COLLABORATION AMONG SMALL SHIPPERS IN CARGO TRANSPORTATION

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ÖZHAN YILMAZ

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submitted by **ÖZHAN YILMAZ** in partial fulfillment of the requirements for the degree of **Master of Science in Industrial Engineering, Middle East Technical University** by,

Prof. Dr. Canan ÖZGEN ___________________
Dean, Graduate School of **Natural and Applied Sciences**

Prof. Dr. Nur Evin ÖZDEMİREL ___________________
Head of Department, **Industrial Engineering**

Asst. Prof. Dr. Seçil SAVAŞANERİL TÜFEKCİ ___________________
Supervisor, **Industrial Engineering, METU**

Examining Committee Members:

Asst. Prof. Dr. Sedef MERAL ___________________
Industrial Engineering Dept., METU

Asst. Prof. Dr. Seçil SAVAŞANERİL TÜFEKCİ ___________________
Industrial Engineering Dept., METU

Assoc. Prof. Dr. Esra KARASAKAL ___________________
Industrial Engineering Dept., METU

Asst. Prof. Dr. Pelin BAYINDIR ___________________
Industrial Engineering Dept., METU

Asst. Prof. Dr. Banu YÜKSEL ___________________
Industrial Engineering Dept., Hacettepe University

Date: December 11, 2009

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Name, Last name :

Signature :

ABSTRACT

COLLABORATION AMONG SMALL SHIPPERS IN CARGO TRANSPORTATION

Yılmaz, Özhan

MSc., Industrial Engineering Department

Supervisor : Asst. Prof. Dr. Seçil Savaşaneril Tüfekci

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As a result of widespread and effective usage of internet, firms tend to collaborate to reduce their operating costs. This thesis analyzes collaboration opportunities for a group of small shippers. A transportation intermediary determining the optimal actions for arriving shippers and a mechanism allocating savings to the shippers is proposed in the thesis. The performance of the intermediary is assessed by using computational analyses. An experimental set is formed that is by changing the parameters that are expected to significantly affect the optimal policy structure and the surplus budget (or deficit) changes. It is seen that increasing variable costs like cross-assignment cost and waiting cost leads to the increase in comparative performance of the optimal policy compared to the naïve policy, which is defined according to a simple rule, although increasing dispatching cost, which can be considered as a fixed cost, leads to an opposite result. The performance of the optimal policy is also assessed by using a myopic policy, in which shippers are trying to maximize their own benefit without considering the overall benefit of the grand coalition.

Keywords: Collaborative logistics, shipper collaboration, saving allocation

ÖZ

YÜK TAŞIMACILIĞINDA KÜÇÜK YÜKLEYİCİ FİRMALAR ARASINDA İŞBİRLİĞİ

Yılmaz, Özhan
Yüksek Lisans, Endüstri Mühendisliği Bölümü
Tez Yöneticisi: Yrd. Doç. Dr. Seçil Savaşaneril Tüfekci

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İnternetin yaygın ve etkili kullanımının bir sonucu olarak firmalar operasyon maliyetlerini azaltmak amacıyla iş birliğine gitmekteler. Bu tezde küçük yükleyici firmalar için işbirliği fırsatları analiz edilmiştir. Gelen yükleyicilerin alacağı en uygun eylemleri belirleyen bir sistem ve taşıma maliyetlerinin düşürülmesi sonucunda elde edilen tasarrufların yükleyiciler arasında dağıtımını sağlayan bir mekanizma önerilmiştir. Bu mekanizmanın performansı çeşitli analizlerle incelenmiştir. En uygun politikanın yapısına ve tasarruf edilen miktar üzerine etkisi olduğu düşünülen parametreler değiştirilerek bir deney seti oluşturulmuştur. Bu analizler sonucunda çapraz atama ve bekleme maliyetleri gibi değişken maliyetlerin mekanizmanın nispi performansını artırdığı gözlenirken gemi gönderme maliyetinin bunun tam tersi bir etkiye sahip olduğu görülmüştür. Bunun yanında, mekanizmanın performansı sistemin faydası yerine gelen yükleyicilerin faydalarını maksimize eden bir politika karşısındaki performansı analiz edilmiştir.

Anahtar Kelimeler: Ortak lojistik, yükleyici işbirliği, tasarruf dağıtımı

To Selen

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CHAPTER 1

INTRODUCTION

Today most of the organizations are focusing on better management of their supply chains for better service, higher quality, lower prices and shorter lead-times to increase their competitiveness in the market. Hence, supply chain collaboration has been attracting widespread attention of businesses to achieve the aforementioned issues. In a collaboration, all the participants work together to achieve the common objectives of the consortia where each participant benefits from the consortium. “Sharing” is the critical term for collaboration and sharing of information, risk, profits and costs are key aspects that are needed to be included to form a successful collaboration. (Erhun and Keskinocak, 2007).

There are different forms of collaboration in supply chains according to the firm levels that take place in collaboration. These forms are: (1) buyer collaboration (2) sellers’ collaboration and (3) collaboration between buyers and sellers.

Buyers tend to collaborate with each other for benefiting from the economies of scale. The collaboration among different buyers leads to increase the bargaining power of the group of buyers and they can purchase goods or services with cheaper prices as a result of the economies of scale principle. Group purchasing is not only common among firms but governmental organizations tend to join together to purchase items in order to negotiate a better deal. State Supply Office[1] of Turkey is a typical group purchasing organization that is procuring the goods and services that are needed by the governmental organizations. Thereby, goods and services demands of organizations are collected and negotiations are conducted over the purchasing of these collected amounts. Consequently, a lower unit purchasing cost is obtained for

[1] State Supply Office Web Site, http://www.dmo.gov.tr. Last visited on December 2009.

every single goods or service. Shippers' collaboration is also handled within this context. In this kind of collaboration, shippers are acting as if they were the same company with an aim of achieving the common objectives of the consortium. They come together and find better lanes to get discounts from carriers by reducing the risk of carriers' expected empty truck movements (Agarwal et al., 2009). According to the packaged foods industry estimations delivery trucks are hauling air 20 % of the time. However, collaborative logistics is used to reduce dead-hauling expenses of firms thanks to the widespread usage of internet. These costs are reflected in the prices paid by the shippers and this leads to higher prices of the goods sold in the markets. Land O'Lakes Inc., which is a U.S. agricultural cooperative based in Arden Hills (Minnesota) focusing on dairy industry, cut her annual freight cost by 15 % thanks to the collaborative logistics (Buss, 2003).

Sellers often collaborate to form alliances to regulate prices and to manage their capacities effectively. Several firms in the industries of air transport, maritime and land transportation are benefiting from the operational synergies to reduce their logistics costs. Hence they form alliances to increase their own profitabilities. Skyteam, Star Alliance, Qualifier and OneWorld are the examples of horizontal cooperation in aviation. Sea-Land and Maersk have been in collaboration since the early 1990s. They share their vessels in the Atlantic and Pacific oceans. OOCL and China Shipping have been offering a collaborative service called the Australia China Express (ACE) since 2003 (Agarwal and Ergun, 2005).

Vertical collaboration, such as collaboration among sellers and buyers, is another form of collaboration. Suppliers and manufacturers often collaborate for increasing forecasting accuracy, reducing inventory levels and achieving efficiencies in all levels of supply chains thanks to information sharing. Vendor managed inventory (VMI), where the manufacturer (or seller) is responsible for maintaining the distributors' (or buyers) inventory level, is a very successful application in collaboration among different levels of participants (Chaovalitwongse et al., 2009). This gives coordination of production and distribution between manufacturers and distributors. Quick Response (QR) and Collaborative Planning, Forecasting and Replenishment (CPFR) are the other types of collaborative activities in vertical collaboration. Zara and Benetton use QR to improve their operations. Wal-Mart and Warner-Lambert eliminated 2 weeks of inventory by using an application of CPFR. By the help of CPFR, Henkel KgaA achieved that number of forecasts with error rate of more than 50 % declined from 50 % to 5 % and number of forecasts with error rate of less than 20 % increased from 20 % to 75 %.

As a result of widespread and effective usage of internet, different level of firms can work together thanks to the increased awareness of benefits of collaboration and capability of information sharing. "The network of networks" serves as an excellent collaboration platform by the help of the connectivity it provides. Internet gives firms opportunity to manage logistical, security and scheduling challenges required to collaborate with other companies. Increased communication opportunities lead to share ubiquitous information easily. Suppliers, consumers and even competitors become collaborative partners and shippers can reduce their "hidden costs" such as asset reposition costs, which are related to empty truck movements from a delivery location to pickup location, by cooperating (Ergun et al., 2007).

So far, we have generalized supply chain collaboration and given examples from practice regarding this issue. Hereafter we will focus on collaborative logistics and discuss its dynamics to gain insights about the collaboration problem in transportation.

As a result of the trend toward smaller and more frequent shipments an interesting paradox takes place in today's logistics market. Lynch (2000) states that this paradox is composed of shortage of available capacity and excess capacities caused by shipments and he proposes collaborative logistics as the solution for this problem. Coalition members collaborate through the internet to fill the excess capacity, thereby reducing shipping costs (Barthlott and Winiger, 1998). It is hard to optimize its transportation activities for a single enterprise without collaboration and undesired results like less-than-truckload shipments, paying spot rates and little opportunities for backhaul become usual payoffs for the enterprise (Langley, 2000).

Langley (2000) states that the key enabler for successful collaboration is the development of collaborative logistics networks between and among shippers and carriers, and suppliers and customers. He identifies the true collaboration rules under seven priorities including fair allocation of gains and losses among coalition members, organically engagement of participants in partnering activities, supporting co-buyer and co-seller relationships, supporting collaboration across all stages of business process integration. These networks are considered as the unique way for coordinating business activities of a community of shippers and carriers. General Mills, which is mainly concerned with products, saves approximately USD 800,000 per year by collaborating with another community member on a single tour. Nabisco (National Biscuit Company), which is American brand of cookies and snacks, estimate that her USD 200 million transportation expenses will be eliminated by 10 % thanks to the collaborative logistics networks. Omni Consulting Group estimates a 12.3 % reduction in overall logistics expense (Lynch, 2000).

Nistevo.com is one of the collaborative logistics networks and was acquired by Sterling Commerce, Inc. in 2006. It provides Web-based access to a collaborative logistics network with more than 1400 carriers. It is a well known example of shipper collaboration where the loads are consolidated into full truckloads. As a result of this achievement shipment cycle times and logistics costs can be reduced significantly (Nandiraju and Regan, 2003). In Nistevo.com, three basic forms of collaboration are used in the analysis of collaborative logistics: shipper to carrier (focusing on contract management between the collaborators and tracking), shipper to shipper (focusing on reducing deadheads and filling carriers), and supplier to retailer to carrier (Malone, 2007). Nistevo.com is not the only Web-based platform within the context of collaborative logistics. Supply chain management solutions provider One Network Enterprises, which recently changed its name from Elogex, provides firms with a collaborative logistics platform where all parties could access in order to coordinate shipping and tracking. By using this platform, firms schedule loads to potential carriers in the network via the platform. These carriers can also obtain their shipments through their Web portals and learn the specific warehouse bay for delivery (Tompkins et al., 2005). Transplace is another Internet-based company that was formed through the merger of several publicly-held truckload carriers in USA.

She has been acting in this business since 2000. Transplace uses a platform with hundreds of shippers and thousands of carriers. It has been reported that the freight transactions of Transplace was worth more than USD 2 Billion in 2002 (Nandiraju and Regan, 2003). Transplace offers a web-enabled platform for both shippers and carriers worldwide. Shippers and carriers come together for collaborating on their transportation logistics planning by this platform (Belman and White, 2005).

However, although horizontal cooperation occurs among individual firms in the theory of supply chain management, the evaluation of a transportation system for a collaboration of several competing firms is not an easy process because of such reasons like the structure of transport market (Krajewska, 2008). Improving coalition profit is not sufficient to form a successful collaboration but “preservations of interests” for each single member should be maintained (Krajewska and Kopfer, 2006). For this reason, allocation of profits (or costs) is an important problem to be discussed to form successful and sustainable collaborations. Cruijssen et al. (2007) find that one of the most severe to form collaborations is the construction of fair allocation mechanisms for the attained savings as a result of the questionnaire they have conducted.

In this chapter, we discuss opportunities and insights gained from collaboration in maritime transportation. Maritime transportation is the major way of transportation in international trade. It is widely acknowledged that there exist three general modes of operation in maritime transportation: industrial, tramp and liner shipping. Cargo owners (or shippers) are having control on ships in industrial shipping. As they control ships they undertake the operation costs. So the main objective is to carry all their cargoes at minimal cost. However, tramp ships possess many similarities with taxis. They follow the available cargoes. A tramp shipping company may have a certain amount of contract cargoes that it is committed to carry and tries to maximize its profit (Christiansen et al., 2004). Ships engaged in the liner shipping operate among the fixed ports following fixed schedules like buses.

Although there exists such a distinction between the modes of maritime transportation, a ship engaged to one mode can easily be transferred to another mode.

In recent years, a significant shift from industrial shipping to tramp shipping has been observed. Bronmo et al. (2007) states that this may be caused by that many shippers prefer to be focused on their own business and they have chosen outsourcing for their other activities like transportation. Actually, industrial shipping is a burdensome activity that forms significant pressure on the cargo owners. As it has been stated before, industrial operators try to minimize their costs while carrying all the cargoes. Industrial operators need to charter in additional vessels in case of insufficient fleet capacity. Whereas liners and tramp operators may give up the excess demand and related income, industrial operators are to carry all the cargoes (Christiansen et al., 2007).

In this thesis, we study the shipper collaboration problem where shippers have small loads that are not sufficient to fill the vehicle. Through collaboration, the shippers consolidate their loads and possibly obtain savings from fixed cost of transportation. We assume that shippers arrive randomly and independently to different locations in the market. If there is sufficient load to fill the vehicle, shippers may decide to leave. In maritime transportation certain shippers prefer liner shipping while there are shippers that arrive at the market unplanned. These shippers are possibly small in nature and transport their cargo with vessels that are engaged to tramp shipping.

We consider a third-party transportation intermediary operating in the tramp shipping business that brings small shippers together to achieve savings through collaboration. Small shippers come together to achieve “better management” of their shipments. The term of better management covers an intelligent decision making process regarding dispatching times of the vessels and cross-assignment of the arriving shipments for reducing variable costs (waiting costs) and fixed costs (dispatching cost) of the system. So they can get chance to ship their cargoes cheaper than the way in which they make the agreement with the carriers on the carriage of their own commodities. The proposed third-party transportation intermediary collects shipment demands from the shippers (or cargo owners) to determine the optimal dispatching time of the shipments. It is assumed that there are sufficient numbers of vessels engaged to tramp shipping activity and these vessels are ready to be dispatched with order of the intermediary. As it has been stated before, a tramp shipping company may have a certain amount of contract cargoes. However, in this thesis the intermediary employs the tramp shipping vessel as if the vessel were used by an industrial operator and it is assumed that tramp shipping company does not make any contract other than the contract with the intermediary. The intermediary guarantees the tramp shipping company to pay a certain amount of money that can be considered as full vessel load freight rate. This amount of money is paid to the company regardless of whether or not the vessel is filled to capacity. It is acknowledged that high fixed transportation costs appear in industries that are managing their own fleet or establishing contracts with carriers guaranteeing a minimum capacity (Griffin et al., 2003).

The proposed intermediary can be considered as a ship-broking company. Shipbrokers are specialized intermediaries between ship owners and cargo owners (shippers) and they are likely to specialize in particular categories of ships and trades (Dockray et al., 2004). Strandenes (2000) indicates the main benefits of using shipbrokers are speeding up searching and matching, obtaining favorable ask/bid prices, and functioning as experts in deals with asymmetric information. They have large databases including information about vessels' positions, shippers' demands and freight rates. They use this information for matching ship owners and shippers to optimize the shipment processes. Consequently, shipbroker firms provide low carriage prices to the shippers while they receive recompenses for their services. A shipbroker's commission is a percentage of freight rates (Stopford, 2003).

Furthermore, the role of ship-broking changes as the time goes. Modern forward-thinking companies are keen on focusing on their core competences for achieving greater productivity and effectiveness. Hence, ship-broking is driven by the factors of logistics, value added and technology (Branch, 2007). Stefansson (2006) proposes a collaborative logistics management model defining the roles of different parties in particular the role of the third-party service providers. In this study, the roles of logistics service intermediaries are defined broadly.

However, main objective of the proposed intermediary is not to generate earnings for its own use but to minimize shipment costs for the shippers. By the help of this intermediary, shippers will be able to ship their commodities on time with a reasonable price that cannot be achieved by using individual bargaining power of shippers.

As we have indicated before, shippers arrive at dispatching locations randomly. We assume that decision epochs are limited to event occurrence times. We model the problem as a Markov Decision Process (MDP). The proposed mathematical model will determine the optimal actions that are to be taken in each state in case of new arrivals for different experimental settings. The action includes the optimal behaviors for each shipper that has the possibility for arrival at the dispatching location.

Because of the fact that the main challenge for the proposed intermediary is convincing the shippers to participate in the system, the intermediary is expected to provide shippers with higher profits. Another model that is allocating the generated earnings to the shippers is introduced in the thesis. This model aims to provide the shippers with the amounts of profits that can convince them to participate in the proposed system. It is obvious that the allocated amounts of payments are expected to be greater than the amounts that can be achieved by the myopic actions taken by the shippers individually. Some game theoretic approaches that are widely used to form fair allocation methods for allocating the generated savings will be considered in the proposed allocation model. Fairness can simply be defined as the following: every carrier in the collaboration should receive equal benefit from collaborating. These theoretical approaches are used to define relevant equations that are forming the constraints of the allocation model.

In the computational analysis chapter of the thesis, the parameters introduced within the context of the model are investigated to form a true notion of the effects of the parameters on the structure of the optimal policy. Whether the optimal actions follow a certain pattern, identifying the conditions under which the existence of the intermediary makes significant difference on the total utility and analyzing how surplus (or deficit) changes with respect to system parameters are the main objectives of the computational analyses. As usual most shippers tend to behave for increasing their own profits (or decreasing their costs) they prefer to take myopic actions during the arrivals. A scenario is formed to display the myopic actions for each state. We compare the results of the myopic action and the optimal policy that is proposed by the mathematical model we will introduce. It is seen that increasing variable costs like cross-assignment cost and waiting cost leads to the increase in comparative performance of the optimal policy compared to the myopic policy, which is defined according to a simple rule, although increasing dispatching cost, which can be considered as a fixed cost, leads to an opposite result.

The rest of the thesis is organized as follows. In the next chapter we give brief information about the literature for collaborative supply chain management, role of information technology in collaboration, cost/profit allocation mechanisms, horizontal collaboration in transport. In Chapter 3, we propose a third-party transportation intermediary. In Chapter 4, we perform computational analyses to assess the performance of the intermediary. Finally, we summarize our discussion in Chapter 5.

CHAPTER 2

LITERATURE REVIEW

Johnson and Whang (2002) are discussing how e-Business is changing supply chains and investigating the topic under three forms: (i) e-Commerce (ii) e-Procurement (iii) e-Collaboration. They underline that the promise of e-Collaboration may be far greater than the achievements of e-Commerce and e-Procurement thus far. They define e-Collaboration as business-to-business interactions facilitated by the Internet. These interactions include such activities like information sharing and integration, decision sharing, process sharing, and resource sharing.

Griffin et al (2003) studies horizontal collaboration among buyers with multiple buyers and suppliers where multi-unit transactions for multiple items take place. It is assumed that buyers arrive with request for quotes (RFQs) for each item they want to buy and trades are initiated by submitting RFQs to the suppliers. That a buyer's demand for an item is met by a single supplier is an important assumption of the paper and this is very common in practice as splitting an order among multiple carriers causes difficulties in order tracking and transportation agreements. A buyer's surplus for an item is defined as the difference between the buyer's reservation price for that item, which is the maximum price for purchasing whole demand for the item, and the final contracting price for the entire demand for that item. They investigate procurement decisions of buyers under different degrees of collaboration: (i) No Collaboration (buyers in the market and functional divisions within companies do not collaborate with each other) (ii) Internal Collaboration (procurement decision is centralized within each company) and (iii) Full Collaboration (third party intermediary enables collaboration among multiple buyers). They study six different buying strategies for the no collaboration model and one strategy that is obtained by solving a linear integer program. They compare the results obtained from these models with the full collaboration model under different market conditions. They find that potential benefits of intermediaries are the highest in capacitated markets when economies of scope (high fixed transportation cost) and economies of scale (high fixed manufacturing and transportation costs) are considered.

Huber et al. (2004) conduct an empirical research investigation on purchasing consortium issues focusing on ICT-based procurement strategies. They explain the theoretical background to the electronic purchasing consortia (EPC) in their research. 17 different hypotheses under 9 main areas are generated based on this theory. Questionnaires are electronically sent to the population of 102 international active e-marketplaces and procurement service providers in the automotive, electronics and closely related industries after the online survey instrument is pre-tested among academics and practitioners. A response rate of 42 % is achieved for the first survey. The second survey is sent to 400 different purchasing organizations in the automotive and electronics industry in Ireland and Germany. A response rate of 32 % (128 organizations) is achieved for the second survey. They discuss the results of the confirmation tests of the hypotheses. The results focus on the effects of organizational, environmental and technological issues on the EPC adoption. In this research, it is found that the majority of adopters are satisfied about EPC and there is a growing realization that over the longer term EPC can play a substantially more important role.

Fu and Piplani (2004) evaluate the value of collaboration in supply chain management by focusing on the supply-side collaboration on inventory decisions between a supplier and a distributor. A traditional supply chain scenario without collaboration and a scenario with supply-side collaboration are compared to determine the value of collaboration. The value of collaboration is measured by the performance indices of percent error of service level and stabilizing effect. They find that supply-side collaboration improves supply chain performance as percent error of service level is decreased from 5 % to 1 % percent and stabilizing effect is increased from 0.35 to 0.55 in the supply-side collaboration.

Caplice (2007) studies the electronic markets from the side of the buyers of truckload (TL) transportation services and gives information about the utilization of electronic markets for these services. He introduces the Winner Determination Problem (WDP) as the key problem of the optimization-based auctions where the WDP assigns volume to carriers by lane or by load. He also discusses some applications regarding business rules and priorities by implementing relative and absolute conditions to the problem. Apart from the combinatorial auctions applications electronic catalogs and exchanges, which take place after the auctions and are widely used are in the literature and business, discussed in his research.

Keskinocak and Savaşaneril (2008) introduce a B2B collaborative procurement model within the context of group purchasing (joint procurement) where the buyers are competing firms. In their model, there is one supplier and several buyers. They assume that the market price of a product is a function of quantity of sold products in the market. They analyze the effects of collaborative procurement on both buyers and supplier, and necessary conditions for a successful joint procurement for different size firms. One of the most important finding of their study is all of the parties in the supply chain are better off under joint procurement including the supplier, the buyers and the end users.

Parkes et al. (2001) propose an allocation mechanism for combinatorial exchanges where the payment scheme is imposed to be BB, IR, fairly efficient and fairly incentive-compatible. Incentive-compatibility (IC) states that truthful bidding forms a Bayesian-Nash equilibrium and every agent can maximize its expected utility by bidding its true values while every other agent is bidding truthfully. A combinatorial exchange is defined as a combinatorial double auction involving multiple sellers and buyers to trade multiple heterogeneous goods. In their research, they propose a payment mechanism taking the Vickrey payment scheme and adapting this scheme to be budget-balanced. They formulate the pricing problem as a mathematical program which is aiming to minimize the distance to Vickrey payments while taking BB and IR as hard constraints. After formulating the problem they introduce several payment rules including payment schemes like “Threshold”, “Large” and “Fractional”. In this study they compare the results of these payment schemes. They conduct theoretical and experimental analyses for each payment schemes and find that higher allocative efficiency is achieved by using Threshold and Large payment schemes.

Ledyard et al. (2002) introduce the first use of combined-value auction for transportation services. Sears Logistics Services is introduced to be the procurer of CVA application that is developed by the founders of Net Exchange (NEX) within the California Institute of Technology. Invited carriers to the auction are determined by using a complex proprietary procedure to be sure that SLS can be confident about relying on the selected carriers. After selecting carriers, they use an iterative version of the sealed-bid procurement auction, in which bidding proceeds in rounds. Iterative auctions are such applications allowing bidders to update their bids. English auction is given as an example for iterative auctions. Bidders submit their bids to the auctioneer verbally. The first bidder's bid becomes the standing bid and other bidders are to submit a better price to win the auction. Whenever a bidder submits a better price for the item this bid becomes the standing bid. They also introduce the stopping rule that is used in this CVA application. The stopping rule is considered to be one of the most critical parts of the application as it is crucial to the performance, both in the final cost of acquisition and the completion time. This rule is used in this simple form: if total acquisition does not decline by at least x percent from the previous round then the just-completed round is declared to be the final round. They give details about the tests conducted for indicating the performance of the application in this study. The performance of the application is tested by using a test bed that operates over a local area network of computers in the Caltech Economics Laboratory. They conduct demonstrations for SLS and trucking firms by using the test bed to convince them to use this application. It is reported that over a three year period SLS saves more than USD 84.75 million (13 percent of total acquisition cost) by using the application.

Schönberger (2005) proposes a model that is adopting uniform allocation. However, this model is focusing on loss sharing in which an external carrier is engaged for the requests that were not chosen by any partner. Increase in cost as a result of engaging an external forwarder is distributed among coalition members uniformly.

Krajewska et al. (2006) propose a profit sharing model which is introducing potential self-fulfillment costs of a request to be used for specifying a set of optimal bundles. In the proposed model, the potential self-fulfillment cost is paid to the coalition by the offering member and transfer price is paid to the serving member. "Collaboration-advantage-indexes" are defined for coalition members and these indexes are used divide surplus budget among members.

Heijboer (2002) describes allocation of cost savings problem in purchasing consortia as a cooperative game which is not common for purchasing consortia in the literature. He analyses allocation methods whether the proposed methods satisfy some properties like "stability", "purchasing power property" and "additivity". In this research, some simple allocation methods like equal allocation, proportional allocation are used as well as complex allocation methods like Shapley value, compromise value and nucleolus. He assumes that price per item function is a convex function and claims that buyers can benefit from the economies of scale. In this research setting up and maintaining consortia cost is not neglected and a cost function with fixed cost and variable cost depending on the number of players in the consortium is inserted in the model. Game-theoretic solutions are found to be better than the common allocation methods introduced in the research.

Fan et al. (2001) and Oum et al. (2002) examine consolidation and alliance opportunities and contributions of horizontal alliances to productivity gains for airline industry based on a number of high-level trends and forces. Strategic alliances are considered as one of ways for market expansion in the air transport industry. Fan et al. (2001) identify three levels of cooperation in their research. These levels are considered to be ordinary, tactical and strategic levels. In the airline industry, ordinary level of cooperation takes place when carriers are serving an airport infrequently. In this level, carriers may choose to outsource the handling of general sales or other functions to other carriers or handling firms. In tactical cooperation level, carriers sell each other's capacity on selected routes. Strategic level of cooperation (strategic alliances) is the last form of cooperation in aviation. These alliances are formed to achieve network-wide cooperation and requiring extensive code-sharing among participants, coordinated schedule and fare planning to provide excellent transport services across the entire alliance network.

Cruijssen et al. (2007) present the results of a questionnaire aiming to reveal potential benefits and impediments of horizontal cooperation. The questionnaire is submitted to a sample of logistics service providers in Flanders. Benefits of the horizontal cooperation are formulated under three areas: (i) Costs and productivity (ii) Service (iii) Market position. Impediments of the horizontal cooperation are formulated under four areas: (i) Partner selection (ii) Determining and dividing the gains (iii) Unequal negotiation positions of partners (iv) Information and communication technology (ICT). The questionnaire is sent to 1537 logistics service provider companies that are active in businesses of freight transportation by road, inland water transportation, cargo handling and storage, freight forwarding, and express carriers. 25 % of the companies are large scale firms and 75 % of the companies are small and medium sized firms. 162 useful responds are returned from the companies where the firms in freight transportation by road business display significant interest on the research. Most of the companies (75 %) agree that horizontal cooperation increases the productivity and a few of them (5 %) disagree with this according to the survey results. The most severe impediments for cooperation are found to be the problems of “finding a reliable party that can coordinate the cooperation in such a way that all participants are satisfied” and “the construction of fair allocation mechanisms for the attained savings” as a result of the survey.

Lei et al. (2006) study collaborative agreements among carriers. They develop mathematical models for three management policies, (1) the non-collaborative policy (aiming at constructing vessel schedules and assigning orders to vessels to minimize an individual carrier’s operating cost without sharing any resource with external carriers), (2) the slot-sharing policy (requiring a pre-fixed percentage of vessel capacity to be exchanged between the independent carriers) and (3) the total collaboration policy (requiring the participating carriers to perform a joint optimization on their vessel departure times and customer-order assignment to the vessels), to empirically investigate the operational performance of container-vessel schedules. For each operation policy container-vessel dispatching and order-vessel assignments problem are solved. Empirical studies are based on 2,040 randomly-generated test cases with a set of real-life parameter values from shipping industries. The performance comparison is made against the width of receiving time windows at the destination port, order waiting time at the origin port and holding cost at the destination port. Empirical studies show that the total collaboration policy outperforms other policies for each comparison.

Song and Regan (2003) propose a Pareto efficient auction based framework for small and medium sized carriers to deliver economically efficient solutions to coalition members. When a load is not cost-effective for a carrier he tries to subcontract this load. In the proposed model each carrier uses the same optimization rules to evaluate whether the load is profitable. They assume that each firm can be a contractor or subcontractor for different auctions in this network. It is claimed that all participants in the proposed network either better off or remain same as the case without collaboration. Whether a carrier should subcontract his new load or not is an important decision that is analyzed in this research. It is assumed that all the carriers can calculate their optimal routes and costs in reasonable time by using commercial optimization tools. Marginal cost and marginal empty cost are defined as corresponding costs by adding a new load. They find that marginal cost is not the only factor on subcontracting decision of carriers but marginal empty cost also needs to be considered. So carriers need to consider future demands in their decisions. Using combinatorial auctions in bid selection is discussed and solving Winner Determination Problem (WDP) is proposed for the optimal solution in this research.

Krajewska and Kopfer (2006) present a collaboration model, which can be applied for a coalition of medium and small sized freight forwarding companies. They divide the collaboration process into three main phases: (i) preprocessing (ii) profit optimization (iii) profit sharing. In the preprocessing phase each participant specifies the lowest costs of fulfillment for each acquired request that they offer to the collaboration partners. Potential self-fulfillment cost of the request is specified by choosing the minimum of the cost of subcontracting and the cost of self-fulfillment. In the profit optimization phase a mapping of requests is generated where the profit of the entire coalition is maximized. Because of the fact that the set of bundles assuring the lowest serving cost leads to the maximum profit of the entire coalition, the optimal set is determined by solving the Combinatorial Auction Problem. In the profit sharing phase the profit obtained as a result of fulfillment of each request is divided among the participants. Residual overall profit of the entire coalition is divided among the coalition members according to an index called collaboration-advantage-index.

Krajewska et al. (2007) study horizontal cooperation among medium-and-small sized carriers focusing on sharing the profits of collaboration by using cooperative game approaches. In their research they propose to use a heuristic, which is a local search method moving within neighborhood, to solve pickup and delivery requests with time windows (PDPTW) problem. They give details about cooperative game theory and its usage in profit sharing mechanisms. In this research, they use the Shapley value that is allocating to each player the weighted sum of his contributions. The authors use three artificial instances and one instance based on real data in the computational analysis part of the research.

Christiansen et al. (2004) discuss research on ship routing, scheduling and related problems in their research. They give brief information about researches regarding strategic planning problems in shipping which are fleet sizing and the design of maritime logistics systems. In their research they investigate the literature for tactical and operational problems in industrial shipping and propose an industrial ship scheduling model which is formulated as a set partitioning (SP) model. They also introduce the literature for tactical and operational problems in tramp shipping. In this research the proposed model for industrial shipping is modified according to the nature of tramp shipping business. In contrast to the industrial shipping, the objective function tries to maximize the profit. Tactical and operational problems in liner shipping are discussed by giving brief information about the literature in this topic. Apart from the commercial vessels naval routing and scheduling problems are handled within the context of this review and it is underlined that the major objective of most naval application is to assign the available fleet to a set of specified that maximizes (or minimizes) a set of measures of effectiveness. They also discuss emerging trends in ocean shipping that are expected to influence decision support systems for ship scheduling significantly. These trends are: (i) Mergers and pooling collaboration resulting in larger operational fleets (ii) New generation of planners with more IT skills and experience (iii) Developments in software and hardware that facilitates rich models and intuitive graphical user interfaces (iv) Shift from industrial shipping to tramp shipping resulting in more market interaction and new opportunities and challenges for optimization-based decision support tools (v) Focus on supply chain performance in the planning of fleet schedules (vi) Strategic planning issues such as fleet sizing.

Sheppard and Seidman (2001) investigate horizontal cooperation for maritime shipping from the carriers' point of view. An alliance is defined as a cooperative operational arrangement between two or more carriers. They state advantages and disadvantages of entering into alliances in their paper. Economies of scale through larger volume shipments and improved customer service are the advantages that are claimed in the paper.

Agarwal and Ergun (2007) investigate the collaboration among carriers acting in liner shipping business in their research. They formulate the problem as "the optimization problem for the grand coalition" to find "the collaborative optimal solution". They consider the combined fleet of all the carriers and the combined demand of all the carriers as inputs of a network design problem. After designing the network of the grand coalition they handle the problem of the allocation of limited capacity among the carriers in the alliance. The problem of assigning ships over all the carriers to the set of selected service routes is considered as the ship assignment problem, which is a generalized assignment problem. They use two different heuristic methods to compute the utility of assigning a ship to a service route for a carrier and the cost incurred by each carrier in the collaborative solution. As the primary objective of an individual carrier is the maximization of his own profits, they model a mechanism to calculate the vector of side payments guaranteeing that each individual carrier will make decisions in line with the collaborative optimal solution.

In their research, they also analyze liner shipping alliances from a quantitative view based on the data simulating real life data from the industry and give insights about effects some factors like size and number of carriers, test classes, additional rationality constraints on the solution.

Agarwal et al. (2009) are discussing two forms of collaboration in cargo transportation: carrier collaboration in maritime and air transportation, and shipper collaboration in trucking. They are addressing the following questions in their research: (i) How does one assess the maximum potential benefit from collaborating? (ii) How should a membership mechanism be formed and what are the desired properties that such a mechanism should have? (iii) How should the benefits achieved as a result of collaboration be allocated among the participants fairly? (iv) Are there insights for collaboration formations to be gained? They discuss liner shipping and air cargo businesses for carrier collaboration in their research where the carriers are following fixed schedules. Their motivation is not only obtaining a good solution but also providing algorithms to share the benefits and costs of an alliance leading that all carriers are convinced to participate in the alliance. As the centralized solution tries to maximize the collective profit of the alliance and the benefits obtained from the centralized solution may not motivate individual carriers for collaboration they provide "side payments". They propose two different models to compute side payments where these models are reflecting different behaviors of the carriers. First model assumes that an individual carrier can modify the flow of other carriers and the other model assumes that this modification is impossible.

Gupta and Baghci (1987) study shipper collaboration within the context of just-in-time (JIT) procurement. They introduce a model with a consolidation center before shipment for calculating the minimum-cost effective load. Consolidation centers (or transshipment points) are special facilities where the packets are consolidated into larger truckloads. They state that frequent deliveries of small less-than-truckload (LTL) quantities are necessary because of the needs of JIT mode of purchasing. This necessity causes high transportation costs for the firms. They propose a model with a consolidation center which involves a number of neighboring suppliers (shippers) for a particular client. The opportunities of freight consolidation are discussed in this model. The goods are pooled to form a truckload (TL) before transportation to the final destination. In this study, it is assumed that vendors are arriving at consolidation center by gamma distributed stationary independent increments and production is based on the JIT principle. They compute a quantity level for the shipments from the consolidation center called minimum economic quantity providing logistic managers with information regarding the consolidation scheme. They analyze the effects of line-haul shipment cost and the transit time on the minimum economic quantity in this study. It is found that minimum economic quantity level increases as line-haul shipment cost increases while it is decreasing as transit time increases.

Ergun et al. (2007a) are focusing on finding optimal path to minimize asset repositioning. They propose two solution methodologies (set covering formulation and greedy algorithm) for the cardinal constrained lane covering problem (CCLCP) formulated in the paper and conduct a computational study to observe the effectiveness of these methodologies. Ergun et al. (2007b) develop an optimization technology for identifying continuous truckload move tours for companies minimizing truck repositioning. They focus on the time-constrained lane covering problem (TCLCP) which is defined as finding a set of tours covering all lanes, minimizing the total duration of the tours and respecting the dispatch windows. In this research a heuristic is developed to solve the TCLCP. A greedy heuristic is used to generate large number of time-feasible cycles. After generating time-feasible cycles, the first arc of the cycle, which is minimizing the cycle duration, is determined by using some algorithms. As the greedy selection may not produce high-quality lane covers, a local improvement scheme is developed in this research. This algorithm merges cycles from a cycle cover by removing the longest repositioning arcs from each cycle and reconnecting the two resulting directed paths optimally to form another cycle. A set of computational experiment is conducted to assess the overall effectiveness of the proposed algorithms and to analyze the impact of instance size and characteristics on the performance in terms of quality efficiency. The effectiveness of local improvement process is investigated by comparing the optimal results and it is found that this process is very effective in terms of quality and time. They also demonstrate the effectiveness of the algorithms by using the instances derived from data obtained from the industry.

Ozener and Ergun (2008) study shippers' collaboration where shippers bundle their shipment requests in order to negotiate better rates with a common carrier. They consider a group of shippers each with a set of lanes to be served and try to minimize the total cost of transportation while satisfying the demand of each shipper in the collaboration. They formulate total transportation costs minimization problem as Lane Covering Problem (LCP). After formulating the integer linear program for LCP, they discuss the correspondence of an optimal dual solution to a budget balanced and stable cost allocation. In a budget balanced allocation, the total cost allocated to the members of the collaboration is equal to the total cost incurred by the collaboration. In a stable allocation, no coalition of members can find a better way of collaborating on their own. They also consider some well known cost allocation methods in cooperative game theory like nucleolus, which is in the core of the game and lexicographically maximizes the minimal gain, and Shapley value. In this research, they propose a cost allocation method in which the allocated costs are proportional to the original lane costs. As the nature of the collaboration is dynamic in practice, they introduce the cross-monotonicity concept that is guaranteeing that when a new member joins a shippers' collaboration network the overall benefit will be non-negative. Since there doesn't exist a cross monotonic cost allocation in the core, authors use some relaxation techniques to find a cross monotonic and stable cost allocation recovering a good percentage of the total cost and a cost allocation with a minimum percentage deviation from stability although stability is considered as the key property to form a sustainable collaboration. In their research, they also discuss some additional cost allocation properties that are desired in practice, including cost allocation with minimum liability restriction where shippers are responsible at least for their truckload lane costs and cost allocation with guaranteed positive benefits.

Most of the collaborative logistics models in the literature study large shippers or carriers that want to get engaged with long-term collaboration contracts. A line of research focus on consolidation of small loads into truckloads. As it has been indicated before, Gupta and Baghci (1987) study shipper collaboration within the context of JIT procurement where shippers consolidate their loads in a consolidation center. In the proposed model, a quantity level is used to make dispatching decisions. Agarwal et al. (2009) also study shipment consolidation to decrease total transportation costs of shippers in the trucking industry. They study the problem as a Lane Covering Problem (LCP) to reduce the inefficiencies caused by dead hauling.

We study collaboration in transportation among small shippers, in which small shippers come together and consolidate their loads to obtain savings. It is assumed that shippers arrive randomly and independently to different dispatching locations, which are considered as harbors in the thesis. A centralized transportation intermediary model, in which assignment and dispatching decisions are made according to the solution set of an MDP problem, and a saving allocation mechanism, which utilizes well-known cooperative game theoretic approaches including budget balance (BB) and individual rationality (IR) properties, is proposed in the thesis.

CHAPTER 3

MODELING THE TRANSPORTATION INTERMEDIARY

As it has been mentioned in the first chapter of this thesis, the main motivation is to study a third-party transportation intermediary operating in the tramp shipping business that brings small shippers together to achieve savings through collaboration. The dynamics of the problem is analyzed to obtain insights as to the form of the system. A mechanism is designed to find the optimal decisions, which maximizes the expected discounted utility of the system, in the first part of this chapter. After solving the mathematical model it would be expected to get some amount of savings in comparison to any traditional system in which shippers take myopic actions. Allocation of these savings is the other problem studied. A mathematical model is proposed to allocate the savings to the shippers in the second part of this chapter while considering some game theoretic approaches.

3.1 Forming a Third-Party Transportation Intermediary

A system consisting of *m* shipper classes is considered. These shippers arrive at *n* different vessel dispatch locations, which could be harbors in maritime context, with unit loads.

- Shippers from each class $i \in I = \{1, 2,..., m\}$, arrive to a dispatch location $j \in J = \{1, 2,...,n\}$ according to an independent Poisson process with rate λ_{ij}.
- Each arriving shipper incurs a waiting cost h_i per unit time. It is assumed that $h_1 > h_2 > h_3 > ... > h_m$.
- A shipper does not leave the system until his load is dispatched.

- It can be considered that waiting costs reflect implicit due dates of the shipper classes, the higher the waiting cost is the tighter is the due date of the shipper class.
- A vessel in dispatch location j has capacity K_j and shippers at the dispatching location j have to pay a total amount of fixed cost D_j for the vessel upon dispatch.
- It is assumed that whenever shippers decide to ship, a vessel can be found available within a negligible amount of time and full vessel cost is incurred by the shippers whenever a vessel is dispatched.
- When a vessel dispatches, the payment to the carrier is equally shared by the shippers in the vessel, since the shippers are identical in terms of capacity requirements in the vessel.
- Although waiting for other shippers may increase the number of shareholders for the dispatching cost, waiting costs are incurred by the shippers as a result of the cost of time. Therefore, there is a tradeoff between dispatching shortly and waiting to fill the vessel.
- Each shipper i is assumed to obtain a utility R_i when her load is carried. It is assumed that $R_1 > R_2 > R_3 > ... > R_m$. In other words, it is assumed that the highest valued shipper has the tightest implicit due date. The utility is assumed to be obtained upon dispatch.
- A shipper arriving at location j may prefer to ship his load on a vessel at location k, if the vessel at k is more likely to dispatch earlier, in which case a cross-assignment (or transfer) cost of c_{jk}, $j, k \in J$, is incurred. We assume c_{jj}=0 for all j.
- The net utility of shipper i is determined by deducing the waiting, dispatch and assignment cost from R_i. This utility is assumed to be "transferable", in other words, it is possible that the centralized mechanism reallocates the total utility to the shippers.

The state of the system at time t can be described by the number of existing shippers at the dispatching locations, devoted by the vector

$X(t) = (X_{11}(t), X_{21}(t),..., X_{m1}(t),..., X_{1n}(t),..., X_{mn}(t))$, where $X_{ij}(t)$, $i \in I$ and $j \in J$, is a non-negative integer denoting the number of Class i shippers in location j. For instance, $X_{3,11}(t)$ indicates the number of shippers coming from Class 3 which are located at the 11th dispatching location. Since the vessels are immediately dispatched when they become full, the total number of shippers coming from each class in each vessel cannot exceed $K_j - 1$.

$$0 \le \sum_{i=1}^{m} X_{ij}(t) \le K_j - 1 \qquad \forall j \tag{1}$$

The state space S is countable and bounded, and its size depends on the size of shipper classes set I, dispatching locations set J and the capacity of the vessel located in the j^{th} dispatching location, K_j.

$$|S| = \prod_{j=1}^{n} \sum_{k=0}^{K_j - 1} \binom{k+m-1}{m-1} \tag{2}$$

where m denotes the number of shipper classes and n denotes the number of dispatching locations. When the vessels at each dispatching location are assumed to be identical and their capacities are set to be K, the number of states would be $\left(\sum_{k=0}^{K-1} \binom{k+m-1}{m-1} \right)^n$ for n different dispatching locations.

For instance, suppose there are 2 different shipper classes and 2 different dispatching locations, $|I| = |J| = 2$, and suppose that the capacity of the vessels at each dispatching location is 6, $K_1 = K_2 = 6$. By using Eq. (1) we have:

$$X_{11}(t) + X_{21}(t) \le 5 \text{ and } X_{12}(t) + X_{22}(t) \le 5 \tag{3}$$

As a result of above inequalities the vector $X(t) = (X_{11}(t), X_{21}(t), X_{12}(t), X_{22}(t))$ showing the state of the system at time t can denote 441 different states, so $|S| = 441$. We let $h(X(t)) = \sum_{j=1}^{n} \sum_{i=1}^{m} h_i(X_{ij}(t))$ denote the total waiting cost rate incurred by all shippers in the system at time t when the state is $X(t)$. Since holding cost is assumed to be incurred per shipper per unit time:

$$h(X(t)) = h_1 X_{11}(t) + ... + h_1 X_{1n}(t) + ... + h_m X_{m1}(t) + ... + h_m X_{mn}(t) \qquad (4)$$

The interarrival times of shippers are exponentially distributed and the system is memoryless. Due to the memoryless property only the policies that depend on the state of the system are considered. Furthermore, we assume that decision epochs are limited to event occurrence times. We model the problem as a Markov Decision Process (MDP). A finite set of actions A available at each state is considered. A policy π specifies for each state $x = (x_{11},..., x_{m1},..., x_{1n},..., x_{mn})$, the action $a^{\pi}(x) = (u_{11},..., u_{mn}, v_{11},..., v_{mn})$, where u_{kl} indicates the assignment location of the Class *k* shipper arriving at the dispatching location *l,* $v_{kl} = D$ means dispatch the vessel after the assignment of the Class *k* shipper arriving at the dispatching location *l* and $v_{kl} = N$ means do not dispatch the vessel after the assignment of the Class *k* shipper arriving at the dispatching location *l*. It is to be noted that actions, where $u_{ij} \in J$ and $v_{ij} \in \{D, N\}$, are state dependent due to the boundary conditions of the capacity limit K_j.

Example. An example can be given to solidify the understanding the structure of the action. Suppose the system is composed of two classes of shippers and two dispatching locations, so both allocation *u* and dispatching *v* parts of the action would be four-dimensional. In this example assignment and dispatching parts of the action can also be written together as $a^{\pi}(x) = (a_{11}, a_{21},..., a_{12},..., a_{m2},..., a_{mn})$ to simplify the notation of the action and to harmonize the notation with defined actions like 1N, 2N etc., where a_{ij} is considered as combination of u_{ij} and v_{ij}. So, a policy π specifies for each state $x = (x_{11}, x_{21}, x_{12}, x_{22})$, the action $a^{\pi}(x) = (a_{11}, a_{21}, a_{12}, a_{22})$, where a_{ij} can be 1N, 1D, 2N or 2D. 1N denotes sending the arriving shipper to the first dispatch location without dispatching; 1D denotes sending the arriving shipper to the first dispatch location and dispatching vessel 1; 2N denotes sending the arriving shipper to the second dispatch location without dispatching and 2D denotes sending the arriving shipper to the second dispatch location and dispatching vessel 2.

For example, the action $a^{\pi}(x)$ = (1D, 1N, 1D, 2N) indicates that whenever the system is in state x;

1) If a shipper of Class 1 arrives at the first dispatching location, assign this shipper to the vessel in the first dispatching location and dispatch the vessel
2) If a shipper of Class 2 arrives at the first dispatching location, assign this shipper to the vessel in the first dispatching location and do not dispatch the vessel
3) If a shipper of Class 1 arrives at the second dispatching location, assign this shipper to the vessel in the first dispatching location and dispatch the vessel
4) If a shipper of Class 2 arrives at the second dispatching location, assign this shipper to the vessel in the second dispatching location and do not dispatch the vessel

In the analysis "expected total discounted profit criterion" is used under infinite planning horizon. The expected total discounted profit (or net utility in this context) over an infinite planning horizon obtained under a policy π and a starting state x, V_x^{π} can be written as:

$$V_x^{\pi} = E_x^{\pi}\left[\begin{array}{l}\sum_{j=1}^{n}\sum_{i=1}^{m}\int_0^{\infty} e^{-\alpha t}\left[-h_i(X_{ij}(t))\right]dt \\ \qquad -\sum_{k=1}^{n}\sum_{j=1}^{n}\int_0^{\infty} e^{-\alpha t} c_{jk}\, dN_{jk}(t) + \sum_{k=1}^{n}\int_0^{\infty} e^{-\alpha t} F_k(X(t))\, dN_k(t)\end{array}\right], \qquad (5)$$

where $\alpha > 0$ is the discount rate, $N_{jk}(t)$ denotes the number of shippers that arrive to location j and assigned to location k up to time t, $N_k(t)$ denotes the number of dispatched vessels from location k up to time t, c_{jk} denotes the assignment costs of arriving shippers, $F_k(X(t))$ is composed of dispatching cost subtracted from the total utility of the shippers in vessel k at time t.

$$F_k(X(t)) = -D_k + \sum_{i=1}^{m} R_i X_{ik}(t) \qquad (6)$$

Under a given policy π, the underlying chain is a continuous time Markov Chain. The continuous chain is converted into a discrete-time Markov Chain through uniformization. Transition rate in each state under any action is assumed to be $\beta = \sum_{j=1}^{n}\sum_{i=1}^{m}\lambda_{ij}$. A summary of the notation used in this chapter is given in Table 1.

Table 1: Table of notation for the total expected discounted profit

α : Discount rate
β : Transition rate
$h(x)$: Waiting cost rate when the state is x
c_{jk} : Assignment cost of an arriving shipper from location j to location k
t_z : Transition times where $0=t_0 < t_1 < t_2 \ldots$
$N_{jk}(t)$: Number of arriving shippers to location j which are assigned to location k up to time t
$N_k(t)$: Number of dispatched vessels from location k up to time t
$F_k(X(t))$: Gained utility of shippers at location k at time of dispatch

Under uniformization and discretization, the total expected discounted profit expression in Eq. (5) can be written as:

$$V_x^{\pi} = E_x^{\pi}\left[\sum_{z=0}^{\infty}\left(\frac{\beta}{\alpha+\beta}\right)^{z}\frac{h(X(t_z))}{\alpha+\beta} + \sum_{z=1}^{\infty}\left(\frac{\beta}{\alpha+\beta}\right)^{z}\left(\sum_{k=1}^{n}\sum_{j=1}^{n} -c_{jk}(N_{jk}(t_z) - N_{jk}(t_{z-1})) + \sum_{k=1}^{n} F_k(X(t_z))(N_k(t_z) - N_k(t_{z-1}))\right)\right]. \quad (7)$$

The transportation intermediary acts as a central mechanism and maximizes the expected total discounted net utility of the shippers. As stated above, only the Markovian policies are considered, in which the action taken only depends on the state and not the time index. To find the optimal actions that the central system will take for all states $x \in S$ and to determine the optimal expected total discounted profit, V_x^*, as a consequence of these actions, the following optimality equation is expressed (under the discretized process):

$$V_x^* = -\frac{h(x)}{\alpha+\beta} + \frac{\beta}{\alpha+\beta}\sum_{j=1}^{n}\sum_{i=1}^{m}\frac{\lambda_{ij}}{\beta}\tau_{ij}V_x^*. \tag{8}$$

where τ_{ij} is an operator defined on V_x:

$$\tau_{ij}V(x) = \max_{k}\left\{-c_{jk} + max\left\{V(x+e_{ik}), V(x_{-k}, 0_k) + F_k(x+e_{ik})\right\}\right\} \tag{9}$$

where e_{ij} is a vector of dimension $m \cdot n$, where $\{(j\text{-}1)n+i\}^{th}$ entry is 1 and other entries are 0. Given a state x, state $(x_{-k}, 0_k)$ denotes the state with only k^{th} vessel is dispatched.

In this setting for a given state x and action $a \in A$ one could express the one-step reward function, $r(x,a)$, and the transition probability function, $P(y \mid x,a)$, as follows:

$$\begin{aligned} r(x,a) = -\frac{h(x)}{\alpha+\beta} &+ \sum_{j=1}^{n}\sum_{i=1}^{m}\frac{\lambda_{ij}}{\alpha+\beta}(-c_{jk})I_{\{u_{ij}=k\}} \\ &+ \sum_{j=1}^{n}\sum_{i=1}^{m}\frac{\lambda_{ij}}{\alpha+\beta}F_k(x+e_{ik})I_{\{u_{ij}=k,\, v_{ij}=D\}} \end{aligned} \tag{10}$$

$$P(y \mid x,a) = \begin{cases} \sum_{j=1}^{n}\frac{\lambda_{ij}}{\beta}I_{\{u_{ij=k},\, v_{ij}=N\}} & y = x+e_{ik} \quad \forall i \\ \sum_{i=1}^{m}\frac{\lambda_{ij}}{\beta}I_{\{u_{ij=k},\, v_{ij}=D\}} & y = (x_{-k}, 0_k) \quad \forall k \end{cases} \tag{11}$$

where the indicator function $I_{\{u_{ij},\, v_{ij}\}}$ would be 0 or 1 according to the actions taken for arriving shippers.

The optimality equation in Eq. (7) is solved using the following LP model:

$$\begin{aligned} & Min \sum_{x\in S}\delta_x V_x \\ & s.t. \\ & \quad V_x \geq r(x,a) + \gamma\sum_{y\in S}P(y \mid x,a)V_y \qquad \forall\, x \in S, a \in A \\ & \quad V_x \text{ unrestricted} \qquad \forall\, x \in S \end{aligned} \tag{12}$$

where, δ_x denotes the probability of being in state x initially, V_x indicates the expected total discounted profit of the state x. The symbol γ indicates that we are taking a discount rate α into consideration and using this rate in our computations. As transition rate in each state under any action is defined as β, $\gamma = \beta/(\alpha+\beta)$. It is assumed that $\delta_x > 0$ and $\sum_{x \in S} \delta_x = 1$ although that the sum of initial probabilities equals one is not a necessary condition but the states' proportionate share of values are critical. To be more explicit, the relatively greater value of the initial probability of a state increases the probability of that the system starts from that state.

Dual model of the proposed model can be written as follows:

$$
\begin{aligned}
& Max \sum_{x \in S} \sum_{a \in A} w_{xa} r(x,a) \\
& s.t. \\
& \qquad \sum_{a \in A} w_{xa} - \gamma \sum_{y \in S} \sum_{a \in A} w_{ya} P(x \mid y,a) = \delta_x \quad \forall\, x \in S \qquad (13) \\
& \qquad w_{xa} \geq 0 \qquad\qquad\qquad\qquad \forall\, x \in S, a \in A
\end{aligned}
$$

where, w_{xa} denotes discounted probability of being in the state x and taking action a.

3.2 Behavior of the Shippers without a Transportation Intermediary

In this part of the thesis two different systems are conjectured in the absence of the transportation intermediary, i.e., in the absence of the centralized decision making.

1- Naïve System: It is assumed that a vessel only dispatches when it is fully loaded. The shippers make vessel selection by themselves as follows. The shippers that have higher waiting costs (or shorter implicit due dates) prefer the vessels with highest number of shippers in it. On the other hand, shippers with low utilities and low waiting costs prefer the vessel at the location where they arrive, to avoid the assignment (transportation) cost. Under the assumption of $h_1 > h_2 > h_3 > ... h_m$ and $R_1 > R_2 > R_3 > ... > R_m$, let L_1 denote the set of shippers that prefer loaded vessels, and L_2 denote the set of shippers that prefer the closest locations. L_1 and L_2 are such that $L_1 \cup L_2 = L$ and $L_1 \cap L_2 = \varnothing$.

Example. We solidify the understanding of the utilized policy under the naïve system by using an example. Let the initial state x be (1, 2, 0, 4), (i.e., there are one Class 1 shipper and two Class 2 shippers at the first dispatching location, there are four Class 2 shippers at the second dispatching location) and the vessels' capacity K_1 and K_2 be 6. In the absence of the centralized decision making Class 1 shippers form the set of L_1 and Class 2 shippers form the set of L_2, $L_1 = \{1\}$ and $L_2 = \{2\}$. So the assignment procedure of the arriving shippers would be as follows:

- When a shipper of Class 1 arrives at the first or second dispatching location the shipper prefers to go to the second dispatching location because the number of shippers at that location is greater than the number of shippers at the first location. So the next state y would be (1, 2, 1, 4).
- When a shipper of Class 2 arrives at the first dispatching location the shipper is assumed to prefer to stay at the first dispatching location. So the next state y would be (1, 3, 0, 4).
- When a shipper of Class 2 arrives at the second dispatching location the shipper prefers to stay at this dispatching location. So the next state y would be (1, 2, 0, 5).

None of the vessels would be dispatched since the arriving shippers could not fill the capacity of the vessels. If the preliminary state x were (1, 2, 0, 5) the vessel at the second dispatching location would be dispatched upon any class of shippers to location 2 or arrival of Class 1 shipper to location 1.

2- Myopic System: The shippers make vessel selection by using myopic actions that are found iteratively. In the first iteration, when a shipper arrives at a dispatching location the shipper tries to maximize her total utility under the assumption of that other shippers follow the aforementioned naïve system in the above part. In the second iteration, the myopic actions, which are found in the first iteration, for each state form the actions set that would be used instead of naïve actions. These steps are pursued until the generated myopic actions are stabilized.

3.3 Designing a Scheme that Reallocates the Savings to Enable Collaboration

Saving allocation is not important only for balancing the budget of the system but also for the system as it is a motivation for shippers to participate in the proposed system. A system bringing more yield than any other choice will definitely attract shippers' attention to join the grand coalition. Hence, saving allocation is to be seen as a factor enabling collaboration and self-sustaining system.

In this part of the thesis, a scheme will be introduced to reallocate the savings, which are obtained under centralized mechanism, to the shippers. The proposed scheme would be expected to satisfy the properties individual rationality (IR) and budget-balance (BB) that are widely used in cooperative game theory. A mathematical model will be proposed for the reallocation of the savings. The model guarantees that the allocated amounts are at least what the shippers get under the system without a transportation intermediary. Within the context of the model, the "payment" concept will be introduced and the expected discounted profits of individual shippers will be computed.

Obviously, the centralized system results in higher total expected discounted net utility than the naïve (or myopic) system. However, it may be that some of the arriving shippers prefer to take the naïve (or myopic) action rather than the optimal action, since expected discounted net utility is higher for that shipper under the naïve (or myopic) action. In order for an arriving shipper to take the optimal action, the shipper must be ensured to get at least what he gets under the naïve (or myopic) action. It is assumed that a payment (in the form of utility) is made to an arriving shipper accordingly. Furthermore, for the formed intermediary to be viable what is totally paid to the shippers must not exceed what is totally received from the shippers.

It is possible to analyze this problem from a game-theoretic view. In cooperative game theory, a core-defining set is an allocation that satisfies “individual rationality (IR)”, “budget balance (BB)” and “stability”. Stability of an allocation ensures that no coalitions are formed among the players except the grand coalition. Due to the stochastic nature of the problem and infinite number of shippers in the “game”, stability of the allocation is not considered but the focus is only on IR and BB properties.

As it has been indicated before, although proposed optimal system guarantees to achieve optimal profit of the whole system it may not guarantee to provide all the shippers with better profits (at least same as before), namely IR property due to the budget limitations. Because of the fact that we are trying to convince shippers for participating in the system it is needed to guarantee IR property. If a shipper gets less than before, then the shipper will do better by opting out. Hence, the proposed solution has to involve a payment structure that satisfies the property of IR.

Besides the IR property there is also another problem to be handled carefully that is distributing the surplus budget to the coalition members (shippers) as the proposed model generates more income in comparison to a traditional model. We can be inspired by the definition of the property of collective rationality above to handle this issue. The collective rationality says that the maximal amount of money should be divided among the coalition members to the last penny. Because of the fact that what is totally paid to the shippers must not exceed what is totally received from the shippers the allocation system needs to satisfy the budget balance property. Nisan (2007) defines budget balance property as incurring charges to the participants where the sum of charges covers the total cost of the grand coalition. This property is important since the money is not injected or removed from the system. If the payments made or received by the players equal to zero, the system is termed as a strict budget balance system. On the other hand, if the payments made or received by the players are not equal to zero but it is nonnegative, then the system is termed as a weak budget balance system. As Rajasekaran et al. (2007) emphasizes that budget balance property is especially important in systems that must be *self-sustaining* and require no external benefactor to input money or central authority to collect payments.

A self sustaining payment system that convinces shippers to form the grand coalition N by using the properties mentioned above can be designed by using the following steps. We are considering a payment system generating payment $P(x)$ to the arriving shipper when the state is x:

1) For the sake of satisfying the individual rationality property payment received by the shipper is not to be less than expected net utility the shipper could get under naïve (or myopic) action. In other words, for state x following condition must be hold:

   $$T(x) \le P(x), \qquad \forall x \tag{14}$$

   where $T(x)$ is simply the minimum expected payment that the central mechanism would make from its pocket in state x, if all possible shipper arrivals at state x and corresponding probabilities of the arrivals are considered. An expression for $T(x)$ will be derived below.

2) Since it is tried to design a self-sustaining system in which there is no need to inject or remove money for balancing, it is needed to define a constraint as follows:

   $$(I - \gamma Q)^{-1} \times (r - P) = 0 \tag{15}$$

   where I is identity matrix, γQ indicates discounted transition probability matrix among states under the optimal policy and r and P are vectors of $r(x)$ and $P(x)$ where $r(x)$ indicates the one-step reward of the state x under the optimal policy. Although the optimal policy is expected to give better solutions than the traditional system there may not be a feasible solution satisfying the Eq. (15) in some cases. As it has been indicated before if the system is desired to start from a specific state the initial probability of that state can be taken relatively very high in comparison to the other states, so the state values can be used for the whole system. For this reason, the Eq. (15) can be relaxed by taking only the first row of $(I - \gamma Q)^{-1}$ matrix in computing.

3) If budget balance property is satisfied and there is surplus then infinitely many allocation of savings is possible. A model that minimizes the variance of the payments will be our purpose. For the sake of minimization of the variance of the payments it is needed to define an objective function aiming to maximize the minimum of differences between expected payment $P(x)$ made at state x and expected minimum payment $T(x)$. Defining y as the difference between the minimum payment and the allocation, maximizing y under the following constraint yields the minimum variance payment.

$$y \le P(x) - T(x) \qquad \forall x \tag{16}$$

It may be impossible to find an optimal y value satisfying all the conditions stated above like IR and budget-balance properties in some cases. For instance, there may be some cases where $(I - \gamma Q)^{-1} \times (r - T)_0 < 0$ which means we would have budget deficit after the central mechanism would make the expected payment from its pocket in the initial state. If the budget-balance property is thought to be satisfied in any condition the budget deficit would be paid by the coalition members, so Eq. (14) would be replaced.

This modification means relaxation of IR property for the sake of balancing the budget of the system. It is obvious that negative y values would be encountered as a result of the optimization problem.

As it has been indicated before $T(x)$ is the minimum expected payment that the central mechanism would make to the arriving shippers at state x, equivalently the expected discounted net utilities of arriving shippers when the state is x. The expected minimum payment $T(x)$ can be calculated as follows:

$$T(x) = \sum_{j=1}^{n} \sum_{i=1}^{m} \frac{\lambda_{ij}}{\beta} T_{ij}(x) \tag{17}$$

where $T_{ij}(x)$ denotes the expected net utility of an arriving Class i shipper to the dispatching location j when the state is x. $T_{ij}(x)$ is obtained as follows:

$$T_{ij}(x) = \frac{\beta}{\alpha+\beta}\left[\begin{array}{l}\left(t_k^i(x+e_{ik}) + (-c_{jk})\right) I_{\{u_{ij}=k,\, v_{ij}=N\}} \\ \qquad\qquad + \left(R_i - D_k/(n_k+1) + (-c_{jk})\right) I_{\{u_{ij}=k,\, v_{ij}=D\}}\end{array}\right] \tag{18}$$

where e_{ik} is a vector that with a dimension of $m \cdot n$, $t_k^i(x+e_{ik})$ denotes the expected discounted profit of an existing shipper coming from Class i in the vessel k when the state is $(x+e_{ik})$, n_k denotes the total number of shippers in the vessel k before the arrival of the shipper.

The expected discounted net utility of an existing shipper accumulated until the dispatch, $t_j^i(x)$, can be calculated as follows:

$$t_j^i(x) = -h_i/(\alpha+\beta) + \sum_{y=1}^{n}\sum_{x=1}^{m}\frac{\lambda_{xy}}{(\alpha+\beta)}\left[\begin{array}{l} t_j^i(x+e_{ij}) I_{\{u_{xy}=j,\, v_{xy}=N\}} + t_j^i(x+e_{ik}) I_{\{u_{xy}=k\neq j,\, v_{xy}=N\}} \\ + \left(R_i - D_j/(n_j+1)\right) I_{\{u_{xy}=j,\, v_{xy}=D\}} + t_j^i(x_{-k}, 0_k) I_{\{u_{xy}=k\neq j,\, v_{xy}=D\}}\end{array}\right] \tag{19}$$

where the first arriving shipper is a Class x shipper which is arriving at the dispatching location y.

It will be shown analytically that the expected minimum payment $T(x)$ can be considered as an indicator for representing for the payment to the arriving shipper when the state is x. We consider a case with single vessel and single Class of shippers. Each shipper is assigned to the same vessel with an assignment cost *c* and the vessel is dispatched when it is fully loaded. The fixed cost for dispatching the vessel is *D* and each shipper obtains utility *R* when the vessel is dispatched. The total capacity of the vessel is considered to be *K*. So we will consider a path starting from State 0 to State *K* as the following:

$$0 \rightarrow 1 \rightarrow 2 \rightarrow 3 \rightarrow \ldots\ldots\ldots\ldots \rightarrow K-1 \rightarrow K$$

The expected discounted net utility of an existing shipper at state *(x+1)* accumulated until the dispatch is defined as the following:

$$t(x+1) = \frac{h}{\alpha+\beta} + \frac{\beta}{\alpha+\beta} t(x+2) \qquad x = 0, 1, \ldots\ldots\ldots\ldots, K-2 \tag{20}$$

where $t(K) = R - D/K$. So we can write the expected discounted net utilities for each state as the following:

$$t(1) = \frac{h}{\alpha+\beta} + \frac{\beta}{\alpha+\beta} t(2)$$

$$t(2) = \frac{h}{\alpha+\beta} + \frac{\beta}{\alpha+\beta} t(3)$$

$$\vdots$$

$$\vdots$$

$$t(K-1) = \frac{h}{\alpha+\beta} + \frac{\beta}{\alpha+\beta} (R - D/K)$$

$$t(K) = R - D/K \tag{21}$$

The expected net utility of an arriving shipper is defined as the following:

$$T(x) = \frac{\beta}{\alpha+\beta} (t(x+1) + c) \qquad x = 0, 1, \ldots\ldots\ldots\ldots, K-1 \tag{22}$$

One-step reward $r(x)$ for state x under a policy is defined as the following:

$$r(x) = \frac{h \cdot x}{\alpha+\beta} + \frac{\beta \cdot c}{\alpha+\beta} \qquad x = 0, 1, \ldots\ldots\ldots\ldots, K-2 \tag{23}$$

where $r(x) = \frac{h \cdot x}{\alpha+\beta} + \frac{\beta \cdot c}{\alpha+\beta} + \frac{\beta}{\alpha+\beta}(K \cdot R - D)$ when $x = K-1$.

We will show that the sum of discounted one-step rewards and the sum of expected net utilities for each state are equal.

$$\sum_{x=0}^{K-1} \left(\frac{\beta}{\alpha+\beta}\right)^x r(x) = \sum_{x=0}^{K-1} \left(\frac{\beta}{\alpha+\beta}\right)^x T(x) \tag{24}$$

$$\sum_{x=0}^{K-1} \left(\frac{\beta}{\alpha+\beta}\right)^x r(x) = \sum_{x=0}^{K-1} \left(\frac{\beta}{\alpha+\beta}\right)^x \frac{h \cdot x}{\alpha+\beta} + \boxed{\sum_{x=0}^{K-1} \left(\frac{\beta}{\alpha+\beta}\right)^x \frac{\beta \cdot c}{\alpha+\beta}} + \left(\frac{\beta}{\alpha+\beta}\right)^{K-1} \frac{\beta}{\alpha+\beta} (K \cdot R - D) \tag{25}$$

$$\sum_{x=0}^{K-1}(\frac{\beta}{\alpha+\beta})^{x} T(x)=\sum_{x=0}^{K-1}(\frac{\beta}{\alpha+\beta})^{x} \frac{\beta}{\alpha+\beta} t(x+1)+\boxed{\sum_{x=0}^{K-1}(\frac{\beta}{\alpha+\beta})^{x} \frac{\beta \cdot c}{\alpha+\beta}} \tag{26}$$

where

$$t(1)=\frac{h}{\alpha+\beta}\left(1+\frac{\beta}{\alpha+\beta}+(\frac{\beta}{\alpha+\beta})^{2}+.......+(\frac{\beta}{\alpha+\beta})^{K-2}\right)+(\frac{\beta}{\alpha+\beta})^{K-1}(R-D/K)$$

$$t(2)=\frac{h}{\alpha+\beta}\left(1+\frac{\beta}{\alpha+\beta}+(\frac{\beta}{\alpha+\beta})^{2}+.......+(\frac{\beta}{\alpha+\beta})^{K-3}\right)+(\frac{\beta}{\alpha+\beta})^{K-2}(R-D/K)$$

$$\vdots$$

$$\vdots$$

$$t(K-1)=\frac{h}{\alpha+\beta}+\frac{\beta}{\alpha+\beta}(R-D/K)$$

$$t(K)=R-D/K$$

We write the first part of the Eq. (26) as the following:

$$\sum_{x=0}^{K-1}(\frac{\beta}{\alpha+\beta})^{x} \frac{\beta}{\alpha+\beta} t(x+1)=\sum_{x=0}^{K-1}(\frac{\beta}{\alpha+\beta})^{x} \frac{\beta}{\alpha+\beta} INV+\sum_{x=0}^{K-1}(\frac{\beta}{\alpha+\beta})^{x} \frac{\beta}{\alpha+\beta} DISP \tag{27}$$

where *INV* represents the holding cost part of the equation and *DISP* represents the utility and dispatching cost part of the equation. So the first part of the equation can be written as follows:

$$\sum_{x=0}^{K-1}\left(\frac{\beta}{\alpha+\beta}\right)^{x}\frac{\beta}{\alpha+\beta}INV$$

$$=\frac{\beta}{\alpha+\beta}\left(1+\frac{\beta}{\alpha+\beta}+\left(\frac{\beta}{\alpha+\beta}\right)^{2}+.......+\left(\frac{\beta}{\alpha+\beta}\right)^{K-2}\right)\frac{h}{\alpha+\beta}$$

$$+\left(\frac{\beta}{\alpha+\beta}\right)^{2}\left(1+\frac{\beta}{\alpha+\beta}+\left(\frac{\beta}{\alpha+\beta}\right)^{2}+.......+\left(\frac{\beta}{\alpha+\beta}\right)^{K-3}\right)\frac{h}{\alpha+\beta}$$

$$+$$

$$\vdots$$

$$\vdots$$

$$+\left(\frac{\beta}{\alpha+\beta}\right)^{K-1}\frac{h}{\alpha+\beta} \quad (28)$$

$$\sum_{x=0}^{K-1}\left(\frac{\beta}{\alpha+\beta}\right)^{x}\frac{\beta}{\alpha+\beta}INV$$

$$=\left(\frac{\beta}{\alpha+\beta}+\left(\frac{\beta}{\alpha+\beta}\right)^{2}+.......+\left(\frac{\beta}{\alpha+\beta}\right)^{K-1}\right)\frac{h}{\alpha+\beta}$$

$$+\left(\left(\frac{\beta}{\alpha+\beta}\right)^{2}+.......+\left(\frac{\beta}{\alpha+\beta}\right)^{K-1}\right)\frac{h}{\alpha+\beta}$$

$$+$$

$$\vdots$$

$$\vdots$$

$$+\left(\frac{\beta}{\alpha+\beta}\right)^{K-1}\frac{h}{\alpha+\beta} \quad (29)$$

When we sum the same exponential expressions together the equation can be written as the following:

$$\sum_{x=0}^{K-1}\left(\frac{\beta}{\alpha+\beta}\right)^{x}\frac{\beta}{\alpha+\beta}INV$$

$$=\left(\frac{\beta}{\alpha+\beta}+2\left(\frac{\beta}{\alpha+\beta}\right)^{2}+3\left(\frac{\beta}{\alpha+\beta}\right)^{3}+.......+(K-1)\left(\frac{\beta}{\alpha+\beta}\right)^{K-1}\right)\frac{h}{\alpha+\beta}$$

So we have the following equation:

$$\sum_{x=0}^{K-1}(\frac{\beta}{\alpha+\beta})^{x}\frac{\beta}{\alpha+\beta}INV=\sum_{x=1}^{K-1}x\cdot(\frac{\beta}{\alpha+\beta})^{x}\frac{h}{\alpha+\beta} \tag{30}$$

The second part of the Eq. (27) as the following:

$$\begin{aligned}
&\sum_{x=0}^{K-1}(\frac{\beta}{\alpha+\beta})^{x}\frac{\beta}{\alpha+\beta}DISP \\
&\quad=\frac{\beta}{\alpha+\beta}\left(\frac{\beta}{\alpha+\beta}\right)^{K-1}(R-D/K) \\
&\quad+\left(\frac{\beta}{\alpha+\beta}\right)^{2}\left(\frac{\beta}{\alpha+\beta}\right)^{K-2}(R-D/K) \\
&\quad+ \\
&\quad\vdots \\
&\quad\vdots \\
&\quad+\left(\frac{\beta}{\alpha+\beta}\right)^{K}(R-D/K)
\end{aligned} \tag{31}$$

After mathematical operations we can write Eq. (31) as the following:

$$\begin{aligned}
\sum_{x=0}^{K-1}(\frac{\beta}{\alpha+\beta})^{x}\frac{\beta}{\alpha+\beta}DISP &= K\cdot\left(\frac{\beta}{\alpha+\beta}\right)^{K}(R-D/K) \\
&=\left(\frac{\beta}{\alpha+\beta}\right)^{K}(R\cdot K-D)
\end{aligned} \tag{32}$$

Eq. (26) can be written as the following:

$$\begin{aligned}
\sum_{x=0}^{K-1}(\frac{\beta}{\alpha+\beta})^{x}T(x)=\sum_{x=1}^{K-1}x\cdot(\frac{\beta}{\alpha+\beta})^{x}\frac{h}{\alpha+\beta}+\left(\frac{\beta}{\alpha+\beta}\right)^{K}(R\cdot K-D) \\
+\sum_{x=0}^{K-1}(\frac{\beta}{\alpha+\beta})^{x}\frac{\beta\cdot c}{\alpha+\beta}
\end{aligned} \tag{33}$$

So we can say that the sum of discounted one-step rewards and expected net utilities for each state are equal. This completes the proof.

Example. Let the capacity of the vessels be 3, K_j=3, there be two dispatching locations and a single shipper class. Arrival rates of the shipper to dispatching locations 1 and 2 are λ and μ, respectively. Let $\lambda=\mu$ = 1, α = 0.1, waiting cost h be 2, the utility of an arriving shipper R be 30, the assignment cost c be 3 and the dispatching cost D be 20. Suppose a policy for the arriving shippers is defined as in the following table:

Table 2: Actions to be taken under the defined policy

	(0,0)	(1,0)	(0,1)	(1,1)	(2,0)	(0,2)	(2,1)	(1,2)	(2,2)
Location 1	1N	1N	2N	1N	1D	2D	1D	2D	1D
Location 2	2N	1N	2N	2N	1D	2D	1D	2D	2D

Note that for the underlying Markov Chain (1, 1), (2, 1), (1, 2) and (2, 2) are the transient states.

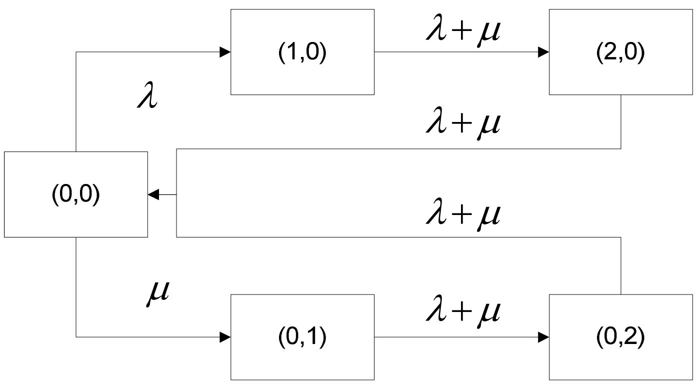

Figure 1: Transition diagram under the defined policy

So recursive equations can be written as the following to find the expected profits of existing shippers:

$$t_1(1,0) = -\frac{h}{\alpha+\beta} + \frac{\lambda}{\alpha+\beta}\big(t_1(2,0)\big) + \frac{\mu}{\alpha+\beta}\big(t_1(2,0)\big) = 19.30461$$

$$t_1(2,0) = -\frac{h}{\alpha+\beta} + \frac{\lambda}{\alpha+\beta}\big(R - D/3\big) + \frac{\mu}{\alpha+\beta}\big(R - D/3\big) = 21.26984$$

$$t_2(0,1) = -\frac{h}{\alpha+\beta} + \frac{\lambda}{\alpha+\beta}\left(t_2(0,2)\right) + \frac{\mu}{\alpha+\beta}\left(t_2(0,2)\right) = 19.30461$$

$$t_2(0,2) = -\frac{h}{\alpha+\beta} + \frac{\lambda}{\alpha+\beta}\left(R - D/3\right) + \frac{\mu}{\alpha+\beta}\left(R - D/3\right) = 21.26984 \qquad (34)$$

And the expected payment at state x, $T(x)$, can be computed as follows:

$$T(0,0) = \frac{\lambda}{\alpha+\beta}(t_1(1,0)) + \frac{\mu}{\alpha+\beta}(t_2(0,1)) = 18.38534$$

$$T(1,0) = \frac{\lambda}{\alpha+\beta}(t_1(2,0)) + \frac{\mu}{\alpha+\beta}(t_1(2,0) - c) = 18.82842$$

$$T(0,1) = \frac{\lambda}{\alpha+\beta}(t_2(0,2) - c) + \frac{\mu}{\alpha+\beta}(t_2(0,2)) = 18.82842$$

$$T(2,0) = \frac{\lambda}{\alpha+\beta}(R - D/3) + \frac{\mu}{\alpha+\beta}(R - D/3 - c) = 20.79365$$

$$T(0,2) = \frac{\lambda}{\alpha+\beta}(R - D/3 - c) + \frac{\mu}{\alpha+\beta}(R - D/3) = 20.79365 \qquad (35)$$

If we investigate the above results thoroughly we find that the expected minimum payment to be paid to an arriving shipper is 18.38534 when the initial state is (0, 0). Since the arrival rates of shippers at different dispatching locations are the same in this example, the expected payments at states with the same number of shippers are the same. When the vessels are getting closer to be full expected profits of the arriving shippers are getting higher. So, it is advantageous for the shipper to arrive at the dispatching location with a loaded vessel.

According to the proposed model arriving shippers are paid at least what they could get under the traditional model, so the individual rationality property is satisfied. However, the leading fact is dividing the surplus budget among shippers as it is needed to divide this amount of money fairly as there is no room for a restless shipper if we want to have a sustainable system. Forming a profitable system that pays to shippers at least as what they get under myopic action definitely attracts shippers to the system but keeping these shippers in the system is necessary for a sustainable system. The method chosen for dividing the surplus budget must not bring forward to a shipper or a group of shippers and all the shippers, who are desired to be involved in the system, need to be convinced that the proposed dividing method is fair enough.

So, an LP model that is used to form a self-sustaining payment system which is fair and pays to the coalition members (shippers) at least as what they get under myopic action can be defined as follows:

(Allocation) *Max y* (36)

s.t.

Eq. (15)

Eq. (16)

where Eq. (36) is the objective function aiming to maximize the minimum of differences between payment $P(x)$ to the arriving shipper and expected minimum payment $T(x)$, Eq. (15) guarantees that what is totally paid to the shippers does not exceed what is totally received from the shippers while Eq. (16) is used for linearization. As Eq. (16) guarantees that payment $P(x)$ is greater than expected minimum payment $T(x)$, there is no need to involve Eq. (14) in the model.

Example. In this part of the thesis, the mathematical model (Allocation) will be solved for some experimental runs to show how the surplus budget can be divided among shippers while individual rationality and budget balance properties are satisfied. In these runs, there will be two dispatching locations and two shipper classes and the capacity of the vessels will be 6, $K_1 = K_2$=6,. Dispatching costs of the vessels in each dispatching location are the same, $D_1 = D_2 = D$.

The following objective value results after the solution of the LP model for each run have been found:

Table 3: Mathematical model results for each experimental run

λ_{11}	λ_{21}	λ_{12}	λ_{22}	D	R_1	R_2	c	h_1	h_2	y
0.3	0.3	0.3	0.9	5	13	10	1	0.6	0.5	1.767
0.3	0.3	0.3	0.9	5	30	10	10	0.6	0.5	2.967
0.3	0.3	0.3	0.9	20	30	10	10	5	0.5	2.877
0.3	0.3	0.6	0.6	5	13	10	3	1	0.5	1.835

The following tables display selected state values regarding the payment received by the shipper $P(x)$, expected minimum payment $T(x)$ and difference of these values for each run.

Table 4: Received and expected payments for the first experimental run (y=1.767)

STATE	$P(x)$	$T(x)$	$P(x)-T(x)$
(0, 0, 0, 0)	7.639	5.872	1.767
(0, 0, 0, 1)	8.417	6.650	1.767
(0, 0, 0, 2)	8.889	7.122	1.767
(0, 0, 0, 3)	9.432	7.665	1.767
(0, 0, 0, 4)	10.005	8.238	1.767

Table 5: Received and expected payments for the second experimental run (y=2.967)

STATE	$P(x)$	$T(x)$	$P(x)-T(x)$
(0, 0, 0, 0)	13.152	10.185	2.967
(0, 0, 0, 1)	12.990	10.023	2.967
(0, 0, 0, 2)	13.628	10.661	2.967
(0, 0, 0, 3)	14.336	11.369	2.967
(0, 0, 0, 4)	15.081	12.114	2.967

Table 6: Received and expected payments for the third experimental run (y=2.877)

STATE	$P(x)$	$T(x)$	$P(x)-T(x)$
(0, 0, 0, 0)	4.899	2.022	2.877
(0, 0, 0, 1)	7.323	4.446	2.877
(0, 0, 0, 2)	8.745	5.869	2.876
(0, 0, 0, 3)	10.260	7.383	2.877
(0, 0, 0, 4)	11.823	8.946	2.877

Table 7: Received and expected payments for the fourth experimental run (y=1.835)

STATE	$P(x)$	$T(x)$	$P(x)-T(x)$
(0, 0, 0, 0)	7.833	5.998	1.835
(0, 0, 0, 1)	8.218	6.383	1.835
(0, 0, 0, 2)	8.832	6.997	1.835
(0, 0, 0, 3)	9.526	7.691	1.835
(0, 0, 0, 4)	10.259	8.424	1.835

The below table is provided to compare the payment values for the initial state (0, 0, 0, 0) for different parameters.

Table 8: Received and expected payments for the initial state as parameters change

λ_{11}	λ_{21}	λ_{12}	λ_{22}	D	R_1	R_2	c	h_1	h_2	$P(x)$	$T(x)$	$P(x)-T(x)$
0.3	0.3	0.3	0.9	5	13	10	1	0.6	0.5	7.639	5.872	1.767
0.3	0.3	0.3	0.9	5	13	10	1	5	0.5	5.409	-0.339	5.748
0.3	0.3	0.3	0.9	5	30	10	10	0.6	0.5	13.152	10.185	2.967
0.3	0.3	0.3	0.9	20	30	10	10	5	0.5	4.899	2.022	2.877
0.3	0.3	0.3	0.9	50	13	10	1	0.6	0.5	0.469	0.008	0.461
0.3	0.3	0.6	0.6	5	13	10	3	1	0.5	7.833	5.998	1.835

As it can be seen from the table the most significant difference between received and expected payments exists in the second row of the table in which the waiting cost of Class 1 shippers is high. That the naive action cannot manage costs efficiently causes burden on the system and expected payment for the initial state (0, 0, 0, 0) becomes negative. However, the central mechanism saves expenses by using the optimal policy and promises higher earnings to the shippers that will convince them to participate in the system.

CHAPTER 4

COMPUTATIONAL STUDY

In this chapter of the thesis an experimental set will be formed to perform computational analysis to assess the performance of the intermediary. Experimental set will include different runs generated by changing the parameters that are expected to significantly affect the optimal policy structure and the surplus budget (or deficit) changes.

As the proposed model pays arriving shippers at least as what they get under the non-optimal policy so it is guaranteed to hold the individual rationality property, budget balance property may not be held in some cases and it is needed to inject some amount of money to the system. The term of "deficit" denotes the injected amount of money to the system. In fact injection of money to the system is not the case of the thesis and the allocation model defined in Chapter 3 will be used to allocate budget deficit as well as budget surplus.

We contrast the performance of the optimal policy against two non-optimal policies: naïve policy and myopic policy. As described in Section 3.2 the naïve policy assumes that Class 1 shippers prefer the vessels with higher number of shippers while Class 2 shippers prefer the closer vessels. Furthermore, a vessel dispatches only when it is full. On the other hand, myopic policy assumes that an arriving shipper takes the action that will maximize his expected net utility.

The aim of the computational analysis can be stated as follows:

1) To gain insights as to the form of the optimal policy under the transportation intermediary and to find out whether the optimal actions follow a certain pattern, or the policies have "monotonic" property which will be defined later.

2) To identify the conditions under which the existence of the intermediary makes significant difference on the total utility and to analyze the performance of the intermediary over the naive policy and a myopic policy with respect to the system parameters.
3) To analyze how surplus (or deficit) changes with respect to system parameters, where surplus is defined as the budget balancing amount that could be allocated after the individual rationality property is satisfied.

4.1 Forming Experimental Set to Assess the Performance of the Intermediary

For the experimental study, a setting consisting of two shipper classes ($I = \{1,2\}$) and two dispatching locations ($J = \{1,2\}$) is considered. It is assumed that the vessels at each location have equal capacities of size K=6 and dispatch price, D, associated with each vessel is the same. The cross-assignment cost, c, for any two different locations is the same. The effect of following parameters is analyzed: $\lambda_{11}, \lambda_{21}, \lambda_{12}, \lambda_{22}$, h_1, R_1, D and c. The value of all parameters used in the experimental study is presented in the following table:

Table 9: Parameter setting for the experimental study

λ_{11}	λ_{21}	$(\lambda_{12}, \lambda_{22})$	h_1	h_2	R_1	R_2	D	c
0.3	0.3	(0.3, 0.9)	0.6	0.5	13	10	5	1
0.6	0.6	(0.6, 0.6)	1		15		20	3
0.9	0.9		5		20		50	5
					30			10

2592 different experimental runs are generated by using the parameter values displayed in Table 9. That different experimental runs are used will contribute to investigate the optimal policy behavior thoroughly under different conditions. For example, behavior of the optimal policy as cross-assignment cost (c) and waiting cost (h) change will be observed. Besides observing the performance of the intermediary over the naïve policy and the myopic policy some cases will be searched in which the intermediary does not have a decide superiority over these policies.

The action to be taken for each state is denoted as $a^{\pi}(x) = (a_{11}, a_{21}, a_{12}, a_{22})$. Each dimension represents the action to be taken in case of the arrival of the corresponding type of shipper and there are a total of 256 different actions that can be taken in each state.

In our example, the capacity of the vessels is set as 6. This means that 21 different shipper allocation combinations can be formed for each vessel. Because of the fact that there are two dispatching location, total number of states would be 441 in the experimental setting.

In Eq. (12) an LP model is introduced to solve the optimality equation in Eq. (7). GAMS 23.0 CPLEX solver has been used to solve the problem.

The values of the probability of being in state *x* initially, δ_x, can be set to design a system starting from a specific state. In the experimental setting, the probability of being in state (0, 0, 0, 0) initially, $\delta(0,0,0,0)$, is set as 0.99999999 and all the other δ_x values are set equal and 2×10^{-11}. Hence, it is assumed that the system's starting point is the state (0, 0, 0, 0). In the solution, if a variable attains a positive value, which is less than 10^{-5}, it is assumed that the state is transient and the positive value is only due to the initialization. In other words, if the system were to start at state (0, 0, 0, 0) with a probability value of 1, these states would never be visited. It is to be noted that 10^{-5} is a relatively high value in comparison to the probabilities of being in relevant states that is 2×10^{-11}.

An allocation mechanism, which is allocating savings to the shippers, has been proposed. An LP model (in Eq. (36)) that is used to form a self-sustaining payment system which is fair and pays to the coalition members at least as what they get under the non-optimal policy has been introduced in the previous chapter. The proposed model is expected to satisfy the properties of individual rationality.

Satisfying individual rationality may lead to a violation of budget balance. The model in Eq. (36) aims to distribute the surplus (or deficit) to the shippers so as to minimize the variance among the payments.

The model in Eq. (36) uses (i) the expected minimum payment that the central mechanism would make from its pocket, $T(x)$, (ii) one-step reward of the state x under the optimal policy, $r(x)$, and (iii) transition probabilities among states under the optimal policy, Q, as input parameters to the constraints and $\alpha/(\alpha+\beta)$ as the discount factor.

MATLAB 7.1 has been used to form relevant Q matrices. The expected minimum payment, $T(x)$, has been computed by solving the corresponding recursive equations in MATLAB. After computing $T(x)$ values for each state $(I-\gamma Q)^{-1}\times(r-T)$ matrix operation has been performed to find the surplus (or deficit) budget after making payments to the shippers where I denotes identity matrix, γ indicates that a discount factor is used, which is $\beta/(\alpha+\beta)$ for the problem, and r is a vector of $r(x)$ denoting the one-step reward of the state x under the optimal policy. As the probability of being in state (0, 0, 0, 0) initially, $\delta(0,0,0,0)$, is set as 0.99999999, that is very close to 1, the value of state (0, 0, 0, 0) has been taken into consideration and the matrix operation has been performed by using only the row of the matrix $(I-\gamma Q)^{-1}$ which is corresponding to the state (0, 0, 0, 0).

4.2 Results on Policy Structure

In this part of this chapter, the policy structure will be investigated with respect to the changing parameters. It will be focused on whether the optimal policies are monotone and how the parameter changes affect the structure of the optimal policies. Different runs that are chosen from the experimental setting in Table 8 are used in observations.

To show how the “monotonicity” property is satisfied the optimal policies for a certain type of shippers, which are generated by using the runs 1297 and 1345 respectively, can be investigated through the Table 10.

Table 10 presents states at the second location and actions taken upon arrival of Class 2 shippers. Number of shippers at the first dispatching location is assumed to be 0. Please note that the actions are likely to change as the number of shippers at the first dispatching location or types of arriving shippers change.

The very left columns of the below tables indicate the numbers of Class 1 shippers at the second dispatching location and the very top rows indicate the numbers of Class 2 shippers at the second dispatching location. For instance, when the number of Class 2 shippers is 2 and the number of Class 1 shippers is 1 for the run 1297 the optimal action for the arriving Class 2 shipper at the second dispatching location will be “2D”. It can be explicitly seen that selected parts of the optimal policies for each run are monotone as the optimal action for the shipper starts with “2N” and becomes “2D” when the number of shippers increase in the vessel (*See Appendix B for details for runs*).

It is to be noted that there are sufficient number of vessels ready to be dispatched and arriving shippers are assigned to the privileged location. If there is at least one shipper at a dispatching location, this makes this location privileged. If there is no shipper at any location an arriving shipper would be assigned to a location randomly.

Table 10: Optimal policies for arriving Class 2 shippers to the second dispatching location where $x_{11}=x_{21}=0$

RUN 1297						
C1/C2	0	1	2	3	4	5
0	2N	2N	2N	2N	2D	
1	2N	2N	2N	2D		
2	2N	2D				
3	2D					
4						
5						

RUN 1345						
C1/C2	0	1	2	3	4	5
0	2N	2N	2N	2N	2N	2D
1	2N	2N	2N	2N	2D	
2	2N	2N	2N	2D		
3	2N	2N	2D			
4	2N	2D				
5	2D					

The structure of the optimal policy will be investigated according to the parameters in this part of the thesis. The effects of assignment cost, dispatching cost, waiting cost and revenue on the optimal policy structure will be observed for different runs by using relevant tables.

The formed tables indicate the actions taken for arriving shippers in the relevant states. As there are two classes of shippers and two dispatching locations we will use the actions a_{11}, a_{21}, a_{12} and a_{22} in the tables. The neighbor states are selected in the tables to show the monotonicity we have defined previously. For example, in Table 11 the number of shippers at first dispatching location and the number of Class 2 shippers at second dispatching location are set to be 0 where the number of Class 2 shippers at second dispatching location is increased incrementally.

4.2.1 Effects of the assignment cost on the optimal policy structure

Chosen runs for the investigation on the effects of assignment cost c on the optimal policy structure are runs 1297, 1300, 1303 and 1306. In these runs, arrival rates of the shippers are all 0.6, dispatching cost D is 5, the initial utility for the Class 1 shippers R_1 is 13, the initial utility for the Class 2 shippers R_2 is 10, waiting cost for the Class 1 shippers h_1 is 0.6 and waiting cost for the Class 2 shippers is 0.5. Assignment cost c is taken as 1, 3, 5 and 10 for these runs respectively. The following observations are made on the structure of the optimal policy.

Table 11: Structure of the optimal policy as cross-assignment cost increases

STATE	1297 (c=1)				1300 (c=3)				1303 (c=5)				1306 (c=10)			
	a_{11}	a_{21}	a_{12}	a_{22}	a_{11}	a_{21}	a_{12}	a_{22}	a_{11}	a_{21}	a_{12}	a_{22}	a_{11}	a_{21}	a_{12}	a_{22}
(0, 0, 0, 0)	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N
(0, 0, 0, 1)	2N	2N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N
(0, 0, 0, 2)	2N	2N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N
(0, 0, 0, 3)	2N	2N	2N	2N	1N	1N	2D	2D	1N	1N	2D	2D	1N	1N	2D	2D
(0, 0, 0, 4)	2D	2D	2D	2D												
(0, 0, 0, 5)																

Observation 4.2.1: Increasing the assignment cost c leads to fewer cross-assignments and early dispatches.

When the assignment cost c is relatively low the system is willing to make higher number of cross-assignments as in Table 11. Lower cross-assignment cost results in better utilization of vessels, and eventually lower waiting costs for the shippers, and higher net utilities. However, under higher assignment costs making cross-assignments is burdensome for the system and the shippers are dispatched from their original ports.

As high assignment costs prevent the system to make frequent cross-assignments, it may be expected to have early dispatches in some cases as in Table 10. For example, when the state is (0, 0, 0, 3) under high assignment costs (runs 1300, 1303 and 1306) the system is willing to dispatch the vessel in case of arrival of shippers to this location because of the fact that it is less burdensome to dispatch the vessel immediately than to increase the number of shippers in the vessel. On the other hand for the same state, the system is willing to wait and increase the number of shippers in the vessel under low assignment cost and the dispatching event occurs when the state is (0, 0, 0, 4). The affect of assignment cost on dispatching time might be found interesting. This case can be explained by the affect of future expectations of the system. When the assignment cost c is low the system can easily make cross-assignment to reduce the burden of waiting cost. The system finds it profitable to wait for the next arriving shipper rather than dispatching until the state (0, 0, 0, 4) when the assignment cost is low, while it is burdensome to wait for dispatching when the assignment cost is relatively high for the same state. As the high assignment cost prevents the system to make cross-assignments expected utility gain of waiting is considerably low than dispatching.

4.2.2 Effect of dispatching cost on the optimal policy structure

Chosen runs for investigation on the effects of dispatching cost D on the optimal policy structure are runs 1297, 1345 and 1393. In these runs, arrival rates of the shippers are all 0.6, the initial utility for the Class 1 shipper R_1 is 13, the initial utility for the Class 2 shipper R_2 is 10, assignment cost c is 1, waiting cost for the Class 1 shipper h_1 is 0.6 and waiting cost for the Class 2 shipper is 0.5. Dispatching cost D is taken as 5, 20 and 50 for these runs respectively. The following observation is made on the structure of the optimal policy.

Table 12: Structure of the optimal policy as dispatching cost increases

STATE	1297 (D=1)				1345 (D=20)				1393 (D=50)			
	a_{11}	a_{21}	a_{12}	a_{22}	a_{11}	a_{21}	a_{12}	a_{22}	a_{11}	a_{21}	a_{12}	a_{22}
(0, 0, 0, 0)	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N
(0, 0, 0, 1)	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N
(0, 0, 0, 2)	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N
(0, 0, 0, 3)	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N
(0, 0, 0, 4)	2D	2D	2D	2D	2N	2N	2N	2N	2N	2N	2N	2N
(0, 0, 0, 5)					2D	2D	2D	2D	2D	2D	2D	2D

Observation 4.2.2: Increasing the dispatching cost D leads to late dispatches.

When the dispatching cost is increased, dispatching becomes more burdensome for the existing shippers, so for the system. The system prefers waiting for additional shippers who will share the increased cost. As it can be seen from the above table, although the system with low dispatching cost (run 1297) is willing to assign all the arriving shippers to the vessel and to dispatch this vessel, which is at the second dispatching location, when there are four shippers in the vessel (state (0, 0, 0, 4)), high dispatching costs (runs 1345 and 1393) make the system not to dispatch the vessel and to wait for additional shippers.

4.2.3 Effect of waiting cost on the optimal policy structure

Chosen runs for analyzing the effects of waiting cost on the optimal policy structure are runs 1297, 1298 and 1299. In these runs, arrival rates of the shippers are all 0.6, dispatching cost D is 5, the initial utility for the Class 1 shippers R_1 is 13, the initial utility for the Class 2 shippers R_2 is 10, assignment cost c is 1 and waiting cost for the Class 2 shippers is 0.5. Waiting cost for the Class 1 shipper is taken as 0.6, 1 and 5 for these runs respectively. The following observation is made on the structure of the optimal policy.

Table 13: Structure of the optimal policy as waiting cost increases

STATE	1297 (h_1=0.6)				1298 (h_1=1)				1299 (h_1=5)			
	a_{11}	a_{21}	a_{12}	a_{22}	a_{11}	a_{21}	a_{12}	a_{22}	a_{11}	a_{21}	a_{12}	a_{22}
(0, 0, 0, 0)	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N
(0, 0, 0, 1)	2N	2N	2N	2N	2N	2N	2N	2N	2D	1N	2D	2N
(0, 0, 0, 2)	2N	2N	2N	2N	2N	2N	2N	2N	2D	2N	2D	2N
(0, 0, 0, 3)	2N	2N	2N	2N	2N	2N	2N	2N	2D	2N	2D	2N
(0, 0, 0, 4)	2D	2D	2D	2D	2D	2D	2D	2D	2D	2N	2D	2N
(0, 0, 0, 5)									2D	2D	2D	2D

Observation 4.2.3: Increasing the waiting cost of Class 1 shippers leads to early dispatches.

Keeping Class 1 shippers in the vessels forms a significant pressure on the system. For this reason, it is expected that the system dispatches the vessel in case of arrival of Class 1 shipper. This effect can be seen explicitly when the waiting cost of Class 1 shipper is considerably high (run 1299) as shown in Table 13. Although the system is willing to dispatch late when the waiting cost of Class 1 shippers is low (runs 1297 and 1298) arriving of Class 1 shippers leads to immediate dispatch of the vessel when the waiting cost of Class 1 shipper is relatively high (run 1299).

Note that the system prefers to wait in case of arrival of Class 2 shippers when the waiting cost of Class 1 shipper is relatively high (run 1299) in state (0, 0, 0, 4) . However, arriving of any class of shippers cause immediate dispatches when the waiting cost of Class 1 shipper is lower (runs 1297 and 1298) as shown in Table 13. This behavior can be explained by the desire of benefiting from the services of the Class 2 shippers whose waiting costs are considerably low compared to the Class 1 shippers. Because of the fact that Class 2 shippers are more profitable than Class 1 shippers when the waiting cost of Class 1 shippers is extremely high (run 1299) keeping Class 2 shippers in the vessel leads to higher gains for the system.

Table 14: Structure of the optimal policy as waiting cost increases when the number of Class 1 shippers is increased

STATE	1297 (h_1=0.6)				1298 (h_1=1)				1299 (h_1=5)			
	a_{11}	a_{21}	a_{12}	a_{22}	a_{11}	a_{21}	a_{12}	a_{22}	a_{11}	a_{21}	a_{12}	a_{22}
(0, 0, 0, 0)	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N
(0, 0, 1, 0)	2N	2N	2N	2N	2N	2N	2N	2N	2D	2D	2D	2D
(0, 0, 2, 0)	2N	2N	2N	2N	2D	2N	2D	2N				
(0, 0, 3, 0)	2D	2D	2D	2D								
(0, 0, 4, 0)												
(0, 0, 5, 0)												

In Table 14 the effect of increasing the waiting cost of Class 1 shippers on the optimal policy structure is seen when there are some numbers of Class 1 shippers at the dispatching location. For example, the system does not dispatch the vessel until state (0, 0, 0, 3) when the waiting cost of Class 1 shippers is 0.6 (run 1297) although the system makes the decision of immediate dispatch for state (0, 0, 0, 1) when the waiting cost of Class 1 shippers is extremely high in value (run 1299). As it has been stated before, keeping Class 1 shippers with high waiting cost causes significant burden on the system and getting rid of this class of shippers is preferred by the optimal system. So we encounter early dispatches when the waiting cost of Class 1 shippers is set to be very high.

Table 15: Structure of the optimal policy as waiting cost increases when there exist shippers at both locations

STATE	1297 (h_1 =0.6)				1298 (h_1 =1)				1299 (h_1 =5)			
	a_{11}	a_{21}	a_{12}	a_{22}	a_{11}	a_{21}	a_{12}	a_{22}	a_{11}	a_{21}	a_{12}	a_{22}
(0, 1, 0, 0)	1N	1N	1N	1N	1N	1N	1N	1N	1D	1N	1D	2N
(0, 1, 0, 1)									1D	1N	2D	2N
(0, 1, 0, 2)									1D	1N	2D	2N
(0, 1, 0, 3)									2D	1N	2D	2N
(0, 1, 0, 4)									2D	1N	2D	2N
(0, 1, 0, 5)									2D	2D	2D	2D

Table 15 shows that the system accumulates all shippers to a certain location as quickly as possible when the cross-assignment cost is very low. It is observed that whenever there exists a shipper at a dispatching location, all the following shippers are assigned to the same location. For example, when the state is (0, 1, 0, 0) all the arriving shippers are assigned to the first location and remaining states would not be visited for runs 1297 and 1298. For this reason there are not any actions to be taken at these states for the relevant runs.

On the other hand, if the waiting cost for Class 1 shippers is extremely high (run 1299) the system tries to dispatch vessels in case of arrival of Class 1 shippers to reduce the waiting cost burden on the system. As it has been stated before, the system tries to keep Class 2 shippers in the vessels because of the fact that keeping these shippers in the vessels leads higher profit for the system.

4.2.4 Effect of initial utility on the optimal policy structure

Runs chosen for analyzing the effects of the initial utility on the optimal policy structure are runs 1297, 1309, 1321 and 1333. In these runs, arrival rates of the shippers are all 0.6, dispatching cost D is 5, initial utility for the Class 2 shippers R_2 is 10, assignment cost c is 1, waiting cost for the Class 1 shippers is 0.6 and waiting cost for the Class 2 shippers is 0.5. Initial utility for the Class 1 shipper is taken as 13, 15, 20 and 30 for these runs respectively. The following observations are made on the structure of the optimal policy.

Table 16: Structure of the optimal policy as initial utility increases

STATE	1297 (R_1=13)				1309 (R_1=15)				1321 (R_1=20)				1333 (R_1=30)			
	a_{11}	a_{21}	a_{12}	a_{22}	a_{11}	a_{21}	a_{12}	a_{22}	a_{11}	a_{21}	a_{12}	a_{22}	a_{11}	a_{21}	a_{12}	a_{22}
(0, 0, 0, 0)	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N
(0, 0, 0, 1)	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N
(0, 0, 0, 2)	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N
(0, 0, 0, 3)	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N	2D	2N	2D	2N
(0, 0, 0, 4)	2D	2D	2D	2D	2D	2D	2D	2D	2D	2D	2D	2D	2D	2N	2D	2N
(0, 0, 0, 5)													2D	2D	2D	2D

Observation 4.2.4: Higher initial utility of Class 1 shippers may lead to early dispatches in case of arrival of Class 1 shippers and late dispatches in case of arrival of Class 2 shippers.

Increasing the initial utility of Class 1 shippers makes this class of shippers comparatively profitable against the Class 2 shippers. For example, although the system is willing to wait in the state (0, 0, 0, 3) when the initial utility for the Class 1 shippers is relatively low (runs 1297, 1309 and 1321), it dispatches the vessel in case of an arrival of a Class 1 shipper when the initial utility of Class 1 shippers is higher (run 1333) as shown in Table 16.

Table 17: Structure of the optimal policy as initial utility increases when the number of Class 1 shippers is increased

STATE	1297 (R_1=13)				1309 (R_1=15)				1321 (R_1=20)				1333 (R_1=30)			
	a_{11}	a_{21}	a_{12}	a_{22}	a_{11}	a_{21}	a_{12}	a_{22}	a_{11}	a_{21}	a_{12}	a_{22}	a_{11}	a_{21}	a_{12}	a_{22}
(0, 0, 0, 0)	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N
(0, 0, 1, 0)	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N
(0, 0, 2, 0)	2N	2N	2N	2N	2N	2N	2N	2N	2D	2N	2D	2N	2D	2D	2D	2D
(0, 0, 3, 0)	2D	2D	2D	2D	2D	2D	2D	2D								
(0, 0, 4, 0)																
(0, 0, 5, 0)																

Table 17, which focuses on existing Class 1 shippers, also shows how increasing the initial utility of Class 1 shippers affects dispatching times of the system. It can be easily seen from the table, that increasing the initial utility of Class 1 shippers shortens dispatching time in the cases with relatively high initial utilities (runs 1321 and 1333).

Increasing the initial utility of Class 1 shippers may lead to interesting results like late dispatches in case of an arrival of Class 2 shippers as shown in Table 16. Although the vessel in the state (0, 0, 0, 4) is dispatched when the initial utility of Class 1 shippers is relatively low (runs 1297, 1309 and 1321), the system prefers waiting in case of an arrival of a Class 2 shipper when the initial utility of Class 1 is higher (run 1333). Because of the fact that the system tries to maximize its profit and has future expectations for the arrival of Class 1 shippers, the system prefers waiting for the next shipper. So, this leads to late dispatches in case of arrival of Class 2 shippers.

We have chosen several settings to gain insight on the behavior and structure of the optimal policy so far. It can be said that cross-assignment gives the system opportunity to dispatch vessels earlier and to cut waiting cost. However, less number of cross-assignments is expected as the cost of cross-assignment increases. Dispatching time is another important feature of the policy that is to be investigated thoroughly to understand the structure of the optimal policy. It is normally expected that dispatching cost and waiting cost are two main parameters that affect the dispatching frequency of the system. High dispatching cost forms pressure on the system for late dispatching as more shippers are needed to share the burden arising from the increasing costs. On the contrary, high waiting cost leads to early dispatches as the system is not willing to wait too much for dispatching. Besides these parameters, we have seen that increasing the initial utility of Class 1 shippers make this type of shippers comparatively profitable against the other types and affect dispatching time of the system.

4.3 Comparing the Optimal Policy with the Naïve and Myopic Policies

The structures of optimal policies for different settings have been observed thus far. Henceforth, the changes in the optimal profit and the surplus (deficit) budget generated by the optimal system after payments will be observed as the parameters change.

In the experimental analysis, the optimal policy is denoted with OPT, the naïve policy or traditional system is denoted with TRAD and the myopic policy is denoted with MYO. The terms of $V_{OPT} - V_{TRAD}$, $\frac{V_{OPT} - V_{TRAD}}{V_{TRAD}}$, V_{SUR}^{TRAD} , $V_{OPT-MYO}$, $\frac{V_{OPT} - V_{MYO}}{V_{MYO}}$ and V_{SUR}^{MYO} are used for the difference between the optimal net utility and the net utility under the naïve policy, the ratio between the optimal net utility and the net utility under the naïve policy, the surplus (or deficit) after payments under the naïve policy, the difference between the optimal net utility and the net utility under the myopic policy and the ratio between the optimal net utility and the net utility under the myopic policy, the surplus (or deficit) after payments under the myopic policy, respectively. The changes of $V_{OPT} - V_{TRAD}$, $\frac{V_{OPT} - V_{TRAD}}{V_{TRAD}}$, V_{SUR}^{TRAD} , $V_{OPT-MYO}$, $\frac{V_{OPT} - V_{MYO}}{V_{MYO}}$ and V_{SUR}^{MYO} values according to the parameters are analyzed.

The performance of the optimal policy is observed as the parameters of cross-assignment cost c and waiting cost of shippers coming from Class 1 change. Cross-assignment cost can be 1, 3, 5 and 10 while waiting cost can take the values of 0.6, 1 and 5. Cross-assignment and waiting costs are not the only parameters whose effects are analyzed during the computational analysis. Analyses are conducted for different dispatching costs to see the effects of dispatching cost levels on the performance of the optimal policy. Low ($D = 5$), medium ($D = 20$) and high ($D = 50$) dispatching costs are taken into consideration in the analyses. The effects of arrival rates of shippers will be searched whether arrival rate has any significant effect on the optimal policy structure. Another parameter that will be used in the analyses is the initial utility of Class 1 shippers. For analyses, a base case is considered as

$\lambda_{11} = \lambda_{21} = \lambda_{12} = \lambda_{22}$=0.6, $c = 1$, h_1=0.6, R_1=13 and $D = 5$. The values of one or two parameters are changed at any time.

4.3.1 Effects of cross-assignment cost and waiting cost

In this part of the analysis low dispatching cost, $D = 5$, is taken into consideration and the structures of $V_{OPT} - V_{TRAD}$, $\frac{V_{OPT} - V_{TRAD}}{V_{TRAD}}$, $V_{OPT-MYO}$ and $\frac{V_{OPT} - V_{MYO}}{V_{MYO}}$ are analyzed to assess the performance of the optimal policy by considering that dispatching event does not form a significant pressure on the system. Because of the fact that low dispatching cost is incurred it is obvious that the dispatching event becomes more frequent. It is to be noted that low dispatching cost would definitely lead to shorter dispatching times. Since dispatching shipments frequently would not cause any significant burden on the system, it would be expected that the optimal policy prefers managing smaller lots of shipments and holding smaller number of shippers in the vessels when waiting cost is set to be high in particular.

We will investigate the effects of cross-assignment cost and waiting cost on the optimal policy. We see how the performance of optimal policy is affected when these costs increase and in which scenarios the optimal policy outperforms the naïve and myopic policies.

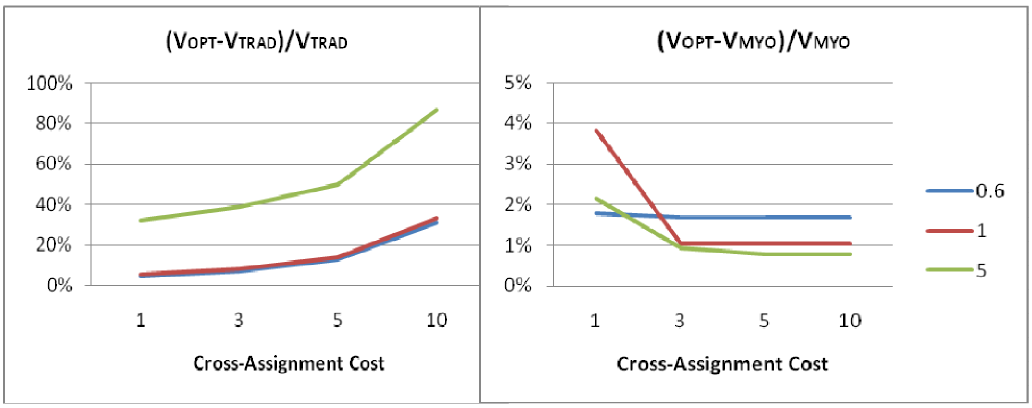

Figure 2: $(V_{OPT} - V_{TRAD})/V_{TRAD}$ and $(V_{OPT} - V_{MYO})/V_{MYO}$ as cross-assignment cost and waiting cost change under the base case

Observation 4.3.1: The performance of the optimal policy increases in comparison to the naive policy as cross-assignment cost increases.

It is obvious that cross-assignment of an arriving shipper forms significant pressure on the system is high. As we have indicated before, the naive policy assigns Class 2 shippers to their original dispatching locations and Class 1 shippers to the location having greater number of waiting shippers regardless of the feasibility of cross-assignment decision. The naive policy cannot manage cross-assignment process efficiently and this brings unnecessary expenditure. For this reason, the weakness of the adopted policies that are managing cross-assignment processes simply can be seen in these cases explicitly. So, the optimal policy outperforms the naive policy as cross-assignment cost increases.

Observation 4.3.2: The performance of the optimal policy decreases in comparison to the myopic policy as cross-assignment cost increases.

As it has been indicated before, the myopic policy is composed of the optimal actions of individual shippers in each state while the shippers are trying to maximize their own utilities. Because of the fact that the aim of the myopic policy is maximizing the net utility of an arriving shipper, cross-assignment and dispatching processes are managed efficiently. Arriving shippers are aware that waiting to be dispatched is a burdensome activity and cross-assignment can be more feasible in most cases as in the optimal policy.

Furthermore, the performance of the optimal policy and the myopic policy converge as cross-assignment cost increases as displayed in Figure 2. If these policies are investigated thoroughly it is seen that early dispatching procedure is preferred instead of cross-assignment in both the optimal and myopic policies leading to the same utility values for high cross-assignment costs.

Observation 4.3.3: The performance of the optimal policy increases in comparison to the naive policy as waiting cost increases.

Increasing the level of waiting cost makes the optimal policy's proportional performance higher in comparison to the naive policy. Because of the fact that the optimal policy manages cross-assignment and dispatching operations effectively to decrease the burden, which arises as a result of waiting of existing shippers in the system, than the naive policy, the superiority of the optimal policy against the naive policy can be seen explicitly in cases with high waiting cost ($h_1 = 5$).

Hence, the optimal policy's capability of managing cross-assignment processes leads to better management of the burden on the system caused by shippers' waiting and dispatching events. The following table displays the optimal actions taken for the selected states under high waiting cost ($h_1 = 5$) and low cross-assignment cost ($c = 1$) and the corresponding naive and myopic actions. It can be easily seen that the optimal policy and myopic policy manage cross-assignment and dispatching of the arriving shippers more intelligently and effectively.

Table 18: Structure of the optimal policy, the naïve policy and the myopic policy under high waiting cost and low cross-assignment cost

STATE	RUN 1299 ($h_1 = 5$ $c = 1$)				NAIVE POLICY				MYOPIC POLICY			
(0, 0, 0, 0)	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2D	2N
(0, 0, 0, 1)	2D	1N	2D	2N	2N	1N	2N	2N	2D	1N	2D	2N
(0, 0, 0, 2)	2D	2N	2D	2N	2N	1N	2N	2N	2D	2D	2D	2D
(0, 0, 0, 3)	2D	2N	2D	2N	2N	1N	2N	2N	2D	2D	2D	2D
(0, 0, 0, 4)	2D	2N	2D	2N	2N	1N	2N	2N	2D	2D	2D	2D
(0, 0, 0, 5)	2D	2D	2D	2D	2D	1N	2D	2D	2D	2D	2D	2D

As high inventory cost forms a significant pressure on the system the optimal policy does not only perform cross-assignment for Class 1 shippers but also for Class 2 shippers. The optimal system tries to increase the number of shippers in the vessel with higher number of shippers by using Class 2 shippers as in Table 18. So this would give chance to perform early dispatches and cut incurred waiting cost. Because of the fact that individual shippers are trying to maximize their own profit in the myopic policy early dispatching events are not encountered only for Class 1 shippers but also for Class 2 shippers in the myopic policy.

When we look at the effects of cross-assignment and waiting costs on the surplus budget of the system after payments to the shippers we find that the savings increase as the cross-assignment and waiting cost increases as shown in Figure 3. This finding is parallel to the previous observations.

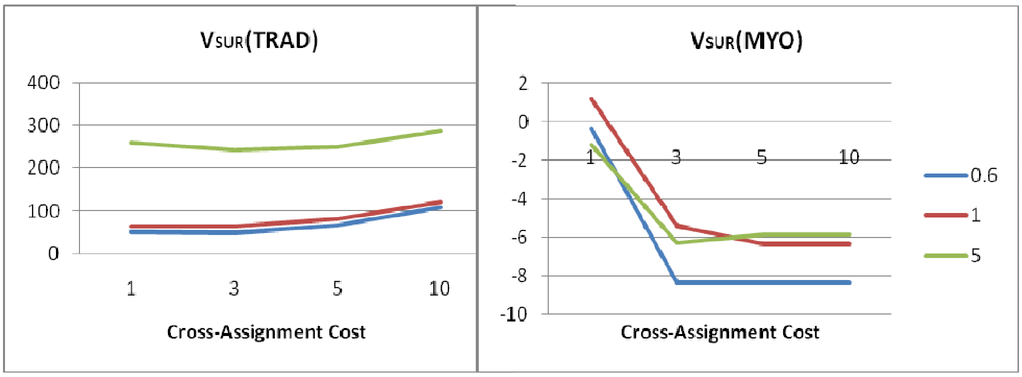

Figure 3: V_{SUR} (TRAD) and V_{SUR} (MYO) as cross-assignment cost and waiting cost change under the base case

In this part of the analysis dispatching cost is increased to 20 and the structures of $V_{OPT} - V_{TRAD}$, $\frac{V_{OPT} - V_{TRAD}}{V_{TRAD}}$, $V_{OPT-MYO}$ and $\frac{V_{OPT} - V_{MYO}}{V_{MYO}}$ are analyzed to assess the performance of the optimal policy. This time the burden caused by dispatching cost on the system is not small as in the previous case and it is expected that times between dispatches get longer.

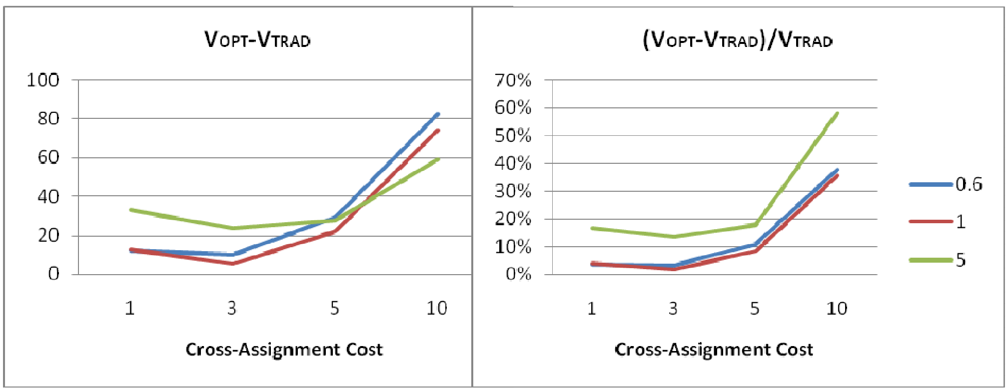

Figure 4: (V_{OPT} - V_{TRAD}) and (V_{OPT} - V_{TRAD})/ V_{TRAD} as cross-assignment cost and waiting cost change under the base case except that D=20

When the dispatching cost is increased to the level of 20 the difference between the optimal net utility and the net utility under the naive policy displays unsteady behavior as the cross-assignment cost increases. When $c = 3$ $V_{OPT} - V_{TRAD}$ gets a smaller value than the value under $c = 1$ as shown in Figure 3. This slight decline occurs because of the fact that V_{OPT} and V_{TRAD} values get smaller values when the cross-assignment cost is increased to a higher level as we have discussed before that increasing cross-assignment cost causes burden on the system.

On the other hand, when we look at $\frac{V_{OPT} - V_{TRAD}}{V_{TRAD}}$ values in Figure 4, it is seen that the performance of the optimal policy with $c = 3$ is worse than that with $c = 1$. When we increase the waiting cost from 1 to 3 the results obtained by the optimal policy and naive policy are getting closer. This situation can be observed for all waiting cost values.

The case displayed in Figure 4 is not the only case displaying this unsteady behavior of the optimal policy but the following figures indicate that cornered structures can be seen in some cases regarding the performance of the optimal policy. To understand this unsteady behavior of the optimal policy a further analysis is made by looking at the impact of cross-assignment cost under different dispatching costs.

Dispatching cost and cross-assignment cost parameters are chosen to be varying parameters in these analyses. Initial utility of Class 1 shippers, R_1, is set to be 20. Besides the performance of the optimal policy the effect of waiting cost on the structure of $V_{OPT} - V_{TRAD}$ is observed by using two different scenarios.

Waiting cost for the shippers coming from Class 1 is considered to be low (h_1=0.6) in the first scenario.

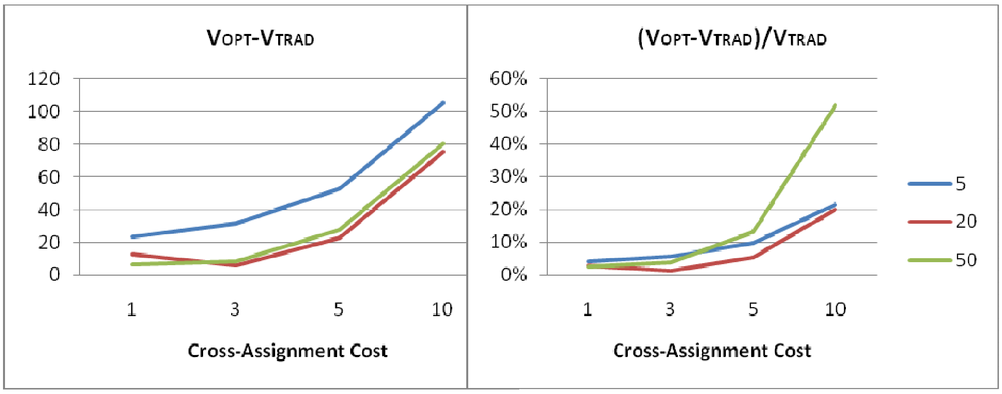

Figure 5: (V_{OPT} - V_{TRAD}) and (V_{OPT} - V_{TRAD})/ V_{TRAD} as cross-assignment cost and dispatching cost change under the base case except that R_1=20

When the waiting cost becomes relatively small in comparison to the cross-assignment cost the optimal policy prefers fewer number of cross assignment processes. If the waiting cost for the shippers coming from Class 1 is taken as 0.6 and dispatching cost is taken as 20, V_{OPT} and V_{TRAD} values become as the following:

V_{OPT} =484.91 and V_{TRAD} =472.10 when c =1

V_{OPT} =456.92 and V_{TRAD} =450.98 when c =3

V_{OPT} =452.62 and V_{TRAD} =429.86 when c =5

V_{OPT} =452.12 and V_{TRAD} =377.05 when c =10

Because of the fact that when the cross-assignment cost is increased V_{OPT} does not change so much, i.e. it differs only 0.5 in value when the cross-assignment cost is increased from 5 to 10, and V_{TRAD} continues to get smaller values, a cornered structure appears as shown in the Figure 5.

When we look at the policy structures of these cases (runs 1375 and 1378) it would be seen that policy structures are very similar as shown in Table 19 for selected states. So we can say that this convergence in value of these cases is caused by the convergence in policy structure and the limits of the optimization problem as well.

Table 19 : Structure of the optimal policy for runs 1375 and 1378

STATE	RUN 1375				RUN 1378			
	a_{11}	a_{21}	a_{12}	a_{22}	a_{11}	a_{21}	a_{12}	a_{22}
(0, 0, 0, 0)	1N	1N	2N	2N	1N	1N	2N	2N
(0, 0, 0, 1)	1N	1N	2N	2N	1N	1N	2N	2N
(0, 0, 0, 2)	1N	1N	2N	2N	1N	1N	2N	2N
(0, 0, 0, 3)	1N	1N	2N	2N	1N	1N	2N	2N
(0, 0, 0, 4)	1N	1N	2N	2N	1N	1N	2N	2N
(0, 0, 0, 5)	1N	1N	2D	2D	1N	1N	2D	2D

Waiting cost for the shippers coming from Class 1 is considered to be high (h_1=5) in the second scenario. When the waiting cost is high the optimal policies for different cross-assignment costs do not converge in value as in the figures below. Slight decreases in both the optimal net utility and the net utility under the naive policy take place. If the waiting cost for the shippers coming from Class 1 is taken as 5 and dispatching cost is taken as 20, V_{OPT} and V_{TRAD} values become as the following:

V_{OPT}=392.14 and V_{TRAD}=355.62 when c=1

V_{OPT}=361.88 and V_{TRAD}=334.50 when c=3

V_{OPT}=344.84 and V_{TRAD}=313.38 when c=5

V_{OPT}=322.80 and V_{TRAD}=260.58 when c=10

It is explicitly seen that both V_{OPT} and V_{TRAD} slightly decreases as the cross-assignment cost increases when the waiting cost is high although V_{OPT} does not change so much as the cross-assignment cost increases when the waiting cost is small in value.

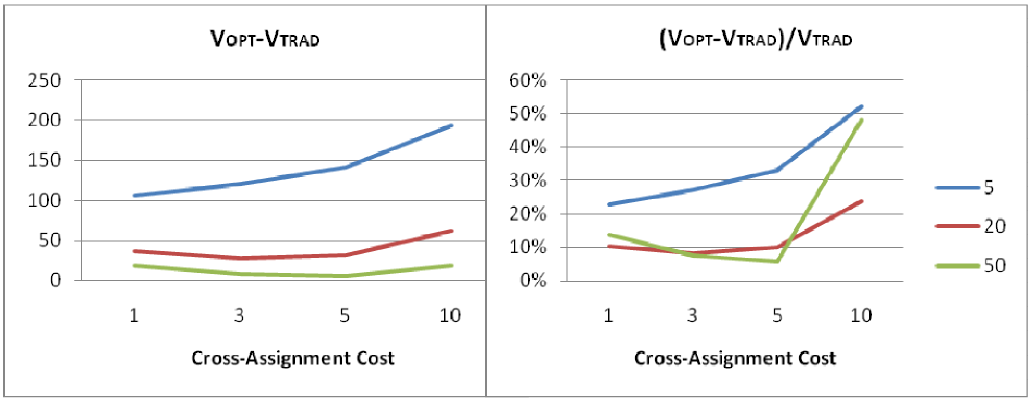

Figure 6: (V_{OPT} - V_{TRAD}) and (V_{OPT} - V_{TRAD})/ V_{TRAD} as cross-assignment cost and dispatching cost change under the base case except that R_1=20 and h_1=5

As it is shown in Table 20, we cannot see the convergence of optimal policies for different cross-assignment cost values for this case as in the case with low waiting cost.

Table 20: Structure of the optimal policy for runs 1375 and 1378

STATE	RUN 1377 (c=5)				RUN 1380 (c=10)			
	a_{11}	a_{21}	a_{12}	a_{22}	a_{11}	a_{21}	a_{12}	a_{22}
(0, 0, 0, 0)	1N	1N	2N	2N	1N	1N	2N	2N
(0, 0, 0, 1)	1N	1N	2N	2N	1N	1N	2N	2N
(0, 0, 0, 2)	1N	1N	2N	2N	1N	1N	2N	2N
(0, 0, 0, 3)	2N	1N	2N	2N	1N	1N	2N	2N
(0, 0, 0, 4)	2N	1N	2N	2N	1N	1N	2N	2N
(0, 0, 0, 5)	2D	1N	2D	2D	1N	1N	2D	2D

When the dispatching cost is increased to the level of 20 the difference between the optimal net utility and the net utility under the myopic policy displays stability in case of low waiting costs and an unsteady behavior in case of high waiting cost as shown in Figure 7. This interaction between these two policies exists in most of the cases with high waiting costs.

Furthermore, the performances of the optimal policy and myopic policy converge to each other when the system has low waiting cost. This convergence can be seen obviously when cross-assignment cost takes the smallest value as shown in Figure 7. So we can say that the comparative performance of the optimal policy decreases as the costs of the system decrease.

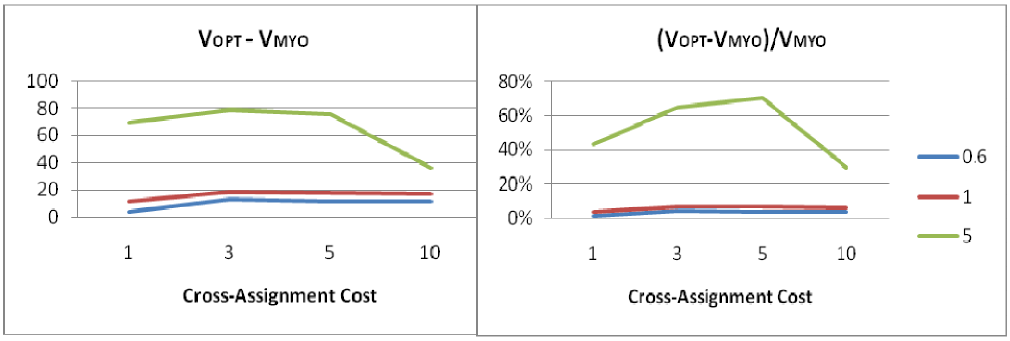

Figure 7: ($V_{OPT} – V_{MYO}$) and ($V_{OPT} – V_{MYO}$)/ V_{MYO} as cross-assignment cost and waiting cost change under the base case except that D=20

4.3.2 Effects of arrival rates of shippers

Four different settings are used in these analyses regarding the naïve and myopic policies. In the first part of the analyses the naïve policy is taken into the consideration and the myopic policy is considered in the second part.

In the first setting the effects of arrival rate of Class 1 shippers arriving at the first dispatching location and waiting cost of Class 1 shippers (h_1) are observed. In the second setting the effects of arrival rates of shippers coming from Class 2 to the first dispatching location and waiting cost h_1 are observed. In the third setting, the effects of arrival rates of Class 1 shippers arriving at the first and second dispatching locations are observed. In the last setting the effects of arrival rates of shippers coming from Class 1 and dispatching cost are observed.

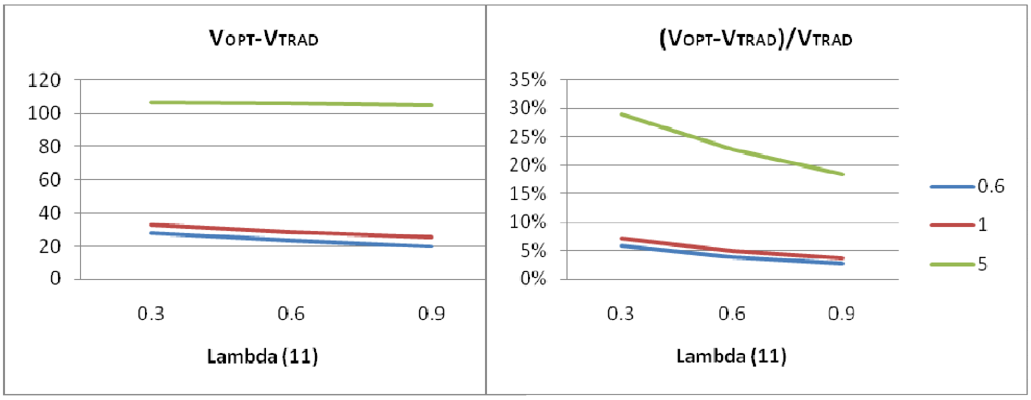

Figure 8: (V_{OPT} - V_{TRAD}) and (V_{OPT} - V_{TRAD})/ V_{TRAD} as waiting cost and arrival rate of Class 1 shippers arriving at the first dispatching location change under the base case except that R_1=20

Observation 4.3.4: Increasing the arrival rate of shippers does not affect the difference between V_{OPT} and V_{TRAD} when dispatching cost is low, but a slight decrease on the comparative performance of the optimal policy occurs.

When arrival rate of Class 1 shippers arriving at the first dispatching location, λ_{11}, is changed from 0.3 to 0.9, there does not occur a significant change in difference between V_{OPT} and V_{TRAD} as shown in Figure 8.

However, when we look at $\frac{V_{OPT} - V_{TRAD}}{V_{TRAD}}$ values the performance of the optimal policy slightly decreases as the arrival rate of Class 1 shippers increase, especially under high waiting costs. As we have indicated before the optimal policy obviously outperforms the naive policy when the waiting cost is set to be high. The performance of the optimal policy under high waiting cost ($h_1 = 5$) is better than those under lower waiting costs as shown in Figure 8. Increasing the arrival rate of Class 1 shippers decrease the comparative performance level ($\frac{V_{OPT} - V_{TRAD}}{V_{TRAD}}$) of the optimal policy for high waiting cost more than the other cases.

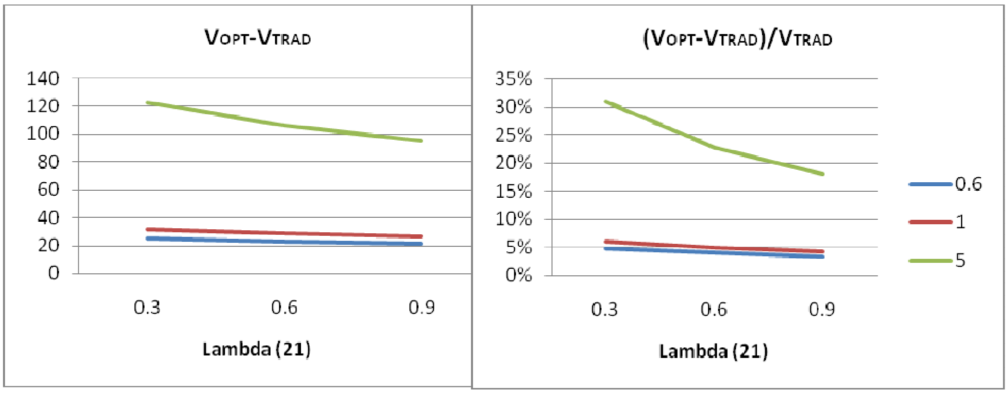

Figure 9: (V_{OPT} - V_{TRAD}) and (V_{OPT} - V_{TRAD})/ V_{TRAD} as waiting cost and arrival rate of Class 2 shippers arriving at the first dispatching location change under the base case except that R_1=20

A similar behavior can be observed when arrival rate of Class 2 shippers arriving at the first dispatching location , λ_{21}, is changed, especially when h_1 is small in value as shown in Figure 9. The comparative performance of the optimal policy changes slightly under low waiting cost of Class 1 shippers. However, under high waiting cost of Class 1 shippers (h_1=5) a dramatic decline is observed in $V_{OPT}-V_{TRAD}$ and $(V_{OPT}-V_{TRAD})/V_{TRAD}$ as λ_{21} is increased in Figure 9.

It is obvious that increasing the arrival rate of shippers leads to speeding up of the dispatching process and shorter dispatching times. So this brings low waiting burden on the system and the comparative superiority of the optimal policy slightly decreases as in Figures 8 and 9 and $(V_{OPT}-V_{TRAD})/V_{TRAD}$ approaches to the levels of the scenarios with low waiting cost values ($h_1=0.6$ or 1).

As a result of this finding, it can be said that increasing the arrival rate of shippers and decreasing the waiting cost have similar effects on the performance of the optimal policy because both of the interventions help to reduce the incurred waiting costs.

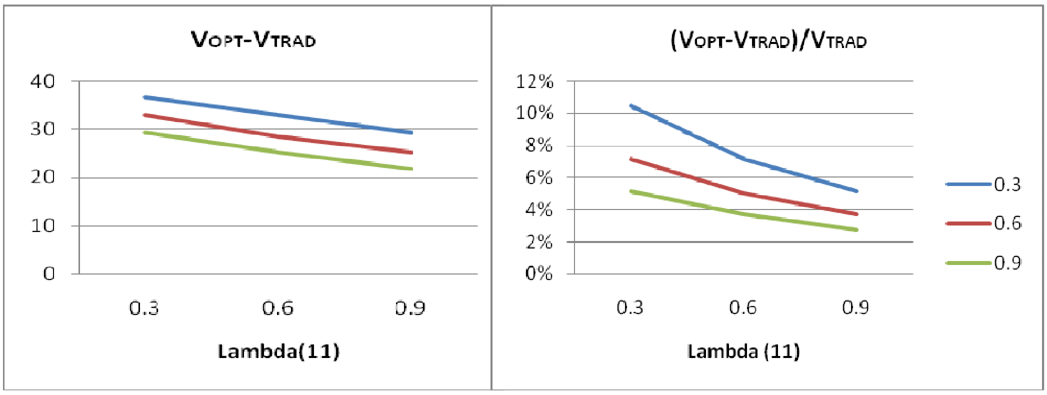

Figure 10: (V_{OPT} - V_{TRAD}) and (V_{OPT} - V_{TRAD})/ V_{TRAD} as arrival rates of Class 1 shippers change under the base except that R_1=20 and h_1=1

When we change the arrival rates of Class 1 shippers arriving at both of the locations under low dispatching cost we observe that the comparative performance of the optimal policy against the naive policy decreases as shown in the Figure 10. This observation supports that increasing the arrival rates make the optimal policy perform close to the naive policy converge to each other. When we look at the values for the condition of $\lambda_{11} = \lambda_{12}$ the comparative performance of the optimal policy decreases as these arrival rates increase as shown in Figure 10. $(V_{OPT} - V_{TRAD}) / V_{TRAD}$ is greater than 10 % when $\lambda_{11} = \lambda_{12} = 0.3$ while it is smaller than 3 % when the arrival rates of these shippers are increased to 0.9.

Observation 4.3.5: Increasing the arrival rate of shippers causes increase on the comparative performance of the optimal policy compared to the naïve policy under high dispatching cost and cross-assignment cost.

When arrival rate of Class 2 shipper arriving at the first dispatching location, λ_{21}, is increased there does not occur a significant change in difference between V_{OPT} and V_{TRAD}, but the comparative performance of the optimal policy decreases under low dispatching cost while it tends to increase under high dispatching cost ($D = 20$ or $D = 50$) as shown in Figure 11.

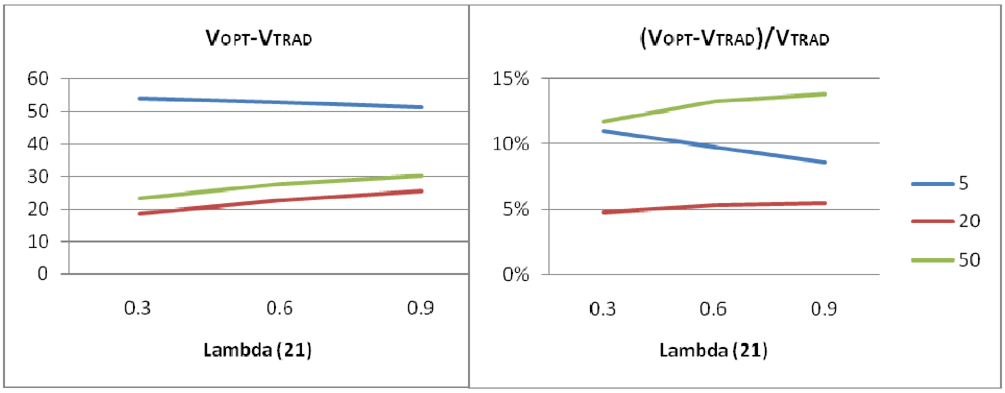

Figure 11: ($V_{OPT} - V_{TRAD}$) and ($V_{OPT} - V_{TRAD}$)/ V_{TRAD} as arrival rate of Class 2 shippers and dispatching cost change under the base case except that R_1=20 and c=5

As it has been stated before high cross-assignment cost (*c*=5) increases the performance of the optimal policy as the optimal policy manages cross assignment of arriving shipper more effectively than the naive policy. When both dispatching cost and cross-assignment cost are set to be high, the optimal policy benefits from the arriving shippers better than the naive policy. $V_{OPT} - V_{TRAD}$ for high dispatching costs ($D = 20$ or $D = 50$) increases as the arrival rate of Class 2 shippers increase as shown in Figure 11. It can be said that the performance of the optimal policy increases depending on this case.

In this part of this section we will analyze the performance of the optimal policy compared to the myopic policy.

Observation 4.3.6: Increasing the arrival rate of Class 1 shippers arriving at the first dispatching location affects the comparative performance of the optimal policy against the myopic policy.

When arrival rate of Class 1 shippers, λ_{11}, is changed from 0.3 to 0.9, a significant change occurs in difference between V_{OPT} and V_{MYO} shown in Figure 12. It can be obviously seen that this difference becomes greater when the waiting cost of Class 1 shippers is high (*c*=1 or *c*=5). Furthermore, when we look at $\frac{V_{OPT} - V_{MYO}}{V_{MYO}}$ values the performance the optimal policy outperforms the myopic policy under high waiting cost as the arrival rate of Class 1 shippers increase. Because of the fact that the optimal policy tries to maximize the total benefit of the grand coalition and the myopic policy tries to maximize shippers' benefits individually, it can be said that the optimal policy manages the system better when the turnover rate of shippers is high. So if the system doesn't have the problem to attract shippers the performance of the optimal policy would be better than the performance of the myopic policy.

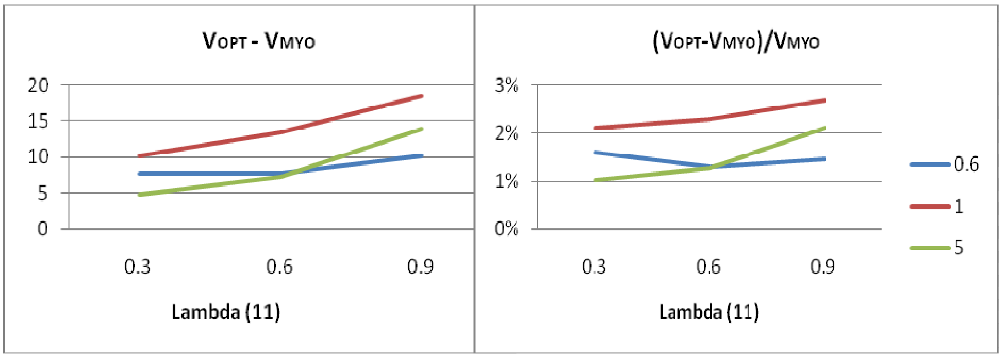

Figure 12: ($V_{OPT} - V_{MYO}$) and ($V_{OPT} - V_{MYO}$)/ V_{MYO} as waiting cost and arrival rate of Class 1 shipper arriving at the first dispatching location change under the base case except that R_1=20

Observation 4.3.7: Increasing the arrival rate of Class 2 shippers arriving at the first dispatching location does not make any significant change on the comparative performance of the optimal policy.

When arrival rate of Class 2 shippers, λ_{21}, is increased there does not occur any significant change in difference between V_{OPT} and V_{MYO}. Furthermore, the comparative performance of the optimal policy does not change as shown in Figure 13.

Because of the fact that both the optimal policy and myopic policy manage cross-assignment and dispatching processes effectively, their performances are seen to be very close in many cases, especially in the cases with very high dispatching cost. When the dispatching cost of vessels is set to be 50 the difference between V_{OPT} and V_{MYO} converges to zero as the arrival rate of Class 2 shippers increase.

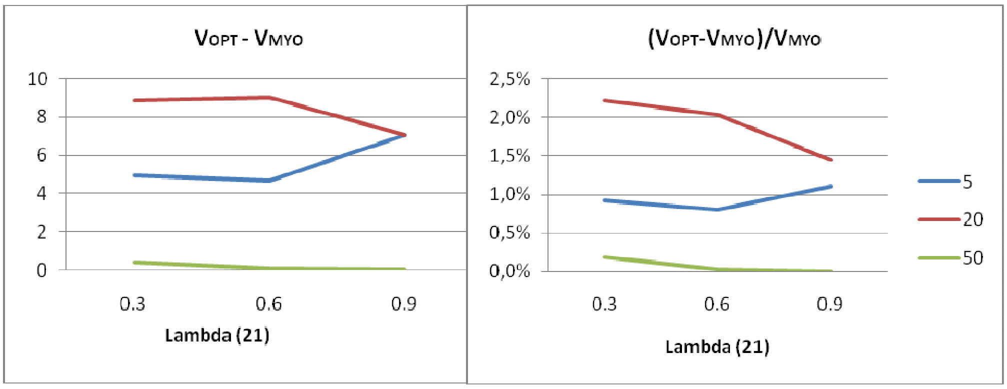

Figure 13: ($V_{OPT} - V_{MYO}$) and ($V_{OPT} - V_{MYO}$)/ V_{MYO} as arrival rate of Class 2 shippers arriving at the first dispatching location and dispatching cost change when initial utility of Class 1 shippers is high (R_1=20) and cross-assignment cost is high (c=5)

4.3.3 Effects of the initial utility, R_1, on the performance of the optimal policy

Two different settings are used in the analyses. In the first setting the effects of initial utility (R_1) and dispatching cost (D) are observed under low cross-assignment cost ($c = 1$). In the second setting the effects of initial utility (R_1) and dispatching cost (D) are observed under high cross-assignment cost ($c = 5$). In the analyses waiting cost is assumed as 0.6. As high waiting cost leads to greater number of cross-assignment processes and shorter dispatching times, it is expected that the effect of dispatching cost is viewed better under low waiting cost.

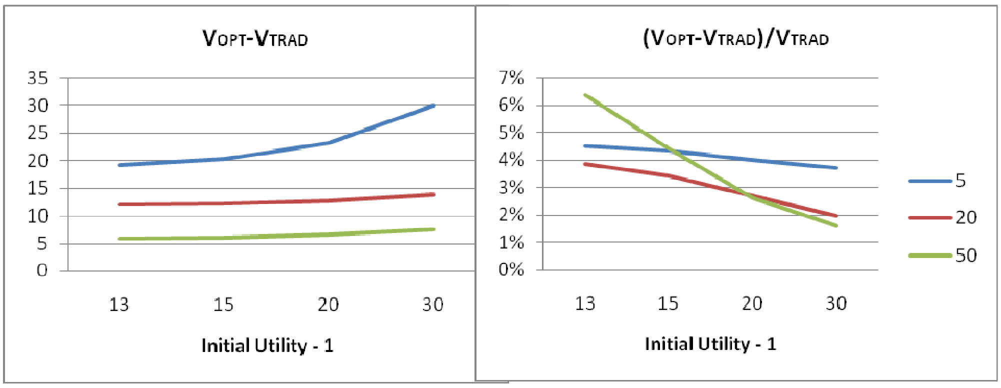

Figure 14: (V_{OPT} - V_{TRAD}) and (V_{OPT} - V_{TRAD})/ V_{TRAD} as dispatching cost and initial utility change under the base case (c=1)

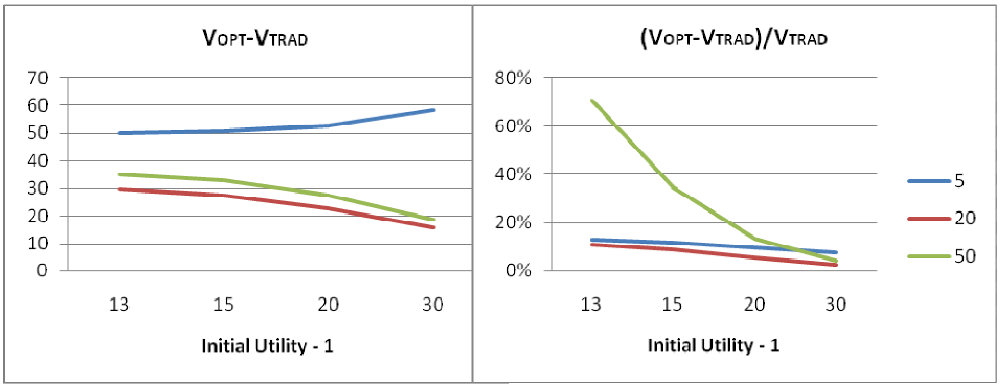

Figure 15: (V_{OPT} - V_{TRAD}) and (V_{OPT} - V_{TRAD})/ V_{TRAD} as dispatching cost and initial utility change under the base case except that c=5

Observation 4.3.8: The performance of the optimal policy compared to the naive policy decreases as the initial utility for Class 1 shippers increases under high dispatching cost.

Although slight increases in the difference between V_{OPT} and V_{TRAD} occur when initial utilities are increased under low cross-assignment cost (in Figure 14) and under high cross-assignment cost and low dispatching cost (in Figure 15), the proportional increase in net utility decreases. Furthermore, the comparative performance of the optimal policy compared to the naïve policy decreases dramatically when the dispatching cost is set to be high (*D*=50).

Furthermore, that any initial utility increase causes comparative performance loss of optimal policy against the naive policy needs to be analyzed. The structures of the optimal policy and naive policy can be investigated to understand the reasons of this case by using the following experimental runs.

As it can be seen from Table 21 the optimal policy converges to the naive policy as R_1 increases. This causes a slight decrease in the performance of the optimal policy in comparison to the naive policy.

Table 21: Structure of the optimal policy for different revenues under high dispatching cost and low cross-assignment cost

STATE	RUN 1393				RUN 1429			
	a_{11}	a_{21}	a_{12}	a_{22}	a_{11}	a_{21}	a_{12}	a_{22}
(0, 0, 0, 0)	1N	1N	2N	2N	1N	1N	2N	2N
(0, 0, 0, 1)	2N	2N	2N	2N	2N	2N	2N	2N
(0, 0, 0, 2)	2N	2N	2N	2N	2N	2N	2N	2N
(0, 0, 0, 3)	2N	2N	2N	2N	2N	2N	2N	2N
(0, 0, 0, 4)	2N	2N	2N	2N	2N	2N	2N	2N
(0, 0, 0, 5)	2D	2D	2D	2D	2D	1N	2D	2D

If R_1 is increased to 70 and all the other parameters are kept constant and the proposed LP model in Eq. (13) is solved by using this new experimental setting the optimal policy for the selected states would be as in the following table:

Table 22: Structure of the optimal policy and the naive policy for R_1=70 under high dispatching cost and low cross-assignment cost

STATE	NEW RUN				NAIVE POLICY			
	a_{11}	a_{21}	a_{12}	a_{22}	a_{11}	a_{21}	a_{12}	a_{22}
(0, 0, 0, 0)	1N	1N	2N	2N	1N	1N	2N	2N
(0, 0, 0, 1)	2N	1N	2N	2N	2N	1N	2N	2N
(0, 0, 0, 2)	2N	1N	2N	2N	2N	1N	2N	2N
(0, 0, 0, 3)	2N	1N	2N	2N	2N	1N	2N	2N
(0, 0, 0, 4)	2N	1N	2N	2N	2N	1N	2N	2N
(0, 0, 0, 5)	2D	1N	2D	1N	2D	1N	2D	2D

It is obviously seen from Table 22 that the optimal policy for this new experimental setting ($D = 50 \quad R_1 = 70 \; h_1 = 0.6 \quad c = 1$) and the naive policy become very similar. This similarity leads to the convergence of the optimal policy and the naive policy when R_1 is increased. Hence, it can be concluded that increasing the initial utility for Class 1 shippers leads to decrease the comparative performance of the optimal policy compared to the naive policy.

This fact can be explained by the decreasing significance of the cross-assignment and waiting costs as a result of increased initial utility. When we increase the initial utility of Class 1 shippers time the proportional values of other costs become small in value compared to the gained utilities of the system. This brings frequent cross-assignment operations for profitable shippers and late dispatches, in particular with high dispatching cost. All these effects of the parameters lead to the convergence of the optimal policy and naive policy.

When we look at the surplus budget regarding the naïve and myopic policies a slight increase in the surplus budget for naïve policy can be seen when the initial utility of Class 1 shippers is increased while we encounter budget deficits in many cases for myopic policy (in Figure 16). Increasing the initial utility has a small and positive effect on the surplus budget for naïve policy. This means savings of the optimal policy are increased as a result of any increase in the initial utility values. However, if the shippers are to be paid what they get under myopic policy the optimal policy may generate budget deficit in some cases as shown in Figure 16. Because of the fact that shippers are trying to maximize their own benefit regardless of the benefit of the grand coalition the system cannot generate sufficient money to meet the demands of shippers if they are aware of what they can get under myopic policy.

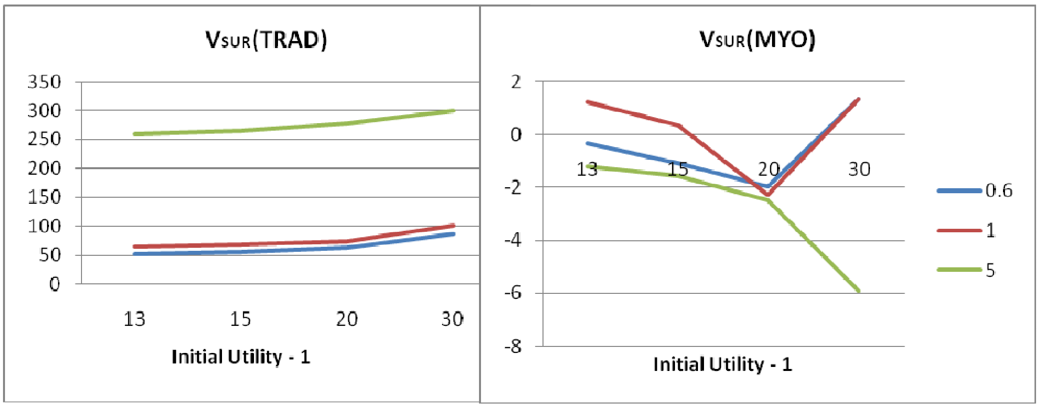

Figure 16: V_{SUR} (TRAD) and V_{SUR} (MYO) as initial utility and waiting cost change under the base case

Note that the optimal policy and the naive policy converge when we increase dispatching cost as shown in Figure 16. As a result of this convergence the surplus budget of the optimal system decreases as dispatching cost increases. It is obvious that increasing the dispatching cost makes dispatching operations highly burdensome and the optimal policy tries to minimize this cost by reducing the number of dispatches. It would be expected that the optimal policy waits to fill the vessel as in the naive policy.

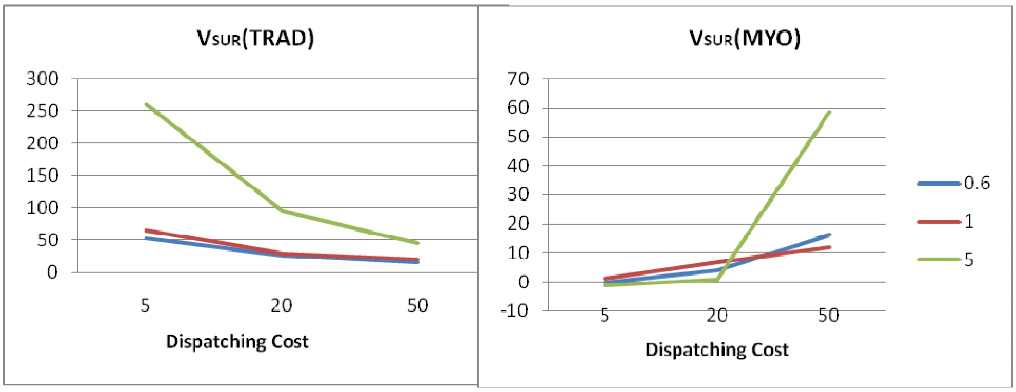

Figure 17: V_{SUR} (TRAD) and V_{SUR} (MYO) as dispatching and waiting cost change under the base case

However, increasing the dispatching cost doesn't have the same effect for the myopic policy as in the naïve policy, especially for high waiting cost (h_1=5). When the costs of dispatching the vessels and holding shippers at the dispatching locations are set to be high, the system under the optimal policy can easily generate what shippers can get under the myopic policy.

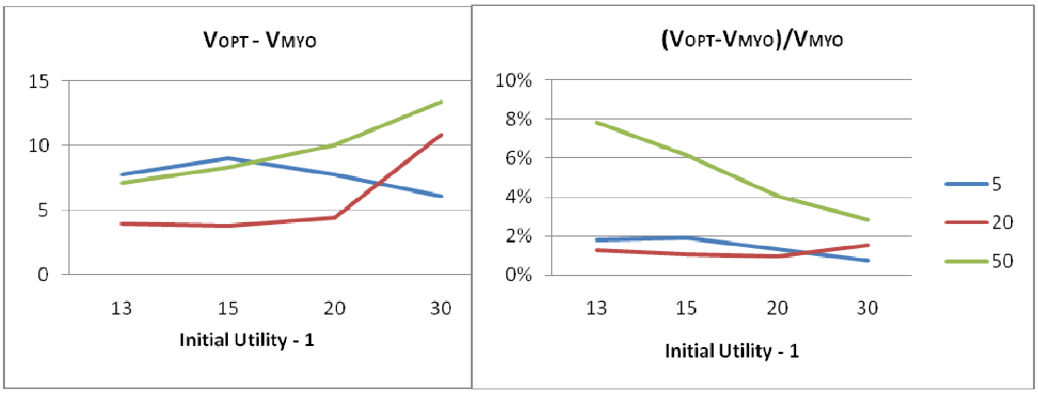

Figure 18: (V_{OPT} – V_{MYO}) and (V_{OPT} – V_{MYO})/ V_{MYO} as dispatching cost and initial utility change under the base case

Observation 4.3.9: The performance of the optimal policy compared to the myopic policy under high dispatching cost decreases as the initial utility for Class 1 shippers increases while there does not occur a significant change in the comparative performance of the optimal policy under low dispatching costs.

When the initial utility for Class 1 shippers is increased the significant change in the comparative performance of the optimal policy occurs in the cases with high dispatching cost as shown in Figure 18. As the myopic policy is trying to maximize the net utility of individual shippers without considering overall net utility, the superiority of the optimal policy can be seen easily in the cases with high dispatching cost and low initial utility. This finding is leading up to that the ratio of initial utility and dispatching is critical to assess the performance of the optimal policy compared to the myopic policies.

CHAPTER 5

CONCLUSION

In this study, we have analyzed a third-party transportation intermediary operating in the tramp shipping business that brings small shippers together to achieve savings through collaboration. A mechanism, which maximizes the expected discounted utility of the system, has been designed to find the optimal decisions for each state of the system.

We have modeled the problem as a Markov Decision Process (MDP) as the interarrival times of shippers are assumed to be exponentially distributed. The proposed model is used to find the optimal actions to be taken by arriving shippers for maximizing the expected utility of the grand coalition that is formed by a group of small shippers. The possible actions to be taken for each state include two types of decisions that are allocation and dispatching. In allocation part of the action, arriving shippers can be assigned to the closest location or to another location. In dispatching part of the action, loaded vessels can be dispatched or kept at the harbor.

We have used a naïve policy and a myopic policy to assess the performance of the intermediary. The structure of the naïve policy is considered to be robust and focusing on minimizing the fixed costs as the vessels are dispatched when they are fully loaded in this policy. However, the structure of the myopic policy is totally different from the naïve policy. In the myopic policy, each arriving shipper is trying to maximize his own benefit without considering the overall benefit of the system.

This structural difference of the policies can be monitored in the analyses. For example, the optimal policy and the naive policy converge when dispatching cost is increased. As a result of this convergence the surplus budget of the optimal system decreases as dispatching cost increases. It is obvious that increasing the dispatching cost makes dispatching operations highly burdensome and the optimal policy tries to minimize this cost by reducing the number of dispatches. It would be expected that the optimal policy waits to fill the vessel as in the naive policy. However, increasing the dispatching cost doesn't have the same effect for the myopic policy as in the naïve policy. When the costs of dispatching the vessels are set to be high, the optimal policy appears to be superior against the myopic policy and the system under the optimal policy can easily generate what shippers can get under the myopic policy.

It is expected that the optimal system can generate some amount of savings in comparison to other policies. As the main challenge for convincing shippers to participate in the system is allocation of savings fairly, allocation of savings problem has been studied in the thesis. A mathematical model has been proposed to allocate the savings to the shippers. This model aims to provide the shippers with the amounts of profits that can convince them to participate in the proposed system. It is obvious that the allocated amounts of payments are expected to be greater than the amounts that can be achieved by the myopic actions taken by the shippers individually. However, we have seen that the proposed system cannot generate enough money to give arriving shippers what they can get under the myopic policy in some cases.

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APPENDIX A

Table A: Actions for Sample Experiment Setting

NO	s_{11}	s_{21}	s_{12}	s_{22}	**NO**	s_{11}	s_{21}	s_{12}	s_{22}	**NO**	s_{11}	s_{21}	s_{12}	s_{22}
1	1D	1D	1D	1D	38	1D	2D	1N	1N	75	1N	1D	2D	2D
2	1D	1D	1D	1N	39	1D	2D	1N	2D	76	1N	1D	2D	2N
3	1D	1D	1D	2D	40	1D	2D	1N	2N	77	1N	1D	2N	1D
4	1D	1D	1D	2N	41	1D	2D	2D	1D	78	1N	1D	2N	1N
5	1D	1D	1N	1D	42	1D	2D	2D	1N	79	1N	1D	2N	2D
6	1D	1D	1N	1N	43	1D	2D	2D	2D	80	1N	1D	2N	2N
7	1D	1D	1N	2D	44	1D	2D	2D	2N	81	1N	1N	1D	1D
8	1D	1D	1N	2N	45	1D	2D	2N	1D	82	1N	1N	1D	1N
9	1D	1D	2D	1D	46	1D	2D	2N	1N	83	1N	1N	1D	2D
10	1D	1D	2D	1N	47	1D	2D	2N	2D	84	1N	1N	1D	2N
11	1D	1D	2D	2D	48	1D	2D	2N	2N	85	1N	1N	1N	1D
12	1D	1D	2D	2N	49	1D	2N	1D	1D	86	1N	1N	1N	1N
13	1D	1D	2N	1D	50	1D	2N	1D	1N	87	1N	1N	1N	2D
14	1D	1D	2N	1N	51	1D	2N	1D	2D	88	1N	1N	1N	2N
15	1D	1D	2N	2D	52	1D	2N	1D	2N	89	1N	1N	2D	1D
16	1D	1D	2N	2N	53	1D	2N	1N	1D	90	1N	1N	2D	1N
17	1D	1N	1D	1D	54	1D	2N	1N	1N	91	1N	1N	2D	2D
18	1D	1N	1D	1N	55	1D	2N	1N	2D	92	1N	1N	2D	2N
19	1D	1N	1D	2D	56	1D	2N	1N	2N	93	1N	1N	2N	1D
20	1D	1N	1D	2N	57	1D	2N	2D	1D	94	1N	1N	2N	1N
21	1D	1N	1N	1D	58	1D	2N	2D	1N	95	1N	1N	2N	2D
22	1D	1N	1N	1N	59	1D	2N	2D	2D	96	1N	1N	2N	2N
23	1D	1N	1N	2D	60	1D	2N	2D	2N	97	1N	2D	1D	1D
24	1D	1N	1N	2N	61	1D	2N	2N	1D	98	1N	2D	1D	1N
25	1D	1N	2D	1D	62	1D	2N	2N	1N	99	1N	2D	1D	2D
26	1D	1N	2D	1N	63	1D	2N	2N	2D	100	1N	2D	1D	2N
27	1D	1N	2D	2D	64	1D	2N	2N	2N	101	1N	2D	1N	1D
28	1D	1N	2D	2N	65	1N	1D	1D	1D	102	1N	2D	1N	1N
29	1D	1N	2N	1D	66	1N	1D	1D	1N	103	1N	2D	1N	2D
30	1D	1N	2N	1N	67	1N	1D	1D	2D	104	1N	2D	1N	2N
31	1D	1N	2N	2D	68	1N	1D	1D	2N	105	1N	2D	2D	1D
32	1D	1N	2N	2N	69	1N	1D	1N	1D	106	1N	2D	2D	1N
33	1D	2D	1D	1D	70	1N	1D	1N	1N	107	1N	2D	2D	2D
34	1D	2D	1D	1N	71	1N	1D	1N	2D	108	1N	2D	2D	2N
35	1D	2D	1D	2D	72	1N	1D	1N	2N	109	1N	2D	2N	1D

Table A Continued

NO	s_{11}	s_{21}	s_{12}	s_{22}	**NO**	s_{11}	s_{21}	s_{12}	s_{22}	**NO**	s_{11}	s_{21}	s_{12}	s_{22}
36	1D	2D	1D	2N	73	1N	1D	2D	1D	110	1N	2D	2N	1N
37	1D	2D	1N	1D	74	1N	1D	2D	1N	111	1N	2D	2N	2D
112	1N	2D	2N	2N	158	2D	1N	2N	1N	204	2N	1D	2D	2N
113	1N	2N	1D	1D	159	2D	1N	2N	2D	205	2N	1D	2N	1D
114	1N	2N	1D	1N	160	2D	1N	2N	2N	206	2N	1D	2N	1N
115	1N	2N	1D	2D	161	2D	2D	1D	1D	207	2N	1D	2N	2D
116	1N	2N	1D	2N	162	2D	2D	1D	1N	208	2N	1D	2N	2N
117	1N	2N	1N	1D	163	2D	2D	1D	2D	209	2N	1N	1D	1D
118	1N	2N	1N	1N	164	2D	2D	1D	2N	210	2N	1N	1D	1N
119	1N	2N	1N	2D	165	2D	2D	1N	1D	211	2N	1N	1D	2D
120	1N	2N	1N	2N	166	2D	2D	1N	1N	212	2N	1N	1D	2N
121	1N	2N	2D	1D	167	2D	2D	1N	2D	213	2N	1N	1N	1D
122	1N	2N	2D	1N	168	2D	2D	1N	2N	214	2N	1N	1N	1N
123	1N	2N	2D	2D	169	2D	2D	2D	1D	215	2N	1N	1N	2D
124	1N	2N	2D	2N	170	2D	2D	2D	1N	216	2N	1N	1N	2N
125	1N	2N	2N	1D	171	2D	2D	2D	2D	217	2N	1N	2D	1D
126	1N	2N	2N	1N	172	2D	2D	2D	2N	218	2N	1N	2D	1N
127	1N	2N	2N	2D	173	2D	2D	2N	1D	219	2N	1N	2D	2D
128	1N	2N	2N	2N	174	2D	2D	2N	1N	220	2N	1N	2D	2N
129	2D	1D	1D	1D	175	2D	2D	2N	2D	221	2N	1N	2N	1D
130	2D	1D	1D	1N	176	2D	2D	2N	2N	222	2N	1N	2N	1N
131	2D	1D	1D	2D	177	2D	2N	1D	1D	223	2N	1N	2N	2D
132	2D	1D	1D	2N	178	2D	2N	1D	1N	224	2N	1N	2N	2N
133	2D	1D	1N	1D	179	2D	2N	1D	2D	225	2N	2D	1D	1D
134	2D	1D	1N	1N	180	2D	2N	1D	2N	226	2N	2D	1D	1N
135	2D	1D	1N	2D	181	2D	2N	1N	1D	227	2N	2D	1D	2D
136	2D	1D	1N	2N	182	2D	2N	1N	1N	228	2N	2D	1D	2N
137	2D	1D	2D	1D	183	2D	2N	1N	2D	229	2N	2D	1N	1D
138	2D	1D	2D	1N	184	2D	2N	1N	2N	230	2N	2D	1N	1N
139	2D	1D	2D	2D	185	2D	2N	2D	1D	231	2N	2D	1N	2D
140	2D	1D	2D	2N	186	2D	2N	2D	1N	232	2N	2D	1N	2N
141	2D	1D	2N	1D	187	2D	2N	2D	2D	233	2N	2D	2D	1D
142	2D	1D	2N	1N	188	2D	2N	2D	2N	234	2N	2D	2D	1N
143	2D	1D	2N	2D	189	2D	2N	2N	1D	235	2N	2D	2D	2D
144	2D	1D	2N	2N	190	2D	2N	2N	1N	236	2N	2D	2D	2N
145	2D	1N	1D	1D	191	2D	2N	2N	2D	237	2N	2D	2N	1D
146	2D	1N	1D	1N	192	2D	2N	2N	2N	238	2N	2D	2N	1N
147	2D	1N	1D	2D	193	2N	1D	1D	1D	239	2N	2D	2N	2D
148	2D	1N	1D	2N	194	2N	1D	1D	1N	240	2N	2D	2N	2N
149	2D	1N	1N	1D	195	2N	1D	1D	2D	241	2N	2N	1D	1D
150	2D	1N	1N	1N	196	2N	1D	1D	2N	242	2N	2N	1D	1N
151	2D	1N	1N	2D	197	2N	1D	1N	1D	243	2N	2N	1D	2D

Table A Continued

NO	s_{11}	s_{21}	s_{12}	s_{22}	**NO**	s_{11}	s_{21}	s_{12}	s_{22}	**NO**	s_{11}	s_{21}	s_{12}	s_{22}
152	2D	1N	1N	2N	198	2N	1D	1N	1N	244	2N	2N	1D	2N
153	2D	1N	2D	1D	199	2N	1D	1N	2D	245	2N	2N	1N	1D
154	2D	1N	2D	1N	200	2N	1D	1N	2N	246	2N	2N	1N	1N
155	2D	1N	2D	2D	201	2N	1D	2D	1D	247	2N	2N	1N	2D
156	2D	1N	2D	2N	202	2N	1D	2D	1N	248	2N	2N	1N	2N
157	2D	1N	2N	1D	203	2N	1D	2D	2D	249	2N	2N	2D	1D
250	2N	2N	2D	1N										
251	2N	2N	2D	2D										
252	2N	2N	2D	2N										
253	2N	2N	2N	1D										
254	2N	2N	2N	1N										
255	2N	2N	2N	2D										
256	2N	2N	2N	2N										

APPENDIX B

Table B: Optimal Actions for Selected Runs

RUNS	λ_{11}	λ_{21}	λ_{12}	λ_{22}	D	R_1	R_2	c	h_1	h_2
1297	0.6	0.6	0.6	0.6	5	13	10	1	0.6	0.5
1298	0.6	0.6	0.6	0.6	5	13	10	1	1	0.5
1299	0.6	0.6	0.6	0.6	5	13	10	1	5	0.5
1300	0.6	0.6	0.6	0.6	5	13	10	3	0.6	0.5
1303	0.6	0.6	0.6	0.6	5	13	10	5	0.6	0.5
1306	0.6	0.6	0.6	0.6	5	13	10	10	0.6	0.5
1309	0.6	0.6	0.6	0.6	5	15	10	1	0.6	0.5
1321	0.6	0.6	0.6	0.6	5	20	10	1	0.6	0.5
1333	0.6	0.6	0.6	0.6	5	30	10	1	0.6	0.5
1345	0.6	0.6	0.6	0.6	20	13	10	1	0.6	0.5
1375	0.6	0.6	0.6	0.6	20	20	10	5	0.6	0.5
1377	0.6	0.6	0.6	0.6	20	20	10	5	5	0.5
1378	0.6	0.6	0.6	0.6	20	20	10	10	0.6	0.5
1380	0.6	0.6	0.6	0.6	20	20	10	10	5	0.5
1393	0.6	0.6	0.6	0.6	50	13	10	1	0.6	0.5

Table B Continued

STATE	1297				1298				1299				1300			
(0, 0, 0, 0)	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N
(0, 0, 0, 1)	2N	2N	2N	2N	2N	2N	2N	2N	2D	1N	2D	2N	1N	1N	2N	2N
(0, 0, 0, 2)	2N	2N	2N	2N	2N	2N	2N	2N	2D	2N	2D	2N	1N	1N	2N	2N
(0, 0, 0, 3)	2N	2N	2N	2N	2N	2N	2N	2N	2D	2N	2D	2N	1N	1N	2D	2D
(0, 0, 0, 4)	2D	2D	2D	2D	2D	2D	2D	2D	2D	2N	2D	2N	0	0	0	0
(0, 0, 0, 5)	0	0	0	0	0	0	0	0	2D	2D	2D	2D	0	0	0	0
(0, 0, 1, 0)	2N	2N	2N	2N	2N	2N	2N	2N	2D	2D	2D	2D	1N	1N	2N	2N
(0, 0, 1, 1)	2N	2N	2N	2N	2N	2N	2N	2N	0	0	0	0	1N	1N	2D	2N
(0, 0, 1, 2)	2D	2N	2D	2N	2D	2N	2D	2N	0	0	0	0	1N	1N	2D	2D
(0, 0, 1, 3)	2D	2D	2D	2D	2D	2D	2D	2D	0	0	0	0	0	0	0	0
(0, 0, 1, 4)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 0, 2, 0)	2N	2N	2N	2N	2D	2N	2D	2N	0	0	0	0	1N	1N	2D	2D
(0, 0, 2, 1)	2D	2D	2D	2D	2D	2D	2D	2D	0	0	0	0	0	0	0	0
(0, 0, 2, 2)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 0, 2, 3)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 0, 3, 0)	2D	2D	2D	2D	0	0	0	0	0	0	0	0	0	0	0	0
(0, 0, 3, 1)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 0, 3, 2)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 0, 4, 0)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 0, 4, 1)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 0, 5, 0)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 0, 0)	1N	1N	1N	1N	1N	1N	1N	1N	1D	1N	1D	2N	1N	1N	2N	2N
(0, 1, 0, 1)	0	0	0	0	0	0	0	0	1D	1N	2D	2N	1N	1N	2N	2N
(0, 1, 0, 2)	0	0	0	0	0	0	0	0	1D	1N	2D	2N	1N	1N	2N	2N
(0, 1, 0, 3)	0	0	0	0	0	0	0	0	2D	1N	2D	2N	1N	1N	2D	2D
(0, 1, 0, 4)	0	0	0	0	0	0	0	0	2D	1N	2D	2N	0	0	0	0
(0, 1, 0, 5)	0	0	0	0	0	0	0	0	2D	2D	2D	2D	0	0	0	0
(0, 1, 1, 0)	0	0	0	0	0	0	0	0	0	0	0	0	1N	1N	2N	2N
(0, 1, 1, 1)	0	0	0	0	0	0	0	0	0	0	0	0	1N	1N	2D	2N
(0, 1, 1, 2)	0	0	0	0	0	0	0	0	0	0	0	0	1N	1N	2D	2D
(0, 1, 1, 3)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 1, 4)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 2, 0)	0	0	0	0	0	0	0	0	0	0	0	0	1N	1N	2D	2D
(0, 1, 2, 1)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 2, 2)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 2, 3)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 3, 0)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 3, 1)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 3, 2)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 4, 0)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table B Continued

STATE	1297				1298				1299				1300			
(0, 1, 4, 1)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 5, 0)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table B Continued

STATE	1303				1306				1309				1321			
(0, 0, 0, 0)	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N
(0, 0, 0, 1)	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N
(0, 0, 0, 2)	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N
(0, 0, 0, 3)	1N	1N	2D	2D	1N	1N	2D	2D	1N	1N	2D	2D	1N	1N	2D	2D
(0, 0, 0, 4)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 0, 0, 5)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 0, 1, 0)	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N
(0, 0, 1, 1)	1N	1N	2D	2N	1N	1N	2D	2N	1N	1N	2D	2N	1N	1N	2D	2N
(0, 0, 1, 2)	1N	1N	2D	2D	1N	1N	2D	2D	1N	1N	2D	2D	1N	1N	2D	2D
(0, 0, 1, 3)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 0, 1, 4)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 0, 2, 0)	1N	1N	2D	2D	1N	1N	2D	2D	1N	1N	2D	2D	1N	1N	2D	2D
(0, 0, 2, 1)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 0, 2, 2)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 0, 2, 3)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 0, 3, 0)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 0, 3, 1)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 0, 3, 2)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 0, 4, 0)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 0, 4, 1)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 0, 5, 0)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 0, 0)	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N
(0, 1, 0, 1)	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N
(0, 1, 0, 2)	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N
(0, 1, 0, 3)	1N	1N	2D	2D	1N	1N	2D	2D	1N	1N	2D	2D	1N	1N	2D	2D
(0, 1, 0, 4)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 0, 5)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 1, 0)	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N
(0, 1, 1, 1)	1N	1N	2D	2N	1N	1N	2D	2N	1N	1N	2D	2N	1N	1N	2D	2N
(0, 1, 1, 2)	1N	1N	2D	2D	1N	1N	2D	2D	1N	1N	2D	2D	1N	1N	2D	2D
(0, 1, 1, 3)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 1, 4)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 2, 0)	1N	1N	2D	2D	1N	1N	2D	2D	1N	1N	2D	2D	1N	1N	2D	2D
(0, 1, 2, 1)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 2, 2)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 2, 3)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 3, 0)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 3, 1)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 3, 2)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 4, 0)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table B Continued

STATE	1303				1306				1309				1321			
(0, 1, 4, 1)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 5, 0)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table B Continued

STATE	1333				1345				1393			
(0, 0, 0, 0)	1N	1N	2N	1N	1N	2N	1N	1N	2N	1N	1N	2N
(0, 0, 0, 1)	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N
(0, 0, 0, 2)	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N
(0, 0, 0, 3)	2D	2N	2D	2D	2N	2D	2D	2N	2D	2D	2N	2D
(0, 0, 0, 4)	2D	2N	2D	2D	2N	2D	2D	2N	2D	2D	2N	2D
(0, 0, 0, 5)	2D	2D	2D	2D	2D	2D	2D	2D	2D	2D	2D	2D
(0, 0, 1, 0)	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N	2N
(0, 0, 1, 1)	2D	2N	2D	2D	2N	2D	2D	2N	2D	2D	2N	2D
(0, 0, 1, 2)	2D	2D	2D	2D	2D	2D	2D	2D	2D	2D	2D	2D
(0, 0, 1, 3)	0	0	0	0	0	0	0	0	0	0	0	0
(0, 0, 1, 4)	0	0	0	0	0	0	0	0	0	0	0	0
(0, 0, 2, 0)	2D	2D	2D	2D	2D	2D	2D	2D	2D	2D	2D	2D
(0, 0, 2, 1)	0	0	0	0	0	0	0	0	0	0	0	0
(0, 0, 2, 2)	0	0	0	0	0	0	0	0	0	0	0	0
(0, 0, 2, 3)	0	0	0	0	0	0	0	0	0	0	0	0
(0, 0, 3, 0)	0	0	0	0	0	0	0	0	0	0	0	0
(0, 0, 3, 1)	0	0	0	0	0	0	0	0	0	0	0	0
(0, 0, 3, 2)	0	0	0	0	0	0	0	0	0	0	0	0
(0, 0, 4, 0)	0	0	0	0	0	0	0	0	0	0	0	0
(0, 0, 4, 1)	0	0	0	0	0	0	0	0	0	0	0	0
(0, 0, 5, 0)	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 0, 0)	1N	1N	1N	1N	1N	1N	1N	1N	1N	1N	1N	1N
(0, 1, 0, 1)	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 0, 2)	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 0, 3)	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 0, 4)	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 0, 5)	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 1, 0)	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 1, 1)	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 1, 2)	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 1, 3)	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 1, 4)	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 2, 0)	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 2, 1)	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 2, 2)	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 2, 3)	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 3, 0)	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 3, 1)	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 3, 2)	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 4, 0)	0	0	0	0	0	0	0	0	0	0	0	0

Table B Continued

STATE	1333				1345				1393			
(0, 1, 4, 1)	0	0	0	0	0	0	0	0	0	0	0	0
(0, 1, 5, 0)	0	0	0	0	0	0	0	0	0	0	0	0

Table B Continued

STATE	1375				1377				1378				1380			
(0, 0, 0, 0)	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N
(0, 0, 0, 1)	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N
(0, 0, 0, 2)	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N
(0, 0, 0, 3)	1N	1N	2N	2N	2N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N
(0, 0, 0, 4)	1N	1N	2N	2N	2N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N
(0, 0, 0, 5)	1N	1N	2D	2D	2D	1N	2D	2D	1N	1N	2D	2D	1N	1N	2D	2D
(0, 0, 1, 0)	1N	1N	2N	2N	2N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N
(0, 0, 1, 1)	1N	1N	2N	2N	2N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2D	2N
(0, 0, 1, 2)	1N	1N	2N	2N	2N	1N	2N	2N	1N	1N	2N	2N	2D	1N	2D	2N
(0, 0, 1, 3)	1N	1N	2N	2N	2D	1N	2D	2N	1N	1N	2N	2N	2D	1N	2D	2N
(0, 0, 1, 4)	1N	1N	2D	2D	2D	1N	2D	2D	1N	1N	2D	2D	2D	1N	2D	2D
(0, 0, 2, 0)	1N	1N	2N	2N	2D	1N	2D	2N	1N	1N	2N	2N	2D	1N	2D	2D
(0, 0, 2, 1)	1N	1N	2N	2N	2D	1N	2D	2N	1N	1N	2N	2N	2D	1N	2D	2N
(0, 0, 2, 2)	1N	1N	2N	2N	2D	1N	2D	2D	1N	1N	2N	2N	2D	1N	2D	2D
(0, 0, 2, 3)	2D	1N	2D	2D	0	0	0	0	1N	1N	2D	2D	0	0	0	0
(0, 0, 3, 0)	1N	1N	2N	2N	0	0	0	0	1N	1N	2N	2N	0	0	0	0
(0, 0, 3, 1)	2N	1N	2N	2N	0	0	0	0	1N	1N	2N	2N	0	0	0	0
(0, 0, 3, 2)	2D	1N	2D	2D	0	0	0	0	1N	1N	2D	2D	0	0	0	0
(0, 0, 4, 0)	2N	1N	2N	2N	0	0	0	0	1N	1N	2D	2N	0	0	0	0
(0, 0, 4, 1)	2D	1N	2D	2D	0	0	0	0	1N	1N	2D	2D	0	0	0	0
(0, 0, 5, 0)	2D	1N	2D	2D	0	0	0	0	2D	1N	2D	2D	0	0	0	0
(0, 1, 0, 0)	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N
(0, 1, 0, 1)	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N
(0, 1, 0, 2)	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N
(0, 1, 0, 3)	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N
(0, 1, 0, 4)	1N	1N	2N	2N	2N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N
(0, 1, 0, 5)	1N	1N	2D	2D	2D	1N	2D	2D	1N	1N	2D	2D	1N	1N	2D	2D
(0, 1, 1, 0)	1N	1N	2N	2N	2N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2N	2N
(0, 1, 1, 1)	1N	1N	2N	2N	2N	1N	2N	2N	1N	1N	2N	2N	1N	1N	2D	2N
(0, 1, 1, 2)	1N	1N	2N	2N	2D	1N	2D	2N	1N	1N	2N	2N	1N	1N	2D	2N
(0, 1, 1, 3)	1N	1N	2N	2N	2D	1N	2D	2N	1N	1N	2N	2N	2D	1N	2D	2N
(0, 1, 1, 4)	1N	1N	2D	2D	2D	1N	2D	2D	1N	1N	2D	2D	2D	1N	2D	2D
(0, 1, 2, 0)	1N	1N	2N	2N	2D	1N	2D	2N	1N	1N	2N	2N	2D	1N	2D	2D
(0, 1, 2, 1)	1N	1N	2N	2N	2D	1N	2D	2D	1N	1N	2N	2N	2D	1N	2D	2D
(0, 1, 2, 2)	1N	1N	2N	2N	2D	1N	2D	2D	1N	1N	2N	2N	2D	1N	2D	2D
(0, 1, 2, 3)	1N	1N	2D	2D	0	0	0	0	1N	1N	2D	2D	0	0	0	0
(0, 1, 3, 0)	1N	1N	2N	2N	0	0	0	0	1N	1N	2N	2N	0	0	0	0
(0, 1, 3, 1)	1N	1N	2N	2N	0	0	0	0	1N	1N	2N	2N	0	0	0	0
(0, 1, 3, 2)	2D	1N	2D	2D	0	0	0	0	1N	1N	2D	2D	0	0	0	0

Table B Continued

STATE	1375				1377				1378				1380			
(0, 1, 4, 0)	1N	1N	2N	2N	0	0	0	0	1N	1N	2D	2N	0	0	0	0
(0, 1, 4, 1)	2D	1N	2D	2D	0	0	0	0	1N	1N	2D	2D	0	0	0	0
(0, 1, 5, 0)	2D	1N	2D	2D	0	0	0	0	2D	1N	2D	2D	0	0	0	0