University of Memphis
University of Memphis Digital Commons

Electronic Theses and Dissertations

2021

Applications of Game Theory for Co-opetition at Marine Container Terminals

Karlis Pujats

Follow this and additional works at: https://digitalcommons.memphis.edu/etd

Recommended Citation
Pujats, Karlis, "Applications of Game Theory for Co-opetition at Marine Container Terminals" (2021). *Electronic Theses and Dissertations*. 2721.
https://digitalcommons.memphis.edu/etd/2721

This Dissertation is brought to you for free and open access by University of Memphis Digital Commons. It has been accepted for inclusion in Electronic Theses and Dissertations by an authorized administrator of University of Memphis Digital Commons. For more information, please contact khggerty@memphis.edu.

APPLICATIONS OF GAME THEORY FOR CO-OPETITION AT MARINE CONTAINER TERMINALS

by

Karlis Pujats

A Dissertation

Submitted in Partial Fulfillment of the

Requirements for the Degree of

Doctor of Philosophy

Major: Civil Engineering

The University of Memphis

May 2021

Acknowledgments

I would like to acknowledge and thank my advisor, Dr. Mihalis Golias, for his assistance, support, and guidance through the process of completing dissertation. I would also like to thank my thesis committee members (in alphabetical order): Profs. Carmen Astorne-Figari, Charles Camp, Dincer Konur, and Sabyasachee Mishra, for their help and guidance in the process of completing my dissertation.

Preface

This dissertation is submitted for the degree of Doctor of Philosophy at the University of Memphis. The research presented herein was conducted under the supervision of Dr. Mihalis Golias, Department of Civil Engineering, the University of Memphis.

Following published or submitted to be published articles have been and used as chapters in this manuscript:

Chapter 2: Pujats, K., M. Golias, and D. Konur. A Review of Game Theory Applications for Seaport Cooperation and Competition. Journal of Marine Science and Engineering, Vol. 8, No. 2, 2020, p. 100. https://doi.org/10.3390/jmse8020100.

Chapter 3: Pujats, K., M. M. Golias, and S. Mishra. Marine Container Terminal Cooperation: A Nash Bargaining Approach. Proceedings of the 97th Annual Meeting of the Transportation Research Board, Washington, DC, 2018.

Chapter 4: Pujats, K., M. Golias, and D. Konur. Marine Container Terminal Cooperation Optimization: A Volume to Vessel Formulations Comparison. Maritime Policy & Management, Vol. (Under Review).

Chapter 5: Pujats, K., M. Golias, and S. Mishra. A Mathematical Framework for Container and Liner Shipping Companies Cooperation and Competition. Proceedings of the Material Handling, Constructions and Logistics, Bar, Montenegro, 2019.

Abstract

In recent years, the maritime shipping industry has endured overcapacity, volatile freight rates, and rising debts, resulting in the creation of large shipping alliances and increased vessel sizes. These changes have increased shipping alliance negotiating power over ports and pressure for more favorable conditions and improved services. Constrained by capacity expansion limitations (e.g., lack of land, high cost of expansion, etc.) while trying to accommodate the growing demand, have brought attention to the importance of planning and operations optimization to increase productivity and profits. In this dissertation, we present the developed game theory models that could assist the maritime container terminal operators and port authorities in their decision-making on the seaport and marine container terminal cooperation and competition. In total, four cooperation game theory models are presented with cooperation policies modeled using the Nash Bargaining Solution, total profit maximization, total minimum profit maximization, the difference of minimum profit maximization, and Shapley Value. Results indicate that the Nash Bargaining Solution and total profit maximization policies outperform the total minimum profit maximization and the difference of minimum profit maximization when a combined uniformity of profit share among the cooperating terminals and size are considered. The Nash Bargaining Solution has a slight edge over the total profit maximization policy as it provides better profits increase for the terminal with the higher V/C ratio and better uniformity. Two mathematical formulations were developed for capacity sharing one based on volume (i.e., demand is measured in TEUs) and one based on vessel (i.e., demand is measured in TEUs per vessel). Results indicate that planning level models provide significant difference to tactical/operational level models with regards to demand diversion between the terminals and overestimation of profits.

Table of Contents

List of Tables

List of Figures

1. Introduction

Maritime transportation is a vital piece of global trade, with approximately 80% of commerce by volume and 70% by value is transported by sea and processed at ports worldwide (*1*). In the past years, the shipping industry has encountered many problems, including overcapacity, volatile freight rates, and rising debts. Under these economic conditions, shipping lines alone cannot provide the same service as before. By entering into alliances, shipping lines could share their resources, which would result in cost reductions and extended service coverage. Because of the shipping alliance size and the volumes they control, they have increased their negotiating power over ports and pressure for more favorable conditions and improved services (*2*). In addition to the creation of the giant shipping alliances, vessel size has continuously been increasing in most of the trade routes, with Drewry Maritime Research (*3*) estimating that 52% of the aggregated capacity of all containership deliveries by 2020 will belong to the class of ultra-large container vessels (i.e., capacity over 18,000 Twenty Foot Equivalent Unit or TEU). The introduction of mega vessels has helped liner shipping companies reduce operating costs by better allocating their resources (high-capacity utilization) and being more fuel-efficient (mainly because of vessel design, optimized engines, and slow steaming), thus reducing shipping costs; although, it has been difficult to capture the theoretical economies of scale that was (partially) the reason behind the trend of mega-vessels. Some research has also indicated cascading effects and diseconomies of scale when port times exceed a certain limit. A study by Guan et al. (*4*) concluded that a one percent increase in vessel size would increase the port time by 2.9%.

Constrained by capacity expansion limitations (e.g., lack of land, high cost of expansion, etc.) while trying to accommodate the growing demand, marine container terminal operators and port authorities have brought attention to the importance of planning and operations optimization to increase productivity and profits. Game theory has given the ability to examine the effects of critical port management decisions such as investments (*5–10*) and pricing policies (*8–21*) under situations when service level differentiation (*11–14*, *18*, *22*, *23*), port ownership (*15*, *19*, *20*), and port regulations (*18*, *24*) are considered. The game theory further enables the analysis of the various competition and cooperation dynamics between port authorities and terminals, amongst terminals within a port, and between ports and shipping lines.

In this dissertation, we seek to present the developed game theory models that would allow Port Authority and Marine Container Terminal Operators (MCTOs) to make effective decisions on the seaport and marine container terminal cooperation and competition. We begin the paper by presenting a review of game theory applications for seaport cooperation and competition published by Pujats et al. (*25*) (Chapter 1). Chapter 3 presents an application of the Nash Bargaining Solution (NBS) to model marine container terminal cooperation with comparison to three other cooperation policies (maximize minimum profit, maximize the minimum difference in profit, and total profit) published by Pujats et al. (*26*). This chapter also introduces the volume to vessel formulation comparison, where the volume formulation can be applied for the planning and the vessel formulation for the tactical/operational level. Chapter 4 expands the volume to vessel formulation comparison and compares it to two cooperation policies based on total and the other one based on minimum profit maximization. Furthermore, this chapter introduces a formulation that considers additional costs for transshipment containers that will have to be moved between terminals or have to be loaded on specific vessels at the port of origin. The article by Pujats et al. (*27*) used for this chapter is currently under review. Chapter 5 presents a mathematical framework for container terminal and liner shipping companies cooperation and competition, where Pujats et al. (*28*) attempted to expand the previously developed game theory models by adding additional stakeholders (a liner shipping companies that are engaged in coalition). Chapter 6 expands on previous container terminal cooperation models' works by presenting a mathematical framework of container terminal cooperation using the Core, Shapley value, and Coalition Structure. This chapter attempts to overcome the previous model limitation, such as finding sub coalitions when players would prefer not to be in the grand coalition, and furthermore provides a fair way to distribute profit generated by the coalition among all players in that coalition. Finally, Chapter 7 concludes the paper and presents future research.

2. A Review of Game Theory Applications for Seaport Cooperation and Competition

Introduction

Maritime transportation is a vital piece of global trade, with approximately 80% of commerce by volume, and 70% by value is transported by sea and processed at ports worldwide (*1*). Liner shipping is the most cost-efficient (and in some instances, the only) way to transfer goods over long distances. Containerships, especially, have large capacities and can carry a large amount of goods worth several large warehouses in a single voyage (*29*). In accordance with the data presented by the United Nations Conference on Trade and Development (*1*), the global seaborne trade came to 11 billion tons in 2018, where minor bulk experienced the fastest growth from 2017 with 3.7% increase in tonnage, followed by the containerized market with 2.6% rise in tonnage, and major bulk increased 1.9% in tonnage. In the past years, the shipping industry has encountered a number of problems including overcapacity, volatile freight rates, and rising debts. Under these economic conditions, shipping lines alone cannot provide the same service as before. By entering into alliances, shipping lines could share their resources, which would result in cost reductions and extended service coverage. As of June 2019, three major alliances (2M, Ocean Alliance, and THE Alliance) collectively accounted for 78% of the global container market (*30*). Because of the shipping alliance size and the volumes they control, they have increased their negotiating power over ports and, thus, can pressure for more favorable conditions and improved services (*2*). In addition to the creation of the giant shipping alliances, vessel size has continuously been increasing in most of the trade routes, with Drewry Maritime

Research (*3*) estimating that 52% of the aggregated capacity of all containership deliveries by 2020 will belong to the class of ultra-large container vessels (i.e., capacity over 18,000 Twenty Foot Equivalent Unit or TEU). The introduction of mega vessels has helped liner shipping companies reduce operating costs by better allocating their resources (high-capacity utilization) and being more fuel-efficient (mainly because of vessel design, optimized engines, and slow steaming), thus reducing shipping costs; although, it has been difficult to capture the theoretical economies of scale that was (partially) the reason behind the trend of mega-vessels. Some research has also indicated cascading effects and diseconomies of scale when port times exceed a certain limit. A study by Guan et al. (*4*) concluded that a one percent increase in vessel size would increase the port time by 2.9%. Constrained by capacity expansion limitations (e.g., lack of land, high cost of expansion, etc.) while trying to accommodate the growing demand, marine container terminal operators and port authorities have brought attention to the importance of planning and operations optimization to increase productivity and profits. Game theory has given the ability to examine the effects of critical port management decisions such as investments (*5–10*) and pricing policies (*8–21*) under situations when service level differentiation (*11–14*, *18*, *22*, *23*), port ownership (*15*, *19*, *20*), and port regulations (*18*, *24*) are considered. Game theory further enables the analysis of various competition and cooperation dynamics between port authorities and terminals, amongst terminals within a port, and between ports and shipping lines. In this study, we seek to present a review of recent game theory applications for seaport and marine container terminal cooperation and competition and suggest possible future research directions.

The remainder of the paper is structured as follows. Next subsection presents a review of recent game theory approaches used to model seaport and container terminal cooperation/competition and co-opetition.

Game Theory Approaches

Port and Container Terminal Cooperation/Competition and Co-Opetition

In this subsection, we review the literature on game theory approaches, factors, and conditions that affect seaports, marine container terminals, and the competition and cooperation dynamics between them. These studies are summarized in Table 1.

Factors and conditions affecting ports, which serve partially overlapping hinterlands, were investigated by Wang et al. (*11*) using a Cournot competition model and a joint profit maximization approach. The game theory model developed by the authors accounted for the institutional and political constraints (e.g., port ownership and management; types of contracting, leasing, and concessions; private profit vs. public welfare) often encountered by ports. Results by Wang et al. (*11*) suggest that alliance formation is highly dependent on the institutional and political factors such as mergers, cross-shareholding, and transfer payments and their authorization to conduct usual business practices. When institutional and political factors prohibit usual business practices, that would otherwise allow allocating the benefits of cooperation properly amongst the partners. Alliance between ports will be established only when there is a balance between increasing prices and switching some of the throughputs from high-cost ports to low-cost ones. Competition and cooperation between three leading transshipment ports situated in Malaysia (Port Klang or PKL, Port of Tanjung Pelepas or PTP) and Singapore (Port of Singapore or PSA) were investigated by Ignatius et al. (*31*), where the authors applied Cournot competition and collusion. Results suggested the creation of a strategic alliance between PSA and PTP, where both the current hub and spoke network would gain more profit, while PKL should not engage in any cooperative strategies with any of the other ports. Similarly, Wang and Sun (*12*) investigated competition and cooperation between ports in the port group based on geographical location. Additionally, the service level and shipping distance were investigated using the Hotelling game model. When the service levels of port enterprises are the same, a cooperative strategy can significantly improve the level of the port group's cumulative profit. When the service levels of the port enterprises are different, the port's service price, market share, and profit are affected by the service level before and after the cooperation, the service level of the port enterprise shows a trend of mutual promotion, and the port group develops into a higher service level. The price strategy of ports serving partially overlapping hinterlands was investigated by Zhou (*13*), where the author used a modified Hotelling model and simulation to analyze the price strategy for three ports from competition and cooperation perspectives. Research results revealed that, when the service levels were the same, the critical factor for competitive ports was location, while service level was the critical factor for the creation of a port alliance. Four types of two-stage games between public/private port authorities were modeled by Ciu and Notteboom (*14*). The authors examined the effects of public/private port authority-oriented objectives and how the level of service changed with differential capacity, service price, profits, and welfare when considering competing or cooperating ports. Results concluded that, under Cournot competition, the formation of an alliance could be successful only when the partial public port authority (PA) agrees to transfer certain profits to the private PA. Under all other types of competitions, the highly private-oriented PA will have the highest willingness to cooperate with the private PA, while under similar conditions, the highly public-oriented PA will have the lowest willingness to cooperate with the private PA.

Different combinations of coalitions between terminals at a single port were investigated by Saeed and Larsen (*32*). The authors applied a two-stage Bertrand game between three container terminals situated in Karachi Port in Pakistan. Grand coalition was found to result in the best payoff, while the terminal at a second port that did not join the coalition earned a better payoff. When discriminatory fees were considered, the overall profit of terminals in Karachi was found to be lower, while users gained most when the nondiscriminatory percentage fees were considered. Competition and coalition between terminals at two ports were investigated by Park and Suh et al. (*15*), where the authors applied competition as a Bertrand game and cooperation as a terminal alliance on four container terminals located in North Port and two terminals in a new port of Busan, Republic of Korea. The goal of the investigation was to find the equilibrium price and profit between competitive container terminals. Terminal cooperation was also investigated by Pujats et al. (*26*), where the authors evaluated and compared four different cooperation policies, with terminals sharing available demand and capacity. The authors also proposed two model formulations, one based on volume and one based on vessels (where the demand shared is measured as the number of TEUs per vessel). Authors concluded that the commonly used volume-based sharing approach could significantly overestimate total profits while underestimating profits of terminals with higher volume-to-capacity ratios.

Table 1 Summary of Port and Container Terminal Cooperation/Competition and Co-opetition

Study	Technique	Methodology	Objective	Results
Wang et al., 2012 (*11*)	Cournot competition/ Joint profit maximization	Ports with differentiated services decide to compete or form an alliance.	Investigate the elements that have an effect on alliance formation for ports in South China with partially overlapping hinterlands.	When institutional and political factors prohibit usual business practices, the alliance will be formed only when there is a balance between increasing prices and switching some of the throughputs from high-cost ports to low-cost ones.
Ignatius et al., 2018 (*31*)	Cournot competition Collusion	Transshipment ports in a proximate region decide to compete or cooperate.	Investigate whether an alliance between three leading transshipment ports situated in Malaysia (Port Klang, Port of Tanjung Pelepas) and Singapore (Port of Singapore) should be formed.	A strategic alliance between Port of Singapore and Port of Tanjung Pelepas would result in greater profit for both the current hub and spoke network. Port Klang should not engage in any cooperative strategies with any of the other ports.
Wang and Sun, 2017 (*12*)	Hotelling model	Port enterprises maximize their profit at the same service level or at a different service level.	Analyze the competition and cooperation among ports based on geographical location, service level, and shipping distance.	When the service levels are the same, a cooperative strategy can significantly improve the level of the port group's profit.
Zhou, 2015 (*13*)	Hotelling model Nash equilibrium	Ports decide on setting prices under cooperation and competition conditions.	Analyze the price strategy for competition and cooperation among ports serving partially overlapping hinterland.	When the service levels are the same, the critical factor for competitive ports is location, while service levels are the critical factor for port alliance formation.
Ciu and Notteboom, 2018 (*14*)	Cournot competition Bertrand competition Quantity–Price game Price–Quantity game	Two-stage game where: Port makes quantity or pricing decisions. Ports decide to cooperate or compete.	Investigate the effects of competition and cooperation on public/private Port Authorities (PA) objectives when the level of service changes with differential capacity, service price, profits, and welfare.	Under Cournot competition, an alliance will be formed only when the partial public PA will agree to transfer certain profits to the private PA. Under all other types of competitions, the highly private-oriented PA will have the highest willingness to cooperate with the private PA.

Table 1 Summary of Port and Container Terminal Cooperation/Competition and Co-opetition (Continued)

Study	Technique	Methodology	Objective	Results
Saeed and Larsen, 2010 (*32*)	Bertrand competition Bertrand–Nash equilibrium	Two-stage game where: Terminals decide to compete or form a coalition. Terminals in coalition play cooperatively, otherwise non-cooperative Nash game	Analyze different combinations of coalitions among three container terminals situated in Karachi Port in Pakistan.	Grand coalition was found to result in the best payoff, while the terminal at a second port that did not join the coalition earned a better payoff. When discriminatory fees were considered, the overall profit of terminals in Karachi was found to be lower, while users gained most when the nondiscriminatory percentage fees were considered.
Park and Suh et al., 2015 (*15*)	Bertrand competition Maximize Total Joint Profit Nash equilibrium	Terminals make pricing decisions under cooperation or competition.	Find the equilibrium price and profit between four container terminals in Busan, the Republic of Korea, in a competitive and cooperative relation.	In a situation when one container terminal will increase price, all other terminals will keep the current price, when one terminal reduces the price, all other terminals will follow.
Pujats et al., 2018 (*26*)	Nash Bargaining Solution Maximize total profits Maximin profit cooperation Maximin profit increase cooperation	For the volume-based formulation, each terminal decides whether to cooperate by receiving or providing the demand. For the vessel-based formulation, each terminal decides on which vessels are served.	Evaluate and compare four different cooperation policies for sharing capacity and compare volume to vessel-based formulations.	The Nash Bargaining Solution and maximization of total profits policies outperform the maximization of minimum profit among all terminals, and maximization of minimum profit increases among all terminals when a combined uniformity of profit is shared among the cooperating terminals and size is considered.

Port and Container Terminal Competition

In this subsection, we present a review of the literature on game theory approaches that model only seaport, marine container terminal competition. These studies are summarized in Table 2.

Effects of service level differentiation in inter- and intra-port competition, in which two ports compete for cargo transshipment, were examined by Van Reeven (*33*). The game was constructed using the Hotelling and Cournot models. The results showed that the highest profits were achieved between vertically separated ports. Furthermore, the vertically separated Landlord Port competition resulted in a Nash equilibrium. A vertically integrated port organization system yields lower profits. Effects of transition from a multiuser terminal to a fully dedicated terminal on inter- and intra-port competition between the multiuser terminals were examined by Kaselimi et al. (*16*). The authors used a two-stage game where, at the first level, a Cournot competition was used to model terminal competition, with terminal capacity as the decision variable, while at the second stage, a Hotelling model was used to determine the Nash equilibrium prices (port dues and terminal service fees). The authors concluded that the introduction of dedicated terminals resulted in less profit for the port authorities and also for the users of multiuser terminals, while multiuser terminals were unaffected by the introduction of dedicated terminals. Terminal concession awarding in inter- and the intra-port competition was studied by Yip et al. (*34*) using a two-stage model, where at the first stage, ports made terminal award decisions, and at the second stage, terminals engaged in Cournot competition.

Model results suggested that terminal operators preferred to govern more terminals in the region. Port authorities with considerable market dominance prefer to introduce inter- and intra-port competition.

Instead of product differentiation, Zhuang et al. (*22*) investigated service differentiation for ports that managed containerized cargo and dry-bulk cargo, where two non-cooperative games (Stackelberg and Nash) were used to model competition between the ports. Results highlighted the importance of proper coordination, as ports may decide on the same infrastructure investments despite that the demand may not be sufficient. The government should intervene in the port specialization process, as it may lead to over-investment and excessive competition. Leading ports benefit from making first moves that result in greater profit and larger traffic volume.

Strategic interaction by setting prices between ports in their networks was empirically analyzed by Nguyen et al. (*17*). By considering berth and channel dues, a two-stage game was applied to three Australian regions, namely Queensland, South Australia and Victoria, and Western Australia, where, at the first stage, ports estimated price response functions, and at the second stage, ports identified links in the port network and analyze strategic interactions. The authors concluded that not all ports set prices through strategic interaction between other ports; some set prices independent of each other. Moreover, the pricing strategy of competing ports may differ from each other. Port capacity investment decisions between the ports of Busan, South Korea, and Shanghai, China, were examined by Anderson et al. (*5*) using Bertrand competition. The authors suggested that investments should not be undertaken throughout East Asia. In addition, governments should be aware of any current or future competitor developments that may have a chance to gain a greater share of the market. Port capacity expansion was also examined by Do et al. (*6*), where the authors modeled competition between Hong Kong and Shenzhen Ports and investigated the decision-making process in capacity expansion investments using uncertain demand and payoff. Shenzhen was found to be the dominant port in a long-term strategy. Strategic port pricing at the time when ports make capacity investment decisions were examined by Ishii et al. (*7*). The inter-port competition between two ports was modeled using the Cournot model. Results indicated setting lower prices when both the demand elasticity and port capacity development activities are high. The actual decision on setting the price of the government was made contrary to the theory. Port capacity investment decisions were also studied by Luo et al. (*8*), where the authors applied a two-stage game to study container port competition between the port of Hong Kong and Shenzhen, where, at the upper-level, ports decide on capacity investment, and at the lower level, they play the Bertrand game. The authors concluded that both ports would expand with the increasing market demand, although the new port with a smaller capacity will be more likely to expand owing to the lower investment costs and higher price sensitivity. In a market situation, when demand is increasing and the new port has higher competitive power, the pricing and capacity expansion, without any nonmarket protective measures, might not be sufficient to suppress the growth of the new port

Table 2 Summary of Port and Container Terminal Competition

Study	Technique	Methodology	Objective	Results
Van Reeven, 2010 (*33*)	Hotelling model Cournot competition	Two-stage game where: Port authorities decide whether to integrate vertically or to separate vertically. All players simultaneously make their final choices.	Analyze the effects of service level differentiation in inter- and intraport competition, in which two ports compete for cargo transshipment.	The highest profits were achieved between vertically separated ports. Furthermore, the vertically separated Landlord Port competition results in a Nash equilibrium. A vertically integrated port organization system yields to lower profits.
Kaselimi et al., 2011 (*16*)	Cournot competition Hotelling model	Two-stage game where Terminal operators compete for quantities by taking consideration of their capacity. Terminals compete in both prices and throughput.	Examine the effects of the transition from a multiuser terminal to a fully dedicated terminal on inter- and intraport competition between the multiuser terminals.	The introduction of dedicated terminals will result in less profit to the port authorities and also to the users of multiuser terminals, while multiuser terminals were unaffected by the introduction of dedicated terminals.
Yip et al., 2014 (*34*)	Cournot competition Nash equilibrium	Two-stage game where: Ports make terminal award decisions. Terminals set port charges competing in quantity.	Examine inter- and the intraport competition on terminal concession awarding.	Terminal operators prefer to govern more terminals in the region. Port authorities with considerable market dominance prefer to introduce inter- and intraport competition.
Zhuang et al., 2014 (*22*)	Stackelberg game Nash equilibrium	Two-stage game where: The leader port decides output volumes for both container and bulk cargo operations. The follower port decides output volumes in container and bulk cargo operations.	Investigate service differentiation for ports that manage containerized cargo and dry-bulk cargo.	Port infrastructure investments should be coordinated adequately with other port infrastructure investments and potential demand. Government intervention may be required, as it may lead to over-investment and excessive competition. Leading ports benefit from making first moves that result in greater profit and larger traffic volume.

Table 2 Summary of Port and Container Terminal Competition (Continued)

Study	Technique	Methodology	Objective	Results
Ishii et al., 2013 (*7*)	A two-person game model with stochastic demand Nash equilibrium	Ports make pricing decisions in the time of capacity investment.	Analyze strategic port pricing in a setting of interport competition and at the time when ports make capacity investment decisions.	When both the demand elasticity and port capacity development activities are high, prices should be set low. The actual decision on setting the price made by the government was made contrary to the theory.
Nguyen et al., 2015 (*17*)	Price leadership Nash equilibrium	Two-stage game where: Ports make pricing decisions to maximize profit. Identification of network links between ports in the network and strategic interaction.	Identify the effects of strategic pricing on ports in their networks in three Australian regions, namely Queensland, South Australia and Victoria, and Western Australia.	Not all ports set prices through strategic interaction between other ports; some set prices independent of each other. Moreover, the pricing strategy of competing ports may differ from each other.
Anderson et al., 2008 (*5*)	Bertrand competition	Each port makes an investment decision by increasing its capacity.	Examine port capacity investment decisions between ports of Busan, Korea, and Shanghai, China.	Investments should not be undertaken throughout East Asia. In addition, governments should be aware of any current or future competitor developments that may have a chance to gain a greater share of the market.
Do et al., 2015 (*6*)	A two-person game model with uncertain demand and payoff Nash equilibrium	Ports decide to invest under consideration that demand is uncertain, or payoff is uncertain.	Examine port capacity investment decisions between ports of Hong Kong and Shenzhen.	Shenzhen was found to be the dominant port in a long-term strategy. Hong Kong should make capacity investments only when Shenzhen does.
Luo et al., 2012 (*8*)	Bertrand competition Nash equilibrium	Two-stage game where: Ports make capacity investment decisions. Ports make pricing decisions.	Examine port capacity investment decisions between ports of Hong Kong and Shenzhen, when the market demand increases and differential service levels.	Both ports would expand with the increasing market demand, although the new port with a smaller capacity will be more likely to expand owing to the lower investment costs and higher price sensitivity.

Government and Container Terminal Competition

This subsection of the paper discusses the reviewed literature on game theory approaches used to model government, port, and marine container terminal competition and cooperation. These studies are summarized in Table 3.

Port regulation modes were examined by Zheng and Negenborn (*24*), where the authors compared the centralization mode and the decentralization mode by modeling a Stackelberg game between the government, ports, and customers. Specifically, the authors investigated how port regulation mode affected optimal tariffs, port capacities, and port efficiency levels. Under the decentralization mode, the tariff, port efficiency level, port service demand, and social welfare were found to be higher. The effects of port regulation mode on port capacity and profit were inconclusive. Port regulation under centralized and decentralized modes was also studied by Yu et al. (*18*). Competition between ports, where the government of ports makes cargo fee decisions and terminals make service quality and price decisions, was modeled using a two-stage Hotelling game. Results indicated government preference towards competitive terminals. Terminals with lower service quality will gain higher profit under a centralized mode compared to the competition instance

Port ownership, and in particular port privatization, was investigated by Czerny et al. (*19*). The authors used a two-stage Hotelling game to model competition between two transshipment ports located in two different countries. At the first stage, ports simultaneously decided whether to privatize or maximize social welfare, and at the second stage, ports made pricing decisions. Results suggest both ports will be privatized in a setting when the transshipment market is significant. Private ports would set higher port charges, and reduction in operational costs will result in higher port charges.

The effects of government-introduced emission tax charges on vessel and port operations were investigated by Cui and Notteboom (*20*), where a private port and Landlord ports either compete using Cournot or Bertrand game, or cooperate with differentiated services. The authors suggested more rigorous environmental protection reinforcements in the case of port cooperation than in port competition. In the case of port cooperation, revenue from the total emission taxes always resulted in greater value than the overall damage to the environment.

Pricing and investment decisions between competing ports with hinterland congestion were studied by De Borger et al. (*9*). The authors investigated how port pricing decisions affected optimal investment policies, and how congestion toll decisions on the hinterland network affected hinterland capacities. Competition between ports was modeled as a two-stage game, where at the first stage, governments played a Cournot type of game by making port and hinterland investment decisions while considering the pricing behavior of ports. At the second stage, ports engaged in a Bertrand game by determining port prices while considering the potential congestion at the port and the hinterland transport network. The authors concluded that capacity investment would result in reduced prices and congestion at each port, but it would increase congestion in the hinterlands. Hinterland investment will likely result in increased prices and congestion at the port, which at the same time will lead to reduced prices and congestion at the competing port. The introduction of congestion tolls will increase both port and capacity investments. Hinterland congestion and seaport competition were further studied by Wan and Zhang (*35*). Similarly to De Borger et al. (*9*), the authors examined pricing and investment decisions between competing ports with hinterland congestion using a two-stage game, where local governments make port and hinterland capacity investment decisions, and ports make congestion toll decisions on the hinterland network. Unlike De Borger et al. (*9*), Wan and Zhang (*35*) studied road tools in a more detailed manner by looking at both fixed-ratio and discriminative tolls. Also, instead of assuming price competition between ports, Wan and Zhang (*35*) used quantity competition. Results suggested that the increase in port hinterland road capacity or tolls may lead to increased ports profits, while at the same time, by tolling above the marginal external congestion costs, the competing port will lose profit. When the discriminative toll system is introduced, commuters will be tolled at the marginal cost, while trucks will be tolled even lower than that price.

Table 3 Summary of Government and Container Terminal Competition

Study	Technique	Methodology	Objective	Results
Zheng and Negenborn, 2014 (*24*)	Stackelberg game	Three-stage game where: Governments make capacity decisions for both private and public terminals. Governments and the private terminal operator engage in a simultaneous duopoly game. Consumers decide between the public and private terminals.	Analyze the effects of port regulation modes on optimal tariffs, capacities, and port efficiency levels for both public and private terminals.	Under the decentralization mode, the tariff, port efficiency level, port service demand, and social welfare were found to be higher. The effects of port regulation mode on port capacity and profit were inconclusive.
Yu et al., 2016 (*18*)	Hotelling model Nash equilibrium	Two-stage game where: Port governments make cargo fee decisions. Terminal operators make service quality and service price decisions.	Analyze the effects of port regulation modes on competing ports, when the government of ports makes cargo fee decisions and terminals make service quality and price decisions.	Governments prefer terminals to compete under the decentralized model. Terminals with lower service quality will gain higher profit under a centralized mode compared to the competition instance.
Czerny et al., 2014 (*19*)	Hotelling model	Two-stage game where: Governments decide to privatize or not. Ports make pricing decisions.	Investigate the effects of port privatization on competition between two transshipment ports located in two different countries.	Both ports will be privatized in a setting when the transshipment market is significant. Private ports would set higher port charges, and reduction in operational costs will result in higher port charges.
Cui and Notteboom, 2017 (*20*)	Cournot competition Bertrand competition Nash equilibrium	Two-stage game where: Governments make decisions on emission control tax and whether to privatize the port. Ports make quantity/price decisions in competition or cooperation settings.	Analyze the effects of government-introduced emission tax charges on vessel and port operations in a setting of private and Landlord port competition and cooperation.	In the case of port cooperation, more rigorous environmental protection should be reinforced, compared to the port competition. In the case of port cooperation, revenue from the total emission taxes will always result in greater value than the overall damage to the environment.

Table 3 Summary of Government and Container Terminal Competition (Continued)

Study	Technique	Methodology	Objective	Results
De Borger et al., 2008 (*9*)	Cournot type competition Bertrand competition	Two-stage game where: Governments make decisions on port capacity, hinterland capacity, and road tolls. Ports make pricing decisions.	Investigate the effects of port pricing decisions on optimal investment policies and congestion toll decisions on the hinterland network capacities between competing ports with hinterland congestion.	The capacity investment would result in reduced prices and congestion at each port, but it will increase congestion at hinterland. Hinterland investment will likely result in increased prices and congestion at the port, which at the same time will lead to reduced prices and congestion at the competing port. The introduction of congestion tolls will increase both port and capacity investments.
Wan and Zhang, 2013 (*35*)	Cournot competition Cournot equilibrium	Two-stage game where: Governments make decisions on port capacity, hinterland capacity, and road tolls. Ports make pricing decisions while competing in quantity.	Investigate the effects of port pricing decisions on optimal investment policies and congestion toll (both fixed-ratio and discriminative) decisions on the hinterland network capacities between competing ports with hinterland congestion.	An increase in port hinterland road capacity or tolls may lead to increased ports profits, while at the same time, by tolling above the marginal external congestion costs, the competing port will lose profit. When the discriminative toll system is introduced, commuters will be tolled at the marginal cost, while trucks will be tolled even lower than that price.

Port and Shipping Line Competition and Cooperation

In this subsection, we review applied game theory approaches on port and liner shipping competition and cooperation. These studies are summarized in Table 4.

Horizontal and vertical interaction between liners and ports were investigated by Song et al. (*36*) in a two-stage game using Bertrand competition and a Multinomial Logit model, where at the first stage, shipping lines made port-of-call decisions, and at the second stage, ports made port pricing decisions. The authors found that, when ports and liners were considered as identical players, the Nash Equilibrium resulted in the lowest possible service charge. When ports and liners were considered as different players, liners increased container volume and kept the service charge the same. Ports with constrained geography and limited capacity would benefit from cooperating with neighboring ports, which would allow redirecting excess demand.

Container port competition and collusion for transshipment cargo in the presence of shipping lines were investigated by Bae et al. (*21*) using a two-stage game, where, at the first stage, ports engaged in Bertrand competition or collusion by making pricing decisions while at the second stage, by observing port capacities, prices, and transshipment levels, shipping lines engaged in Cournot competition and made port-of-call decisions. The authors concluded that higher-level transshipment ports that have sufficient capacity to handle excess traffic are more attractive to shipping lines. Ports with excess capacity can attract more demand by lowering prices, while the unused capacity can dissipate the congestion effect. In a setting when both ports are congested, which results in increased shipping lines costs, the high-level transshipment port decreases the price to maintain its demand. The port collusion model will lead to a higher port price compared to the non-cooperative model. Container terminal and liner shipping company cooperation and competition using the Stackelberg model were modeled by Pujats et al. (*28*). The developed model considered competition between shipping lines and marine container terminal operators (MCTOs). The former players are part of an alliance, while the latter players engage in a capacity-sharing, cooperative agreement. At the upper level, the shipping lines act as the leader minimizing the shipping costs and terminal fees, while at the lower level, the container terminals, as the followers in the game, decide to compete or engage in cooperation with the objective to maximize individual profits.

Route network design in a setting of port and shipping company cooperation and competition was examined by Asgari et al. (*37*). A two-stage game was modeled, where, at the first stage, shipping companies made route network design decisions by playing the Stackelberg game, and at the second stage, ports made total handling cost decisions by playing the Nash game. Three types of strategies were considered: perfect hub competition, perfect hub cooperation, and cooperation between the shipping companies and the hub ports. Results indicated that the short term was the easiest way to control pricing; also, changing handling charges gave control over capacity and competitive power. In the medium term, cooperation with the dominant shipping line may partially secure market share. In the long run, cooperation between ports is beneficial as port capacity may be constrained by geography and neighboring ports. Competition and cooperation between a hub and spoke ports in a shipping network were examined by Tuljak-Suban (*38*), where the author investigated the relationship between port container terminal incomes and the shipping operator incurred costs in the North Adriatic hub and spoke system, where shipowners were modeled as leaders. The author used a two-stage Stackelberg game, where, at the first stage, the shipping companies acted as leaders and solved the Vehicle Routing Problem with Pickup and Delivery by taking into account the navigation and handling costs to make port-of-call decisions, and at the second stage, the spoke ports decided on handling charges under port cooperation, competition, or cooperation between spoke ports and shipping companies. Results showed that there was no optimal strategy between the ship companies and spoke ports, port competition could lead to a reduction in the activities of the weaker port, and port cooperation between spoke ports could raise incomes and improve container transshipment services. The optimum set of liner services modeled as monopoly or duopoly was analyzed by Angeloudis et al. (*39*) using a three-stage game, where at the first stage, shipping lines or alliances made fleet investment decisions; at the second stage, shipping lines or alliances made service design decisions, and the route assignment problem was solved; and at the final stage, shipping lines or alliances made freight rate decisions on each leg. The authors showed that when a duopoly was considered, shipping lines or alliances selected different service networks, thus reducing the competitive pressure.

.

Table 4 Summary of Port and Shipping Line Competition and Cooperation

Study	Technique	Methodology	Objective	Results
Song et al., 2016 (*36*)	Bertrand competition Multinomial Logit model Nash equilibrium	Two-stage game where: Shipping lines make a port-of-call decisions. Ports make pricing decisions.	Examine horizontal and vertical interactions between liners and ports.	When ports and liners are considered as identical players, the Nash equilibrium results in the lowest possible service charge. When ports and liners are considered as different players, liners will increase container volume and keep the service charge the same. Ports with constrained geography and limited capacity would benefit from cooperating with neighboring ports, which would allow redirecting excess demand.
Bae et al., 2013 (*21*)	Bertrand competition and collusion Cournot competition	Two-stage game where: Ports make pricing decisions. Shipping lines make port-of-call decisions.	Analyze container port competition and collusion for transshipment cargo in the presence of shipping lines.	The higher-level transshipment ports that have sufficient capacity to handle excess traffic are more attractive to shipping lines. Ports with excess capacity can attract more demand by lowering prices, while the unused capacity can dissipate the congestion effect. The port collusion model will lead to a higher port price compared to the non-cooperative model.
Pujats et al., 2019 (*28*)	Stackelberg game Nash equilibrium	Two-stage game where: Shipping lines in an alliance make shipping size decisions Container terminals decide to cooperate or compete by utilizing their capacities.	Develop a mathematical framework for container terminal and liner shipping company cooperation and competition using the Stackelberg model.	The developed game theory-based model not only could assist marine container terminal operators and port authorities in identifying optimal contractual agreements, but it also could help identify optimal operational plans that support the implementation of such contractual agreements.

Table 4 Summary of Port and Shipping Line Competition and Cooperation (Continued)

Study	Technique	Methodology	Objective	Results
Asgari et al., 2013 (*37*)	Stackelberg game Nash equilibrium	Two-stage game where: Shipping companies make route network design decisions. Hub ports make total handling cost decisions.	Develop route network design in a setting of port and shipping company cooperation and competition.	Short term is the easiest way to control pricing; also, change in handling charges gives control over capacity and competitive power. In the medium term, cooperation with the dominant shipping line may partially secure market share. In the long run, cooperation between ports is beneficial as port capacity may be constrained by geography and neighboring ports.
Tulja-Suban, 2017 (*38*)	Stackelberg game Nash equilibrium	Two-stage game where: Shipping operators make port-of-call decisions. Spoke ports make handling charge decisions under one of the cooperation/competition scenarios.	Examine competition and cooperation between a hub and spoke ports in a shipping network.	There is no optimal strategy between the ship companies and spoke ports, port competition could lead to a reduction in the activities of the weaker port, and port cooperation between spoke ports could raise incomes and improve container transshipment services.
Angeloudis et al., 2016 (*39*)	Bertrand competition Nash equilibrium	Three-stage game where: Shipping lines or alliances make fleet investment decisions. Shipping lines or alliances make service design decisions, and the route assignment problem is solved. Shipping lines or alliances make freight rate decisions on each leg.	Determine the optimum set of liner services modeled as a monopoly or duopoly.	When a duopoly was considered, shipping lines or alliances selected different service networks, thus reducing the competitive pressure.

Other Type of Maritime Transportation Cooperation and Competition

In this subsection, we discuss the reviewed literature on other types of maritime transportation cooperation and competition that utilizes game theory approaches. These studies are summarized in Table 5.

Pricing and routing decisions between ocean carriers, land carriers, and terminal operators in a maritime freight transportation network were investigated by Lee et al. (*23*). The authors used a non-cooperative hierarchical game model, where at the first stage, carriers determined service charges and delivery routes; at the second stage, terminal operators decided on port throughput and service cost; and at the final stage, land carriers decided on service demand and land transportation costs.

The effects of port privatizations on port usage fees, firm profits, and welfare in a setting of port and manufacturing firm competition located in two countries, home and foreign, were investigated by Matsushima and Takauchi (*40*). The authors used a three-stage game, where at the first stage, governments made a decision on whether to privatize ports; at the second stage, ports made port usage fee decisions; and at the final stage, firms in both countries determined quantities. Results indicated that under low (per unit) transportation costs either both or none of the ports will be privatized, under moderate transportation costs both ports will be privatized, and under high transportation costs, none of the ports will be privatized.

Government strategic investment decisions on inland transportation infrastructure in the port catchment area and common hinterland with competing ports were investigated by Basso et al. (*10*). The authors used a three-stage Hotelling model, where at the first stage, governments made packability investment decisions; at the second stage, ports made pricing decisions; and at the final stage, shippers made decisions on port of call and demand for the product. Results indicated that increased investment in the hinterland would decrease charges at both ports, but increased investment in a port catchment area would significantly decrease its charges compared to the rival port.

Table 5 Summary of Other Types of Maritime Transportation Cooperation and Competition

Study	Technique	Methodology	Objective	Results
Basso et al., 2013 (*10*)	Hotelling model	Three-stage game where: Governments make packability investment decisions. Ports make pricing decisions. Shippers make decisions on whether to accept the port of call and demand the product.	Investigated government strategic investment decisions on inland transportation infrastructure in the port catchment area and common hinterlands with competing ports	Increased investment in the hinterland would decrease charges at both ports, but the increased investment in a port catchment area will significantly decrease its charges compared to the rival port.
Matsushima and Takauchi, 2014 (*40*)	Bertrand competition Cournot competition	Three-stage game where: Governments make decisions on whether to privatize or not. Ports make port usage fee decisions. Firms in both countries make quantity decisions.	Examine the effects of port privatizations on port usage fees, firm profits, and welfare in a setting of port and manufacturing firm competition located in two countries: home and foreign.	Under low (per unit) transportation costs either both or none of the ports are privatized, under moderate transportation costs both ports are privatized, and under high transportation costs none of the ports are privatized.
Lee et al., 2012 (*23*)	A game model with Oligopolistic players Nash equilibrium	Three-stage game where: Ocean carriers make service charges and delivery route decisions. Terminal operators make port throughput and service cost decisions. Land carriers make service demand and land transportation cost decisions.	Investigate pricing and routing decisions between ocean carriers, land carriers, and terminal operators in a maritime freight transportation network.	Provided a tool to evaluate ocean carrier, terminal operator, and land carrier decision-making processes in the freight shipping market.

Discussion

In this study, we have reviewed 33 studies that used game theory models for investigating seaport and container terminal competition and cooperation involving various stakeholders with dating publication years from 2008 to 2019. Almost half of the studies included some variation of cooperation strategy with ports and container terminals. Among all game theory approaches used in the studies, the most applied was found to be the Bertrand type of game, which accounted for 37% of all instances, followed by Cournot (29%), Hotelling (20%), Stackelberg (12%), and Nash Bargaining (2%). Almost half of all games were modeled in two stages, followed by one-stage games that accounted for one-third of all models, and the rest were three-stage games.

In the reviewed literature, the main topics of interest when considering port and terminal cooperation, competition, or both, were service level differentiation in combination with and without shipping distances; port ownership with and without level of service differentiation; pricing policies, capacity utilization, and comparison of various cooperation policies and effects of service level differentiation in inter- and intra-port competition, when considering transshipment cargo; competition between multiuser terminals; terminal concession awarding; and port capacity investments when ports set prices under various types of demand. Reviewed studies also considered seaport and container terminal competition, cooperation, or both, including government, and some of the topics discussed were port regulation under different scenarios; port ownership; emission control strategies; and pricing and investment decisions between ports with hinterland congestion under various scenarios. Also, the reviewed literature included liner shipping companies and port cooperation and competition, where studies focused on horizontal and vertical interactions between liners and ports, hub ports, and hub–spoke ports including game theory network design models.

The growing demand, mega alliances, and increased vessel sizes are some of the main contributing factors that have shifted the balance of negotiation power between shipping lines and container ports. The resulting implications have created an increasingly competitive environment between ports, where container ports compete by increasing their service levels in favor of liner shipping companies. A number of reviewed studies used service level differentiation between ports to model port competition and cooperation. Common factors used to model port competition and cooperation with service level differentiation include service quality, service type, geographic location, capacity, price, profits, and welfare. Zhou (*13*) suggested future research could include a comparison of competition with cooperation strategies of ports serving partially overlapping hinterlands in a situation when ports compete in price and geographic location. Incorporation of more practical problems in the models that would increase the applicability of model at different settings to help robustness was suggested by Ciu and Notteboom (*14*).

In order to meet the growing demand, while at the same time trying to comply with shipping line demands, container ports have experienced pressure to improve productivity and invest in more capacity and new facilities. This limited capacity has motivated numerous authors to study strategic port and hinterland capacity investment decisions; a well-researched direction. Luo et al. (*8*) suggested that there is an opportunity to investigate optimal pricing strategies when port capacity investments are made in a setting where competition between terminals serving the hinterland and terminals that are managed by the same port operator have different operating costs. Also, analysis of the impact of port capacity investment decisions on both the shipping operations and port development policy could be explored. Investigation of various coalition formations between local governments when strategic investment decisions on inland transportation are made in a setting of port competition was identified by Basso et al. (*10*) as another potential future research area.

While the increase of capacity is needed, the investment costs are high and have become a financial challenge for container port authority operators. Privatization of ports and container terminal privatization were found to be solutions on how to finance investments in ports (*41*). A future research direction considering the effects on port ownership was suggested by Kaselimi et al. (*16*), where the authors noted that models should adopt more objectives that maximize welfare or incorporate both maximizing welfare and profit, as not all port and terminal operators maximize profit. One future avenue suggested by Czerny et al. (*19*) could include investigating the impact of scale economies and carrier market power on port competition and transshipment routes when port privatization is considered. The effects of port privatization on consumer and social welfare when considering the competition between international ports, government, and manufacturing firms was one research direction unexplored by Matsushima and Takauchi (*40*).

Another potential solution, through port cooperation, to address capacity limitations and increase port efficiency was proposed by Pujats et al. (*26*). The authors also proposed as future research the investigation of additional costs for transshipment containers (but also inbound and outbound at a smaller scale) that would have to be moved between terminals or to specific vessels at the port of origin/destination.

As the demand for containers will continue to increase, so will the shipping emissions. Environmental control measures and their implications on the maritime industry most likely will become a critical issue as more regulatory policies are implemented. The evaluation of container port environment performance will become critical, and game theory could assist port authority operators by investigating strategic measures that would improve port environmental performance in settings of port competition and cooperation. Only one study used a game theory approach to model port competition and emission control (emission tax), a study done by Cui and Notteboom (*20*), where the authors, as a future research direction, suggested investigating emission controls in port areas with a third market (transit market) and their effects on emission tax and port privatization. Another environmental control solution that can reduce emissions at ports includes cold ironing, which is a process where shorepower is used to run the ship at the port of call. In a study done by Zis (*42*), the author concluded that in the setting of the introduction of new environmental regulatory measures and an increase in fuel prices, the use of cold ironing could lead to lower ship operating costs. This result could have a significant effect on port and terminal competition and cooperation and should be evaluated with further research. The author suggested that future research could include evaluation of cold ironing berth availability at different port congestion levels or the required cold ironing berth conversions at a given terminal. Another operational process that could reduce emissions is the implementation of a Virtual Arrival policy. It is a process that is applied when delay at the port is known for vessels to reduce their speeds to meet the required arrival time at the port. A study by Jia et al. (*43*) found that the implementation of a Virtual Arrival policy could benefit both the ship operators and port authorities, which could result in fuel savings for ship operators and emission reductions for both parties by reducing port wait times. Jia et al. (*43*) suggested that further research should investigate the adoption of Virtual Arrival policy through the creation of new contractual arrangements that would share the fuel savings gained from Virtual Arrival implementation between shipowners, charterers, and port authorities.

Some of the future avenues to model port and liner shipping competition, cooperation, or both were considered by Song et al. (*36*), where the authors highlighted that future work on port and liner shipping competition, cooperation, or both could involve modeling accessibility to multimodal transportation and port location to acquire more port capacity. The revenue allocation mechanism between cooperating ports and liners was another research direction suggested by authors. One potential research direction suggested by Angeloudis et al. (*39*) could include exploring network differentiation between shipping lines or alliances to reduce competition among themselves and optimize costs of their network structure. From the reviewed studies, one of the most suggested points for future research is to include uncertain or stochastic demand. Only two studies (*6*, *7*) have used this assumption in their research. Data unavailability is another major issue noted in the reviewed literature, which restrains researchers from more realistic model development (*5*, *6*, *15*, *17*, *31*, *32*, *37*, *38*).

3. Marine Container Terminal Cooperation: A Nash Bargaining Approach

Introduction

Port and marine terminal cooperation is a hot topic in public and business circles, and bibliometric studies on port-related academic research show that port cooperation/integration is an emerging theme (*44*). Heaver et al. (*45*) examined strategic measures between port authorities and terminals, in particular, cooperation and competition amongst terminals within a port and between ports. Song (*46*) applied the concept co-opetition, the combination of competition and cooperation, to explain the relationships of the container ports in Hong Kong and South China. Notteboom (*47*) provided an overview of the challenges facing port and maritime companies in a rapidly changing environment and analyzed the paths shipping lines, and terminal operating companies are walking in the highly competitive container and logistics markets. The author noted that cooperation is likely to be advantageous when the combined costs of operations or buying transactions (such as negotiating and contracting) are lower than the cost of operating alone. Van Der Horst et al. (*48*) analyzed coordination problems in hinterland chains of seaports and different arrangements and concluded that underdevelopment of coordination in hinterland chains may be explained of a lack of contractual relations, information-asymmetry, and a lack of incentives for cooperation. Brooks et al. (*49*) discussed the nature of peripheral ports followed by a conceptualization of two development strategies: cooperation among seaports and coordination of supply chain operators with the emphasis on cooperation. Hoshino (*50*) analyzed Japanese container port strategy against intense regional competition from China and Korea and suggested that ports located on Tokyo and Osaka Bays could advance their collaboration and be managed by a single port authority to strengthen their competitive power. Fu and Chen (*51*) analyzed China's Yangtze River Delta ports Ningbo-Zhoushan and Shanghai competition and cooperation by studying model of famous foreign ports, recognizing the urgent need to establish two-port's healthy competition and cooperation relations. Lee and Lam (*52*) attempted to evaluate port competitive edge of major Asian container ports, i.e. Busan, Hong Kong, Shanghai, and Singapore, referring to the customer-centric community ports, so-called the Fifth Generation Ports (5GP). Authors highlighted that port cooperation is in need in the era of 5GP, which embraces the concept of clustering and community impact. Parola et al. (*53*) presented a hierarchy of key drivers and suggested that economies of scales in shipping, port governance changes, coopetition among ports in proximity, inter-firm networks, and green and sustainability challenges, moderate the influential role of traditional drivers and reshuffle their relative salience.

Several studies used quantitative methods to describe/model cooperation between ports and terminals. Li and Oh (*54*) analyzed the relationship between neighboring ports of Shanghai port and Ningbo-Zhoushan port in China, using HHI Index model. The authors suggested that ports should cooperate to increase competitive power in Yangtze River Delta region. Jeon et al. (*55*) analyzed research trends in port competition and cooperation using social network analysis to identify the changes and evolution in trends, the research timeframe was divided into three periods between 1980 and 2015. Mclaughlin and Fearon (*56*) presented new cooperation/competition matrix framework that identifies four forms of cooperation as response strategies to the major maritime dynamics. The authors examined the degree of cooperation in relation to inter-port rivalry and the influence of private-sector drivers.

Various game-theoretic models have been developed to address port cooperation. Saeed and Larsen (*32*) analyzed the different combinations of coalitions among the three terminals at Karachi Port by developing a two-stage Bertrand game. Wang et al. (*11*) investigated the factors and conditions affecting alliance formations for ports serving partially overlapping hinterlands in

South China by developing a game theory model for Pearl River Delta (Hong Kong and Shenzhen). Asgari et al. (*37*) examined the competition–cooperation scheme between two leading Asian hub ports: Singapore and Hong Kong in the presence of shipping companies. An interval branch and bound was used to solve the models. Wang and Sun (*12*) applied the Hoteling game model to analyze the competition and cooperation among ports in the port group based on geographical location, service level, and shipping distance.

Research in maritime transportation has been on the rise in the last decade. One research direction that has been proposed is the development of models that can capture cooperation between marine container terminal operators (MCTOs) and/or liner shipping companies (*57*). MCTO and/or port cooperation (*32*, *37*, *58*) seems like a natural reaction to the rapid changes in the liner shipping industry (*59–61*) in the form of new (and perhaps unstable) alliances (*53*), (*62*), (*63*) and demand/supply volatility(*63*). In this study, we evaluate the Nash Bargaining Solution (NBS) applicability to model marine container terminal cooperation and compare it to three other cooperation policies. The NBS has proposed a "*new treatment*" for the bargaining game (*64*), (*65*), where parties involved are rational, can compare their utilities for different actions, and have full knowledge of the preferences of each other. The proposed cooperative game is applicable in the situation where the two individuals have interests that are neither "*completely opposed nor coincident*" and are willing to discuss, develop, adopt, and commit to a common plan (*64*).

The rest of the paper is structured as follows. The Next section presents the assumptions about the handling cost and fees functions and the mathematical formulations of both the volume and vessel-based models. The third section presents results from preliminary numerical experiments that compare the four cooperation policies and the two formulations. The last section concludes the paper and proposes future research avenues.

Problem Formulation

In the research presented herein, we assume that MCTOs can negotiate and share the available (seaside and landside) resources/capacity to maximize profits. MCTOs cooperation, in the sense of resource sharing, optimizes capacity utilization without capital investment (see concept of operational excess capacity in Haralambides (*66*) which in turn can lead to higher profitability, sustainability, and resilience to market fluctuations (*46*)). In this study, we assume that MCTOs have already formed a strategic alliance that allows them to share their resources. The objective of the paper is to evaluate and compare four different cooperation policies (i.e., objective functions) for sharing capacity (i.e., the allocation of demand to terminals) and compare a volume (demand is measured in TEUs) to vessel (demand is measured in vessels) based formulations. The former formulation can be viewed as a planning tool, while the latter as a tactical/operational tool.

Let $I = \{1, \dots, i)$ be the set of terminals, $C_i, i \in I$ the capacity of terminal $i \in I$, and $V_i, i \in I$ the volume of containers handled at terminal $, i \in I$ without cooperation. We define the handling fees, handling costs, and total profit functions as follows:

Terminal handling cost function (cost endured by the terminal operator)

$$hc_i(V_i) = \left[\alpha_1 \left(\frac{V_i}{C_i}\right)^2 + \alpha_2 \left(\frac{V_i}{C_i}\right) \quad + pc_i\right] \tag{3.1}$$

where pc_i is the base container handling cost for terminal $i \epsilon I$ without cooperation.

Terminal handling fees function (user cost) – (see Saeed and Larsen (32))

$$hf_i(V_i) = \left[\beta_1 \left(\frac{V_i}{C_i}\right)^2 + \beta_2 \left(\frac{V_i}{C_i}\right) \quad + pf_i\right] \tag{3.2}$$

where pf_i is the base container handling fee charged by terminal $i \epsilon I$.

Terminal Profit Function

$$\pi_i(V_i) = (hf_i(V_i) - hc_i(V_i))V_i \quad (3.3)$$

Table 6 shows an example of the terminal profit, handling fees, and handling cost functions by container (left side) and total (right side). Based on Haralambides (*66*) the maximum profit for the terminal is achieved at V/C ratios in the vicinity of 60% to 80% (although these can be higher or lower depending on the technology and equipment used by terminal). Haralambides (*66*) states that "o*nce a port reaches 70% capacity utilization, congestion ensues in terms of unacceptable waiting times*". Reduction in profits, once V/C ratios exceed this limit, can be attributed to many factors with the main one being reduction in productivity from berth and yard congestion. In this study, we investigate if cooperation between terminals in terms of shared capacity can be beneficial in increasing profits without the need of capital investment to secure "*excess capacity*". We propose two approaches for cooperation: one based on volume assignment (which can be used for planning purposes) and one based on vessel assignment (that can be used for tactical/operational purposes). The volume based formulation is more flexible and provides an upper bound to the objective function value of each policy for the vessel based formulation as its relaxation (integrality constraint of demand). In this study, we further assume that handling fees for any diverted demand will not exceed the handling chargers at the origin terminal (i.e., terminal demand is diverted from). In simple terms, any demand that is diverted from one terminal (from now on referred to as origin terminal) to another (from now on referred to as destination terminal) cannot be penalized by higher handling fees than agreed upon with the origin terminal operator. Next, we present the mathematical formulations of both cooperation approaches.

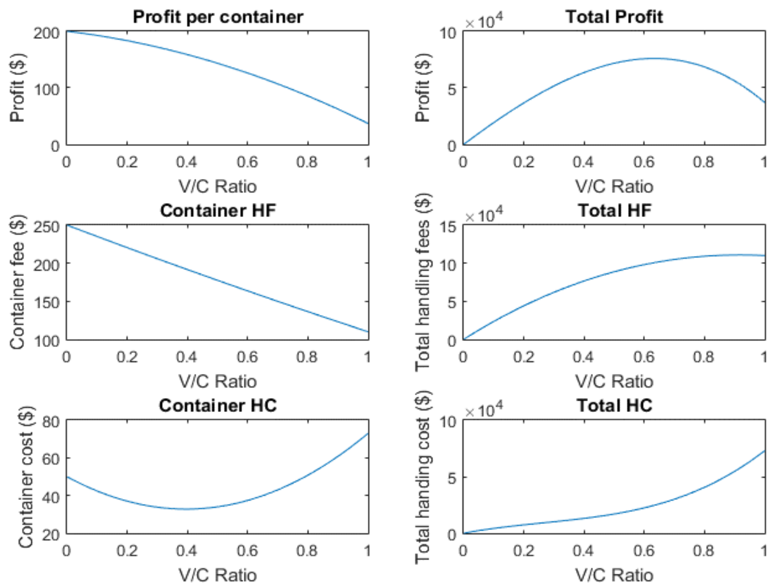


Figure 1 Example Profit, Handling Cost and Handling Fee Functions Plots

Volume Based Formulation (VoBF)

Let $x_{ab}, a \neq b \in I$ be the volume (TEUs) transferred from terminal $a \in I$ to terminal $b \in I$ under cooperation, $pf_a^c, a \in I$ handling fee per container for demand diverted to terminal $a \in I$, $r_a = 1, a \in I$ if containers are transferred to terminal $a \in I$, $w_a = 1, a \in I$ if containers are transferred from terminal $a \in I$, prg_a , $a \in I$ profit increase of terminal $a \in I$ from handling fees of diverted demand from any other terminals, prl_a , $a \in I$ profit loss from handling fees of diverted demand from terminal $a \in I$ to any of the other terminals , and p the percentage of the origin terminal handling fee charged at the destination terminal (for diverted demand diverted). In this study (as discussed in the previous section) we consider and compare four different objective functions: i) NBS, ii) Maximization of total profits, iii) Maximization of minimum profit among all terminals that cooperate, and iv) Maximization of minimum profit increase among all terminals that cooperate.

Objective Function 1: NBS

$$NBS: maximize \prod_a \left(\pi_a(V_a^c) - \pi_a(V_a) + 1\right) \tag{3.4}$$

The +1 component in the NBS objective function accounts for cases where for a subset of terminals cooperation may not be profitable or the profit remains unchanged (which can be the case for concave profit functions). In that case if the term +1 was omitted from the objective function any solution -for the terminals that would cooperate- would be optimal with an objective function value equal to zero.

Objective Function 2: Total Profit

$$MaxProfit\colon maximize \sum_a \left(\pi_a(V_a^c)\right) \tag{3.5}$$

Objective Function 3: Maximize Minimum Profit

$$MaxMin\colon maximize \ \min_a \left(\pi_a(V_a^c)\right) \tag{3.6}$$

Objective Function 4: Maximize Minimum Profit Increase

$$MaxMinDiff\colon maximize \ \min_a \left(\pi_a(V_a^c) - \pi_a\left(V_a \ \right)\right) \tag{3.7}$$

Constraints

A terminal can either receive or provide demand (but not both)

$$\sum_a (r_a + w_a) \leq 1, \forall a \in I \tag{3.8}$$

Demand at any terminal cannot exceed capacity (this constraint is not necessary and can be dropped in cases of monotonically increasing profit function for any of the terminals)

$$V_a^c \leq C_a \ , \forall a \in I \tag{3.9}$$

Profit for any terminal under any cooperation scenario will be greater or equal to its profits under the no cooperation scenario

$$\pi_i(V_a^c) - \pi_i\left(V_a \ \right) \geq 0, \forall a \in I \tag{3.10}$$

Profit under cooperation for terminal $a \in I$

$$\pi_i(V_a^c) = hc_i\big(V_a\ \big) + \sum_b x_{ba} pf_b^c - \sum_b x_{ab} hf_a\ - hc_i(V_a^c) \forall a \in I \tag{3.11}$$

Volume (TEUs) transferred from terminal $a \in I$ to a terminal $b \in I$ has to be less than or equal to the demand at terminal $a \in I$ under no cooperation

$$\sum_b x_{ab} \le w_a\ V_a\ \ , \forall a \in I \tag{3.12}$$

Volume handled at terminal $a \in I$ under cooperation

$$V_a^c = V_a\ \ + \sum_b x_{ba} - \sum_a x_{ab}\, , a \in I \tag{3.13}$$

Containers transferred to terminal $a \in I$ cannot exceed the available demand at all the other terminals

$$\sum_b x_{ba} \le r_a\ \Big(\sum_{b \neq a} V_b\ \ - V_a\ \ \Big), \forall a \in I \tag{3.14}$$

Handling fee of transferred demand is (100-p)% of the handling fees at the origin terminal (under no cooperation).

$$pf_a^c \le p * hf_b\big(V_a\ \big)\ \forall a \in I, p \le 1 \tag{3.15}$$

Estimation of profit increase (handing fees portion) for demand diverted to terminal $a \in I$

$$prg_a = \sum_b x_{ab} pf_{ab}^c\, , \forall a \in I \tag{3.16}$$

Estimation of profit loss (handing fees portion) for demand diverted from terminal $a \in I$

$$prl_a = \sum_b x_{ba} hf_a\ \forall a \in I \tag{3.17}$$

Total volume handled before is equal to total volume handled after

$$\sum_a V_a^c = \sum_a V_a \tag{3.18}$$

Vessel Based Formulation (VeBF)

Let J_i be the set of vessels served at terminal $i \in I$ under no cooperation, x_{ji}, y_{ji} be the vessel to terminal assignment before and after cooperation, V_j be the volume of vessel $j \in J$, $V_i = \sum_{j\in J_i} x_{ji}V_J$ volume served at terminal $i \in I$ before cooperation, $V_i^c = \sum_{j\in J_i} y_{ji}V_J$ volume served at terminal $i \in I$ after cooperation, $hf_i^c, i \in I$ handling fee per container for demand originating from terminal, $r_i = 1, i \in I$ if vessels are transferred to terminal $i \in I$, $w_i = 1, i \in I$ if vessels are not transferred from terminal $i \in I$,and $M = |J|$.

Objective Function 1: NBS

$$NBS\colon maximize \prod_i \left(\pi(V_i^c) - \pi_i\left(V_i\right) + 1\right) \tag{3.19}$$

Objective Function 2: Total Profit

$$MaxProfit\colon maximize \sum_i \left(\pi(V_i^c)\right) \tag{3.20}$$

Objective Function 3: Minimum Profit

$$MaxMin\colon maximize \min_i \left(\pi(V_i^c)\right) \tag{3.21}$$

Objective Function 4: Minimum Profit Increase

$$MaxMinDiff\colon maximize \min_i \left(\pi(V_i^c) - \pi_i\left(V_i\right)\right) \tag{3.22}$$

Constraints

Every vessel is served at one terminal (under cooperation)

$$\sum_{i \in I} y_{ji} = 1, \forall i \in I \tag{3.23}$$

Volume at terminal $i \in I$ under cooperation

$$V_i^c = \sum_j y_{ji} V_j\,, \forall i \in I \tag{3.24}$$

Profit increase/loss of terminal $i \in I$ under cooperation

$$\pi(V_i^c) = \pi_i(V_i \quad) + prg_i - prl_i - hc_i(V_i^c), \forall i \in I \tag{3.25}$$

Estimate profit increase is demand is diverted to terminal $i \in I$

$$prg_i = \sum_{j \in J_{\gamma \neq i}, \gamma \neq i} y_{ji} hf_\gamma^c\, V_j, \forall i \in I \tag{3.26}$$

Estimate profit loss if demand is diverted from terminal $i \in I$

$$prl_i = \sum_{j \in J_i, \gamma \neq i} y_{j\gamma} hf_i^c\, V_j, \forall i \in I \tag{3.27}$$

Demand at any terminal cannot exceed capacity (this constraint can be removed)

$$\sum_j y_{ji} V_J \leq C_i, \forall i \in I \tag{3.28}$$

Profit for any terminal under any cooperation scenario must be greater or equal to its profits under the no cooperation scenario

$$\pi(V_i^c) - \pi_i(V_i \quad) \geq 0, \forall i \epsilon I \tag{3.29}$$

Handling fee per container of demand that moved cannot exceed a percentage of the handling fee at the origin terminal b.

$$hf_a^c \leq p * hf_a \; \forall a \in I \tag{3.30}$$

A terminal can either receive or provide vessels (but not both)

$$\sum_{a}(r_a + w_a) \leq 1, \forall a \in I \ \ eqe \tag{3.31}$$

If a vessel is not transferred to a terminal $i \in I$ make those y's zero

$$\sum_{j \in J_{\gamma \neq i}, \gamma \neq i} y_{ji} \leq Mr_i \, , \forall i \in I \tag{3.32}$$

A vessel is not transferred from a terminal $i \in I$ make those y's zero

$$prl_i = \sum_{j \in J_i, \gamma \neq i} y_{j\gamma} \, , \leq Mw_i \forall i \in I \tag{3.33}$$

Demand at any terminal cannot exceed capacity (this constraint is not necessary and can be dropped in cases of monotonically increasing profit function for any of the terminals)

$$V_i^c \leq C_i \quad , \forall i \in I \tag{3.34}$$

Numerical Experiments

We developed thirty (30) data sets with varying demands (i.e., V/C ratios) for three terminals with the same capacity based on the uniform distributions shown in Table 6. Note that these demand levels are for a planning period. In other words, T3 might have the low demand and T1 the high demand for some periods of the year and vice versa. For each one of the thirty data sets we evaluated both model formulations for four different profit functions (shown in Table 7) obtained by varying the cost function coefficient β_2, and two different cooperation cases: i) Cooperation Case 1 where terminals one (T1) and three (T3) cooperate, and ii) Cooperation Case 2 where terminals two (T2) and three (T3) cooperate.

Table 6 Numerical Experiments Input Data

	T1	**T2**	**T3**
Demand	U[10, 25]	U[35, 65]	U[90, 100]
Capacity	12000	12000	12000
Vessels	5	5	10
$\boldsymbol{\beta_1, \beta_2, pf_i}$	[10, $\boldsymbol{\beta_2}$, 250]		
$\boldsymbol{\alpha_1, \alpha_2, pc_i}$	[110, 87, 50]		
$\boldsymbol{\beta_2}$	[170, 180, 190, 200]		

The four profit functions differ on the V/C ratio point where the terminal's productivity reaches its maximum efficiency (after which point any additional demand handled will result in a profit reduction). Note that the case of terminals T1 and T2 cooperating is not considered as their V/C ratios are too low to support cooperation (i.e., profits before cooperation lie on the left side of the maximum of the profit function). In this study BARON (*67*) was used for both models. All the data and model formulations are available upon request. Next, we present a discussion on the results from the 480 data sets [(thirty datasets) x (four profit functions) x (two cooperation cases) x (two problem formulations)].

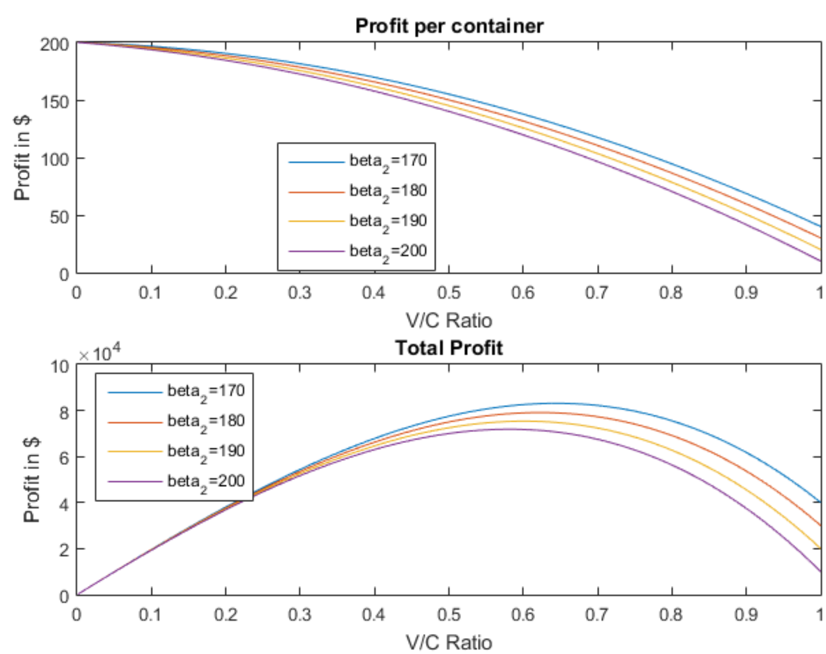


Figure 2 Profit Functions (Per Container and Total)

Profit Distribution Comparison

Figure 3 and 4 show histograms of the total profit share (%) of each terminal pair for the two cooperation cases (terminals T1 and T3, and terminals two T2 and T3), for both model formulations (vessel and volume based), and the four cooperation policies (NBS, MaxProfit, MaxMin, and MaxMinDiff) respectively. For example, the top left graph in Figure 3 shows the histograms of the total profit share of terminals T1 (yellow bars) and T3 (blue bars) for the VeBF and the NBS cooperation policy. As expected, the MaxMinDiff results in the most uniform profit share but, as we will see in the next subsection, this policy also results in the smallest total and per terminal profit increase. The NBS and MaxProfit policies favour the terminal with the lowest V/C ratio (i.e., terminals T1 and T2) with NBS exhibiting a more uniform distribution than MaxProfit. The MaxMin policy provides the worst (overall) profit distribution among the terminals, favouring the ones with the highest V/C ratio (except for the VoBF for cooperation case of terminals T1 and T3). Next, we present results and discussion on the profit size differences for the terminals, the four cooperation policies, and two formulations.

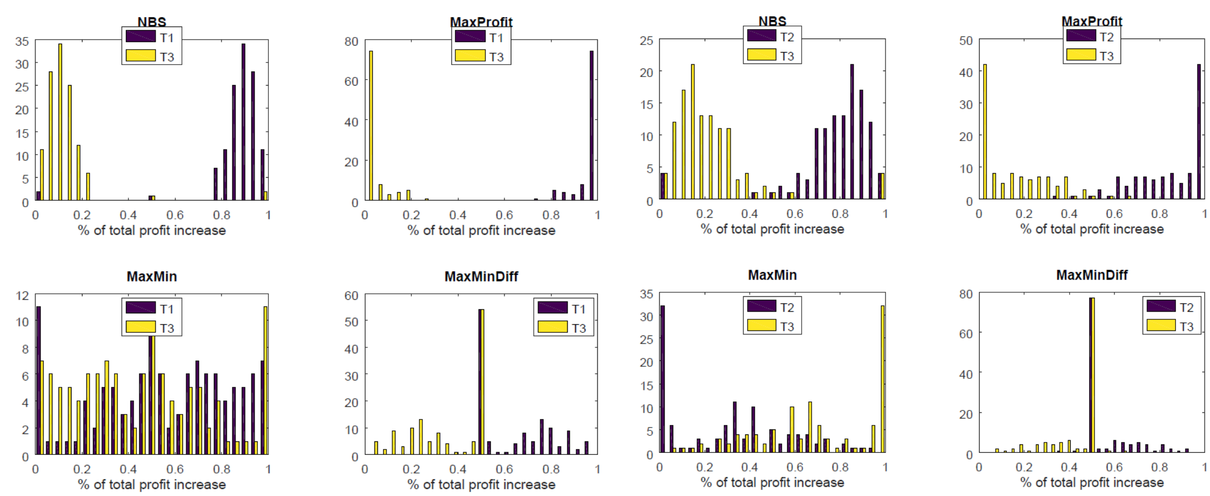


Figure 3 Total Profit Increase Distribution Among Terminals by Objective Function (VoBF)

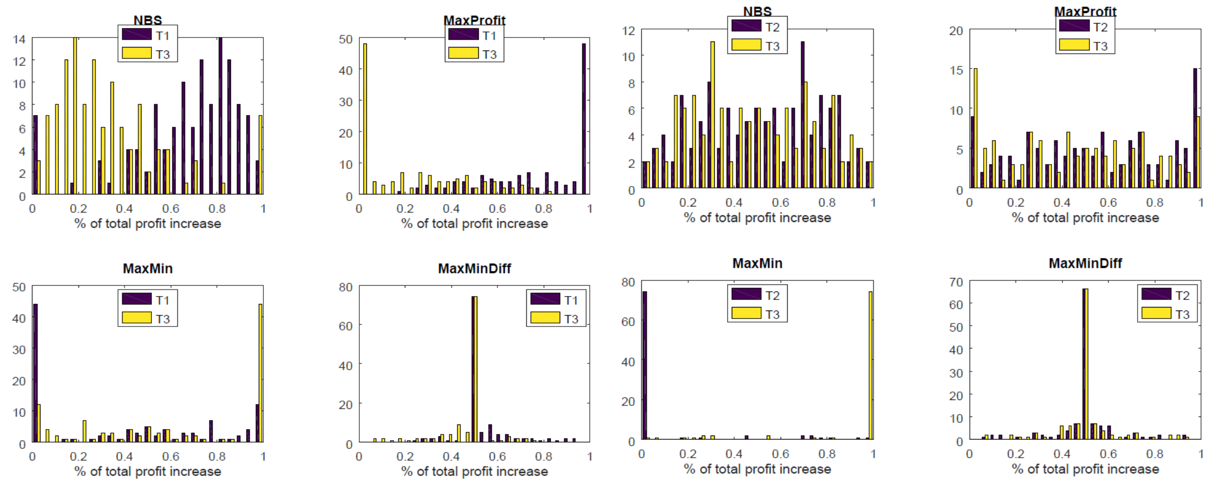
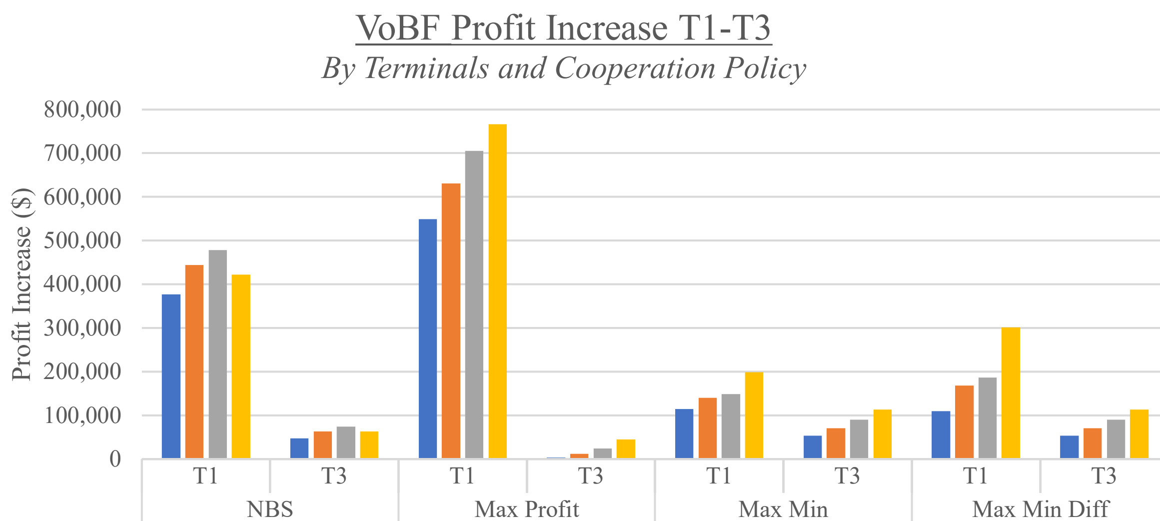


Figure 4 Total Profit Increase Distribution Among Terminals by Objective Function (VeBF)

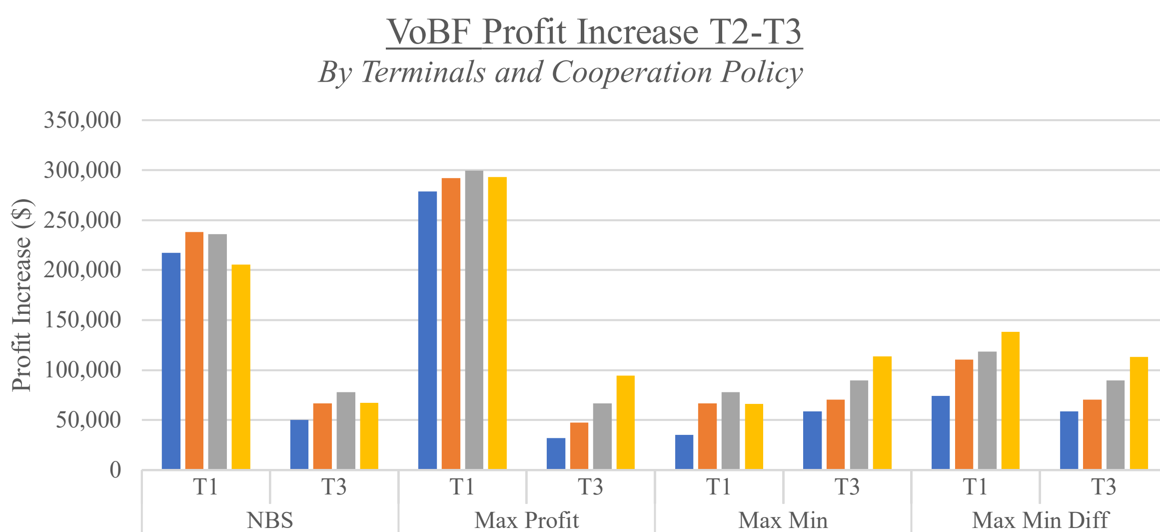
Cooperation Policy Comparison: Profit Increase

Figure 5 and 6 show the mean profit increase for each terminal under each cooperation policy. In the case of the VoBF, all four policies provide higher profit increases for the terminals with the lower V/C ratio (i.e., terminals one and two) with the exclusion of the MaxMin policy for the T2-T3 terminal cooperation case. That is not the case with the VeBF where for the NBS, MaxProfit, and MaxMin policies T3 profits increase and T1 and T2 profits decrease with the increase of parameter β_2. We also observe that, the NBS policy, provides a better balance of profit increase amongst the terminals, except for the VoBF for cooperation case 2 and the VeBF for the cooperation case 1 (both for β_2=200). Note that the differences seem to dissipate when the VeBF is applied and the difference of V/C ratios between the cooperating terminals decrease. Next, we present a comparison of the VoBF and VeBF with regards to profit increases (total and by terminal).



	NBS T1	NBS T3	Max Profit T1	Max Profit T3	Max Min T1	Max Min T3	Max Min Diff T1	Max Min Diff T3
β2=170	377,426	47,832	549,699	3,518	114,548	53,029	109,971	53,536
β2=180	443,896	63,068	631,508	12,078	140,540	70,176	168,666	70,331
β2=190	478,537	73,887	705,023	24,630	148,258	90,187	186,552	90,309
β2=200	421,968	63,478	766,157	44,747	198,683	113,713	301,250	113,713

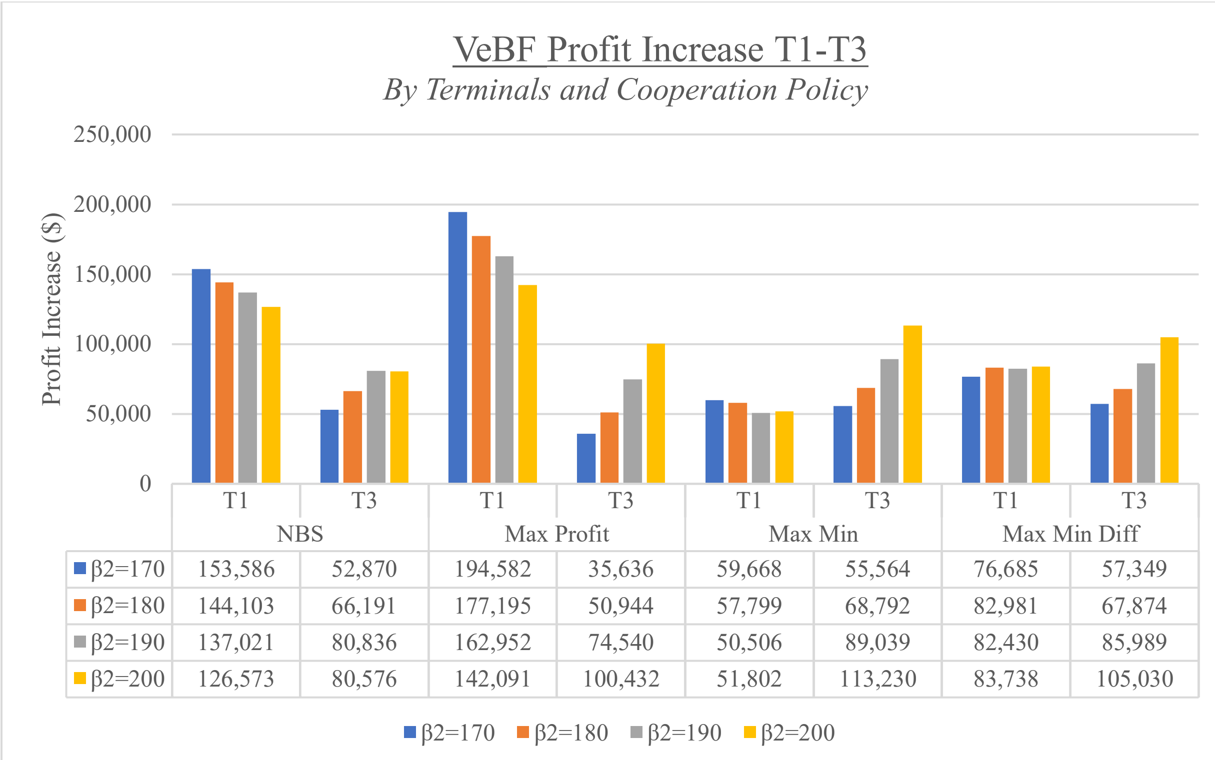
β2=170 β2=180 β2=190 β2=200



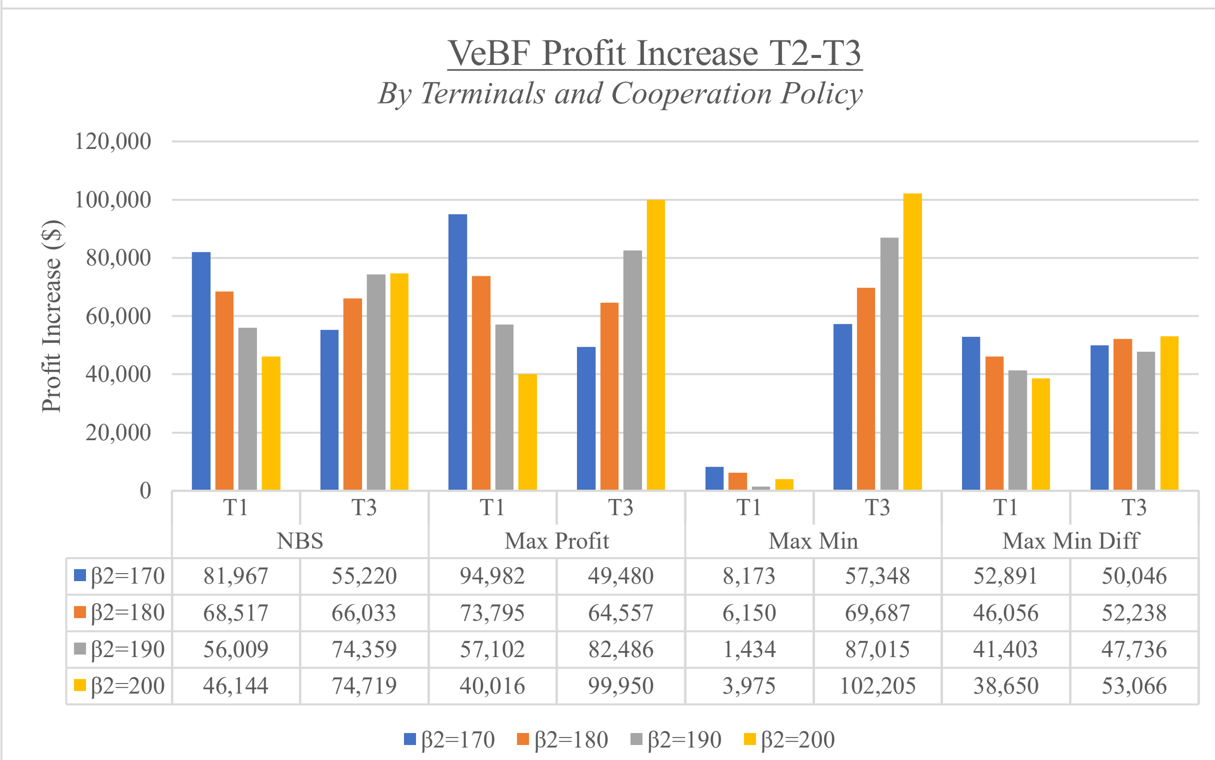
	NBS T1	NBS T3	Max Profit T1	Max Profit T3	Max Min T1	Max Min T3	Max Min Diff T1	Max Min Diff T3
β2=170	217,313	50,189	278,858	31,897	35,184	58,915	73,980	58,797
β2=180	237,925	66,714	291,818	47,538	66,541	70,331	110,750	70,331
β2=190	236,089	77,782	299,352	66,840	77,733	89,567	118,584	89,427
β2=200	205,342	67,354	293,242	94,425	66,187	113,713	138,311	113,136

β2=170 β2=180 β2=190 β2=200

Figure 5 Individual Terminal Profit Increase by Cooperation Policy (VoBF)



	NBS		Max Profit		Max Min		Max Min Diff	
	T1	T3	T1	T3	T1	T3	T1	T3
β2=170	153,586	52,870	194,582	35,636	59,668	55,564	76,685	57,349
β2=180	144,103	66,191	177,195	50,944	57,799	68,792	82,981	67,874
β2=190	137,021	80,836	162,952	74,540	50,506	89,039	82,430	85,989
β2=200	126,573	80,576	142,091	100,432	51,802	113,230	83,738	105,030



	NBS		Max Profit		Max Min		Max Min Diff	
	T1	T3	T1	T3	T1	T3	T1	T3
β2=170	81,967	55,220	94,982	49,480	8,173	57,348	52,891	50,046
β2=180	68,517	66,033	73,795	64,557	6,150	69,687	46,056	52,238
β2=190	56,009	74,359	57,102	82,486	1,434	87,015	41,403	47,736
β2=200	46,144	74,719	40,016	99,950	3,975	102,205	38,650	53,066

Figure 6 Individual Terminal Profit Increase by Cooperation Policy (VeBF)

Volume to Vessel Formulation Comparison

Table 7 shows the percentage of the average profit increase difference of the VoBF to VeBF for each terminal, cooperation policy, and profit function. For example, T1 exhibits 59% higher profits increase under the VoBF for the NBS policy and β_2=170. From these results, we observe the following:

i. VoBF overestimates the total profit increase and the profit increase of the terminals with the low V/C ratio;

ii. In terms of total profit MaxMinDiff and MaxMin exhibit the smallest overestimation, while NBS and MaxMin policies exhibit the highest with similar ranges;

iii. For the MaxMin and MaxMinDiff policies the overestimation increases with the β_2 coefficient;

iv. The VoBF underestimates the profit increase of the terminal with the highest V/C ratio in both NBS and MaxMin policies (in most of the cases);

v. The MaxProfit policy VoBF exhibits the highest profit increase underestimation for the terminal with the highest V/C ratio (i.e., terminal three) in the cooperation case of terminals 1 and 3.

Table 7 VoBF to VeBF: Mean Profit Increase Difference (by Terminal and Cooperation Policy)

	Mean Profit Increase Difference: VoBF to VeBF (T1 & T3)											
	NBS			MaxProfit			MaxMin			MaxMinDiff		
	T1	T3	Total	T1	T3	Total	T1	T3	Total	T1	T3	Total
β_2=170	59%	-11%	51%	65%	-913%	58%	48%	-5%	31%	30%	-7%	13%
β_2=180	68%	-5%	59%	72%	-322%	65%	59%	2%	40%	51%	3%	26%
β_2=190	71%	-9%	61%	77%	-203%	67%	66%	1%	41%	56%	5%	29%
β_2=200	70%	-27%	57%	81%	-124%	70%	74%	0%	47%	72%	8%	38%
	Mean Profit Increase Difference: VoBF to VeBF (T2 & T3)											
	NBS			MaxProfit			MaxMin			MaxMinDiff		
	T2	T3	Total	T2	T3	Total	T2	T3	Total	T2	T3	Total
β_2=170	62%	-10%	49%	66%	-55%	54%	77%	3%	30%	29%	15%	20%
β_2=180	71%	1%	56%	75%	-36%	59%	91%	1%	45%	58%	26%	37%
β_2=190	76%	4%	58%	81%	-23%	62%	98%	3%	47%	65%	47%	50%
β_2=200	78%	-11%	56%	86%	-6%	64%	94%	10%	41%	72%	53%	58%

Note: Red cells indicate higher profit increase by the VeBF

Terminal Efficiency Impact

For the same 480 datasets we re-run the models but with different handling fees and cost functions parameters (shown in Table 8) for each terminal. We assumed that the intercept of the handling fees and cost functions (i.e., pf_i and pc_i) decrease and increase respectively with the V/C ratio (i.e., terminal one will have a higher handling cost function intercept and a lower handling fee function coefficient when compared to terminals two and three). These assumptions are meant to reflect lower efficiencies and negotiating power (with the liner shipping companies) for the terminals with the lower V/C ratios and vice versa. For the remainder of the paper we will refer to these terminals as lower efficiency terminals and to the terminals used in the previous section as high efficiency terminals.

Table 8 Parameters of Handling Cost and Fees Functions by Terminal

Handling Cost and Fee Functions Parameters	T1	T2	T3
$[\boldsymbol{pf_1}, \boldsymbol{pf_2}, \boldsymbol{pf_3}]$	[200, 225, 250]		
$[\boldsymbol{pc_1}, \boldsymbol{pc_2}, \boldsymbol{pc_3}]$	[70, 60, 50]		

From these numerical experiments, and due to the paper length limitations, we only present results (in Table 9) that compare the profit increase differences between the low and high efficiency terminals for each terminal, as a percentage of their total profit increase. For example, in Table 9 for the VeBF and NBS policy high efficiency terminal T1 (i.e., pf_1=250, pc_1=50) has a 9% higher share of the total profit increase when compared to the low efficiency terminal one (i.e., pf_1=200, pc_1=70). It is notable that terminal three, which has the highest efficiency exhibits a loss when cooperating with terminals with lower efficiency for both problem formulations and all policies except for certain cases of the MaxMin policy (for certain values of parameter β_2).

Table 9 Profit Increase Difference (as a Percentage of Total Profit Increase) by Terminal (Same and Different Handling Fees, Cost, and Profit Functions)

	NBS		Max Profit		Max Min		Max Min Diff	
	T1	**T3**	**T1**	**T3**	**T1**	**T3**	**T1**	**T3**
	VeBF							
β_2=170	9%	-9%	11%	-11%	-23%	23%	5%	-5%
β_2=180	12%	-12%	13%	-13%	-17%	17%	6%	-6%
β_2=190	16%	-16%	16%	-16%	-11%	11%	8%	-8%
β_2=200	20%	-20%	20%	-20%	0%	0%	7%	-7%
	VoBF							
β_2=170	8%	-8%	8%	-8%	-12%	12%	0%	0%
β_2=180	9%	-9%	10%	-10%	-5%	5%	10%	-10%
β_2=190	11%	-11%	11%	-11%	-2%	2%	6%	-6%
β_2=200	13%	-13%	13%	-13%	6%	-6%	12%	-12%
	VeBF							
β_2=170	8%	-8%	8%	-8%	-7%	7%	6%	-6%
β_2=180	9%	-9%	12%	-12%	0%	0%	-1%	1%
β_2=190	10%	-10%	10%	-10%	-2%	2%	3%	-3%
β_2=200	12%	-12%	9%	-9%	4%	-4%	4%	-4%
	VoBF							
β_2=170	10%	-10%	11%	-11%	-2%	2%	3%	-3%
β_2=180	12%	-12%	14%	-14%	5%	-5%	10%	-10%
β_2=190	15%	-15%	17%	-17%	21%	-21%	9%	-9%
β_2=200	18%	-18%	20%	-20%	11%	-11%	9%	-9%

Note: Red cells indicate that the models with the same cost, handling fee and profit functions for all terminals are lower

Conclusion

MCTOs to share available demand and capacity. Results from this research indicate that the NBS and MaxProfit policies outperform the MaxMin and MaxMinDiff when a combined uniformity of profit share among the cooperating terminals and size are considered. The preliminary results, presented in this paper, also indicate that the NBS has a slight edge over the MaxProfit policy as it provides better profits increase for the terminal with the higher V/C ratio (which may also hold a stronger negotiating power) and better uniformity (i.e., does not neglect the terminals with the lower V/C ratio). An extension to the work presented herein would be to combine these two policies and develop a cooperation scheme that outperforms both (e.g., a compensation scheme for the terminal with the highest V/C ratio that most likely will lead to a Stackelberg (*68*) type game). Our research also showed that the commonly used volume based formulation (which is unrealistic for tactical/operational cooperation plans) can significantly overestimate total profits while at the same time underestimate the profits of the terminals with the higher V/C ratios. Finally, the preliminary results presented in this paper indicate that terminals with high efficiency and high V/C ratios benefit from collaborations with other high efficiency and low V/C ratios.

There are several future research directions that may be explored including but not limited to: (i) Perform more analysis for various values of demand, capacity. number of terminals etc., (ii) Develop solution algorithms that can handle more terminals (currently after four terminals the exact solution algorithm becomes inefficient), (iii) Develop the formulation and solution algorithm that estimates the Nash Equilibrium, (iv) Develop a formulation that considers additional costs for transshipment containers that will have to be moved between terminals or have to be loaded on specific vessels at the port of origin, (v) Consider uncertain demand (at the tactical or planning level).

4. Marine Container Terminal Cooperation: A Volume to Vessel Comparison

Introduction and Literature Review

Port and marine terminal cooperation is a hot topic in public and business circles, and bibliometric studies on port-related academic research show that port cooperation/integration is an emerging theme (*44*). Heaver et al. (*45*) examined strategic measures between port authorities and terminals, in particular, cooperation and competition amongst terminals within a port and between ports. Song (*46*) applied the concept co-opetition, the combination of competition and cooperation, to explain the relationships of the container ports in Hong Kong and South China. Notteboom (*47*) provided an overview of the challenges facing port and maritime companies in rapidly changing environment and analyzed the paths shipping lines and terminal operating companies are walking in the highly competitive container and logistics markets. The author noted that cooperation is likely to be advantageous when the combined costs of operations or buying transactions (such as negotiating and contracting) are lower than the cost of operating alone. Van Der Horst et al. (*48*) analyzed coordination problems in hinterland chains of seaports and different arrangements and concluded that underdevelopment of coordination in hinterland chains may be explained of a lack of contractual relations, information-asymmetry, and a lack of incentives for cooperation. Brooks et al. (*49*) discussed the nature of peripheral ports followed by a conceptualization of two development strategies: cooperation among seaports and coordination of supply chain operators with the emphasis on cooperation. Hoshino (*50*) analyzed Japanese container port strategy against intense regional competition from China and Korea and suggested that ports located on Tokyo and Osaka Bays could advance their collaboration and be managed by a single port authority to strengthen their competitive power. Fu and Chen (*51*) analyzed China’s Yangtze River Delta ports Ningbo-Zhoushan and Shanghai competition and cooperation by studying model of famous foreign ports, recognizing the urgent need to establish two-port's healthy competition and cooperation relations. Lee and Lam (*52*) attempted to evaluate port competitive edge of major Asian container ports, i.e. Busan, Hong Kong, Shanghai, and Singapore, referring to the customer-centric community ports, so-called the Fifth Generation Ports (5GP). Authors highlighted that port cooperation is in need in the era of 5GP which embraces the concept of clustering and community impact. Parola et al. (*53*) presented hierarchy of key drivers and suggested that economies of scales in shipping, port governance changes, coopetition among ports in proximity, inter-firm networks, and green and sustainability challenges, moderate the influential role of traditional drivers and reshuffle their relative salience.

Several studies used quantitative methods to describe/model cooperation between ports and terminals. Li and Oh (*54*) analyzed the relationship between neighboring ports of Shanghai port and Ningbo-Zhoushan port in China, using HHI Index model. Authors suggested that ports should cooperate to increase competitive power in Yangtze River Delta region. Jeon et al. (*55*) analyzed research trends in port competition and cooperation using a social network analysis, to identify the changes and evolution in trends, the research timeframe was divided into three periods between 1980 and 2015. Mclaughlin and Fearon (*56*) presented new cooperation/competition matrix framework that identifies four forms of cooperation as response strategies to the major maritime dynamics. The authors examined the degree of cooperation in relation to inter-port rivalry and the influence of private-sector drivers.

Various game-theoretic models have been developed to address port cooperation. Saeed and Larsen (*32*) analyzed the different combinations of coalitions among the three terminals at Karachi Port by developing a two-stage Bertrand game. Wang et al. (*11*) investigated the factors and conditions affecting alliance formations for ports serving partially overlapping hinterlands in South China by developing a game theory model for Pearl River Delta (Hong Kong and Shenzhen). Asgari et al. (*37*) examined the competition–cooperation scheme between two leading Asian hub ports: Singapore and Hong Kong in the presences of shipping companies. An interval branch and bound was used to solve the models. Wang and Sun (*12*) applied Hoteling game model to analyze the competition and cooperation among ports in the port group based on geographical location, service level and shipping distance.

Research in maritime transportation has been in the rise in the last decade and one research direction that has been proposed is the development of models that can capture cooperation between marine container terminal operators (MCTOs) and/or liner shipping companies (*57*). MCTO and/or port cooperation (*32*, *37*, *58*) seems like a natural reaction to the rapid changes in the liner shipping industry (*59–61*) in the form of new (and perhaps unstable) alliances (*53*), (*62*), (*63*), and demand/supply volatility (*63*). To the best of the authors knowledge, literature published on terminal cooperation, focus on the planning level, and consider volume (i.e., total TEU) as the decision variable. At the tactical/operational level, the vessel provides a more realistic selection of the decision variable. In the research presented herein, we propose two mathematical models to quantify, evaluate, and compare cooperation between marine container terminal at the planning (from now own as volume-based formulation or VoBF) and tactical/operational level (from now own as vessel-based formulation or VoBF). For both models we consider two different cooperation policies. The first cooperation policy maximizes the total profit increase from all the terminals, while the second policy maximizes the minimum profit increase amongst all the terminals, who cooperate. Under both policies, a terminal has the option of not participating in the cooperation scheme if participation will not result in a profit increase.

The rest of the paper is structured as follows. The next section presents the assumptions about the handling cost and fee functions and the mathematical formulation of the two models. The third section presents the results of the numerical experiments that compare the two formulations. The last section concludes the paper and proposes several future research avenues.

Problem Description and Formulation

In this section we introduce the problem, nomenclature, cost, fee, and profit functions, the equations that describe the physical problem, and finally the cooperation policies and the corresponding objective functions. As briefly discussed in the previous section, in this paper we study the cooperation of container terminals located at the same port with an established strategic alliance that allows them to share their seaside resources and demand from vessels. The container terminals cooperate to better utilize existing capacity, avoid capital investment (see, e.g., the concept of operational excess capacity in Haralambides (*66*)), and achieve higher profitability, sustainability, and resilience to market fluctuations (*46*).

Cost, Fee, and Revenue Functions

Let $I = \{1, \dots, i)$ be the set of terminals at the port, and C_i and V_i the capacity and demand (TEUs (un)loaded to/from vessels) at terminal $i \in I$, respectively, before cooperation. We define the handling cost, handling fee, terminal profit, and revenue functions as follows:

Handling cost per TEU (cost incurred by the terminal operator for (un)loading)

$$\mathrm{hc_i}(\mathrm{V_i}) = \left[\alpha_1 \left(\frac{\mathrm{V_i}}{\mathrm{C_i}}\right)^2 + \alpha_2 \left(\frac{\mathrm{V_i}}{\mathrm{C_i}}\right) + \mathrm{hc_i^0}\right], \forall \mathrm{i} \in \mathrm{I} \quad (4.35)$$

where hc_i^0 is the base (zero volume) container handling cost for terminal $i \in I$ and α_1 and α_2 are coefficients. This function has been adopted from Saeed and Larsen (*32*).

Handling fees per TEU (fees by liners to the terminal operator for (un)loading)

$$\mathrm{hf_i(V_i) = max\left(hf_i^{min}, \left(\frac{V_i}{C_i}\right)\beta_1 + hf_i^0\right), \forall i \in I} \tag{4.36}$$

where $\mathrm{hf_i^0}$ is the base (zero volume) container handling fee charged by terminal $i\epsilon I$ and hf_i^{min} is the minimum handling fee charged.

Terminal Revenue

$$\mathrm{r(V_i) = V_i hf_i(V_i)\ , \forall i \in I} \tag{4.37}$$

Terminal Profit

$$\mathrm{\pi_i(V_i) = [hf_i(V_i) - hc_i(V_i)]V_i\ , \forall i \in I} \tag{4.38}$$

Figure 7 shows an example of the handling fee and cost, profit and revenue functions. Based on Haralambides (*66*), the maximum profit for the terminal is achieved at volume to capacity (V/C) ratios in the vicinity of 60% to 80% (although these can be higher or lower depending on the technology and equipment used by terminal). Haralambides (*66*) states that "o*nce a port reaches 70% capacity utilization, congestion ensues in terms of unacceptable waiting times*". Reduction in profits, once V/C ratios exceed this limit, can be attributed to many factors with the main one being reduction in productivity from berth and yard congestion.

In this study, we investigate if cooperation between terminals in terms of shared capacity can be beneficial in increasing profits without the need of capital investment to secure "*excess capacity*". We propose two models for cooperation: one based on VoBF assignment (which can be used for planning/tactical purposes) and one based on VeBF assignment (that must be used for tactical/operational purposes). Note that, the optimal value of VoBF provides an upper bound for the optimal value of VeBF (for either cooperation policy) since the feasible space of the latter is a subspace of the former. Next, we present the mathematical formulations of both cooperation approaches.

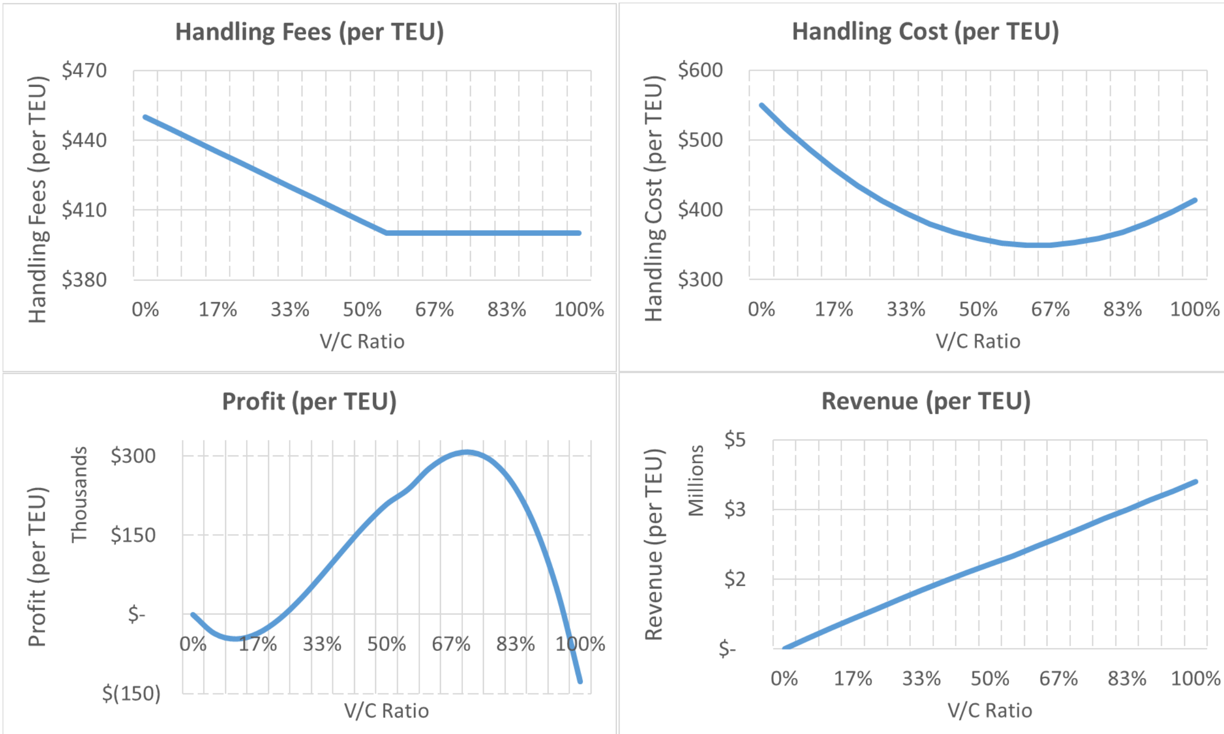


Figure 7 Example Handling Fees, Handling Cost, Profit, and Revenue Function Plots

Common Constraints for Both Formulations

Let $comp_i$, $i \in I$ be the compensation terminal $i \in I$ will pay any of the cooperating terminals to handle its diverted volume, $w_i = 1, i \in I$ if containers/vessels are diverted from terminal $i \in I$ to the other terminals and zero otherwise, $r_i = 1, i \in I$ if containers/vessels are diverted to terminal $i \in I$ from the other terminals and zero otherwise, $u_i = 1, i \in I$ if terminal $i \in I$ does not participate in the cooperation scheme, $\mathrm{V_i^c}$ the volume handled by terminal $i \in I$ under cooperation, $\mathrm{comp_i}$ the compensation ($USD per TEU) paid by terminal $i \in I$ to the other terminals for handling part of its demand, and $\mathrm{R_i^c}$ the revenue of terminal $\mathrm{i} \in \mathrm{I}$ under cooperation (4.48).

Profit of any terminal that cooperates will be greater than or equal to its profits under no cooperation

$$\pi_i(V_i^c) - \pi_i(V_i) \geq 0, \forall i \in I \tag{4.39}$$

Profit of terminal $i \in I$ under cooperation

$$\pi_i(V_i^c) = R_i^c - V_i^c hc_i(V_i^c), \forall a \in I \tag{4.40}$$

Total demand before cooperation equal to after cooperation

$$\sum_i V_i^c = \sum_i V_i \tag{4.41}$$

A terminal can either supply or accept containers to/from another terminal but not both

$$w_i + r_i + u_i = 1, \forall i \in I \tag{4.42}$$

Volume-Based Formulation Additional Equations

In this subsection, we present the additional constraints needed for the VoBF model. Let $x_{ib}, i \neq b \in I$ be the volume (TEUs) diverted from terminal $i \in I$ to terminal $b \in I$ under cooperation.

A terminal can either divert or accept containers to/from another terminal

$$w_i \leq x_{ib} \leq w_i V_i, \forall i, b \in I \tag{4.43}$$

$$r_i \leq x_{bi} \leq r_i V_i, \forall i, b \in I \tag{4.44}$$

$$x_{ib} + x_{bi} \leq (1 - u_i)(V_i + V_b), \forall i, b \in I \tag{4.45}$$

Volume handled at terminal $i \in I$ under cooperation

$$V_i^c = V_i + \sum_b x_{bi} - \sum_b x_{ib}, \forall i \neq b \in I \tag{4.46}$$

Revenue under cooperation of terminal $i \in I$

$$R_i^c = V_i hf_i(V_i) + \sum_b x_{bi} comp_b - \sum_b x_{ib} comp_i \quad , \forall i \neq b \in I \tag{4.47}$$

Vessel-Based Formulation Additional Equations

In this subsection, we define the additional sets, variables, and parameters and present the additional constraints for the VeBF model. Let J be the set of all vessels, $J_i \subseteq J$ the set of vessels served at terminal $i \in I$ under no cooperation ($J_a \cap J_b = \emptyset, \forall a \neq b \in I$), $x_{ji} = 1$ if vessel $j \in J$ is served at terminal $i \in I$ and zero otherwise, $y_{ji} = 1$ if vessel $j \in J$ is served at terminal $i \in I$ under cooperation and zero otherwise, V_j the volume of vessel $j \in J$, $V_i = \sum_{j \in J_i} x_{ji} V_j$, $\forall i \in I$ the total volume served at terminal $i \in I$ before cooperation, $M = |J|$, and N a large number. Next, we present the additional constraints for the VeBF model.

Under cooperation every vessel is served at one terminal

$$\sum_{i \in I} y_{ji} = 1, \forall i \in I \tag{4.48}$$

Volume at terminal $i \in I$ under cooperation

$$V_i^c = \sum_j y_{ji} V_j, \forall i \in I \tag{4.49}$$

A terminal can either divert or accept vessels to/from another terminal

$$r_i \leq \sum_{j \in J_{\gamma \in I \neq i}} y_{ji} \leq M r_i, \forall i \in I \tag{4.50}$$

$$w_i \leq \sum_{j \in J_i, \gamma \in I \neq i} y_{j\gamma}, \leq M w_i, \forall i \in I \tag{4.51}$$

$$\sum_{j \in J_{\gamma \in I \neq i}} y_{ji} + \sum_{j \in J_i, \gamma \in I \neq i} y_{j\gamma}, \leq M(1 - u_i), \forall i \in I \tag{4.52}$$

Revenue under cooperation of terminal $i \in I$

$$R_\iota^c = V_i hf_i(V_i) + \sum_{j \in J_{\gamma \in I \neq i}} y_{ji} V_j comp_\gamma - \sum_{j \in J_i, \gamma \in I \neq i} y_{j\gamma} V_j comp_\iota \quad \forall \iota \in I \tag{4.53}$$

Cooperation Policies

In this study, we consider two different cooperation policies (i.e., objective functions for both models presented in the previous subsection): 1) maximization of total profit of terminals that participate in the cooperation scheme (4.54), and 2) maximization of the lowest profit of any terminal that participates in the cooperation scheme (4.55). The first policy maximizes total welfare while the second equity.

Total Profit Maximization

$$\Pi 1: \max \sum_{i \in I} \left(\pi_i (V_i^c) \right) \tag{4.54}$$

Minimum Profit Maximization

$$\Pi 2: \max \min_{i \in I} \left(\pi_i (V_i^c) \right) \tag{4.55}$$

Numerical Experiments

In this section, we present results from numerical experiments aimed at evaluating and comparing the two formulations (i.e., volume- vs. vessel-based formulations) and the two policies (i.e., maximization of the total profit vs. maximization of the minimum terminal profit). We consider that there are three terminals such that each terminal has a different V/C ratio value, where the maximum productivity is achieved. We assume that terminals 1, 2 and 3 (from now on referred to as T1, T2, and T3) have the same capacity and achieve their maximum productivity when the V/C ratio values are 90%, 70%, and 60%, respectively. We developed 400 different problem instances by randomly (uniform distribution) varying individual terminal demand between 30% and 100% of their capacity. It is assumed that a terminal will not participate in the cooperation if its demand would drop below 30% of its capacity. The rational for adding this constraint is to avoid solutions where a terminal will choose to forfeit all its demand (due to the shape of the profit function where negative profits are observed for low demand cases). In practice, a terminal would never follow such a practice and would rather accept the loss in profit.

For each one of the 400 problem instances, we consider three distribution patterns, of the total demand, between the terminals before any cooperation takes place. In the first case (from now on referred to as the random case), the total demand is randomly assigned amongst the three terminals. In the second case (from now on referred to as the ascending case), the total demand is distributed amongst the terminals in an ascending order of the maximum productivity V/C ratio. Finally, in the third case (from now on referred to as the descending case) the total demand is distributed amongst the terminals in a descending order of the maximum productivity V/C ratio. For each problem instance, the total volume remains the same amongst the three cases, but the number of vessels vary. We assumed that a vessel will (un)load anywhere between 500 to 3,000 containers at a terminal. Table 10 provides an example of one problem instance for each one of the three demand distribution patterns.

Table 10 Example of Problem Instance

Demand Distribution Pattern	Total Demand (TEU)	Demand per Terminal (TEU)			# of Vessels per Terminal		
		Terminal 1 (T1)	Terminal 2 (T2)	Terminal 3 (T3)	T1	T2	T3
Ascending	21 633	5 676	7 442	8 515	4	6	5
Descending		8 515	7 442	5 676	4	6	3
Random		7 442	8 515	5 676	6	6	4

We also considered seven compensation strategies (listed in Table 11) i.e., the price terminal $i \in I$ will pay another terminal for each container it diverts. The first three policies set a bound for the compensation price, while the last three fix the compensation price equal to the upper bounds of the former three cases, respectively. The upper bounds for the compensation prices are set equal to the average, minimum and maximum value of the hf_i^{min} parameter (i.e., minimum handling fee charged at each terminal) over all three terminals. The seventh and last policy evaluated in this research sets a simple non-negativity bound.

Table 11 Compensation Strategy Per Container Diverted

Case	Constraint Type	$comp_i$ range
Case 1	Upper Bound	$0 \leq \boldsymbol{comp_i} \leq \underset{i}{ave}(hf_i^{min})$
Case 2		$0 \leq \boldsymbol{comp_i} \leq \underset{i}{min}(hf_i^{min})$
Case 3		$0 \leq \boldsymbol{comp_i} \leq \underset{i}{max}(hf_i^{min})$
Case 4	Fixed Value	$\boldsymbol{comp_i} = \underset{i}{ave}(hf_i^{min})$
Case 5		$\boldsymbol{comp_i} = \underset{i}{min}(hf_i^{min})$
Case 6		$\boldsymbol{comp_i} = \underset{i}{max}(hf_i^{min})$
Case 7	No bound	$\boldsymbol{comp_i} \geq \boldsymbol{0}$

All problem instances were solved using GAMS and Matlab on an AMD Ryzen 7, 3.2 GHz Eight-Core Processor with 32.0 GM memory. The maximum solution time for a problem instance was less than 5 minutes.

Individual Terminal Profit Increase and Total Profit Increase Share

In this subsection, we present and discuss results on the profit increase of each terminal (i.e., difference of profit after and before cooperation). For each compensation case, demand distribution pattern, cooperation policy, and demand unit, we calculated the mean profit increase of each terminal by fitting a normal distribution over the 400 problem instances. Results are summarized in Table 12 through Table 15. Table 12 and Table 13 show the difference of the mean profit increase while Table 14 and Table 15 show the mean profit increase share for each terminal between the two formulations two cooperation policies, respectively.

Results in Table 12 indicate, as expected, significant profit overestimation by the VoBF when compared to the VeBF. A small number of cases exist (for all three terminals) where the VoBF provides a better solution (i.e., higher profit increase) for individual terminals. Terminals 2 and 3 (i.e., the terminals with the average and low productivity) show the highest difference under policy 1 while Terminals 1 and 2 (i.e., the terminals with the high and average productivity) under policy 2. Terminal 3 shows small differences under policy 2.

Results in Table 13 suggest that Policy 1 is the most and worst beneficial for the least and most productive terminals, respectively (i.e., Terminal 3 and Terminal 1) for the ascending demand case (i.e., Terminal 3 received the lowest and Terminal 1 the highest demand). The descending demand case is the most beneficial for the most productive terminal (i.e., Terminal 1), unfavorable for Terminal 2 and almost non-consequential for Terminal 3. The random demand case favors Terminal 3 and shows mixed results for Terminals 1 and 2.

Table 12 Mean Profit Increase Difference: Volume to Vessel Based Formulation

			Policy 1			Policy 2		
Demand Split	**Compensation Case**		**T1**	**T2**	**T3**	**T1**	**T2**	**T3**
Random	**Upper Bound**	**Case 1**	22%	-2%	-2%	8%	15%	1%
		Case 2	10%	3%	4%	8%	12%	0%
		Case 3	14%	0%	3%	8%	16%	2%
	Fixed	**Case 4**	12%	45%	31%	36%	55%	12%
		Case 5	-30%	37%	25%	0%	28%	7%
		Case 6	33%	49%	37%	53%	61%	11%
	No Bound	**Case 7**	33%	-16%	1%	7%	15%	1%
Ascending	**Upper Bound**	**Case 1**	17%	12%	-12%	14%	14%	-4%
		Case 2	7%	11%	-2%	13%	15%	-9%
		Case 3	14%	10%	-7%	13%	14%	-5%
	Fixed	**Case 4**	-16%	71%	77%	60%	81%	4%
		Case 5	-61%	53%	52%	-3%	49%	6%
		Case 6	23%	77%	81%	100%	86%	9%
	No Bound	**Case 7**	28%	2%	-13%	13%	14%	-6%
Descending	**Upper Bound**	**Case 1**	8%	3%	9%	6%	10%	5%
		Case 2	9%	4%	7%	5%	9%	5%
		Case 3	8%	3%	9%	5%	10%	5%
	Fixed	**Case 4**	23%	28%	14%	15%	36%	12%
		Case 5	-1%	18%	7%	-1%	17%	7%
		Case 6	25%	29%	17%	16%	39%	15%
	No Bound	**Case 7**	13%	-4%	11%	5%	10%	5%

Table 13 Mean Profit Increase Difference: Policy 1 to Policy 2

			VoBF			VeBF		
Demand Split	**Compensation Case**		**T1**	**T2**	**T3**	**T1**	**T2**	**T3**
Random	**Upper Bound**	**Case 1**	-2%	-13%	27%	-21%	12%	30%
		Case 2	-19%	8%	27%	-22%	20%	22%
		Case 3	0%	-20%	32%	-8%	1%	30%
	Fixed	**Case 4**	0%	-20%	32%	33%	-7%	4%
		Case 5	-24%	11%	29%	18%	0%	4%
		Case 6	1%	-23%	37%	29%	-7%	1%
	No Bound	**Case 7**	13%	-31%	32%	-22%	11%	32%
Ascending	**Upper Bound**	**Case 1**	-68%	-12%	89%	-73%	-8%	100%
		Case 2	-72%	2%	87%	-64%	6%	77%
		Case 3	-67%	-15%	89%	-69%	-10%	94%
	Fixed	**Case 4**	-70%	-18%	99%	35%	-4%	0%
		Case 5	-69%	0%	89%	10%	-6%	25%
		Case 6	-74%	-16%	99%	32%	-4%	-1%
	No Bound	**Case 7**	-51%	-26%	87%	-71%	-9%	96%
Descending	**Upper Bound**	**Case 1**	11%	-11%	5%	7%	0%	-1%
		Case 2	10%	2%	-1%	4%	8%	-4%
		Case 3	12%	-12%	6%	9%	-3%	1%
	Fixed	**Case 4**	12%	-12%	4%	2%	-1%	3%
		Case 5	9%	3%	-2%	10%	2%	-3%
		Case 6	13%	-13%	6%	0%	-1%	3%
	No Bound	**Case 7**	16%	-19%	8%	5%	1%	0%

Results in Table 14 do not reveal any clear patterns with regards to the total profit increase share between the two formulations except for the fixed compensation case under random and ascending demand splits. For these cases, there is a clear high overestimation of the VoBF for the profit share of Terminal 1 and an underestimation for Terminals 2 and 3 for Policy 1 and Terminal 2 for Policy 2.

With regards to the total profit increase share under the two policies (Table 15), a pattern emerges where both cooperation policies favor Terminal 3 (with some small exceptions). The ascending/descending demand split case provide the worst results Terminals 1 and 2 respectively (for both formulations).

Table 14 Total Mean Profit Increase Split: Volume to Vessel Based Formulation

			Policy 1			Policy 2		
Demand Split	Compensation Case		T1	T2	T3	T1	T2	T3
Random	Upper Bound	Case 1	10%	-6%	-4%	-2%	4%	-2%
		Case 2	3%	-3%	0%	-1%	3%	-2%
		Case 3	4%	-4%	-1%	-3%	3%	-1%
	Fixed	Case 4	-35%	22%	13%	-20%	20%	0%
		Case 5	-31%	17%	13%	-14%	12%	2%
		Case 6	-43%	27%	15%	-17%	21%	-4%
	No Bound	Case 7	16%	-14%	-2%	-2%	3%	-1%
Ascending	Upper Bound	Case 1	5%	3%	-8%	0%	3%	-3%
		Case 2	1%	2%	-3%	1%	4%	-5%
		Case 3	3%	2%	-6%	0%	3%	-3%
	Fixed	Case 4	-54%	27%	27%	-25%	29%	-4%
		Case 5	-37%	19%	18%	-18%	17%	1%
		Case 6	-61%	31%	31%	-29%	30%	-1%
	No Bound	Case 7	9%	-1%	-8%	0%	3%	-3%
Descending	Upper Bound	Case 1	4%	-10%	6%	2%	-2%	0%
		Case 2	5%	-11%	6%	2%	-3%	2%
		Case 3	2%	-8%	6%	1%	-2%	0%
	Fixed	Case 4	11%	14%	-26%	7%	15%	-22%
		Case 5	-16%	10%	6%	-13%	9%	3%
		Case 6	17%	30%	-47%	2%	31%	-32%
	No Bound	Case 7	10%	-19%	9%	1%	-2%	0%

Table 15 Total Mean Profit Increase Split: Policy 1 to Policy 2

			VoBF			VeBF		
Demand Split	Compensation	Case	T1	T2	T3	T1	T2	T3
Random	Upper Bound	Case 1	-3%	-8%	11%	-15%	2%	13%
		Case 2	-12%	0%	11%	-16%	6%	10%
		Case 3	-2%	-11%	14%	-9%	-4%	14%
	Fixed	Case 4	-2%	-11%	13%	13%	-13%	1%
		Case 5	-14%	2%	12%	3%	-4%	1%
		Case 6	-3%	-13%	16%	23%	-19%	-4%
	No Bound	Case 7	3%	-17%	13%	-16%	1%	15%
Ascending	Upper Bound	Case 1	-22%	-4%	26%	-26%	-5%	31%
		Case 2	-24%	-1%	25%	-24%	0%	23%
		Case 3	-21%	-5%	26%	-24%	-5%	29%
	Fixed	Case 4	-22%	-7%	29%	6%	-4%	-2%
		Case 5	-24%	-2%	26%	-4%	-4%	8%
		Case 6	-23%	-6%	29%	9%	-7%	-2%
	No Bound	Case 7	-17%	-9%	25%	-25%	-5%	30%
Descending	Upper Bound	Case 1	9%	-12%	4%	7%	-4%	-3%
		Case 2	7%	-4%	-3%	4%	4%	-8%
		Case 3	10%	-14%	4%	9%	-8%	-1%
	Fixed	Case 4	11%	-14%	3%	6%	-13%	7%
		Case 5	7%	-2%	-4%	10%	-3%	-7%
		Case 6	11%	-15%	4%	-4%	-14%	19%
	No Bound	Case 7	14%	-20%	7%	5%	-3%	-2%

Terminal Participation

In this subsection, we present and discuss results on the differences in terminal participation under the two formulations and policies over the 400 different problem instances. Table 16 and Table 17 show a summary of the results from this analysis. Table 16 shows the difference in terminal participation between the two formulations for each policy. A clear pattern emerges where all three terminals significantly reduce their participation (with some exceptions) under both cooperation policies when it is based on the VeBF. This means that cooperation success is highly overestimated at the planning level (VoBF) when compared to the tactical/operational level (VeBF). Between the two policies (Table 17) a different pattern emerges where terminal 2 is more likely to participate under policy 2. Terminal 3 shows a much higher participation rate under Policy 1 for the random and ascending demand case. Terminal 1 is more likely to participate under Policy 1 for the random and descending demand case.

Table 16 Participation Difference: Volume to Vessel Based Formulation

			Policy 1			Policy 2		
Demand Split	Compensation Case		T1	T2	T3	T1	T2	T3
Random	Upper Bound	Case 1	22%	18%	19%	5%	12%	3%
		Case 2	17%	14%	14%	5%	15%	9%
		Case 3	22%	21%	23%	6%	12%	5%
	Fixed	Case 4	53%	60%	53%	45%	61%	33%
		Case 5	1%	15%	28%	-3%	15%	11%
		Case 6	69%	71%	71%	63%	76%	34%
	No Bound	Case 7	23%	9%	15%	7%	12%	0%
Ascending	Upper Bound	Case 1	15%	16%	1%	0%	10%	-6%
		Case 2	14%	12%	3%	1%	11%	3%
		Case 3	16%	14%	1%	0%	10%	-5%
	Fixed	Case 4	41%	73%	43%	42%	62%	-11%
		Case 5	0%	12%	25%	5%	11%	7%
		Case 6	60%	83%	61%	65%	79%	3%
	No Bound	Case 7	16%	9%	-3%	0%	10%	-8%
Descending	Upper Bound	Case 1	26%	11%	24%	13%	11%	11%
		Case 2	21%	12%	29%	8%	12%	16%
		Case 3	21%	12%	26%	11%	10%	13%
	Fixed	Case 4	78%	69%	64%	53%	79%	55%
		Case 5	14%	12%	24%	-1%	12%	21%
		Case 6	87%	81%	74%	59%	91%	65%
	No Bound	Case 7	26%	-2%	27%	14%	10%	12%

Table 17 Participation Difference: Policy 1 to Policy 2

			VoBF			VeBF		
Demand Split	Compensation Case		T1	T2	T3	T1	T2	T3
Random	Upper Bound	Case 1	13%	-6%	27%	-4%	-12%	12%
		Case 2	9%	-3%	17%	-3%	-2%	11%
		Case 3	14%	-10%	33%	-2%	-18%	15%
	Fixed	Case 4	15%	-10%	25%	6%	-9%	5%
		Case 5	9%	-2%	18%	5%	-2%	0%
		Case 6	12%	-10%	37%	6%	-5%	0%
	No Bound	Case 7	13%	-15%	34%	-4%	-13%	19%
Ascending	Upper Bound	Case 1	-5%	-4%	52%	-20%	-10%	44%
		Case 2	-5%	0%	38%	-18%	0%	37%
		Case 3	-2%	-5%	53%	-18%	-9%	48%
	Fixed	Case 4	-2%	-4%	60%	0%	-15%	6%
		Case 5	-5%	0%	43%	0%	0%	25%
		Case 6	-4%	-7%	64%	1%	-11%	6%
	No Bound	Case 7	-2%	-10%	54%	-18%	-10%	50%
Descending	Upper Bound	Case 1	30%	-8%	10%	17%	-8%	-4%
		Case 2	29%	0%	1%	17%	0%	-13%
		Case 3	30%	-9%	10%	20%	-11%	-4%
	Fixed	Case 4	28%	-10%	9%	4%	0%	0%
		Case 5	27%	0%	-4%	13%	0%	-7%
		Case 6	28%	-10%	9%	0%	0%	0%
	No Bound	Case 7	29%	-18%	13%	16%	-6%	-2%

Diverted Demand

In this subsection we present and discuss results on the differences in the role of each terminal in the cooperation scheme (i.e., does it divert or accept demand from/to the other terminals) under the two formulations and policies over the 400 different problem instances. Table 18 and Table 19 show a summary of the results from this analysis. Table 18 shows the difference in the demand accepted by each terminal between the two formulations for each policy. A clear pattern emerges where Terminal 1 is the least affected by the cooperation policy.

On the other hand, the VoBF overestimates the demand diverted to Terminals 2 and 3 under both cooperation policy. This would mean that resources scheduled under the VoBF would not be used when the actual schedule, based on the VeBF, would be implemented. With regards to the two policies only Terminal 3 (terminal with the lowest productivity) shows significant differences for the VoBF and for a few cases for the VeBF.

Table 18 Diverted Demand Difference: Volume to Vessel Based Formulation

			Policy 1			Policy 2		
Demand Split	**Compensation Case**		**T1**	**T2**	**T3**	**T1**	**T2**	**T3**
Random	**Upper Bound**	**Case 1**	3%	14%	8%	3%	16%	18%
		Case 2	3%	14%	8%	5%	15%	21%
		Case 3	2%	14%	8%	4%	16%	20%
	Fixed	**Case 4**	2%	63%	44%	4%	65%	58%
		Case 5	4%	15%	37%	6%	15%	53%
		Case 6	1%	73%	52%	3%	74%	67%
	No Bound	**Case 7**	3%	14%	7%	3%	16%	20%
Ascending	**Upper Bound**	**Case 1**	0%	12%	2%	0%	13%	3%
		Case 2	0%	12%	2%	0%	11%	9%
		Case 3	0%	12%	2%	0%	13%	3%
	Fixed	**Case 4**	0%	75%	42%	0%	75%	46%
		Case 5	0%	12%	26%	0%	11%	43%
		Case 6	0%	88%	59%	0%	87%	65%
	No Bound	**Case 7**	0%	12%	2%	0%	13%	3%
Descending	**Upper Bound**	**Case 1**	6%	10%	9%	8%	9%	19%
		Case 2	7%	10%	10%	14%	9%	22%
		Case 3	6%	9%	9%	8%	9%	21%
	Fixed	**Case 4**	8%	69%	33%	13%	69%	46%
		Case 5	10%	11%	35%	19%	11%	49%
		Case 6	8%	76%	33%	12%	77%	48%
	No Bound	**Case 7**	6%	9%	9%	8%	8%	19%

Table 19 Diverted Demand Difference: Policy 1 to Policy 2

			VoBF			VeBF		
Demand Split	Compensation Case		T1	T2	T3	T1	T2	T3
Random	Upper Bound	Case 1	-1%	-3%	-11%	-1%	-1%	-2%
		Case 2	-2%	-3%	-9%	0%	-2%	5%
		Case 3	-2%	-1%	-13%	1%	0%	-1%
	Fixed	Case 4	-2%	-3%	-12%	1%	0%	2%
		Case 5	-3%	-2%	-7%	-1%	-2%	9%
		Case 6	-2%	-1%	-14%	1%	0%	1%
	No Bound	Case 7	-1%	-1%	-14%	-1%	0%	-2%
Ascending	Upper Bound	Case 1	0%	0%	1%	0%	1%	2%
		Case 2	0%	0%	7%	0%	0%	14%
		Case 3	0%	1%	0%	0%	1%	1%
	Fixed	Case 4	0%	0%	1%	0%	0%	5%
		Case 5	0%	0%	6%	0%	0%	24%
		Case 6	0%	1%	0%	0%	0%	6%
	No Bound	Case 7	0%	1%	-1%	0%	1%	1%
Descending	Upper Bound	Case 1	-3%	0%	-14%	-1%	0%	-4%
		Case 2	-8%	0%	-17%	-2%	0%	-5%
		Case 3	-3%	0%	-16%	-1%	0%	-3%
	Fixed	Case 4	-4%	0%	-13%	1%	-1%	0%
		Case 5	-9%	0%	-14%	-1%	0%	0%
		Case 6	-3%	0%	-16%	1%	2%	0%
	No Bound	Case 7	-2%	0%	-13%	0%	0%	-4%

Conclusion and Future Research

In this paper we proposed two mathematical formulations to model intraport terminal cooperation at the planning and tactical/operational level. Numerical experiments with simulated data were used to evaluate and compare the two models for two cooperation policies maximizing total profit increase of all terminals and minimum profit increase of any terminal. Results indicate that planning level models provide significant difference to tactical/operational level models with regards to demand diversion between the terminals and overestimation of profits. Future research should focus on including a differential pricing policy by customer (e.g., liner company or alliances), allow demand to exceed capacity, and develop a mechanism for profit sharing between the coalition members that would ensure stability.

5. Mathematical Framework for Container Terminal and Liner Shipping Companies Cooperation and Competition

Introduction

Maritime transportation is a critical component of international trade with approximately 90% of the global trade volume carried by deep-sea vessels (*69*). The World Shipping Council, 2014 (*29*) indicates that "*it would require hundreds of freight aircraft, many miles of rail cars, and fleets of trucks to carry the goods that can fit on one large liner ship*." According to the data provided by the United Nations Conference on Trade and Development (*70*), the overall international seaborne trade reached 9.8 billion tons in 2014 with a significant increase of containerized (5.6% in tonnage), dry (2.4% in tonnage), and major bulk cargo (6.5% in tonnage) from 2013. Similar growth is expected to continue. Most of the high-value cargo and general consumer goods are shipped in a containerized form. Liner shipping companies, looking for transport efficiency and economies of scale, have increased vessel size on most of the trade routes. The Journal of Commerce, 2015 (*71*) highlights that CMA CGM placed an order for six vessels with 14,000 TEU capacity in the first half of 2015 after an earlier order for three 20,000 TEU vessels. Maersk has recently ordered eleven 19,500 TEU vessels, while MOL and OOCL placed orders for vessels with 20,000 TEU capacity. Note that the number of megaships is projected to increase by at least 13% by 2020 (*71*).

To meet the growing demand, while facing capacity expansion limitations (e.g., lack of land, high cost of expansion, etc.), marine container terminal operators and port authorities have emphasized the importance of planning and operations optimization as a means to increase productivity (see for example (*8*, *72–77*)). A terminal capacity can be increased by upgrading the existing or constructing the new infrastructure, but that requires a significant capital investment (*76*, *78*). Alternatives to the construction of the new infrastructure include improvement of conventional equipment and productivity by introducing new forms of technology (*79*), information systems (*80*), and work organization (*81*). One approach that can increase productivity without capital investment is better utilization of the existing berthing capacity between terminal operators, ports or both through collaborative agreements (*82*, *83*). One may view such agreements as the answer of port authorities and terminal operators to alliances, formed by liner shipping companies (*84*) that allow vessels from different liner shipping companies to be served at different terminals of the same or different ports (*85–87*).

In this study, we model cooperation and competition, between marine container terminal operators (MCTOs) and liner shipping alliances. The objective is to develop a mathematical framework that will maximize container terminal revenues, minimize terminal costs and increase freight fluidity. This research builds upon and expands on existing research (*45*), (*53*), (*57*), (*58*), (*62*), (*88*), and proposes a game theory based mathematical model. To our knowledge, only four studies have been published to date that addresses terminal resource allocation at the operational level (*58*, *88–90*).

Conceptual and Mathematical Framework and Complexity Analysis

In this section, we present the conceptual (Figure 9) and mathematical framework for terminal operators, and liner shipping companies cooperation and competition. We use the Stackelberg game, where the shipping lines in alliance act as leaders by minimizing shipping costs and terminal fees, and the container terminals act as followers by making decision to compete or engage in cooperation with the other terminal by utilizing each other's capacities with the objective to maximize profit. The relationship between the container terminal capacity utilization and congestion effects has been modeled based on (*66*), where it was reported that the maximum profit for the terminal is achieved at V/C ratios in the vicinity of 60% to 80%

(although these can be higher or lower depending on the technology and equipment used by the terminal). Haralambides, 2002 (*66*) states that "o*nce a port reaches 70% capacity utilization, congestion ensues in terms of unacceptable waiting times*". Reduction in profits, once V/C ratios exceed this limit, can be attributed to many factors with the main one being the reduction in productivity from berth and yard congestion. Figure 8 shows theoretical graphs of the handling cost (5.56), handling fees (5.57), and terminal profit (5.69) as a function of V/C ratio per TEU (left side) and total demand (right side).

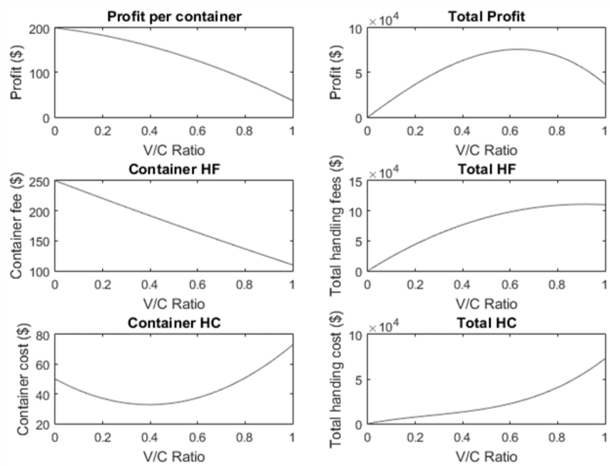


Figure 8 Example Profit, Handling Cost and Handling Fee Functions Plots

Our study is an extension of (*26*), where authors investigated cooperation between terminals in terms of shared capacity can be beneficial in increasing profits without the need of capital investment to secure "*excess capacity*" and evaluated four different cooperation policies and two different demand assumptions.

The game theoretic model developed in this research analysis competition between two shipping lines in an alliance and two MCTOs that have already engaged in a cooperative agreement and are in two different ports makes several assumptions. First, we assume that the MCTOs can negotiate and share the available (seaside and landside) resources/capacity to maximize profits. Second, we assume that the shipping lines of the alliance can utilize each other's capacity, due to already negotiated Vessel Sharing Agreement(s), where each shipping line shares vessel capacity, proportional to total shipping line capacity with the objective to minimize shipping costs and terminal fees. Third, the model only considers shipping lines of a single alliance and assumes that both shipping lines depart from a single port, thus excluding any costs associated with container transfer between shipping lines. We model competition between the alliance shipping lines and MCTOs as a Stackelberg leadership game, where, the leader of the game, the shipping lines, makes decisions first and the follower the MCTOs responds. At the first stage of the game, the alliance is simultaneously minimizing shipping costs and terminal fees, where the shipping costs $sc_{ij}(q_{ij})$, see (5.58), (per TEU) are given as a function of number of containers shipped q_{ij} by shipping line $i \in I$ to terminal $j \in J$ and terminal fees $hf_{ij}(V_{ij}^{a})$, see (5.57), are given as a function of volume containers handled at terminal $j \in J$ after shipping lines $i \in I$ shipment. Shipping line alliance is minimizing the shipping costs and terminal fees by utilizing shipping line capacity through a container volume transfer x_{ab}^{SL} between shipping lines and deciding on the volume of containers q_{ij} shipped by shipping line $i \in I$ to terminal $j \in J$. At the second stage of the game MCTOs decide to engage in a cooperative or non-cooperative game. MCTOs under cooperation maximize their profits by utilizing their capacities through container volume transfer x_{ab}^{P} between container terminals.

The model is constructed as a non-cooperative game between the shipping lines and the container terminals, where at each level a cooperative game is formulated. The optimal outcome of a non-cooperative game between the shipping lines and container terminals can be determined using Nash-equilibrium, which describes a set of strategies between the players, such that no player can gain more by changing his or her strategies. Furthermore, as the model is constructed as a sequential game, it involves multi-stage decisions; thus the Nash-equilibrium is determined using backwards inductions starting by first determining the equilibrium for the last sub-game.

Our model also includes two cooperative subgames, where at the upper-level, liner shipping alliance seek to achieve Pareto-efficiency a state where the containers are distributed among the shipping lines in the most efficient way, so that no shipping line can be put in a better position, without worsening the position of other shipping lines. Similarly, at the lower level, if container terminals engage in cooperation then Pareto-efficiency should be achieved; otherwise, containers terminals play a non-cooperative game, and the optimal outcome is determined using Nash-equilibrium. Also, when cooperative games are considered, the stability of coalition and fairness of payoff distribution among players should be considered. Next, we present the conceptional and mathematical framework.

Let $i \in I$ be the set of shipping lines, where $i \in (1, 2)$, $j \in J$ the set of container terminals, where $j \in (1, 2)$. Following parameters are used at the model in the shipping line, alliance stage: Q_i^{SL} shipping lines $i \in I$ demand, Q_{ij}^{SL} shipping lines $i \in I$ demand to terminal $j \in J$, C_{ij}^{SL} shipping lines $i \in I$ available capacity to terminal $j \in J$ (Vessel Sharing Agreement), Q_j alliances demand to terminal $j \in J$, sc_{ij} shipping lines $i \in I$ shipping cost to terminal $j \in J$ per container, c_{ij} shipping lines $i \in I$ shipping cost shipping containers to terminal $j \in J$, q_{ij}^c volume of containers shipped by shipping line $i \in I$ to terminal $j \in J$ under cooperation, $r_a^{SL} = 1$ if containers are transferred to shipping line $a \in I$, $w_a^{SL} = 1$ if containers are transferred from shipping line $a \in I$. Following decision variables are used at the model in the shipping line, alliance stage: q_{ij} the container volume demand by shipping line $i \in I$ to terminal $j \in J$, x_{ab}^{SL} the volume of containers transferred from shipping line $a \in I$ to shipping line $b \in I$ under cooperation.

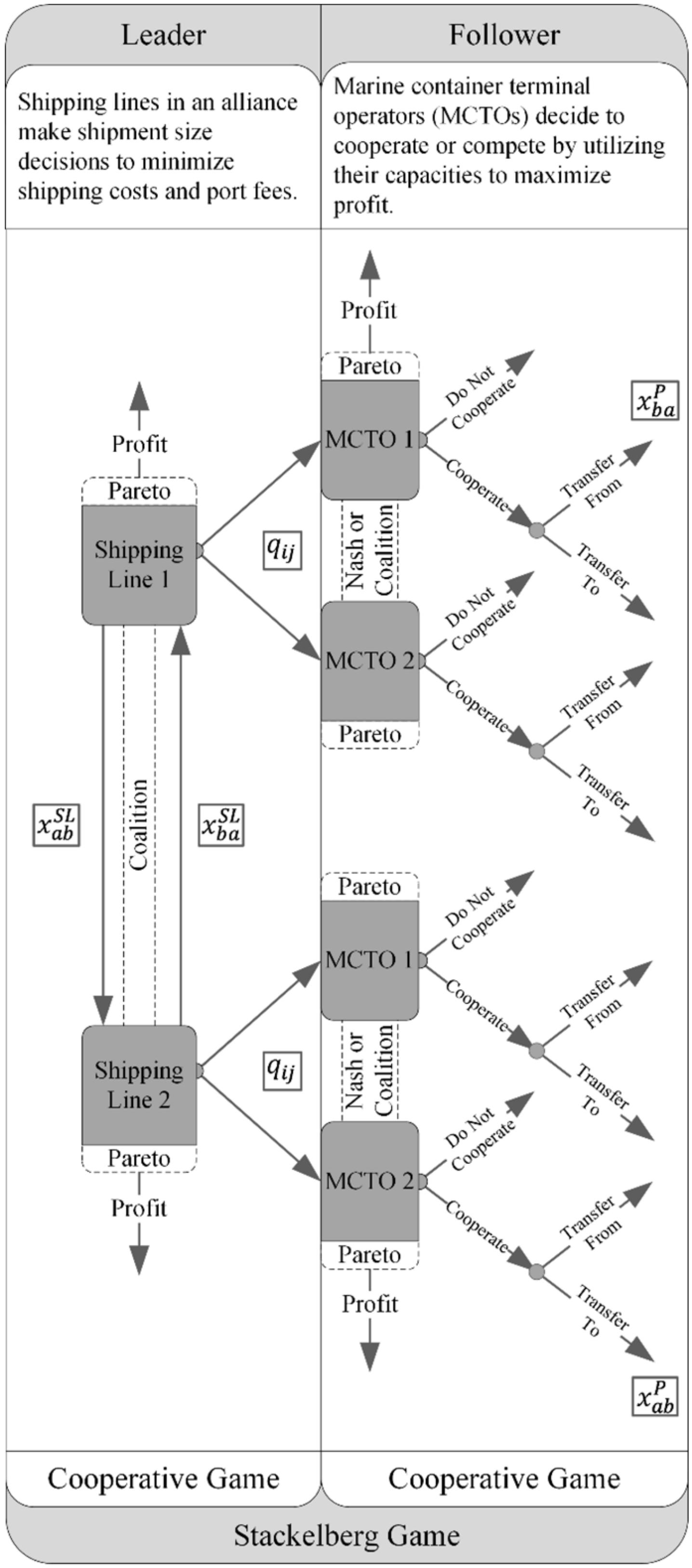


Figure 9 Conceptional Model for Two-Stage Stackelberg Game

Following parameters are used at the model in the marine container terminal operator stage: C_j^P terminal $j \in J$ capacity, hc_{ij} terminal $j \in J$ handling cost of handling one unit of container shipped by shipping line $i \in I$, hf_{ij} terminal $j \in J$ handling fee of handling one unit of container shipped by shipping line $i \in I$, V_j^b volume of containers handled at terminal $j \in J$ before shipping lines $i \in I$ shipment, V_{ij}^a volume of containers handled at terminal $j \in J$ after shipping lines $i \in I$ shipment, V_j volume of containers handled at terminal $j \in J$, pf_a^c handling fee per container for demand diverted to terminal $a \in J$, $r_a^P = 1$ if containers are transferred to terminal $a \in J$, $w_a^P = 1$ if containers are transferred from terminal $a \in J$, prl_a terminal $a \in J$ profit loss from handling fees of diverted demand from any other terminals, p the percentage of the origin terminal handling fee charged at the destination terminal (for diverted demand). Following decision variables are used at the marine container terminal operator stage: x_{ab}^P volume of containers (TEUs) transferred from terminal $a \in J$ to terminal $b \in J$ under cooperation, where $a \neq b \in J$. Next, we define the handling fees, handling costs, shipping costs, and total profit functions.

Terminal handling cost function per TEU (cost endured by the terminal operator) - (see (*26*)*)*

$$hc_{ij}(V_{ij}^a) = \left[\alpha_1 \left(\frac{V_{ij}^a}{C_j^P}\right)^2 - \alpha_2 \left(\frac{V_{ij}^a}{C_j^P}\right) + pc_j\right] \tag{5.56}$$

, where pc_j is the base container handling cost for terminal $j \in J$ without cooperation and α_1, α_2 are the cost function coeficients.

Terminal handling fees function per TEU (user cost) - (see (*32*)*)*

$$hf_{ij}(V_{ij}^a) = \left[\beta_1 \left(\frac{V_{ij}^a}{C_j^P}\right)^2 - \beta_2 \left(\frac{V_{ij}^a}{C_j^P}\right) + pf_j\right] \tag{5.57}$$

, where pf_j is the base container handling fee charged by terminal $j \in J$ and β_1, β_2 are the fee function coefficients.

Shipping cost function per TEU (cost endured by shipping lines)

$$sc_{ij}(q_{ij}) = \frac{c_{ij}}{q_{ij}} \tag{5.58}$$

At the first stage of the model shipping lines in an alliance cooperate by making shipment size decisions with the objective to minimize shipping costs and terminal fees. Next, we define an objective function for the shipping line alliance and each shipping line and under cooperation and non-cooperative scenario.

Shipping lines objective function:

$$\min \pi_i = \sum_{j \in J} \left(sc_{ij}(q_{ij}) + hf_{ij}(V_{ij}^{a}) \right) q_{ij}, \forall\, i \in I \tag{5.59}$$

Shipping lines objective function under cooperation

$$\min \pi_i = \sum_{j \in J} \left(sc_{ij}(q_{ij}^{c}) + hf_{ij}(V_{ij}^{a}) \right) q_{ij}^{c}, \forall\, i \in I \tag{5.60}$$

Shipping line alliance objective function

$$\min \pi = \sum_{i \in I} \sum_{j \in J} \left(sc_{ij}(q_{ij}^{c}) + hf_{ij}(V_{ij}^{a}) \right) q_{ij}^{c} \tag{5.61}$$

Next section defines the constraints that are enforced at the first stage of the model.

Container volume shipped should satisfy the demand

$$Q_j = \sum_{j \in J} q_{ij} \;\; \forall i \in I \tag{5.62}$$

Container volume shipped to terminal j by shipping line i should not exceed shipping lines i available capacity to terminal j

$$\sum_{j\in J} q_{ij} \leq C_{ij}^{SL} \tag{5.63}$$

Container volume shipped by shipping line $a \in I$ under cooperation

$$q_{ij}^{c} = q_{aj} + \sum_{b\in I} x_{ba}^{SL} - \sum_{a\in I} x_{ab}^{SL}, \forall a \in I \tag{5.64}$$

Shipping lines either receive or provide demand (but not both

$$r_{a}^{SL} + w_{a}^{SL} \leq 1, \forall a \in I \tag{5.65}$$

Volume (TEUs) transferred from shipping line $a \in I$ to a shipping line $b \in I$ has to be less than or equal to the demand at shipping line $a \in I$ under no cooperation

$$\sum_{b\in J} x_{ab}^{SL} \leq w_{a}^{SL}(q_{aj}),\ \forall a \in I \tag{5.66}$$

Containers transferred to shipping line $a \in I$ cannot exceed the available demand at all the other shipping lines

$$\sum_{b\in I} x_{ba}^{SL} \leq r_{a}^{SL}(\sum_{b\neq a\in I} q_{bj} - q_{aj}), \forall a \in I \tag{5.67}$$

Joint profit of alliance under cooperation scenario will be greater or equal to its profits under the no cooperation scenario

$$\sum_{i\in I} \pi_i(q_{ij}^{c}) - \pi_i(q_{ij}) \geq 0 \tag{5.68}$$

The second stage of the model is adopted from (*26*), where container terminals decide to cooperate or to compete by utilizing each other capacities with the objective to maximize profit. Following section defines objective function for each container terminal under cooperation and non-cooperative scenario.

Terminal profit function under competition

$$\max \pi_j = \sum_{i \in I} \left(hf_{ij}\left(V_{ij}^a\right) - hc_{ij}\left(V_{ij}^a\right) \right) q_{ij}, \forall\, j \ \in J \tag{5.69}$$

Terminal a ∈ I Profit Function under cooperation

$$\max \pi_j^c = \sum_{b \neq a \in I} hf_{ij}(V_{ia}^a)(V_{ia}^a) - \sum_{b} x_{ba}^P pf_b^c - \sum_{b} x_{ab}^P hf_a - hc_{ij}(V_a^c)V_a^c, \forall\, j \in J \tag{5.70}$$

Next section defines the constraints that are enforced at the second stage of the model.

The volume of containers handled at terminal j after shipping lines i shipment

$$V_{ij}^a = V_j^b + q_{ij} \tag{5.71}$$

The volume of containers handled at terminal j

$$V_j = \sum_{i \in I} V_{ij}^a \ , \forall\, j \in J \tag{5.72}$$

A terminal can either receive or provide demand (but not both)

$$r_a^P + w_a^P \leq 1, \forall a \in J \tag{5.73}$$

Demand at any terminal cannot exceed capacity (this constraint is not necessary and can be dropped in cases of monotonically increasing profit function for any of the terminals)

$$V_a^c \leq C_a^P, \forall a \in J \tag{5.74}$$

Profit for any terminal under any cooperation scenario will be greater or equal to its profits under the no cooperation scenario

$$\pi_i(V_a^c) - \pi_i(V_{ia}^a) \geq 0, \forall a \in J \tag{5.75}$$

Volume (TEUs) transferred from terminal $a \in J$ to a terminal $b \in J$ has to be less than or equal to the demand at terminal $a \in I$ under no cooperation

$$\sum_{b \in J} x_{ab}^{P} \leq w_{a}^{P}(V_{ia}^{a}),\ \forall a \in J \tag{5.76}$$

The Volume handled at terminal $a \in I$ under cooperation

$$V_{a}^{c} = V_{ia}^{a} + \sum_{b \in J} x_{ba}^{P} - \sum_{a \in J} x_{ab}^{P}\ , \forall a \in J \tag{5.77}$$

Containers transferred to terminal $a \in I$ cannot exceed the available demand at all the other terminal

$$\sum_{b \in I} x_{ba}^{P} \leq r_{a}^{P}\left(\sum_{b \neq a \in J} V_{b} - V_{ia}^{a}\right), \forall a \in J \tag{5.78}$$

Handling fee of transferred demand is (100-p) % of the handling fees at the origin terminal (under no cooperation

$$pf_{a}^{c} \leq p * hf_{b}(V_{ia}^{a})\ \forall a \in J, p \leq 1 \tag{5.79}$$

Estimation of profit increase (handing fees portion) for demand diverted to terminal $a \in J$

$$prg_{a} = \sum_{b \in J} x_{ab}^{P} pf_{ab}^{c}\ , \forall a \in J \tag{5.80}$$

Estimation of profit loss (handing fees portion) for demand diverted from terminal $a \in J$

$$prl_{a} = \sum_{b} x_{ba}^{P} hf_{a}, \forall a \in J \tag{5.81}$$

Total volume handled before is equal to total volume handled after

$$\sum_{a \in J} V_{a}^{c} = \sum_{a \in J} V_{ia}^{a} \tag{5.82}$$

Model Complexity

Our model complexity arises from the point that it has been constructed as a bilevel optimization problem in which a sequential game is played between shipping lines and container terminals. Bilevel models are difficult to solve, even when each subproblem at each level is easy to solve. In our case, the subproblems are also difficult to solve, where at the first level, the leader, shipping lines, make strategic decisions to optimize their objective functions, then given shipping line strategies the follower, container terminals, makes decisions to optimize objective functions. Model complexity further has been increased at both stages of the model, where at the first stage shipping lines have formed an alliance and play a cooperative game to minimize cost and at the second stage container terminals must decide to play a cooperative or non-cooperative game with the objective to maximize profits. Due to the complexity of the bilevel problem, a heuristic (preferably hybrid) needs to be developed to solve the bilevel problem.

Conclusion

In this study we presented a conceptual and mathematical framework for container terminals, and liner shipping alliance cooperation and competition, using a two-stage Stackelberg game. The developed game theory based model not only could assist marine container terminal operators and port authorities in identifying optimal contractual agreements (for sharing capacity and with liner shipping companies) but also could help identify optimal operational plans that support implementation of such contractual agreements (i.e., contractual agreements are usually based on total demand handled while operational plans are based on vessel assignment and terminal resource allocation at the operational level).

6. Container Terminal Cooperation Using the Core, Shapley Value, and Coalition Structure

Introduction

In this study, we seek to develop a mechanism for profit sharing between the coalition members that would ensure stability. A mathematical framework was developed that model cooperation between marine container terminal operators (MCTOs) using Core, Shapley Value, and Coalition structure solution concepts. The objective is to develop a mathematical framework that utilizes capacity sharing agreements to maximize container terminal profit while keeping the coalition stable and achieving a fair profit distribution among the coalition members using the Shapley Value.

Next we introduce the Core, Shapley Value, and Coalition structure solution concepts and present characteristics functions that can be used with the already developed maritime container terminal cooperation model in Chapter 4.

The Mathematical Framework

We use cooperative game theory to investigate which coalitions are formed and how are the payoffs of these coalitions distributed among themselves using the Core, Shapley Value, and Coalition structure solution concepts. In particular, we assume that all payoffs are measured in the same units and that there is a transferable utility (TU) that allows side payments to be made among players. A cooperative game is usually denoted by (N, v), where N is the set of players, and v is the characteristic function. Coalitions among players are denoted as $S \subseteq N$. Each coalition S has a value denoted as $v(S)$. A payoff distribution for coalition S is a vector of real numbers (x_i) $\forall$ i $\in$ S.

The Core

In order to check if the coalition is stable, the core has to be nonempty. For the core to be nonempty, both the individual rationality and collective rationality have to be satisfied. For a given cooperative game (N, v), a benefit allocation $x = (x_1, x_2, \dots, x_n) \in R^N$ of real numbers has to satisfy the following conditions:

Individual Rationality

$$x_i \geq v(\{i\}) \text{ for all } i \in \mathrm{N} \tag{6.83}$$

The following equation states that each player is willing to participate in a coalition if the payoff is at least as the player can gain on its own.

Collective Rationality

$$x(N) = \sum_{i \in \mathrm{N}} x_i = v(N) \tag{6.84}$$

For a coalition to satisfy the minimal conditions of rationality, the sum of the player payoffs should be equal to the value that is guaranteed by the characteristic function.

Coalitional Rationality

$$x(S) \geq v(S) \text{ for all nonempty coalitions } S \subseteq N \tag{6.85}$$

For any sub-coalitions, the payoff should be less than the payoff received remaining in the grand coalition.

The core of (N, v) is the set

$$C(N, v) = \{x \in R^n \mid x(N) = v(N), x(S) \geq v(S) \text{ for all } S \subseteq N\} \tag{6.86}$$

The core of the cooperative game (N, v) is the set of all efficient and coalitionally rational payoff distributions Peters (*91*).

Bondareva-Shapley Theorem

The existence of the core $C(N, v)$ can be characterized using the Bondareva-Shapley theorem (92) (93). Theorem describes a TU characteristic function that has a nonempty core if and only if it is balanced. Let (N, v) be a coalitional game. A set of weights $w(S)$, where $0 \leq w(S) \leq 1$, for all $S \subseteq N$, is a balancing set of weights if $\forall i \in N$.

$$\sum_{S, i \in S} w(S) = 1 \tag{6.87}$$

A coalitional game (N, v) is balanced if and only if, for every balancing set of weights w, the following condition holds:

$$\sum_{\emptyset \neq S \subseteq N} w(S) v(S) \leq v(N) \tag{6.88}$$

,where $w(S)$ is balancing coefficient.

The Shapley Value

The core suffers from the problems that it is sometimes empty and that when the core is nonempty, it usually has a set of solutions. In contrast to the Core, the Shapley value always exists and is unique. The Shapley value is used to allocated profits among container terminals. The estimated values measure the contribution of each container terminal in the coalition. Given a coalitional game (N, v) the Shapley value divides payoffs among containers according to:

The Shapley value payoff to player i ∈ N, is given by

$$\phi_i(N, v) = \frac{1}{N!} \sum_{S \subseteq N\{i\}} |S|! \, (|N| - |S| - 1)! \; [v(S \cup \{i\}) - v(S)] \tag{6.89}$$

A value function ϕ, is a function that assigns to each possible characteristic function of an n-person game, v, an n-tuple, $\phi(v) = (\phi_1(v), \phi_2(v), \dots, \phi_n(v))$ of real numbers. Here $\phi_i(v)$

represents the worth or value of player i in the game with characteristic function v. The axioms of fairness are placed on the function, ϕ. The Shapley Axioms for $\phi(v)$:

Efficiency

$$\sum_{i \in \mathrm{N}} \phi_i\,(v) = v(N) \tag{6.90}$$

The Efficiency axiom is group rationality that the total value of the players is the value of the grand coalition.

Symmetry

If i and j are such that $v(S \cup \{i\}) = v(S \cup \{j\})$ for every coalition S not containing i and j, then $\phi_i(v) = \phi_j(v)$. In other words, if the characteristic function is symmetric in players i and j, then the values assigned to i and j should be equal.

Dummy Axiom

If i is such that $v(S) = v(S \cup \{i\})$ for every coalition S not containing i, then $\phi_i(v) = 0$. The Dummy axiom says that if player i is a dummy in the sense that he neither helps nor harms any coalition he may join, then his value should be zero.

Additivity

If u and v are characteristic functions, then $\phi(u + v) = \phi(u) + \phi(v)$. The Additivity axiom represents a situation when the value of two games played at the same time should be the sum of the values of the games if they are played at different times. If u and v are characteristic functions, then so is $u + v$.

Coalition Structure

However, Shapley value allocation is not always rational. It is not always in the core, which means some of the players or sets of players would prefer not to be in the grand coalition. When the formation of the grand coalition is not feasible, a grand coalition is split into disjoint subgames, which maximize the total payoff. A subgame of the game (N, v) is any game of the from (S, v), where $S \subseteq N$. We can formulate the coalition structure generation as an integer problem. Let $N = \{1, \dots, i)$ be the set of terminals, $S = \{S_1, \dots, S_\omega)$ be set of all possible coalitions, where $\omega = 2^n - 1$ are all the possible combinations for n players, let k be coalition number, where $k \in$ K and $K = \{1, \dots, \omega\}$, and $T = \{T_1, \dots, T_{B^n})$ be the set formed by all possible combinations of the elements in S, where $B^n < \left(\frac{0.792*n}{\ln(n+1)}\right)^n$ is the Bell number which is an upper bound for the number of coalitional structures.

<u>The coalition structure generation can be modeled as follows (maximizing welfare) Rahwan et al.</u> (*94*)*<u>:</u>*

Integer Programming Approach

$$\text{Maximize} \sum_{k=1}^{2^n} v(S_k) \cdot x_k \tag{6.91}$$

$$\text{subject to} \sum_{k=1}^{2^n} z_{i,k} \cdot x_k = 1, \forall\, i \in N \tag{6.92}$$

$$x_k \in \{1, 0\} \tag{6.93}$$

,where x_k is the decision variable for the coalition S_k to be selected in the solution and $z_{i,k} \in$ Z, where Z is $n \times 2^n$ binary matrix.

<u>The container terminal coalition characteristic function is defined as follows (All the previous container terminal cooperation formation from Chapter 4):</u>

$$v(S_k) \tag{6.94}$$

$$= \max \sum_{i \in S_k \subset T_l} \left(\mathrm{V_i^c hf_i(V_i^c)} + \sum_{b} \mathrm{x_{bi} comp_b^c} - \sum_{b \in I} \mathrm{x_{ib} comp_i^c} - \mathrm{V_i^c hc_i(V_i^c)} \right), \forall\, \mathrm{i} \neq \mathrm{b}$$

$, S_k \subseteq N$

, where $T_l \in T$.

For every coalition S_k we calculate welfare value and then find the best coalition structure, and finally compute the Shapley values.

Conclusion

In this study, we have expanded on the works presented in Chapter 4 by introducing a mechanism for profit sharing between the coalition members that would ensure stability and fair profit distribution among coalition members. Future research could include performing experiments for profit sharing between the coalition members that would ensure stability using the Core and Shapley Value and compare Shapley Value profit allocation to previously applied policies, such as Nash Bargaining Solution and total profit maximization policies outperform the total minimum profit maximization and, the difference of minimum profit maximization.

7. Conclusion and Future Directions

In this dissertation, we have proposed and developed game theory models that could assist the Maritime Container Terminal Operators (MCTOs) and Port Authorities in their decision making on the seaport and marine container terminal cooperation and competition, such as identifying optimal contractual agreements (for sharing capacity with container terminals) but also could help identify optimal operational plans that support the implementation of such contractual agreements (i.e., contractual agreements are usually based on total demand handled while operational plans are based on vessel assignment and terminal resource allocation at the operational level). In total, we have developed four maritime container terminal cooperation game theory models that employed cooperation policies using Nash Bargaining Solution, total profit maximization, total minimum profit maximization, the difference of minimum profit maximization, and Shapley Value. Results indicate that the Nash Bargaining Solution and total profit maximization policies outperform the total minimum profit maximization and the difference of minimum profit maximization when a combined uniformity of profit share among the cooperating terminals and size are considered. The Nash Bargaining Solution has a slight edge over the total profit maximization policy as it provides better profits increase for the terminal with the higher V/C ratio and better uniformity. Two mathematical formulations were developed for capacity sharing one based on volume (i.e., demand is measured in TEUs) and one based on vessel (i.e., demand is measured in TEUs per vessel). Results indicate that planning level models provide significant differences to tactical/operational level models with regards to demand diversion between the terminals and overestimation of profits.

There are several future research directions that may be explored, including but not limited to: (i) Develop solution algorithms that can handle more terminals (currently, after four terminals, the exact solution algorithm becomes inefficient), (ii) Develop the formulation and solution algorithm that estimates the Nash Equilibrium, (iii) Consider uncertain demand (at the tactical or planning level). (iv) Include a differential pricing policy by customer (e.g., liner company or alliances), allow demand to exceed capacity. (v) Perform experiments for profit sharing between the coalition members that would ensure stability using the Core and Shapley Value. (vi) Compare Shapley Value profit allocation to different policies.

References

1. UNCTAD. Review of Maritime Transport 2019. *United Nations Publications 300 East 42nd Street New York, New York 10017 United States of America*, 2019, p. 129.
2. Shipping Alliances: What Do They Do and What Does It Mean? *FreightHub*. https://freighthub.com/en/blog/shipping-alliances-mean/. Accessed Jun. 1, 2019.
3. Drewry Maritime Research. *Container Forecast December 2018*. Drewry Financial Research Services Ltd, 2018, p. 87.
4. Guan, C., S. Yahalom, and J. Yu. Port Congestion and Economies of Scale: The Large Containership Factor. Presented at the Annual Conference of the International Association of Maritime Economists, Kyoto, Japan, 2017.
5. Anderson, C. M., Y.-A. Park, Y.-T. Chang, C.-H. Yang, T.-W. Lee, and M. Luo. A Game-Theoretic Analysis of Competition among Container Port Hubs: The Case of Busan and Shanghai 1. *Maritime Policy & Management*, Vol. 35, No. 1, 2008, pp. 5–26. https://doi.org/10.1080/03088830701848680.
6. Do, T. M. H., G.-K. Park, K. Choi, K. Kang, and O. Baik. Application of Game Theory and Uncertainty Theory in Port Competition between Hong Kong Port and Shenzhen Port. *International Journal of e-Navigation and Maritime Economy*, Vol. 2, 2015, pp. 12–23. https://doi.org/10.1016/j.enavi.2015.06.002.
7. Ishii, M., P. T.-W. Lee, K. Tezuka, and Y.-T. Chang. A Game Theoretical Analysis of Port Competition. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 49, No. 1, 2013, pp. 92–106. https://doi.org/10.1016/j.tre.2012.07.007.
8. Luo, M., L. Liu, and F. Gao. Post-Entry Container Port Capacity Expansion. *Transportation Research Part B: Methodological*, Vol. 46, No. 1, 2012, pp. 120–138. https://doi.org/10.1016/j.trb.2011.09.001.
9. De Borger, B., S. Proost, and K. Van Dender. Private Port Pricing and Public Investment in Port and Hinterland Capacity. *SSRN Electronic Journal*, 2008. https://doi.org/10.2139/ssrn.1024691.
10. Basso, L. J., Y. Wan, and A. Zhang. Seaport Competition and Strategic Investment in Accessibility. 2013, p. 15.
11. Wang, K., A. K. Y. Ng, J. S. L. Lam, and X. Fu. Cooperation or Competition? Factors and Conditions Affecting Regional Port Governance in South China. *Maritime Economics & Logistics*, Vol. 14, No. 3, 2012, pp. 386–408. https://doi.org/10.1057/mel.2012.13.
12. Wang, J., and S. Sun. The Game about Competition and Cooperation in Port Group. In *Proceedings of the 23rd International Conference on Industrial Engineering and Engineering Management 2016* (E. Qi, J. Shen, and R. Dou, eds.), Atlantis Press, Paris, pp. 215–219.
13. Zhou, X. Competition or Cooperation: A Simulation of the Price Strategy of Ports. *International Journal of Simulation Modelling*, Vol. 14, No. 3, 2015, pp. 463–474. https://doi.org/10.2507/IJSIMM14(3)8.303.
14. Cui, H., and T. Notteboom. A Game Theoretical Approach to the Effects of Port Objective Orientation and Service Differentiation on Port Authorities' Willingness to Cooperate. *Research in Transportation Business & Management*, Vol. 26, 2018, pp. 76–86. https://doi.org/10.1016/j.rtbm.2018.03.007.
15. Park, N. K., and S. C. Suh. Port Competition Study: Cooperative Game Model. *Journal of contemporary management*, Vol. 4, No. 3, 2015, p. 16.

16. Kaselimi, E. N., T. E. Notteboom, and B. De Borger. A Game Theoretical Approach to Competition between Multi-User Terminals: The Impact of Dedicated Terminals. *Maritime Policy & Management*, Vol. 38, No. 4, 2011, pp. 395–414. https://doi.org/10.1080/03088839.2011.588260.
17. Nguyen, H.-O., A. Chin, J. Tongzon, and M. Bandara. Analysis of Strategic Pricing in the Port Sector: The Network Approach. *Maritime Economics & Logistics*, 2015. https://doi.org/10.1057/mel.2015.9.
18. Yu, M., J. Shan, and L. Ma. Regional Container Port Competition in a Dual Gateway-Port System. *Journal of Systems Science and Systems Engineering*, Vol. 25, No. 4, 2016, pp. 491–514. https://doi.org/10.1007/s11518-015-5288-7.
19. Czerny, A., F. Höffler, and S. Mun. Port Competition and Welfare Effect of Strategic Privatization. 2014, p. 20.
20. Cui, H., and T. Notteboom. Modelling Emission Control Taxes in Port Areas and Port Privatization Levels in Port Competition and Co-Operation Sub-Games. *Transportation Research Part D: Transport and Environment*, Vol. 56, 2017, pp. 110–128. https://doi.org/10.1016/j.trd.2017.07.030.
21. Bae, M. J., E. P. Chew, L. H. Lee, and A. Zhang. Container Transshipment and Port Competition. *Maritime Policy & Management*, Vol. 40, No. 5, 2013, pp. 479–494. https://doi.org/10.1080/03088839.2013.797120.
22. Zhuang, W., M. Luo, and X. Fu. A Game Theory Analysis of Port Specialization—Implications to the Chinese Port Industry. *Maritime Policy & Management*, Vol. 41, No. 3, 2014, pp. 268–287. https://doi.org/10.1080/03088839.2013.839517.
23. Lee, H., M. Boile, S. Theofanis, and S. Choo. Modeling the Oligopolistic and Competitive Behavior of Carriers in Maritime Freight Transportation Networks. *Procedia - Social and Behavioral Sciences*, Vol. 54, 2012, pp. 1080–1094. https://doi.org/10.1016/j.sbspro.2012.09.823.
24. Zheng, S., and R. R. Negenborn. Centralization or Decentralization: A Comparative Analysis of Port Regulation Modes. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 69, 2014, pp. 21–40. https://doi.org/10.1016/j.tre.2014.05.013.
25. Pujats, K., M. Golias, and D. Konur. A Review of Game Theory Applications for Seaport Cooperation and Competition. *Journal of Marine Science and Engineering*, Vol. 8, No. 2, 2020, p. 100. https://doi.org/10.3390/jmse8020100.
26. Pujats, K., M. M. Golias, and S. Mishra. Marine Container Terminal Cooperation: A Nash Bargaining Approach. Presented at the Transportation Research Board 97th Annual Meeting, Washington, DC, 2018.
27. Pujats, K., M. Golias, and D. Konur. Marine Container Terminal Cooperation Optimization: A Volume to Vessel Formulations Comparison. *Maritime Policy & Management*, Vol. (Under Review).
28. Pujats, K., M. Golias, and S. Mishra. A Mathematical Framework for Container and Liner Shipping Companies Cooperation and Competition. Presented at the Material Handling, Constructions and Logistics, Bar, Montenegro, 2019.
29. Why Is the Liner Shipping Industry so Important Economically? *The World Shipping Council*. http://www.worldshipping.org/industry-issues/environment/air-emissions/faqs-answers/a1-why-is-the-liner-shipping-industry-so-important-economically. Accessed Jun. 1, 2019.

30. Alphaliner TOP 100. *Alphaliner*. https://alphaliner.axsmarine.com/PublicTop100/. Accessed Jun. 1, 2019.
31. Ignatius, J., T. Siang Tan, L. Dhamotharan, and M. Goh. To Cooperate or to Compete: A Game Theoretic Analysis on Ports in Malaysia and Singapore. *Technological and Economic Development of Economy*, Vol. 24, No. 4, 2018, pp. 1776–1800. https://doi.org/10.3846/20294913.2016.1213206.
32. Saeed, N., and O. I. Larsen. An Application of Cooperative Game among Container Terminals of One Port. *European Journal of Operational Research*, Vol. 203, No. 2, 2010, pp. 393–403. https://doi.org/10.1016/j.ejor.2009.07.019.
33. van Reeven. The Effect of Competition on Economic Rents in Seaports. *Journal of Transport Economics and Policy*, Vol. 44, 2010, p. 14.
34. Yip, T. L., J. J. Liu, X. Fu, and J. Feng. Modeling the Effects of Competition on Seaport Terminal Awarding. *Transport Policy*, Vol. 35, 2014, pp. 341–349. https://doi.org/10.1016/j.tranpol.2014.04.007.
35. Wan, Y., and A. Zhang. Urban Road Congestion and Seaport Competition. *Journal of Transport Economics and Policy*, Vol. 47, No. 1, 2013, pp. 55–70.
36. Song, L., D. Yang, A. T. H. Chin, G. Zhang, Z. He, W. Guan, and B. Mao. A Game-Theoretical Approach for Modeling Competitions in a Maritime Supply Chain. *Maritime Policy & Management*, Vol. 43, No. 8, 2016, pp. 976–991. https://doi.org/10.1080/03088839.2016.1231427.
37. Asgari, N., R. Z. Farahani, and M. Goh. Network Design Approach for Hub Ports-Shipping Companies Competition and Cooperation. *Transportation Research Part A: Policy and Practice*, Vol. 48, 2013, pp. 1–18. https://doi.org/10.1016/j.tra.2012.10.020.
38. Tuljak-Suban, D. Competition or Cooperation in a Hub and Spoke-Shipping Network: The Case of the North Adriatic Container Terminals. *Transport*, Vol. 33, No. 2, 2017, pp. 429–436. https://doi.org/10.3846/16484142.2016.1261368.
39. Angeloudis, P., L. Greco, and M. G. H. Bell. Strategic Maritime Container Service Design in Oligopolistic Markets. *Transportation Research Part B: Methodological*, Vol. 90, 2016, pp. 22–37. https://doi.org/10.1016/j.trb.2016.04.010.
40. Matsushima, N., and K. Takauchi. Port Privatization in an International Oligopoly. *Transportation Research Part B: Methodological*, Vol. 67, 2014, pp. 382–397. https://doi.org/10.1016/j.trb.2014.04.010.
41. Yeo, H. Participation of Private Investors in Container Terminal Operation: Influence of Global Terminal Operators. *The Asian Journal of Shipping and Logistics*, Vol. 31, No. 3, 2015, pp. 363–383. https://doi.org/10.1016/j.ajsl.2015.09.003.
42. Zis, T. P. V. Prospects of Cold Ironing as an Emissions Reduction Option. *Transportation Research Part A: Policy and Practice*, Vol. 119, 2019, pp. 82–95. https://doi.org/10.1016/j.tra.2018.11.003.
43. Jia, H., R. Adland, V. Prakash, and T. Smith. Energy Efficiency with the Application of Virtual Arrival Policy. *Transportation Research Part D: Transport and Environment*, Vol. 54, 2017, pp. 50–60. https://doi.org/10.1016/j.trd.2017.04.037.
44. Call for Papers for RTBM Special Issue on Port Co-Operation. *The International Association of Maritime Economists (IAME)*. https://www.mar-economists.org/blog/2017/03/21/call-for-papers-for-rtbm-special-issue-on-port-co-operation/. Accessed Jul. 20, 2017.

45. Heaver, T., H. Meersman, and E. Van De Voorde. Co-Operation and Competition in International Container Transport: Strategies for Ports. *Maritime Policy & Management*, Vol. 28, No. 3, 2001, pp. 293–305. https://doi.org/10.1080/03088830110055693.
46. Song, D.-W. Port Co-Opetition in Concept and Practice. *Maritime Policy & Management*, Vol. 30, No. 1, 2003, pp. 29–44. https://doi.org/10.1080/0308883032000051612.
47. Notteboom, T. E. Container Shipping and Ports: An Overview. *Review of network economics*, Vol. 3, No. 2, 2004.
48. Van Der Horst, M. R., and P. W. De Langen. Coordination in Hinterland Transport Chains: A Major Challenge for the Seaport Community. *Maritime Economics & Logistics*, Vol. 10, No. 1–2, 2008, pp. 108–129. https://doi.org/10.1057/palgrave.mel.9100194.
49. Brooks, M. R., R. McCalla, A. A. Pallis, and L. M. van der Lugt. Coordination and Cooperation in Strategic Port Management: The Case of Atlantic Canada's Ports. *Atlantic Gateway Initiative Working Paper*, 2009.
50. Hoshino, H. Competition and Collaboration among Container Ports. *The Asian Journal of Shipping and Logistics*, Vol. 26, No. 1, 2010, pp. 31–47. https://doi.org/10.1016/S2092-5212(10)80010-0.
51. Fu, P., and Y. Chen. Analysis of Competition and Cooperation of Ningbo-Zhoushan Port and Shanghai Port. In *Computer, Informatics, Cybernetics and Applications* (X. He, E. Hua, Y. Lin, and X. Liu, eds.), Springer Netherlands, Dordrecht, pp. 1559–1567.
52. Lee, P. T.-W., and J. S. L. Lam. Container Port Competition and Competitiveness Analysis: Asian Major Ports. In *Handbook of Ocean Container Transport Logistics* (C.-Y. Lee and Q. Meng, eds.), Springer International Publishing, Cham, pp. 97–136.
53. Parola, F., M. Risitano, M. Ferretti, and E. Panetti. The Drivers of Port Competitiveness: A Critical Review. *Transport Reviews*, Vol. 37, No. 1, 2017, pp. 116–138. https://doi.org/10.1080/01441647.2016.1231232.
54. Li, J., and Y. Oh. A Research on Competition and Cooperation Between Shanghai Port and Ningbo-Zhoushan Port. *The Asian Journal of Shipping and Logistics*, Vol. 26, No. 1, 2010, pp. 67–91. https://doi.org/10.1016/S2092-5212(10)80012-4.
55. Jeon, J. W., Y. Wang, and G. T. Yeo. SNA Approach for Analyzing the Research Trend of International Port Competition. *The Asian Journal of Shipping and Logistics*, Vol. 32, No. 3, 2016, pp. 165–172. https://doi.org/10.1016/j.ajsl.2016.09.005.
56. Mclaughlin, H., and C. Fearon. Understanding the Development of Port and Regional Relationships: A New Cooperation/Competition Matrix. *Maritime Policy & Management*, Vol. 40, No. 3, 2013, pp. 278–294. https://doi.org/10.1080/03088839.2013.782966.
57. Lee, C.-Y., and D.-P. Song. Ocean Container Transport in Global Supply Chains: Overview and Research Opportunities. *Transportation Research Part B: Methodological*, Vol. 95, 2017, pp. 442–474. https://doi.org/10.1016/j.trb.2016.05.001.
58. Karafa, J., M. M. Golias, S. Ivey, G. Saharidis, and N. Leonardos. Berth Scheduling at Dedicated Marine Container Terminals: Limited Berth Capacity Case. Presented at the Transportation Research Board 90th Annual Meeting, Washington D.C., 2011.
59. Mooney, T. Hong Kong Terminals Join Forces as Alliances Challenge Ports. *Journal of Commerce (JOC)*. http://www.joc.com/port-news/asian-ports/port-hong-kong/hong-kong-terminals-join-forces-alliances-challenge-ports_20161220.html. Accessed Jul. 23, 2017.
60. Hutchins, R. Global Terminal Operators, Rotterdam Seek Cooperation to Deal with Carriers. *Journal of Commerce (JOC)*. http://www.joc.com/regulation-

policy/transportation-policy/us-transportation-policy/global-terminal-operators-rotterdam-seek-cooperation-deal-carriers_20161221.html. Accessed Jul. 23, 2017.
61. Hutchins, R. Georgia, Virginia Ports Plan Cooperation to Gain Edge. *Journal of Commerce (JOC)*. http://www.joc.com/port-news/us-ports/port-virginia/georgia-virginia-ports-plan-cooperation-gain-edge_20170227.html. Accessed Jul. 23, 2017.
62. Midoro, R., and A. Pitto. A Critical Evaluation of Strategic Alliances in Liner Shipping. *Maritime Policy & Management*, Vol. 27, No. 1, 2000, pp. 31–40. https://doi.org/10.1080/030888300286662.
63. Mooney, T. PORT PRODUCTIVITY: Finding New Efficiencies through Collaboration. *Global Ports Maritime & Trade IHS Markit*, 2017.
64. Nash, J. F. The Bargaining Problem. *Econometrica*, Vol. 18, No. 2, 1950, p. 155. https://doi.org/10.2307/1907266.
65. Nash, J. F. Equilibrium Points in N-Person Games. *Proceedings of the National Academy of Sciences of the United States of America*, Vol. 36, No. 1, 1950, pp. 48–49.
66. Haralambides, H. E. Competition, Excess Capacity, and the Pricing of Port Infrastructure. *International journal of maritime economics*, Vol. 4, No. 4, 2002, pp. 323–347. https://doi.org/10.1057/palgrave.ijme.9100053.
67. Tawarmalani, M., and N. V. Sahinidis. A Polyhedral Branch-and-Cut Approach to Global Optimization. *Mathematical Programming*, Vol. 103, No. 2, 2005, pp. 225–249. https://doi.org/10.1007/s10107-005-0581-8.
68. Stackelberg, H. von, D. Bazin, L. Urch, and R. Hill. *Market Structure and Equilibrium*. Springer, Heidelberg [Germany] ; London ; New York, 2011.
69. JOC. Maritime News. Journal of Commerce (JOC), , 2014.
70. UNCTAD. Review of Maritime Transport 2015. *United Nations Conference on Trade and Development, New York and Geneva*, 2015, p. 122.
71. JOC. Largest Container Ships on Order to Rise 13 Percent by 2020. Journal of Commerce (JOC), , 2015.
72. Forster, F., and A. Bortfeldt. A Tree Search Procedure for the Container Relocation Problem. *Computers & Operations Research*, Vol. 39, No. 2, 2012, pp. 299–309. https://doi.org/10.1016/j.cor.2011.04.004.
73. Golias, M., I. Portal, D. Konur, E. Kaisar, and G. Kolomvos. Robust Berth Scheduling at Marine Container Terminals via Hierarchical Optimization. *Computers & Operations Research*, Vol. 41, 2014, pp. 412–422. https://doi.org/10.1016/j.cor.2013.07.018.
74. Mauri, G. R., G. M. Ribeiro, L. A. N. Lorena, and G. Laporte. An Adaptive Large Neighborhood Search for the Discrete and Continuous Berth Allocation Problem. *Computers & Operations Research*, Vol. 70, 2016, pp. 140–154. https://doi.org/10.1016/j.cor.2016.01.002.
75. Nguyen, P. K., T. G. Crainic, and M. Toulouse. A Tabu Search for Time-Dependent Multi-Zone Multi-Trip Vehicle Routing Problem with Time Windows. *European Journal of Operational Research*, Vol. 231, No. 1, 2013, pp. 43–56. https://doi.org/10.1016/j.ejor.2013.05.026.
76. Petering, M. E. H., and K. G. Murty. Effect of Block Length and Yard Crane Deployment Systems on Overall Performance at a Seaport Container Transshipment Terminal. *Computers & Operations Research*, Vol. 36, No. 5, 2009, pp. 1711–1725. https://doi.org/10.1016/j.cor.2008.04.007.

77. Preston, P., and E. Kozan. A Tabu Search Technique Applied to Scheduling Container Transfers. *Transportation Planning and Technology*, Vol. 24, No. 2, 2001, pp. 135–153. https://doi.org/10.1080/03081060108717664.
78. Cordeau, J.-F., G. Laporte, and A. Mercier. Improved Tabu Search Algorithm for the Handling of Route Duration Constraints in Vehicle Routing Problems with Time Windows. *Journal of the Operational Research Society*, Vol. 55, No. 5, 2004, pp. 542–546. https://doi.org/10.1057/palgrave.jors.2601707.
79. Emde, S., N. Boysen, and D. Briskorn. The Berth Allocation Problem with Mobile Quay Walls: Problem Definition, Solution Procedures, and Extensions. *Journal of Scheduling*, Vol. 17, No. 3, 2014, pp. 289–303. https://doi.org/10.1007/s10951-013-0358-5.
80. Henesey, L. E. Enhancing Container Terminal Performance: A Multi Agent Systems Approach. 2004, p. 136.
81. Paixão, A. C., and P. Bernard Marlow. Fourth Generation Ports – a Question of Agility? *International Journal of Physical Distribution & Logistics Management*, Vol. 33, No. 4, 2003, pp. 355–376. https://doi.org/10.1108/09600030310478810.
82. Canonaco, P., P. Legato, R. M. Mazza, and Roberto Musmanno. A Queuing Network Model for the Management of Berth Crane Operations. *Computers & Operations Research*, Vol. 35, No. 8, 2008, pp. 2432–2446. https://doi.org/10.1016/j.cor.2006.12.001.
83. Report: Container Shipping Vulnerable at Puget Sound Ports. Cargo Business, , 2014.
84. Panayides, P. M., and R. Wiedmer. Strategic Alliances in Container Liner Shipping. *Research in Transportation Economics*, Vol. 32, No. 1, 2011, pp. 25–38. https://doi.org/10.1016/j.retrec.2011.06.008.
85. JOC. Georgia, Virginia Ports Plan Cooperation to Gain Edge. Journal of Commerce (JOC), , 2017.
86. JOC. Global Terminal Operators Rotterdam Seek Cooperation Deal Carriers. Journal of Commerce (JOC), , 2016.
87. JOC. Hong Kong Terminals Join Forces as Alliances Challenge Ports. Journal of Commerce (JOC), , 2016.
88. Golias, M., S. Mishra, and K. Pujats. *Game Theory Applications for Seaport Cooperation, Competition, and Co-Opetition*. Publication Final Report Y1R5-17. Freight Mobility Research Institute, 2019.
89. Dulebenets, M. A., M. M. Golias, and S. Mishra. A Collaborative Agreement for Berth Allocation under Excessive Demand. *Engineering Applications of Artificial Intelligence*, Vol. 69, 2018, pp. 76–92. https://doi.org/10.1016/j.engappai.2017.11.009.
90. Imai, A., E. Nishimura, and S. Papadimitriou. Berthing Ships at a Multi-User Container Terminal with a Limited Quay Capacity. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 44, No. 1, 2008, pp. 136–151. https://doi.org/10.1016/j.tre.2006.05.002.
91. Peters, H. *Game Theory*. Springer Berlin Heidelberg, Berlin, Heidelberg, 2015.
92. Bondareva, O. The Theory of the Core in an N-Person Game. Vestnik Leningrad. Univ, , 1962.
93. Shapley, L. S. On Balanced Sets and Cores. *Naval Research Logistics Quarterly*, Vol. 14, No. 4, 1967, pp. 453–460. https://doi.org/10.1002/nav.3800140404.
94. Rahwan, T., T. P. Michalak, M. Wooldridge, and N. R. Jennings. Coalition Structure Generation: A Survey. *Artificial Intelligence*, Vol. 229, 2015, pp. 139–174. https://doi.org/10.1016/j.artint.2015.08.004.