are captured within traversal time increases. These scenarios and their impacts are listed in Table 4.

To fully explore the multi-stakeholder, protective port investment problem, four investment strategies are considered:

4- No investment: With no investment, the problem reduces to a route assignment problem as found in the lower level. This will produce similar results to that obtained by solving the liner-shipping problem in Achurra-Gonzalez et al. (2016) and can provide a check of consistency.

5- Restricted game: Ports are only permitted to make investments in their own facilities. This is achieved by fixing all external investment variables to zero.

6- Unrestricted game: Investments in any or all ports are permitted. Improved reliability in terms of continuance of operations in the face of disruption can be observed when such freedom in investment is granted.

7- Semi-restricted game: Only a portion of the ports in the network are willing to invest in another port. Benefits and disadvantages of investing in others when is it not reciprocated are investigated.

8- System perspective: Optimal investments are sought under a single, centralized budget with the aim of maximizing welfare. Investments are made in the port network such that a maximum demand is met (an extension could address demand elasticity to changes in network or route reliability). Findings from this strategy provide an upper bound on system performance. They also give insights into the differences between centralized (selfless) and more realistic, decentralized (selfish), decision-making.

Port investment decisions with consequent market share, total throughput and shipping costs under each investment strategy and scenario are suggested from model runs. All three types of games (unrestricted, semi-restricted, and restricted) are simultaneous and ultimately produce equilibrium solutions. Such solutions have the property that no port can unilaterally change its investment strategy and improve its market share. It is possible that multiple such equilibria will exist, in which case identifying more than one equilibrium may be useful. Thus, for runs of these three strategies, multiple starting points and a reordering of an investor list used within the code were used in starting the diagonalization technique to increase the likelihood of finding additional equilibria.

4.2 RESULTS

The outcomes of the numerical runs are provided in Table 5. For this example problem, the MPEC has 389 continuous variables, 191 binary variables and 585 constraints. With appropriate M settings, the solution time for each MPEC ranged from a couple of seconds to one minute. The scenario's characteristics do not impact solution times. Thus, solutions were obtained for the p ports over n iterations required to achieve convergence in a few minutes. The number of binary variables will have greatest impact for large problem instances, as for large networks $(2od + a \times d + l + p) \approx (p^2 \times r)$. These results were studied to investigate answers to a number of questions. These questions and findings or observations and the runs from which the findings are obtained are given in Table 6.

Table 5 Numerical Run Outcomes

#	Scenario	Investment Strategies	Network Cost $ millions	o-d Flows TEU 1,000s		Port Throughput TEU 1,000s				Investments			Leg Flows TEU							
													Leg				Leg			
				OD	Flows	Port	Trans	Land-Sea	Total	Internal		External	Start	End	Service	Flow	Start	End	Service	Flow
1	0	No investment	2.372	1	18.0	A	0.0	18.0	18.0	-	-	-	S	P	5	250	B	P	4	2000
				2	2.0	E	0.0	20.0	20.0	-	-	-	A	S	3	750	B	E	5	2000
				3	3.0	P	1.3	5.0	7.5	-	-	-	S	E	5	750	S	P	3	2750
				4	2.0	S	0.8	3.0	4.5	-	-	-	A	P	3	1250	A	E	1	8000
						B	2.0	2.0	6.0	-	-	-	P	E	5	1250	A	E	2	8000
						J	0.0	2.0	2.0	-	-	-	J	B	4	2000				
2	0	Unrestricted	2.306	1	18.0	A	0.0	18.0	18.0	0.0	-	-	A	E	1	8825	B	P	4	2000
				2	2.0	E	0.0	20.0	20.0	0.0	-	-	B	E	1	425	P	E	5	1575
				3	3.0	P	1.6	5.0	8.2	1000.0	-	-	A	E	2	9175				
				4	2.0	S	0.0	3.0	3.0	186.0	-	-	S	P	3	3000				
						B	1.1	2.0	4.2	0.0	-	-	J	B	4	425				
						J	0.0	2.0	2.0	0.0	-	-	J	P	4	1575				
3	1	No investment	1.917	1	16.6	A	0.0	16.6	16.6	-	-	-	A	P	3	170	P	E	5	2250
				2	0.0	E	0.0	16.6	16.6	-	-	-	A	S	3	1030	A	E	1	6640
				3	3.0	P	2.3	3.0	7.5	-	-	-	S	P	3	1030	A	E	2	6720
				4	0.0	S	1.0	3.0	5.1	-	-	-	S	E	5	1030				
						B	0.0	0.0	0.0	-	-	-	S	P	5	1970				
						J	0.0	0.0	0.0	-	-	-	A	P	4	2080				
4	1	Restricted	2.107	1	18.0	A	0.0	18.0	18.0	0.0	-	-	A	E	1	7890	B	P	4	664
				2	0.6	E	0.0	18.6	18.6	0.0	-	-	A	E	2	7942	S	P	5	2113
				3	3.0	P	2.2	3.7	8.2	1000.0	-	-	A	S	3	511	S	E	5	511
				4	0.7	S	0.5	3.0	4.0	0.0	-	-	A	P	3	1657	P	E	5	2243
						B	0.0	0.7	0.7	1000.0	-	-	S	P	3	887				
						J	0.0	0.6	0.6	1000.0	-	-	J	P	4	586				
5-1*	1	Unrestricted	2.315	1	18.0	A	0.0	18.0	18.0	0.0	-	-	A	E	1	7890	B	P	4	664
				2	2.0	E	0.0	20.0	20.0	0.0	J	3170.1	A	E	2	7942	S	P	5	2617
				3	3.0	P	2.2	3.7	8.2	1000.0	-	-	A	S	3	1925	S	E	5	1925
				4	0.7	S	1.9	3.0	6.8	0.0	J	1241.5	A	P	3	243	P	E	5	2243
						B	0.0	0.7	0.7	1000.0	-	-	S	P	3	383				
						J	0.0	2.0	2.0	17.7	-	-	J	P	4	2000				

5-2*	1	Unrestricted	2.315	1	18.0	A	0.0	18.0	18.0	0.0	-	-	A	E	1	7890	B	P	4	664
				2	2.0	E	0.0	20.0	20.0	0.0	J	2284.6	A	E	2	7942	S	P	5	700
				3	3.0	P	2.2	3.7	8.2	1000.0	-	-	A	S	3	1925	S	E	5	1925
				4	0.7	S	1.9	3.0	6.8	0.0	J	1000.0	A	P	3	243	P	E	5	2243
						B	0.0	0.7	0.7	1000.0	-	-	S	P	3	2300				
						J	0.0	2.0	2.0	884.6	-	-	J	P	4	2000				
6	1	Centralized Investment (pooled budget)	2.323	1	18.0	A	0.0	18.0	18.0	0.0			J	S	4	750	S	P	5	3000
				2	2.0	E	0.0	20.0	20.0	0.0			A	S	3	878	A	E	1	8542
				3	3.0	P	1.3	5.0	7.5	0.0			J	P	4	1250	A	E	2	8580
				4	2.0	S	1.6	3.0	6.3	0.0			P	E	5	1250				
						B	0.0	2.0	2.0	3010.7			S	E	5	1628				
						J	0.0	1.3	1.3	3411.2			B	P	4	2000				
7	2	No investment	1.717	1	15.6	A	0.0	15.6	15.6	-	-	-	B	P	4	750				
				2	0.0	E	0.0	15.6	15.6	-	-	-	A	S	3	3600				
				3	0.0	P	0.0	0.8	0.8	-	-	-	S	E	5	3600				
				4	0.8	S	3.6	0.0	7.2	-	-	-	A	E	1	5600				
						B	0.0	0.8	0.8	-	-	-	A	E	2	6400				
						J	0.0	2.0	2.0	-	-	-								
8	2	Restricted	2.241	1	18.0	A	0.0	18.0	18.0	0.0	-	-	A	E	A	7073	B	E	5	2000
				2	2.0	E	0.0	20.0	20.0	1422.5	-	-	A	E	E	7840				
				3	0.0	P	0.0	1.4	1.4	1000.0	-	-	A	S	P	3087				
				4	1.4	S	3.1	0.0	6.2	0.0	-	-	J	B	S	2000				
						B	2.0	1.4	5.4	0.0	-	-	B	P	S	1400				
						J	0.0	2.0	2.0	0.0	-	-	S	E	B	3087				
9-1*	2	Unrestricted	2.271	1	18.0	A	0.0	18.0	18.0	0.0	-	-	A	E	A	7073	B	E	5	2000
				2	2.0	E	0.0	20.0	20.0	0.0	-	-	A	E	E	7840				
				3	0.0	P	0.0	1.9	1.9	1000.0	-	-	A	S	P	3087				
				4	1.9	S	3.1	0.0	6.2	0.0	-	-	J	B	S	2000				
						B	2.0	1.9	5.9	0.0	P	1000.0	B	P	S	1900				
						J	0.0	2.0	2.0	0.0	B	780.3	S	E	B	3087				
9-2*	2	Unrestricted	2.269	1	18.0	A	0.0	18.0	18.0	0.0	-	-	A	E	A	7073	B	E	5	2000
				2	2.0	E	0.0	20.0	20.0	631.1	-	-	A	E	E	7840				
				3	0.0	P	0.0	1.9	1.9	1000.0	-	-	A	S	P	3087				
				4	1.9	S	3.1	0.0	6.2	0.0	-	-	J	B	S	2000				
						B	2.0	1.9	5.9	0.0	P	1000.0	B	P	S	1900				
						J	0.0	2.0	2.0	0.0	-	-	S	E	B	3087				
10	2	Centralized Investment (pooled budget)	2.272	1	18.0	A	0.0	18.0	18.0	0.0			B	E	B	6	A	E	1	9642
				2	2.0	E	0.0	20.0	20.0	0.0			B	E	E	1994				
				3	3.0	P	0.0	5.0	5.0	6538.5			J	B	S	2000				
				4	2.0	S	0.0	3.0	3.0	0.0			B	P	S	2000				

						B	2.0	1.4	5.4	0.0			S	P	P	3000				
						J	0.0	2.0	2.0	0.0			A	E	E	8358				
11	2	Semi-restricted: {E,P,B} restricted; {A,S,J} unrestricted	2.244	1	18.0	A	0.0	18.0	18.0	0.0	-	-	A	E	A	7073	B	E	5	2000
				2	2.0	E	0.0	20.0	20.0	533.1	-	-	A	E	E	7840				
				3	0.0	P	0.0	1.4	1.4	1000.0	-	-	A	S	P	3087				
				4	1.4	S	3.1	0.0	6.2	0.0	-	-	J	B	S	2000				
						B	2.0	1.4	5.4	76.6	-	-	B	P	S	1400				
						J	0.0	2.0	2.0	0.0	B	1000.0	S	E	B	3087				
12	2	Semi-restricted: {A,P,J} restricted; {E,S,B} unrestricted	2.269	1	18.0	A	0.0	18.0	18.0	0.0	-	-	A	E	A	7073	B	E	5	2000
				2	2.0	E	0.0	20.0	20.0	631.1	-	-	A	E	E	7840				
				3	0.0	P	0.0	1.9	1.9	1000.0	-	-	A	S	P	3087				
				4	1.9	S	3.1	0.0	6.2	0.0	-	-	J	B	S	2000				
						B	2.0	1.9	5.9	0.0	P	1000.0	B	P	S	1900				
						J	0.0	2.0	2.0	0.0	-	-	S	E	B	3087				

It is assumed that the shippers will assign sufficient capacity to meet unserved demand in a following week if it cannot be met in the current week, thus no opportunity for increase in throughput is rejected by a port. Moreover, a 4% opportunity cost, cargo depreciation and rental costs are used in calculation of the delay cost. These assumptions are consistent with those made in (Achurra-Gonzalez et al., 2016).

Table 6 Investigation of the Results: Questions and Findings

Multiple Equilibria			
Question	Finding	Changes Observed	Runs Compared
Are multiple equilibria observed?	Yes, for both disaster scenarios two different equilibria are found in an unrestricted game.	-	5-1, 5-2; 9-1, 9-2
Are differences between equilibria noted when two or more equilibria are identified?	Differences are observed in investments; however, leg flows and consequently port throughput/total network cost are identical. Only in Scenario 2 does the total network cost vary while leg flows remain unchanged.	Scenario 1: Not changed: total cost, leg flows and total served demand. Changed: investments	5-1, 5-2

		Scenario 2: Not changed: leg flows and total served demand. Changed: investments, total shipping costs	9-1, 9-2
How are the equilibria solutions different for a specific port that makes external investments? Could one solution be preferred to the other for such a port?	While attracting the same amount of throughput, differences in marginal values of throughput per $ spent may exist. Yes, the equilibrium solution found in 5-2 is preferable for both Ports E and S.	5-1: E: 0.446 TEU/unit of investment S: 1.139 TEU/ unit of investment 5-2: E: 0.619 TEU/ unit of investment S: 1.414 TEU/ unit of investment	5-1; 5-2
Value of Co-opetition: Restricted vs. Unrestricted Games			
Question	Finding	Changes Observed	Runs Compared
Will the ports make external investments when allowed? How are they benefited by those investments?	Yes, results of restricted and unrestricted games show that ports can benefit by making external investments.	E: +1414 E: 0.446 TEU/unit of investment S: +1414 S: 1.139 TEU/ unit of investment	4 5-1
Who benefits from external investments?	The investing port and often the target port benefits from the investment. No other ports were noted to benefit from the investment; however, no ports were disadvantaged by these investments.	Scenario 1: J: +1414 TEUs Scenario 2: P: +500 TEUs	4,5-1, 5-2 8,9-1 9-2
Will external investment increase total served demand?	Yes, total served demand is increased when external investments are allowed.	Scenario 1: Served: +1414 TEUs Scenario 2: Served: +500 TEUs	4,5-1, 5-2 8,9-1 9-2

Does the unrestricted investment strategy decrease total network shipping cost compared to costs incurred with a restricted strategy?*	Yes, for both scenarios the network costs decrease when ports are allowed to make external investments.	Scenario 1: 5-1/5-2 vs. 4: -3.0% Scenario 2: 9-1 vs. 8: -2.4% 9-2 vs. 8: -2.5%	4,5 9-1,8 9-2,8

Gains and Losses in Market Share in Disaster

Question	Finding	Changes Observed	Runs Compared
Does any port benefit from a disaster scenario (without further investment)?	Yes, Port S takes greater market share in the aftermath of Scenario 1. However, it is worth noting that this port loses under Scenario 2.	Scenario 1: S: +280 TEUs Scenario 2: S: -150 TEUs	1,3 1,7
Can internal-only investments harm any port in terms of throughput?	Yes, Port S serves fewer units when under the restricted investment strategy, showing that the other ports, through self-investment, can outcompete Port S for market share.	Scenario 1: S: -519 TEUs Scenario 2: S: -513 TEUs	3,4 7,8

Centralized Decision Making

Question	Finding	Changes Observed	Runs Compared
Does centralizing investments increase total throughput for the port network?	Yes, a centralized approach leads to greater total throughput under either disaster scenarios. The results indicate a reduction in total transshipments, but an increase in land-sea throughput.	Scenario 1: Trans.:-1290 TEUs Land-Sea:+1921 TEUs Total:+632 TEUs Scenario 2: Trans.:-3087 TEUs Land-Sea:+5600 TEUs Total:+2513 TEUs	5-1, 5-2,6 9-1, 9-2,10
Who wins or loses under a centralized investment scheme?	Ports S and J lose under Scenario 1, while Ports S and B lose under Scenario 2. Port B wins under Scenario 1, and Port P wins under both scenarios.	Scenario 1: S :-297 TEUs J: -750 TEUs P: +343 TEUs B: +1336 TEUs Scenario 2: S: -87 TEUs	5,6 9,10

		B: -500 TEUs P: +3100 TEUs	
How significant is the gain to the system of a centralized investment scheme in helping the system to recover from a disaster event?	Considering scenario 1, an increase in total served demand of 12.36% and 5.64% compared with restricted and unrestricted investment approaches, respectively, and 27.29% compared with no investment is noted.	Served: 6 vs. 3: +2749 TEUs 6 vs. 4: +1336 TEUs 6 vs. 5-1,5-2: +5360 TEUs	5,6 9,10
Does a centralized investment scheme reduce total network shipping cost?*	Yes.	Scenario 1: 6 vs. 1: -2.1% 6 vs 5-1,5-2: -10.2% Scenario 2: 10 vs. 1: -4.2% 10 vs. 2: -1.5% 10 vs. 9-1: -21.6% 10 vs. 9-2: -21.6%	 6,1 6,5 10,1 10,2 10,9-1 10,9-2
Benefits of Unreciprocated Investments			
Finding	Changes Observed	Runs Compared	
If some ports do not consider external investment, will other ports still invest in them?	Yes, Port B invests in Port P even when Ports A, P and J do not consider making external investments. However, when Port B restricts itself to an internal investment strategy, Port J stops making external investments in Port B.	No change in Port B external investments J: -780.33 TEUs	12,9-1 11-2, 9-1
Do ports that invest only internally gain or lose?	They can lose, but did not gain. When E, P and B only invest internally, Ports B and P lose market share. When A, P and J only invest internally, no port experiences a change in market share.	P: -400 TEUs B: -400 TEUs E: No change P: No change B: No change E: No change	9,11 9,12

These experiments helped to gain insights into the potential benefits of a co-opetitive approach to global port. The results indicate that while a port may gain throughput when no investments are made under a particular scenario, they are not likely to gain under all scenarios. Moreover, the total market served may be reduced in which case gains may exist in market share, but not necessarily in throughput or revenue. Ports can themselves gain by helping to protect other ports in the global supply chain. Gains can be achieved even when investments are not reciprocated. Facilitating a co-opetitive environment supports greater overall throughput and reduces overall network shipping costs as compared to using similar funds for only internal investments. Benefits are obtained for both ports and shippers alike.

5.0 CONCLUSIONS AND DISCUSSION

This paper develops a formulation and solution technique for a co-opetitive, protective investment problem arising in a maritime port network that serves a common liner shipping market. This work adds to the rich body of literature in port and maritime resiliency by conceptualizing multi-port investments and liner-shipping network response as a multi-leader, common-follower game. As compared to non-cooperative approaches, in the presence of a disaster event, the proposed co-opetitive approach was found to lead to increased served total demand, significantly increased market share for many ports and improved services for shippers, thus creating greater system-wide resiliency. As in any competitive environment, there are winners and losers. This work shows that it is often beneficial to an individual port in terms of market share to invest in another part of the maritime port network. This modeling framework allows for: the simultaneous consideration of market interactions; disaster and investment impacts; inter-port, service-level dependencies; cooperation; and competition. This structure helps in providing a more realistic assessment compared to traditional centralized or independent formulation schemes, and enables quantification of benefits of varying co-opetitive approaches and effectiveness of chosen investments. It quantifies the losses due to myopic intra-port (as opposed to inter-port) investments. A stochastic extension of the proposed EPEC aimed at identifying investment strategies that simultaneously hedge against multiple potential hazard scenarios is the subject of ongoing work by the authors.

As is common in equilibria modeling, more than one equilibrium may exist. These solutions may not be equivalent or may better serve one stake-holder over another. An objective function can be added to the EPEC formulation to guide the formulation toward a solution that best serves that objective. Alternatively, multiple equilibria can be sought through multi-start techniques as implemented herein to produce a set of equilibria solutions if more than one equilibrium exists and a best compromise solution much like in multi-objective decision-making can be chosen.

The ports serve not only the liner shipping market, but local, regional and national businesses and manufacturers who depend on both the raw or processed materials they supply as well as the transport of finished goods to retailers across the world. Port reliability also concerns end-customers who are affected by increases in the price of goods.

Solution of the EPEC formulation involved several computational challenges. Inconsistencies between solutions of the equivalent KKT conditions of the common liner shipping problem were sometimes noted. Use of very small integrality gaps in solution of the MPEC MIPs was required to ensure numerical stability and consistency across players. The solution technique was found to be sensitive to the setting of M. This setting affected both the ability to obtain a solution and the speed at which a solution was found. M is introduced through linearization of the complementarity constraints associated with the KKT conditions of the lower-level problem through a disjunctive constraints approach. An alternative method might be to apply Schur's decomposition (Horn & Johnson 1985) using Special Ordered Sets of Type 1 (SOS1) variables (Siddiqui & Gabriel 2013).

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