REVENUE-DRIVEN DYNAMIC PRICING AND OPERATIONAL PLANNING IN MULTIMODAL FREIGHT TRANSPORTATION

by

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<< to my beloved family >>

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ABSTRACT

Multimodal freight transport developed in the transportation sector as an alternative to unimodal transport faced with the challenges brought by the growing global demand for transporting goods. Multimodal transport is the transportation of goods using at least two modes of transport, usually door-to-door. The common transport modes include railways, maritime routes, and the roads. Multimodal transport network has an inherently complex structure with numerous stakeholders. Sea-rail multimodal freight transportation is an environmentally sustainable transport chain against road transportation; however, this environmental impact should be considered together with economic aspects in order to make multimodality more competitive in the sector. This thesis first provides a taxonomic review of multimodal transportation literature enumerating its components: data, demand, cost and time management, modal shift, collaboration, sustainability, governmental policy-setting, operational planning and modeling, revenue management and joint optimization of slot allocation and pricing strategies. Next, it proposes a dynamic pricing approach against fixed pricing to increase the revenue of multimodal transport providers. For slot allocation and cost component of dynamic pricing equation, a time-space diagram is developed to include time dimension and the sea-rail multimodal freight transportation problem is formulated as a linear network flow model. Thus, this study of operational planning and dynamic pricing strategy from multimodal transport provider's perspective provides managerial insights on the advantages of multimodality.

KOMBİNE YÜK TAŞIMACILIĞI YÖNETİMİNDE OPERASYONEL PLANLAMA VE GELİR ODAKLI DİNAMİK FİYATLANDIRMA

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ÖZET

Kombine taşımacılık, diğer bir isimle çok türlü taşımacılık, uluslararası yük taşıma zincirinde genellikle tek tip taşıma türü olan kara yolu yerine, en az iki farklı taşıma türünün birleştirilmesi ile yapılan taşımacılığı ifade etmektedir. Kombine yük taşımacılığı yükün müşteriden alınan kabul noktasından varış noktasına en az iki taşıma türünün kombinasyonları kullanılarak nakledilmesidir; genellikle kullanılan taşıma türleri karayolları, deniz yolları ve demiryolu sistemleridir. Çok türlü taşımacılık ağı, birçok paydaşın iletişim içinde olduğu, doğal olarak karmaşık bir yapıya sahip olan bir ulaşım ağıdır. Bu tez, ilk olarak, çok türlü taşımacılık literatürünün bileşenlerini taksonomik olarak şu başlıklar altında inceler: veri, talep, maliyet ve zaman yönetimi, taşıma türü değişimi, işbirliği, sürdürülebilirlik, ilgili devlet politikaları belirleme, operasyonel planlama ve modelleme, gelir yönetimi, fiyatlandırma stratejileri ve yer tahsisinin ortak optimizasyonu. Deniz-demiryolu kombine taşımacılığı, karayolu taşımacılığına kıyasla çevresel olarak daha sürdürülebilir bir taşıma zinciridir; bununla birlikte, çok türlü taşımacılığın sektörde daha rekabetçi hale gelmesi için bu çevresel etkinin yanında ekonomik yönleriyle birlikte ele alınmalıdır. Bu nedenle, bu tez, çok türlü taşımacılık operatörlerinin gelirini artırmak için sabit fiyatlandırmaya karşı dinamik bir fiyatlandırma yaklaşımı önermektedir. Yer tahsisi ve dinamik fiyatlandırma denkleminin maliyet kalemini belirlemek için, zaman boyutunu da içeren bir uzay-zaman ağı oluşturulmuş ve bu deniz-demiryolu çok türlü taşımacılık problemi doğrusal ağ akış modeli olarak tasarlanmıştır. Böylece, bu çok türlü taşımacılık operatörleri bakış açısıyla sürdürülen operasyonel planlama ve dinamik fiyatlandırma çalışması, çok türlü ulaşımın avantajlarına yönelik yönetim anlayışları sunmaktadır.

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Chapter 1

Introduction

Multimodal freight transport developed in the transportation sector as an alternative to unimodal transport faced with the challenges brought by the growing global demand for transporting goods. The use of the Rhone River for transportation which dates back to the 17th century is the first time when two means of transport utilized in order to facilitate the work ahead. This method, nowadays, is preferred and encouraged since it is more advantageous and solution oriented in terms of cost efficiency, traffic congestion, environmental concerns and freight safety throughout the transport process. Multimodal transport is the transportation of goods using at least two modes of transport, usually door-to-door and the transfer from one mode to another is performed at an intermodal terminal. The common transport modes include railways, maritime routes, inland waters, airways, and the roads. Moreover, United Nations Economic Commission for Europe (2008) defined this concept as "the movement of goods in one and the same loading unit or road vehicle, which uses successively two or more modes of transport are used to transport the same loading unit or truck in an integrated manner, without loading or unloading, in a door to door transport chain".

Multimodal transport is mostly preferred because of its flexibility compared to using a single mode and its environmental benefits towards sustainable transportation. The global environmental issues and carbon dioxide mitigation problems have induced the importance of maritime and rail transport since these transport modes play an important role in reducing carbon footprints (Pruzan-Jorgensen et al., 2010; SteadieSeifi et al., 2004). One of the strategies of the European Commission to lower transport emissions in the EU as in the rest of the world is optimization of multimodal logistic chains for a competitive and sustainable transport system. Actions foreseen in the area of multimodal freight transports aim 30% of road freight over 300 km should shift to other modes such as rail or waterborne transport by 2030, and more than 50 % by 2050, facilitated by efficient and green freight corridors. By 2020, the establishment of the framework for a European multimodal transport information, management and payment system is targeted for better integration of modes and smart pricing system (White Paper on Transport, 2011). To be competitive against road transport, multimodal transport chain requires a smart and applicable pricing approach in order to maximize revenue from the operator’s point of view and to be preferable and reasonable from the customer’s point of view. Multimodal transport network has an inherently complex structure with numerous stakeholders. The effective usage of the rail and sea modes increases even more with the right decisions and accurate system implementations. In other words, efficiency and efficacy are directly linked with the construction of right conditions and choices of operational planning strategies (Caris et al., 2008; Guajardo et al., 2015).

Multimodal transportation management is a transportation network and a supply chain system which is composed of several sub-groups. These groups emphasized in the literature can be enumerated: Data, demand, cost and time management, modal shift, collaboration, sustainability, governmental policy-setting, operational planning and modeling, revenue management, joint optimization of slot allocation and pricing strategies. A vast collection of scientific literature focuses on different objectives taking into account various limitations. For instance, in the context of short-term planning, the challenge is to take real-time decisions considering the interests of all stakeholders. With the need for real-time decision making, this problem becomes complex, dynamic, and stochastic. Its planning involves a multi-criteria decision making process where the objectives might consist of the minimization of cost, time, and/or carbon emissions as well as improvement of service levels and utilization (Chang, 2008). Stakeholders establish horizontal collaborations across the same or different type of modes where it is necessary to gain benefits during the seamless transition of consecutive modal shift processes (Kayikci et al., 2012; Krajewska et al., 2008; Mutlu et al.; 2017). Efficient slot allocation and capacity management throughout the multimodal freight transport chain have a critical importance at the operational level of stakeholders' collaboration. However, the allocation of the benefits achieved through collaboration among the corresponding stakeholders and beneficiaries arises as a key issue to be resolved.

Intensive research has been conducted multimodal transport planning problem at the strategic, tactical, and operational decision-making levels. However, a successful implementation of multimodality requires other technology integrated and innovative concepts: a different point of view and an appropriate pricing strategy for multimodal transport service. Li et al. (2015) claim that the pricing strategy has the power to affect the competitiveness of multimodal freight transport and the mode choice during modal shift process. This pricing strategy and revenue management can be defined basically as a searching for a strategy to find the optimal maximum quantity of freight traveling along each leg and their prices in order to maximize the revenue over a time horizon. In the literature, effective and efficient strategies of freight transport have been examined widely together with multimodality, advantages, and disadvantages; however, examination of smart pricing strategies is scarce.

In this thesis, we are motivated by the bringing of a dynamic pricing approach together with slot allocation. In the developed model, sea-rail transport chain is taken into consideration and operators providing the ship and train transportation services cooperate to provide combined and synchronized transport of goods. Multimodal freight transport providers manage their services applying mainly a fixed/list price policy in the current sector. Conversely, we have demonstrated the possibility of the increase in total revenue by applying dynamic pricing which is a strategy often seen in airline and hotel management as a complement to the operational planning and slot allocation.

The remainder of the thesis is organized as follows: Chapter 2 reviews the related literature extensively and presents taxonomy on multimodal transportation's operational planning and revenue management. Chapter 3 describes the problem and proposes a dynamic pricing approach on top of the operational planning of a sea-rail multimodal freight transportation problem. The experimental studies comparing outcomes of different demand scenarios are provided in Chapter 4. Finally, Chapter 5 concludes the thesis with general remarks and directions for future research.

Chapter 2

Taxonomic Review of Literature

Freight transportation is the fundamental part of each modern supply chain since it undertakes moving raw materials, semi-finished and final products from origin source to destined customers. Multimodal freight transportation is the backbone of international freight trade and economic globalization. Transportation of freight from origin to destination by a sequence of at least two transportation modes, namely, multimodal transportation is established by several actors who are in interaction with each other, decision makers and operational conductors. This characterization makes the system multi-actor involved a complex system which needs a broad investigation and comprehensive operations management (Crainic et al, 2017). Shippers generate the demand, carriers provide the service, and related authorities establish the rules while operating several transportation infrastructures; each actor cares about their interests and overall gains of the system and decides on strategies accordingly (Ghiani et al., 2004). Careers, indeed, perform the transport service to meet the demand created by shippers and are responsible to arrange a sufficient number of vehicles needed (Crainic et al, 2017). While some carriers operate dedicated services to a single customer, most of them operate on the consolidation basis and they can own the vehicles or hire for need base customization. In addition to these stakeholders, freight forwarders play an important role in sea routes, acting as agents of shippers who are less popular to reach customers (Lu, 2013).

For the multimodal freight transportation where the combination of at least two modes of transportation is operated, an additional actor, classified as Multimodal Transport Providers (MTPs) are included into play. The latter are the companies that can offer multimodal transport operations within the framework of national and international trade and transport practices in the sector (Lu, 2013). In most cases, a shipper is a company that is responsible for initiating a shipment and who may also decide on the total freight cost. This type of member has control over the supply chain and is capable of stabilizing the financial part of improving their cost levels, service capabilities and environmental footprint (Cruijssen, 2012). However, shipper, who becomes the customer of MTPs, needs to decide on the MTP to conduct transport of their freight. Since carriers take the charge of providing services from origin to destination, shippers can select the MTP in a modal-free environment. This setting establishes gradually with the maritime container terminal operators developed into MTP (Ypsilantis and Zuidwijk, 2013).

The freight transport network consists of three essential components including pre-haulage, main-haulage, and end-haulage as illustrated in Figure 2.1. While pre-haulage and end-haulage are usually provided by road transport for short distances, the main-haulage is carried out by using other types of transport such as rail, sea, and inland water for longer distances. It is recognized that multimodal transport is competitive during main-haul transportation if the transported distances are beyond 300 km which is longer than one day of trucking (SteadieSeifi et al., 2014; Tavasszy and Van Meijeren, 2011). Rodrigues et al. (2016) claimed that the distances above 500 km (longer than one day of trucking) usually require intermodal transportation.

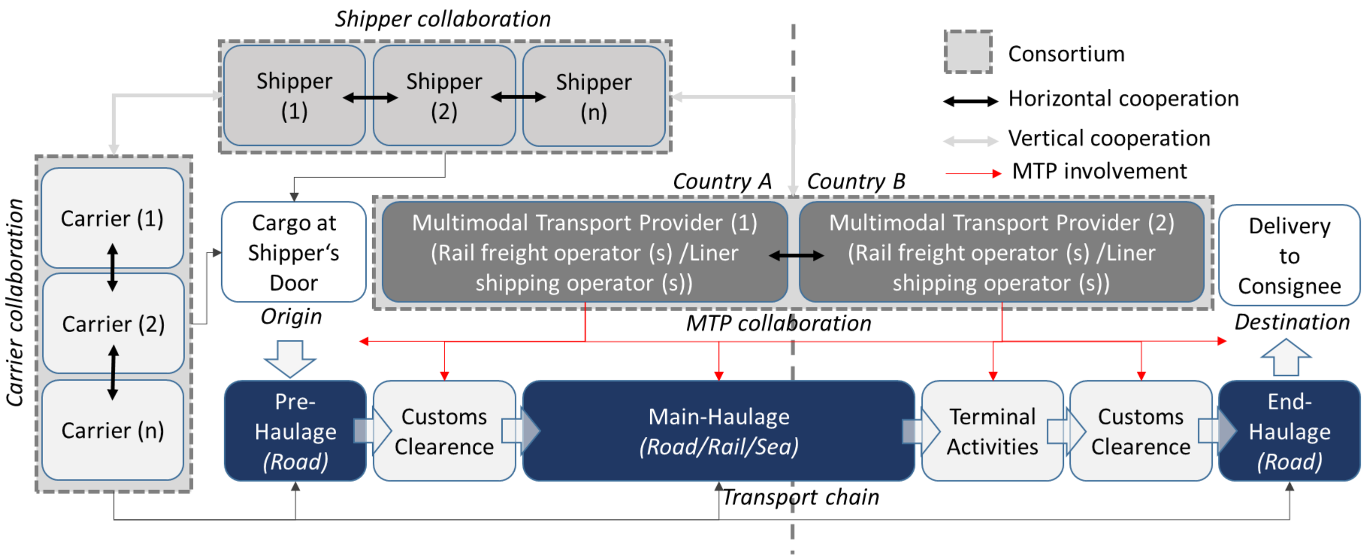

Figure 2.1: Multimodal Freight Transport Network, MTP Collaboration

Essentially, it depends on the geographic conditions of the aforementioned distance and governmental transportation policies. To illustrate, European countries limit the usage of road by big vehicles and trucks favoring rail usage in order to reduce their road depreciation and maintenance cost.

SteadieSeifi et al. (2014) described that multimodal transport is simply the transport of goods by at least two different means of transport such as various combinations of road, rail, sea, and air. The freights are generally transported by means of transport units: transportable containers, trailers, semi-trailers or freight carriers. Existing literature puts forward different definitions of the "usage of more than one mode of transport"; principally there is a consensus on 4 distinguished terms depending on the use of different transport networks in different circumstances over the years: multimodal, intermodal, co-modal, synchromodal. As a fifth term, Reis (2015) included combined transport, multimodal transport concept caring sustainability, after classification under four different domains: technological, organizational and managerial, production, externalities domains. The definitions are organized according to the nature of freight content, properties of modal shift, frequency, origin-destination terminals, and sequence of legs through entire trip which is perceived as a whole. The relation and the distinction of each concept clearly pinpointed in Figure 2.2 by Reis (2015), the original concept is multimodal and each new concept inherits properties of the original term and gains more complex structure.

Intermodal transport is another type of multimodal transportation during which the freight is carried from the starting point to the destination point as one and the same transport unit without handling it at any terminal (Crainic and Kim, 2007). To specify, a unitized good/sealed freight is carried from origin to destination without any processing or handling during ant transshipment period. Co-modal transportation is based on the efficient use of transport means. It is defined as the selection of the most effective and efficient combinations that can be useful for all types of transportation. Each stakeholder's profit is protected and all types of collaborations (horizontal, vertical) between the stakeholders are encouraged thanks to co-operated modal shift. Shapley value is a method generally used to assign fair profit allocation among the stakeholders (Dai and Chen, 2012).

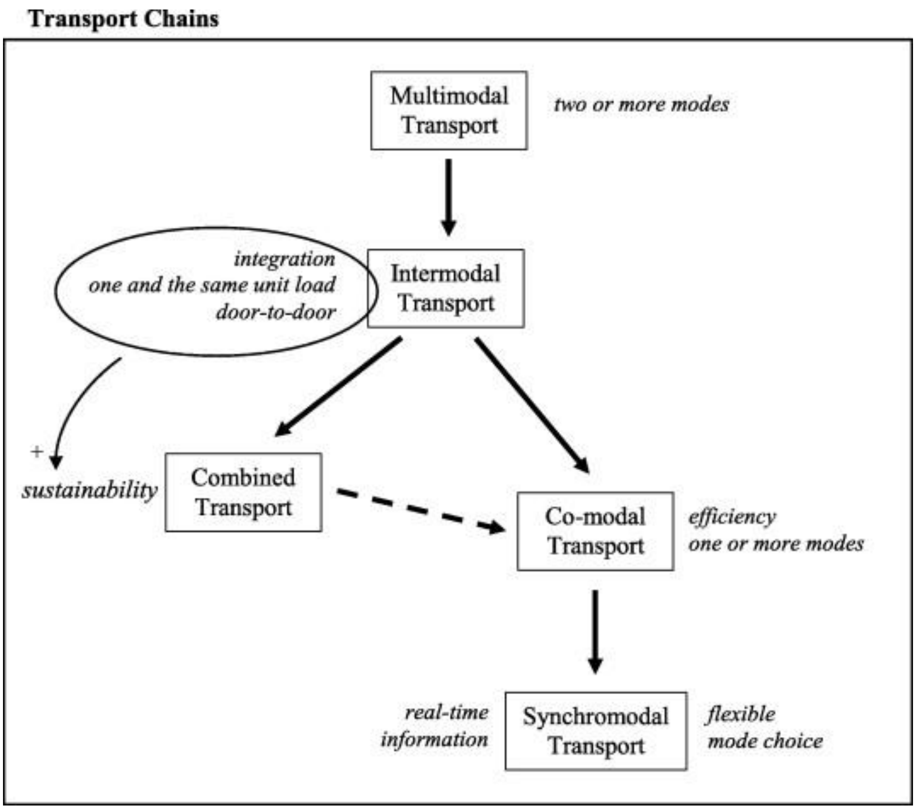

Figure 2.2: Difference in the terminology of "multimodal" in transport chains (Reis, 2015)

Synchromodal transportation is a freight transport chain in which all combined transport types are hybridized according to the choices of the customers, based on the efficiency and the conditions of the operation. This type of transportation is seen as a logical choice in terms of increasing efficiency and making loading capacity flexible and effective. Verweij (2011) defined it for the first time as the ability to switch liberally between different modes via only one consignment through whole flow. In addition to this, definitions on synchromodality accumulated on the idea of optimal operational alignment providing flexible, efficient, sustainable, and cost-effective transport. However, it is not widely preferred in business life since it is difficult to plan and implement, requires a long laborious process. In academia, research began to intensify during the last decade on this topic comprising synchronization of service schedules and operations amongst modes of transport, the main goal is to provide seamless operations decreasing delays and waiting time during transshipments which lead to a reduction in total cost. This seamless flow continuity and compatibility of transshipment nodes of the network are key elements while deciding on the transport mode together with customer's preferences, freight types and mode choices (Huang et al., 2011). Synchromodality has a role of adding more flexibility to the usage of different modes capturing demand variability and speeding up the terminal operations. To exemplify, train schedules especially Ro-La (as known as Rolling Highway) timetables are very strict and before the freight loading at the terminal, only one expert has a right to monitor visually each trailer and confirm their suitability to fast movement of Ro-La. Synchromodality can handle this situation by aligning the schedules and eliminating the number of expert monitoring.

Multimodal transportation management is a transportation network design and supply chain management which is composed of several sub-groups. These groups emphasized in the literature can be listed (Figure 2.3): Data, demand, cost and time management, modal shift, collaboration, sustainability, governmental policy-setting, operational planning and modeling, revenue management, and joint optimization of slot allocation and pricing strategies. A vast collection of scientific literature focuses on different objectives taking into account various limitations. Additionally, these enumerated groups are not separated strictly; they tend to cover each other for different objectives and applications. To illustrate, demand management is the core of multimodal transport management; subsequently, the core of other components.

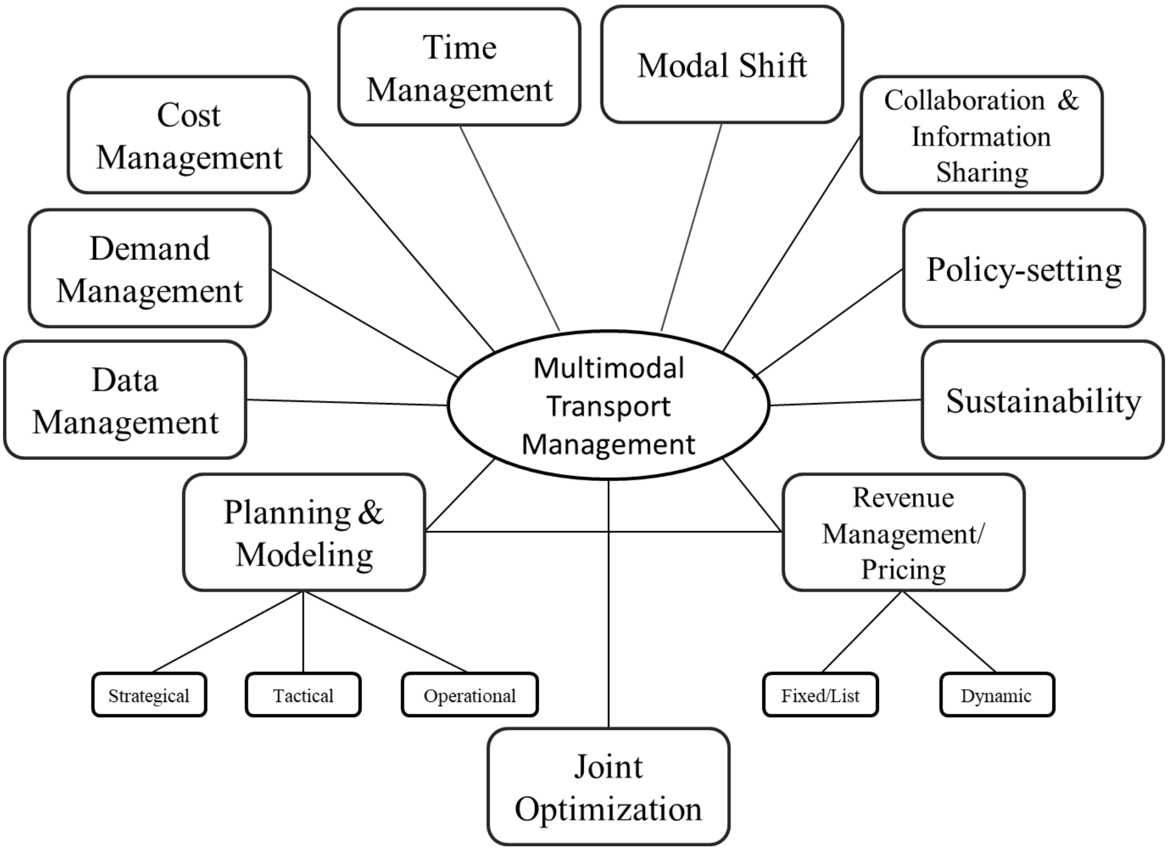

Figure 2.3: Components of Multimodal Transport Management

2.1 Demand Management

Demand management is the mainstream area of interest for each supply chain network, especially multimodal freight network in order to supply the demanded service. Demand management builds up the basis of all the other components. To illustrate, demand management appears in the literature with terms demand estimation, forecasting (Fite et al., 2002), impacts of demand changes, drivers/barriers of demand change and demand learning (Bertsimas and Perakis, 2006; Escobari, 2012; Lin, 2006).

2.2 Collaboration and Information Sharing

Main topics discussing impacts of collaboration and role of information sharing in the multimodal transport chain are profit sharing, cooperation, interest sharing, information sharing (Zuidwijk and Veenstra, 2015), profit allocation (Dai and Chen, 2012), consortium, horizontal and/or vertical collaboration (Mason et al., 2007), empty container transportation and value of sharing (Qui and Lam, 2018).

In the multimodal transport chain, cooperation can be established between carriers, shippers, and all MTPs. Different forms of collaboration, both vertical and horizontal are important to ensure the competitiveness of companies. The system where the operators and shippers work together is considered as the most suitable combination of these collaborations; however, it is also the most difficult system to establish and maintain despite being the most effective. The cost components of this system should be identified and the distribution of income should be arranged carefully; since it is necessary to consider revenue and cost allocations, risks, and involvement of each operator. Describing and measuring the performance of different stakeholders in the collaboration are one of the key points in allocating revenue. At the core of their partnership lies the fact that each shipping or transport company has to reduce or share their costs while they are satisfying the demands of the shippers (Ergun et al., 2007). These horizontal collaborations reduce costs and increase productivity. A good example is the replacement of empty container shipments with those that are filled in a coordinated manner, and the transfer of loads in rapid coordination instead of waiting for the storage and landfilling. For this purpose, multiple carriers can form an alliance gathering under an umbrella consortium by sharing demand requests and their vehicle capacities. This will be a win-win situation by increasing vehicle utilization and reducing empty backhauls (Dai and Chen, 2011).

Horizontal collaboration and vehicle co-loading will serve to reduce the number of operations resulted in carbon dioxide (CO2) emission reduction also. Qiu and Lam (2018) shed light on the value of sharing and gave managerial implications: Dry port profit improved with shared transport services, usage of large equipment ensured the cost savings for shippers. Nevertheless, they disproved the environmental benefits of the sharing, since the distance of large vehicle operated can be longer if the shippers are far from each other and heavy freight vehicles emit more harmful gases. In order to provide environmentally friendly shared transport service, performance measurements should consider the trade-off between CO2 savings and cost savings.

On the other hand, time to share information and mutual self-sacrifice is required to establish and maintain mutual trust and transparency among collaborative stakeholders (Caris et al., 2008). Motivators, facilitators, limitations, and different scenarios of information sharing and transportation-based collaboration are broadly examined by Gonzalez-Feliu and Morana (2011). They suggest that forming an efficient information system is the first step and the must of horizontal and vertical collaboration in the international freight transportation sector. Security and reliability can be kept under control by a special scoring system in the collaborated system (SteadieSeifi et al., 2017). Information is an indispensable element of sharing. Tools currently utilized to data exchange between stakeholders are Electronic Data Interchange (EDI) and system to trace freights is Radio Frequency Identification (RFID) (Gonzalez-Feliu and Morana, 2011). Use of information and information sharing between stakeholders may increase network utilization and performance by reducing uncertainties (Zuidwijk and Veenstra, 2015). Although, quantitative modeling on the value of information enables increase performance of transportation planning; quantitative studies on information through the multimodal network chain is scarce. Intelligent transportation systems such as demand learning, information sharing must be assessed in the planning model as a component. On the other hand, if there should be no disclosure of the confidential data between the providers, a coordination scheme can be elaborated without sharing the private information. Puettmann and Stadtler (2010) propose a quantitative collaborative method to study service coordination of independent providers.

2.3 Cost Management

Strategies of cost management coincide greatly with collaboration strategies. The expressions of cost management are generally cost minimization, cost calculation, actors and factors who affect cost components, cost sharing, cost-benefit analysis, external costs and monetary costs. Minimization of cost items is the primary objective of operational planning and routing at the multimodal service network.

Wang et al. (2015) claim that container freight shipping is the biggest part of maritime transportation by relying on UNCTAD reports. The operational cost of liner shipping has two components: fixed and variable cost. Fixed costs are indispensable expenses to operate the ship and crew. Variable costs are dependent costs: the amount of fuel consumption, terminal operations, loading, unloading, handling, type of freights, cargo characteristics and sudden disruptions. These properties can be applied to all kind of freight transportation transported by different means. Cost saving strategies allow MTPs to be more competitive in terms of providing cheaper price for the same quality transportation and reliability.

As a transportation network, multimodal transportation carries external costs associated with environmental and societal issues depending on the transport mode. For instance, Demir et al. (2015) classified these negativities in six groups including air pollution, greenhouse gasses and CO2 emissions, noise and water pollution, congestion, accidents, and land damages. They point out the importance of being aware of these negativities of each transport mode and inventing the model to measure the tradeoff between disadvantages and users' preferences. If they are not internalized as monetary values into cost calculations, they are measured and included as willingness-to-pay or selection among Pareto optimal solutions (Janic, 2007).

Globalization and improvement in the communication facilities have encouraged the multimodalism and the latter is recognized worldwide as an efficient way to reduce logistics cost exploiting different operational methods. To illustrate, the collaboration between the carriers and also between the MTPs is an important example of cost-saving approaches. Through collaboration, MTPs decide together on which shippers' reservations can be executed, postponed, or canceled by analyzing different slot allocation scenarios. If they accept the reservation of a shipper, they arrange all the necessary slots from both vessels and trains simultaneously on the main-haul.

2.4 Data Management

Data management is listed as a separate subgroup in order to emphasize the importance of data keeping, collection and validation, data sharing (Agamez-Arias and Moyano-Fuentes, 2017), machine learning and automatization. It is the core of the other components allowing accurate estimation and compatibility with real-life applications.

2.5 Time Management

Time management contains delays, terminal operations, fuel consumption calculations, disruption management (Huang et al. 2011), berth usage and scheduling. Time management is mostly correlated with cost management during operational planning.

One of the advantages of multimodality is gain of time due to bureaucratic documentation gathered at one hand. Instead of protecting their rights and giving service permission to transport providers of each mode separately, the documentation and responsibility are collected under MTP's control and customs paper works are simplified. This documentation of accepted freight is called a bill of lading, a term used generally for sea transport. It can be more ameliorated utilizing electronic documentation system; but, this requires a complex and thorough system which is known as blockchain technology. Implementation of blockchain will definitely decrease the cost of documentation on paper separately and waiting time for the documentation process and in-between coordination. Autonomous adaptation to changing and disruptions by adapting each leg of the system, in other words, self-organization of the network, is the aim of the future routing and supply chain management network (Rodrique et al., 2016).

2.6 Modal Shift Policy

The need for the modal shift was examined and discussed in the literature through various measurement methods and several solution methodologies were proposed for achieving competitive advantages against unimodal transportation. Mode change and the need for the modal shift is affected by demand, capacity, environmental concerns, governmental investments, and infrastructure, in other words, whole multimodal transport network relies on the feasibility of modal shift (Tavasszy and Van Meijeren, 2011). It is broadly studied inclining on best route selection (Frejinger et al., 2009), modal choice (Arencibia et al., 2015; Combes and Tavasszy, 2016; Shinghal and Fowkes, 2002), modal split (Ferrari, 2015), customer choice, decision support systems (DSS), technology integrated systems and intelligent transportation systems.

The modal shift focuses on evaluating multimodal transport policy measures and aims to raise awareness and consideration towards the change of transportation mode as a transport policy option. It also includes various collaboration settings throughout the freight flow from the origin to the final destination. Usual freight mode choice model is based on the estimation of the utility functions representing the values of each mode, leg, travel time and the transport providers' preferences. This classic model only satisfies a part of the reasoning behind the modal choice. To improve the aforesaid old model, Combes and Tavasszy (2016) proposed an approach on inventory theory including shipment size as decision criteria. Ferrari (2015) evaluated the system as a whole flow network, antecedent and precedent events of modal split forecasting its phases as stable and unstable as freight transport is a dynamic system with dynamic characteristics. Macharis et al. (2011) put forward the DSS involving three components:

a Geographic Information System (GIS), network planning and pricing part and lastly simulation model for performance measurement. Due to economies of scale, modal shift and multimodality have an impact on the reduction of total transport costs thanks to the usage of more efficient modes and intermodal operations. Especially freight rail can provide transportation service during long-haulage at a lower cost than road transportation by trucks (Rodrique et al., 2016). If the capacity utilization of ships and trains, in other words, the load factor is kept as high as possible, benefits of transport service will increase too in terms of cost reduction, time management, and reliability.

In multimodal freight transportation, uncertainties, and randomness always take place throughout the freight flow process. This complexity increases the importance of reliability, smart disruption management, and sustainability of the operation while determining the decision criteria (Huang et al., 2011). Ferrari (2015) concluded that dynamic parameters of the modal split of a multimodal freight transport system between origin and destination are gathered under three subtitles. These are the increase rate of overall freight flow, the delay, and the dynamic cost functions of different modes. Since the multimodal network is complex and dynamic, determining dynamic characteristics and modeling modal split is useful to forecast overall freight flow and to decide accordingly on the uncertainties of future time periods.

2.7 Sustainability

Sustainability, environmental concerns, reduction of CO2 emissions and greenhouse gases (GHG) mitigation are unseen criteria for selecting multimodality against unimodal road transportation. In order to be competitive in the transport sector, service providers should be more flexible favoring multimodal choices such as the combination of road, sea, rail, and air. At this point, the transport service provided should be preferable by shippers and also MTPs should arrange their services environmentally friendly. Rail is a green alternative in the transport sector and one of the efforts of European countries to reduce harmful gases emissions is increasing rail usage for freight and passenger transport (Armstrong et al., 2010). Increase in the usage of multimodal transportation can gradually improve the environmental benefits of freight transport, especially international freight transport (Dong et al., 2017). Flodén et al. (2017) gathered key factors contributing to the decision making processes such as cost, quality, reliability, transport time, and sustainability of the system and environment. In general, reduction of carbon dioxide (CO_2) emissions through the terminal network design and operations are the objectives of the governments and CO_2 pricing can be regulated accordingly as a part of the cost structure (Zhang et al., 2015).

2.8 Policy-setting

Governmental policy-setting is long-term planning of the multimodal transportation, that is to say, strategical planning. It includes schedule arranging, multimodal rule regulations, infrastructure works, and paperwork during operations ensuring the reliability of the service. Essentially policymakers and political authorities appreciate multimodality and modal shift as the favorable savior from the environmental problems and congestion caused by unimodal road transportation. Thus, they encourage related projects favoring modal shift strategies, to illustrate, European Commissions reports, OECD reports, Intergovernmental Panel on Climate Change and European Environment Agency Air Reports.

2.9 Operational Planning and Modeling

In the literature, the decision process to select most effective modes of transport and the establishment of collaborations are categorized into three sub-headings as strategic, tactical and operational planning (SteadieSeifi et al., 2014). Strategic planning defines broadly the operating strategy of the network chain, preparing physical network and expensive equipment to run the chain in the big picture. This network chain where the movements of freights and services of transport providers are conducted simultaneously is exerted at the international, national, and regional level (Crainic, 2007). Briefly, strategic issues are the decisions which affect the long-term process of multimodal transportation for instance customer classes, geographical localization, and collaboration. Tactical level planning arranges the available resource allocation to meet the demand involving medium-term decisions being vehicle scheduling and routing, fixed pricing strategies and equipment preparation (Li and Tayur, 2005). Operational level deals with short-term planning, urgent adjustments, real-time decisions involving dynamic pricing, revenue management and freight assignments (Ghiani et al., 2004; Li and Tayur, 2005). Various models and solution techniques are suggested to ameliorate operational planning, routing, service network design, and mode choice comprising several actors and influencing factors; including newly emerging areas such as synchromodality, machine learning, and technology-based DSS.

The operational planning basically consists of deciding on which freight to accept or reject for routing and planning the overall route to transport selected vessel, train and trucks. Freight mode choice is one of the most problematic issues while preferring the multimodal transportation. The main drivers of the decision-making process are cost, transit time, reliability, and frequency of the service. Frequency is usually preferred by manufactured good sectors while temporal reliability and security of the service are mostly preferred by automobile manufacturers and exporters (Shinghal and Fowkes, 2002; Cho et al., 2012). In addition to these, constraints related to the capacity of modes and nodes, pickup and delivery times should also be incorporated into the model and the associated data should be collected and gathered for taking the necessary actions. The selection of the non-dominated and applicable routes to construct multiple Pareto solutions pool is achieved via various mathematical models (Zuidwijk and Veenstra, 2015). The subsequent phase is determining the best route according to the user's preferences among the optimal alternatives.

The operational planning part contains practical planning techniques and case studies that deal with the implementation of multimodal transport at the operational level in order to assess the feasibility of a modal shift. Each mode of transportation has its own characteristics, limitations, similarities and differences, advantages and disadvantages. Planning each of them separately requires different techniques, but planning them together within a systemic framework coherently needs more complex techniques and models. Various operations research techniques are widely utilized in order to improve the design and operations of multimodal networks (Gorman et al., 2014). Furthermore, transport solutions have to be realizable, flexible, easy to apply, reliable, transparent, and efficient to cope with the preferences of different decision makers operating in the multimodal transport network (Caramia and Guerriero, 2009). The solution techniques for operational planning are mainly classified as direct solution methods using linear programming; stochastic solution methods using dynamic programming; heuristics; decision analysis models for mode choice, and other methods such as survey and simulations.

In general, minimizing cost and transport time are the two main objectives that service providers and researchers have looked after. In addition to these, awareness towards the environment, willingness to pay, and service quality are the additional objectives and constraints to satisfy. Multi-objectivity requires using a combination of several methods. The crucial point is to choose the appropriate model type(s) after the examination of the acquired information about the system. Deterministic models give fairly enough discrete values in order to use in planning but they do not cover the reality completely; so, some dynamic properties and randomness in the data require stochastic models. Besides these, probabilistic models are utilized to come up with estimations directly such as the mode choice and shipment size (De Jong et al., 2016).

2.10 Revenue Management and Pricing

Revenue management is the crucial part where multimodality becomes attractive for service providers; for MTPs mainly. It investigates pricing strategies, dynamic pricing approaches (Bertsimas and Perakis, 2006), capacity control (Gönsch, 2017), several models and solution techniques, pay attention to customer's willingness-to-pay (Chen et al., 2016; Wittman et al., 2016).

Traditionally, revenue management objective is to maximize revenues via capacity control assigning different, fixed/list price classes gradually; but recently, online booking systems allow frequent and spontaneous price deviations. Industries practice RM, in fact, to balance uncertain, stochastic demand and inflexible capacity. Classical approaches take care of only uncertain variables, demand, following a known distribution without risk component to maximize expected revenue (Gönsch, 2017). It is basically setting the right price at the right time to maximize revenue (Gallego et al., 2014). However, modern RM begins to focus on dynamic pricing thanks to strategically developed pricing policies which can keep the price under the level of maximum willingness-to-pay. Avlonitis and Indounas (2005) listed pricing objectives of a firm who provide the services as profit and sale maximization, capacity utilization, maintenance of the existing customers, discouragement of new competitors, fair pricing, and long-term sustainability of the firm. All of these express main goals of the service sectors such as insurance companies, transport providers, medical services and IT products. Furthermore, dynamic pricing methods are mostly practiced in industries such as hotels (Aydın and Birbil); airlines (Williams, 2017) where the capacity is fixed and slots/rooms are perishable in the short-term. To facilitate and improve the implementation of dynamic pricing approaches, systems require past demand data and decision-support tools to analyze available demand structure (Elmaghraby and Keskinocak, 2003). Ng et al. (2017) support this idea by dividing RM research into four modules: demand management, resource management, data analytics and data collection.

Wittman defines the willingness-to-pay information as private budget information about the passenger, different customer types and transport providers are not aware of the distributions of this dynamic component, willingness-to-pay. Different customer classes' willingness to pay is inherently heterogeneous; but, each of them is aware of that they receive the same service simultaneously sharing the common areas of the vehicle (Kostami et al., 2017). The providers should estimate willingness-to-pay budget for different customer classes and plan its dynamic availability accordingly. Customers usually are willing to pay more if they want to book slots closer to departure time. National MTP's representatives that we met to get information about the conduct of the multimodal freight industry also confirmed that the customers who need quick and urgent service are willing to pay more than normal slot prices. Willingness to pay (WTP) measures provide a quantitative measure of the monetary cost that a user would pay for improving the level of service in the attributes of transport alternatives.

One of the fixed pricing strategies to determine transport service prices is cost-plus-pricing strategy proposed by Li et al. (2015) as a strategy that accepts transport provider's operational costs and wages as a base and adds targeted profit margins. Koenig et al. (2010) compare list pricing to dynamic pricing and summarize that the dynamic pricing policy amends prices, again and again, resolving the underlying problem every determined time period, where the list pricing policy sets static prices from beginning only once but controls the capacity by allowing or preventing slot bookings. Also, it is confirmed this resolving the deterministic problem at each time step and making necessary updates and implementations give better results than sticking to the initial problem. The only trade-off between them is the cost of price change, if the costs exceed the profitability of dynamic pricing, the latter will not be preferable in the short term. For the long-term average profit, for example, without relying on seasonality but considering all-year long time period, costs of price changes lost its importance as a component in the cost calculation. Thus, these updates of prices transform dynamic pricing into capacity control problem.

A case of dynamic pricing approaches is setting price levels and the limited number of slots for each customer type. Similar approach is practiced for the airline pricing process for years by predefining complete set of several price options and related slot capacities for each fare (Cizaire et al., 2013; Yoon et al., 2017). The main two reasons for dynamicity in pricing listed by Zhao et al. (2000) are statistical fluctuations of demand and the revenue impact. Dynamic pricing strategies are widely studied and currently applied in the airline industry. Firms having fixed capacities of multiple types of products prefer also different dynamic pricing strategies to maximize total expected revenue over a finite time horizon (Maglaras and Meissner, 2006). Even though freight industry has some similarities with other industries applying dynamic pricing strategies and wants to imitate their planning and pricing approaches, the additional actors, factors, and constraints turn processes of multimodal freight transport management into complex and difficult to solve problems (Armstrong et al., 2010).

The capacity management during routing and scheduling is the crucial success factor for the sustainability of the multimodal transport, especially in sea-rail legs. The capacity of vessels and trains should be filled at least 70% per trip in order to maintain profitability (Kayikci, 2014). And we did not consider air transportation as one of the mode choices; because load units of sea and rail transports are different from air. At this point, revenue management and pricing strategies may help decision makers, principally MTPs; to increase their profit by augmenting the capacity utilization rate. So; the main goal is to find the maximum freight traveling along each possible leg in order to maximize the revenue by minimization of costs, allocation of slots, and dynamic pricing. It is demonstrated that the application of different fare and customer classes may help to achieve up to 2% increase in revenue per multimodal trip while the minimum capacity requirements are fulfilled. This application is required due to different arrival/booking times of shippers. Customer types can be divided into three reasonable clusters: the first group is contracted shippers who are loyal and subject to an annual fixed price, shippers who book their slots during the booking time form the second group and finally urgent customers whose demands may be supplied with a higher fare. Price discrimination may be applied to the different contents of containers or semi-trailers since hazardous and perishable products require additional equipment and care.

Capacity control problem put forward demand management decisions as the main uncertainty of revenue management and dynamic pricing approaches. Talluri and van Ryzin (2004) classify the RM into two subgroups after reviewing the concept comprehensively: price varying in time, dynamic pricing and capacity allocation according to customer classes, capacity management. Demand function is mostly unknown in practice for the providers; but studies estimate the available demand and its fluctuations in order to elaborate on further (Gallego et al., 2012). The successful approach of dynamic pricing depends on accurate demand forecasting (Lin, 2006). At this point, the term ‘demand learning' is a newly emerging technique in the literature and deals with uncertainties about customer behaviors, natural unpredictable factors, distribution of arrival rate and reservation prices. Ting and Tzeng (2004) summarize the major problems of the liner shipping industry as a vicious circle in cost reduction competition, wrong pricing strategy, and empty container repositions. The providers always try to increase space to increase the quantity of freight carried by providing additional capacity and cutting costs to compete by reducing freight rates; however, this can lead them to suffer from low rates, unutilized capacity because of uncertain demand, fuzzy brand recognition, weak loyalty, and expensive equipment during disruptions. Hence, providing smart pricing strategies will allow providers to plan the operations ahead and guarantee revenue while the demand is weak. In the big picture, the multimodal transport providers will stay in the industry since they will have an attractive revenue share in order to sustain their transport management.

2.11 Joint Optimization of Operations and Revenue Management

Since pricing and slot allocation problems highly correlated in revenue management studies, these two problems ought to be handled jointly (Ypsilantis and Zuidwijk, 2013). There is extensive research on the planning of multimodal transportation at each level: strategical, tactical and operational. Besides the planning part, revenue management and pricing of multimodal transportation is also emphasized in the literature. Agamez-Arias and Moyano-Fuentes (2017) claimed that optimization of multimodal systems rotates around the trade-off between minimization cost and time and maximizing users' profit. The term of "user" depends on the perspective of problem setting; however, problem objectives are the same and they should be handled jointly. Despite the fact that researchers generally considered these two problems separately, slot allocation and pricing are interrelated; so, the need is joint optimization of pricing and operational planning –slot allocation- in the multimodality sector (Moon et al., 2017; Williams, 2017; Zhao et al., 2017). Thus, hybrid solution strategies and holistic approaches which are developed to deal with planning, technological changes, information sharing, dynamic pricing, and even governmental issues all together. For this reason, our study inclined to dynamic pricing approach together with slot allocation on a rolling horizon basis. Normally, dynamic pricing influences demand by price adaptations over time (Gönsch, 2017).

In our study, strategical and tactical levels are already prepared for service, type of commodities to carry and origin-destination points are determined via sea routes and rail lines. Their schedules and frequencies are known and capacities are organized to be allocated to customers. Terminal operations' equipment, regulations, labor quantity and terminal area for repositioning are also agreed previously for each terminal. Strategic planning approaches and models are widely available in the literature. Price of fully loaded shipment from origin to destination is recognized; but the demand is stochastic and at the operational level, an MTP needs dynamic slot allocation of its available vehicles (train, vessel) without knowing the demand and fulfillment rate at the end. Using strategies such as dynamic pricing according to booking time and customer type to maximize the fill rate and revenue, MTP should decide on acceptance or rejection of each good to carry and allocate its available and determined resources. Another option would be hiring contracted vehicles, conducting consolidation-based transportation in order to meet the demand at hand in a rolling horizon basis. At the current freight transportation system in Turkey, strategic planning part has already missing phases such as data collection and preparation, demand management, and performance control. Hence, the operational planning level becomes more challenging and demanding while modeling the optimization on the network representation of the transportation system.

Since multimodal transportation is essentially a supply chain where the urgency, the uncertainty and the complexity run in the whole process; coordination and rapid gathering of information between stakeholders enhance the logistics and supply chain management of international freights. To shed light on the multimodal freight network management, this literature review is conducted using a desktop research methodology; i.e. our study reviews articles related to multimodal transport management published in major academic journals and conference papers addressing multimodal transportation.

Published papers are collected from 2000 to 2018. Few papers published before 2000 are excluded from this study since they have already been referred to in the recent literature and our primary objective is to shed light on the recent developments on the topic.

Firstly, a keyword search in major digital academic journal databases including ScienceDirect, INFORMS, Emerald Insight, Wiley Online Library, Taylor & Francis Online and Springer has been performed. The principal keywords utilized are “multimodal transportation”, “multimodal collaboration”, “multimodal transport provider”, “planning multimodal transportation”, “revenue management”, “yield management” and “dynamic pricing”. Furthermore, the reference lists of selected articles have also been carefully exploited in order to form a large database of articles. In consequence, this comprehensive subject is widely studied in the literature, and a total of 293 articles were gathered, classified and schematized in Figure 3. Hence, following taxonomic review of literature is emerged showing problem contents and solution methods used for operational planning and/or revenue management of multimodal transportation. Each model has its own set of assumptions and definitions in terms of objective(s) and constraints. We scrutinized the articles carefully and selected 20 articles which are leading and compact researches summarizing the studies in the area of multimodal transportation management in general (Table 2.1). There are many valuable articles that we could not include in this taxonomic table.

There are articles that present taxonomy of the related literature of various research areas. While building this taxonomy we benefit from discussions of Agamez-Arias and Moyano-Fuentes (2017), Başar et al. (2011) and Crainic at al. (2017). Taxonomy reveals the studies on operational planning and slot allocation in the multimodal transport network, revenue management and pricing multimodal transportation, and joint optimization of both operational planning and revenue management. This taxonomy presents the settings of the model such as objective function(s), parameters, decision variable(s) and constraints together with the type of model and solution.

Taxonomy:

A. Operational Planning of Multimodal Freight Transport ✗

B. Revenue Management ✔

C. Joint Optimization ✗✔

1. Modeling
    1.1. Objective Function
        1.1.1. Number of Objective(s)
            1.1.1.1. Single
            1.1.1.2. Multiple
        1.1.2. Content of Objective(s)
            1.1.2.1. Cost
            1.1.2.2. CO2 Emission
            1.1.2.3. Time
            1.1.2.4. Revenue
            1.1.2.5. Price
                1.1.2.5.1. Fixed Price
                1.1.2.5.2. Dynamic Price
            1.1.2.6. Mode Choice/ Operator Choice
    1.2. Parameter(s)
        1.2.1. Demand
        1.2.2. Time/ Distance
        1.2.3. Capacity/Slot
        1.2.4. Cost
        1.2.5. Reliability
        1.2.6. Price
            1.2.6.1. Fixed Price
            1.2.6.2. Dynamic Price
        1.2.7. Frequency
        1.2.8. Mode Choice/ Customer Choice/ Ratio
        1.2.9. Commodity/ Freight Type
        1.2.10. CO2 Emissions/ Environmental Concerns
    1.3. Decision Variable(s)
        1.3.1. Binary/ 0-1 Integer

1.3.2. Integer

1.3.3. Continuous

1.3.4. Slot Allocation Variables/ Flow

1.3.5. Mode Choice

1.3.6. Price

1.3.6.1. Fixed Price

1.3.6.2. Dynamic Price

1.3.7. Demand

1.3.8. Time/ Waiting Time

1.3.9. Terminal Operations/ Holding Amount

1.4. Constraint(s)

1.4.1. Capacity

1.4.2. Capacity Utilization Rate/ Load Factor

1.4.3. Demand/ Flow Balance

1.4.4. Price (Upper-Lower Bound)

1.4.5. Speed (Upper-Lower Bound)

1.4.6. Time/ Distance (Upper-Lower Bound)

1.4.7. Modal Shift

2. Types of Model

2.1. Linear Programming

2.2. Integer Programming

2.3. Mixed Integer Programming

2.4. Dynamic Programming

2.5. Non-linear Programming

2.6. Chance Constrained/ Two-Stage/ Stochastic Programming

2.7. Probabilistic Programming

2.8. Fuzzy Programming

2.9. Goal Programming

3. Type of Solution

3.1. Optimal

3.2. Pareto Optimal Alternative(s)

3.3. Heuristic

3.4. Metaheuristic

3.5. Simulation/Survey/Others

Table 2.1: Taxonomy of Operational Planning and Revenue Management in Multimodal Transportation

A : ✗ --- B : ✔ --- C: ✗✔	1.1.1.1	1.1.1.2	1.1.2.1	1.1.2.2	1.1.2.3	1.1.2.4	1.1.2.5.1	1.1.2.5.2	1.1.2.6	1.2.1
Verga (2018)	✗		✗							✗
Sun and Lang (2013)		✗	✗		✗					✗
Wang and Meng (2017)	✗		✗							✗
Bhattacharya et al. (2013)	✗		✗							
Zhang and Pel (2016)		✗	✗	✗						✗
Cho et al. (2010)	✗		✗							✗
Kalinina et al. (2013)		✗	✗	✗	✗					✗
Yamada et al. (2009)	✗		✗				✗			✗
Goel (2010)	✗		✗							
Behdani et al. (2016)	✗		✗		✗					✗
Baykasoğlu and Subulan (2016)		✗	✗	✗	✗					✗
Bouchery and Fransoo (2015)		✗	✗	✗						✗
Dong et al. (2018)	✗		✗	✗					✗	✗
Lee et al. (2007)	✔					✔				✔
Wang et al. (2015)	✔		✔			✔				✔
Li et al. (2015)	✔		✔		✔					✔
Reis (2018)	✔								✔	
Lui and Yang (2015)	✗✔							✗✔		✗✔
Parthibaraj et al. (2016)	✗✔		✗✔					✗✔		✗✔
Ypsilantis and Zuidwijk (2013)	✗✔		✗✔			✗✔	✗✔	✗✔		✗✔

1.2.2	✗	✗			✗	✗	✗	✗		✗		✗	✗		✔	✔				✗ ✔
1.2.3			✗	✗	✗	✗	✗	✗	✗	✗	✗			✔	✔	✔		✗ ✔		
1.2.4	✗	✗		✗		✗	✗			✗	✗	✗	✗		✔	✔			✗ ✔	
1.2.5																	✔			
1.2.6.1								✗								✔	✔			✗ ✔
1.2.6.2																		✗ ✔	✗ ✔	✗ ✔
1.2.7										✗					✔					✗ ✔
1.2.8		✗			✗			✗		✗	✗		✗	✔		✔				
1.2.9				✗	✗	✗	✗									✔				
1.2.10					✗		✗				✗	✗	✗							
1.3.1		✗	✗	✗	✗	✗	✗			✗	✗			✔	✔					✗ ✔
1.3.2	✗	✗	✗	✗				✗	✗	✗	✗		✗	✔	✔	✔		✗ ✔	✗ ✔	✗ ✔
1.3.3										✗	✗	✗						✗ ✔		

1.3.4	✗	✗	✗	✗				✗		✗	✗			✓	✓			✗ ✓	✗ ✓	✗ ✓
1.3.5													✗				✓			
1.3.6.1																	✓			
1.3.6.2																		✗ ✓		✗ ✓
1.3.7																✓				
1.3.8											✗									
1.3.9				✗									✗							
1.4.1	✗	✗		✗	✗	✗	✗		✗	✗	✗	✗		✓	✓	✓		✗ ✓	✗ ✓	✗ ✓
1.4.2				✗			✗				✗		✗	✓			✓			
1.4.3	✗		✗		✗	✗	✗		✗	✗	✗		✗	✓	✓	✓			✗ ✓	✗ ✓
1.4.4																✓	✓	✗ ✓	✗ ✓	
1.4.5															✓					
1.4.6	✗				✗		✗			✗	✗	✗	✗		✓	✓				✗ ✓
1.4.7	✗											✗	✗			✓				

2.1								✗	✗							✔			✗ ✔	
2.2					✗		✗											✗ ✔		
2.3		✗		✗						✗	✗			✔	✔					✗ ✔
2.4						✗														
2.5			✗												✔					
2.6								✗										✗ ✔		
2.7				✗																
2.8	✗										✗						✔			
2.9		✗									✗									
3.1			✗	✗						✗			✗		✔	✔		✗ ✔		✗ ✔
3.2		✗				✗	✗					✗								
3.3			✗		✗			✗	✗		✗	✗	✗				✔		✗ ✔	✗ ✔
3.4	✗													✔						
3.5							✗				✗		✗							

This taxonomy represents the distribution of the studies between operational planning and revenue management as a miniature sample of the whole literature of multimodal transportation. It is notable that revenue management part of the studies takes a small space; dynamic pricing approaches are even scarcer in the literature. However, problem settings are almost the same as the additional price related parameters, objectives, and constraints. Generally used objectives are cost and time management; pricing problems add one more dimension to the existing problem settings only. Parameters of demand, time, capacity, and cost are generally included in the model; but, these are differently calculated or extracted from the sector in each study according to nature of the problem and network. Flow balance and capacity constraints are the constraints inevitable for both types of problems. Problems are mostly formulated as Mixed Integer Programming models and they are solved directly to optimality or mostly with various heuristics: agent-based, search-based, schedule-based, simulation-based, and sampling-based. Our study, using basic settings of the slot allocation problem which is already widely studied, aims to enhance the existing literature by adding a new and easy to implement dynamic pricing approach.

Since there are various transport chain properties, similarities and differences in the terminology, the usage of terms may change from country to country in the literature. Herewith, we decided to use only the original term "multimodal", even if we include sustainability, competitive strategies to reach a synchronized transportation system. Our research requires more supplies including governmental policies and ensured infrastructure to be optimized in an orchestrated manner to be denominated as "synchromodal" transport. Besides these, we elaborate on this multimodal transport chain from multimodal transport providers' point of view; that is to say, from the transportation perspective. Shippers' point of view is the concern of supply chain management which allows broader perspective on the shipper-based synchromodal transport chain. This is proposed by Dong et al. (2017) as a new concept which is called synchromodality from a supply chain perspective (SSCP). If shippers prefer relying on the MTPs' choice, it means they are undertaking a modal free consignment. Gorris et al. (2011) note that transport providers who are MTPs apply the horizontal integration of different mode choices and arrange the internal freight flow processes according to their benefits. They can buy required transport means or affreight, use on a contracted base without referring shippers. Also, the shippers only decide on the MTPs, not the modes or the legs of network, their goods are carried according to scheduled service and agreed prices. Selection of operation route is done by only MTPs. In sum, our study contributes to this wide research area as an operational planning model on a time-space network from the MTPs perspective and promotes multimodality proposing a dynamic pricing strategy instead of classical fixed price per slot.

Chapter 3

Dynamic Pricing and Slot Allocation Methodology

3.1 Problem Description

Revenue management and pricing together with slot allocation targets to determine the optimal quantity of freight transported from origin to destination, on each leg, to maximize the total revenue. This goal can be accomplished by various strategies: minimizing cost, arranging infrastructure and schedules, increasing price, and promoting the reliable services. In our study, a revenue-driven dynamic pricing approach from the MTPs perspective is proposed with the aim of encouraging continuity of multimodal transportation. Because multimodality has many advantages through right conditions and planning strategies comparing to unimodal road transportation: more flexible, more efficient and effective, sustainable choice, less CO2 emissions, less monetary cost, less external cost, less total cost, less transport time, less documentation time, less congestion on roads, and less accidents. Determination of these right conditions and strategies take time and effort, but, once established, multimodal transportation pays back to MTPs who are operating the system and customers who are getting a seamless transport service at a price rate lower than road transportation by truck. At this point, our proposed approach of dynamic pricing plays an important role in encouraging MTPs to widen their operation network and continue to their service or encouraging shippers to become an MTP. Because our approach plays with the price offered to customers keeping it between the limits of base price and trucking price.

3.2 Dynamic Pricing Formulation

Using linear algebra notation, a multiple linear regression model with k predictor variables x_1, x_2, x_3 … x_k and a response Y , can be written as

$$\mathbf{Y} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1} * x_1 + \boldsymbol{\beta_2} * x_2 + \boldsymbol{\beta_3} * x_3 + \cdots + \boldsymbol{\beta_k} * x_k + \boldsymbol{\varepsilon}$$

ε being the residual terms of the model, namely, error terms showing model deviations. Regression residuals generally have a normal distribution with mean 0 and variance σ^2. As a predictive analysis, a multiple linear regression model is used to explain the relationship between one continuous dependent variable (response) and two or more independent variables (predictor). A linear relationship is assumed between the dependent variable and the independent variables. Since we have not enough and related data to realize this regression and discover model parameters by conducting performance measurements, we decided to use only this dynamic pricing equation, determine independent variables which affect price changes and then estimated the parameters in order to increase the revenue without exceeding willingness-to-pay of the customers. Since the dynamic pricing is not applied in the current multimodal transportation industry, the related past data cannot be collected and be utilized for regression analysis. However, we have benefited from this multilinear regression equation using it as a dynamic pricing equation by defining variables and estimating the parameters applying scenario based calculations.

Extensive research of the related literature and website of current MTPs in addition to conversations with national MTPs (UNRORO, Ekol Logistics, and Arkas Logistics) supported to determine independent variables influencing slot prices. These declared variables are vehicle's capacity utilization rate at the moment of demand arrival, the day of the booking period with T=10 being the first day of the period and T=1 being the last day, number of demand arrived at the moment and marginal cost of the current demand calculated by the operational planning model (Section 3.2.3). The dynamic pricing equation becomes:

$$\boldsymbol{Price_i} = \boldsymbol{\alpha_i} + \boldsymbol{\beta_{1,i}} * FillRate_i + \boldsymbol{\beta_{2,i}} * BookingDay_i + \boldsymbol{\beta_{3,i}} * DemandQuantity_i + \boldsymbol{\beta_{4,i}} * MarginalCost_i$$

The subscript i refers to the i^{th} demand arrived in the rolling horizon for a vessel. The vessel type is Ro-Ro in this case, it stands for "Roll-on, Roll-off" which takes mostly wheeled vehicles. Since the vessel is the biggest and first vehicle in our determined network, departure point coincides with the vessel's departure point in the system. It is interpreted that each β_i coefficient represents the change in the mean response, price, per unit increase in the associated predictor variable when all the other predictors are kept constant. To illustrate, β_1 represents the change in the mean response, price, per unit increase (decrease if β_i is negative) in $FillRate$ while holding other variables $BookingDay$, $DemandQuantity$, and $MarginalCost$ constant. The intercept term β_0 denotes the mean $Price$ while other predictors kept unchanged.

To apply this approach, it is necessary to determine meaningful model parameters α and β_k of the price function. It would be very straightforward to calculate the parameters after pre-processing of the related data if there is a related database keeping the available past data. Since this dynamic pricing approach is new for the transportation service provided by MTPs on the determined network, because of the lack of data, we were required to elaborate on the model parameters by trying different scenarios and parameters and select the best which will serve our revenue maximization goal respecting possible ranges. For this reason, after several initial trials and tests concerning the industrial attitudes and literature outcomes, we come up with the aforementioned parameters.

- $FillRate$ notes the capacity utilization rate and it changes from 0 to 1. A vessel (240 slots) has to be filled at least 70% in order to be profitable. By the courtesy of economic rules in the market, price increases as the inventory decreases; so, β_1 should be a positive number.

- $BookingDay$ denotes the sequence of the day when the demand arrived in the booking period. In the sector, it is known that the willingness-to-pay of customers is higher when the departure time is close. However, price can decrease with time for the same inventory level due to resource perishability effect. Hence, β_2 is not straightforward to assign directly, it might depend on the arrival day and fill rate.

- $DemandQuantity$ indicates the total number of slot demand arrived together. Since multiple slot purchases should be encouraged, β_3 should be negative.

- $MarginalCost$ signifies marginal cost per slot calculated via operational planning model of a sea-rail multimodal freight transportation problem configured on a time-space diagram, formulated as a linear network flow model.

3.2.1 Sea-Rail Multimodal Freight Transportation Problem Network Settings

Our network flow problem, also, we can say slot allocation problem is formulated on a directed graph G= (V, A). Vertex set V stands for the set of facilities for each mode such as terminals, dry-ports, freight villages, hubs. And arcs in the set A show the possible flow links, connecting routes between these facilities. These vertices represent origins (O), destinations (D), and transshipment (S) points in the network chain. In our designated network (Figure 3.1) the origin is Istanbul where the vessel begins shipping the freights. Destinations to where demands are assigned are Hamburg, Duisburg, and Rotterdam. Transshipment points are Trieste, Salzburg, and Ludwigshafen together with Duisburg when it is needed to direct the flow in order to meet the demand of destination points Rotterdam and Hamburg. This network is a sample of real multimodal freight network currently utilized by national MTPs. While freights are generally containers, semi-trailers, and trailers, we assume that all the commodities are carried with semi-trailers and capacities are determined accordingly. Each arc defined together with its assigned cost and capacity. The cost paid by an MTP for transporting a shipment is straightforward since the operational costs such as wages, fuel, vehicle, sustaining the operation, insurance, and land occupancy depends on time and distance. Other factor related to collaboration, hiring a vehicle, using a public carrier, consolidation, and handling costs have an impact to influence the cost on a large scale. Cost calculation and allocation is a major research subject in itself; because of this reason, we assigned costs proportional to the distances between OD pairs and relying on the website of currently operating companies. Terminal operations cost together with delay/waiting time costs during these operations are assigned to waiting arcs according to the real costs of chosen terminals. Cost function normally embodies external cost like congestion, air pollution, CO2 emission, noise, accidents and land use besides monetary costs. However, since we exclude road transportation, maritime and rail routes add less external costs comparing to road usage, we find considering only monetary costs is sufficiently enough to construct network flow considering only repositioning during transport service and waiting time costs at the transshipment points.

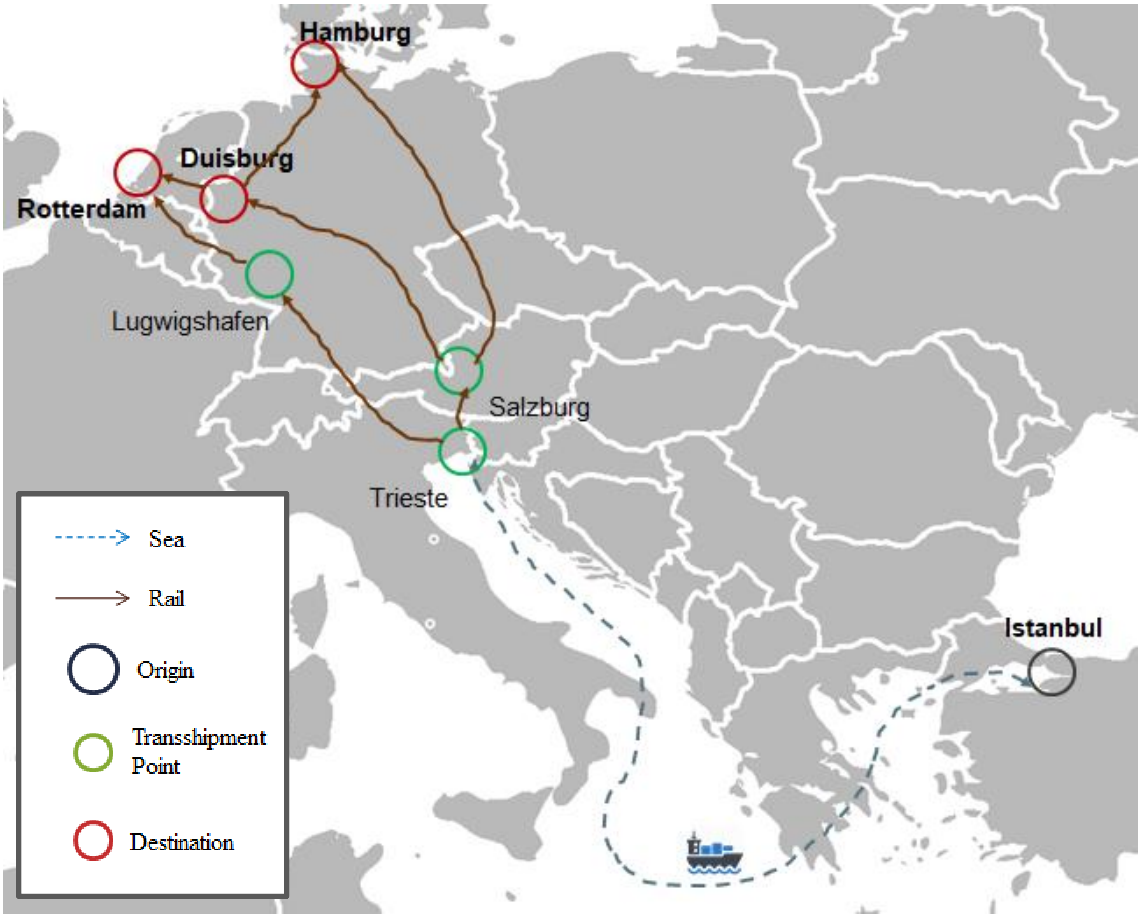

Figure 3.1: Designated Multimodal Transport Network

We put a space-time diagram into use as we need a time dimension to show travel time of vehicles and penalize waiting times at the terminals over a given planning horizon through this time-space network, in order words, a time-expanded directed graph. Yang and Meng (1998) used the abbreviation of STEN which stands for space-time expanded network representing time-varying traffic flow. Yang and Meng's (1998) statement of dynamic pricing in general networks supports our study's aim since this type of network is required to emphasize the dynamicity in the network. Ghiani et al. (2004) defined the horizon in a time-expanded directed graph with two dimensions: one dimension is time with many periods (hours, quarter days, days, and weeks) and the other one is the physical network, the static representation of physical network is replicated in each determined time period. When transportation schedules are designed and if goods have a due date to be sent before, a time dimension must be explicitly identified in the formulation. This is easily realized by using a space-time network. Temporal arcs, in other words, waiting arcs are the connections that link two nodes of the same terminal at two different time periods representing the terminal operations, waiting time at the transshipment node or delay. Service arcs, namely, operation links are the connections that link two nodes of different terminals together with two different time periods as much as transport time between those two terminals. Costs related to each arc determined by terminal operations costs, waiting costs or transportation cost relying on the distance and the mode (Crainic, 2007).

Generally, time-dependent service network design problems have two types of decision variables inherently. One of them is integer design variable which is 1 if there is a service on that arc and 0 otherwise. The second one is continuous variable standing for representation of the related freight flow on that arc. In the service network, distribution of flows –if there is any- can be observable through these continuous decision variables. Our formulation does not contain integer design variable for the sake of simplicity since most of the arcs should be utilized in order to meet the shippers' demand, the cost of each arc will allow the flow transmission between the arcs explicitly.

3.2.2 Assumptions and Limitations

- Cancellations, no-shows, and overbooking are not considered.

- A request for booking of multiple slots is either satisfied or denied it entirely.
- Whenever a request arrives, a decision about its acceptance has to be made by customer and service provider directly.
- Vehicle capacities are fixed and reordering is not possible since they are accepted as perishable inventories.
- Type of freight is only semi-trailer.

Type of freight is only semi-trailer. Normally, containers also can be carried by Ro-Ro and Ro-La; but, in the Ro-Ro, containers can be stacked on top of other containers. Whereas one slot can be sold up to five containers instead of one semi-trailer, containers need extra equipment while loading and unloading at the terminal and require extra time and effort for leashing and unleashing to stabilize in the Ro-Ro. Furthermore, containers are available in different capacities and dimensions: 1 twenty-foot equilibrium unit (1 TEU), 1 forty-foot equilibrium unit (1 FEU), shown as 20’, 40’, 45’, 48’, 53’, ISO etc. With the simple modeling, it is difficult to include the effect of size diversities, because of this; we assume freights in unique shape and size, as semi-trailers that are ready to occupy only one slot in the Ro-Ro and Ro-La having fixed capacity. This size problem of diversities can be further modeled by counting capacity as volume and weight and freight size relying on several modes of transportation. Besides the lack of size unity, several sections of the ship can be used by diverse type and number of freights. To illustrate, one slot of a train can be loaded by two container double-stacked and upper deck of a ship can be utilized to put hazardous material filled containers/semi-trailers, cold cargoes, multiple-stacked containers favoring reachability by cranes.

3.2.3 Formulation

This section presents the formulation of the multimodal network flow problem as single-objective linear programming model on a time-space network. Each node in the physical base network is represented by the number of mode type at each time period of the planning horizon. The simple formulation of the sea-rail multimodal freight transportation problem as a linear network flow model follows:

Parameters

$\boldsymbol{i}$ Origin index

$\boldsymbol{j}$ Destination index

$\boldsymbol{t}$ Current time index

$\boldsymbol{\tau_{i,j}}$ Lead time (service or waiting) index of each arc from i to j

$\boldsymbol{T}$ Booking day of reservation period with customer types:

$\boldsymbol{T}$ **=** 11 (dummy day) is for contracted customers

$\boldsymbol{T}$ **=** 10, 9, 8, 7, 6, 5, 4, 3, 2 days for normal booking period customers

$\boldsymbol{T}$ **=** 1 is for last minute demand arrivals, urgent customers

$\boldsymbol{Q^v}$ Vessel capacity

$\boldsymbol{Q^t_{i,j}}$ Train capacity at time t from i to j

$\boldsymbol{D_{j,T,d}}$ Demand of customers/shippers

$\boldsymbol{c_{i,j,t}}$ Cost of each arc at time t from i to j relying on waiting times or distances

Decision Variables

$\boldsymbol{X_{i,j,t}}$ Number of slots allocated (flow assigned) at time t from i to j according to demand and capacity

Objective Function

Minimize $\sum_i \sum_j \sum_t \sum_\tau (\boldsymbol{X_{i,j,t}} * \boldsymbol{c_{i,j,t}})$

Constraints

Capacity constraints:

$\boldsymbol{X^t_{1,2}} \leq \boldsymbol{Q^v}$ $\forall$ t **(1)**

$\boldsymbol{X^t_{i,j}} \leq \boldsymbol{Q^t_{i,j}}$ $\forall$ i≠1; $\forall$ j≠2; $\forall$ t **(2)**

Flow balance constraints:

$$\sum_i \boldsymbol{X}_{i,j}^{t-\tau_{i,j}} - \sum_j \boldsymbol{X}_{j,i}^{t} = \mathbf{0} \qquad \forall\, i \in \mathbf{S};\ \forall\, j \in \mathbf{S},\ \forall\, t \qquad \mathbf{(3)}$$

$$\sum_i \boldsymbol{X}_{i,j}^{t-\tau_{i,j}} - \sum_j \boldsymbol{X}_{j,i}^{t} = \sum_{T,d} \boldsymbol{D}_{j,T,d}; \qquad \text{for } j \in \mathbf{D} \text{ and } \forall\, t \qquad \mathbf{(4)}$$

$$\boldsymbol{X}_{1,2}^{t} = \sum_{j,T,d} \boldsymbol{D}_{j,T,d}\,; \qquad \text{for } t=0 \qquad \mathbf{(5)}$$

$$\boldsymbol{X}_{i,j,t} \geq \mathbf{0} \qquad \forall\, i;\ \forall\, j;\ \forall\, t \qquad \mathbf{(6)}$$

The marginal cost calculation per slot is conducted with this formulation which aims at minimizing the cost and assigns the freight flows on each arc accordingly. Constraints 1 and 2 limit the capacity according to vehicle type. Actual capacity of an arc depends on the daily frequency of the vehicle on that leg; however, since we developed the space-time diagram, there is no need to insert frequency parameter to the formulation. Constraints 3, 4, and 5 are the famous constraints of flow balance which are indispensable for this kind of network flow problems. Integrality constraint is not required since all the parameters and limitations are integer, the decision variables result in directly integer values. Fourer et al. (1993) defend that many solvers result in integer solutions if the bounds are integral, explains this concept by the use of integer bounds and integral data in the model.

Chapter 4

Experimental Studies

Pricing part consists of four components: time (remaining days before departure/day of booking), capacity (remaining slot/fill rate), the quantity of demand (slot), and marginal cost obtained from operational planning part. Pricing rules are set according to previous studies on airline industry and meeting notes from national multimodal transport providers. Firstly intuitive then proved with appropriate case studies, Escobari (2012) argues that the price increases as the inventory decreases and price decreases as there is less time to sell. Furthermore, Pang et al. (2014) demonstrated that a lower inventory level yields a higher optimal bid price at any time; it means customers' willingness-to-pay increases as the remaining number of slots decreases. This is referred as the resource scarcity effect. Moreover, the optimal bid price decrease with time for the same inventory level because of resource perishability effect. This proves that the last slots can be given at a lower price if departure time is really close because slots are perishable inventories without salvage value after departure. If the time for departure approaches and there are a lot of empty slots, providers can consider decreasing the price or inversely increasing the price dramatically in order to close the profit gap addressing the last minute comers whose willingness-to-pay is higher. Cutting off the price if there is not enough slot sold or if there is a few slots to sell is a good idea since empty slots are worth nothing after the departure of the vehicle. The estimation of parameters should cover these already-known concerns.

Firstly, beginning with the marginal cost calculation, the process of flow on the time-space network is explained as follows:

There are three types of customers in our multimodal network chain; they are classified according to demand arrival time for the known vessel. The first type is contracted customers who sign an annual agreement for the pre-determined number of slots which are reserved to them. Even if they did not send any freight for that reserved slots, they should pay the price. Their prices are fixed prices and it is the smallest possible price proposed for a customer. Briefly, contracted customers are the loyal segment of the customers who commit long-term agreement for the definite amount of slots. Accordingly, they are charged less than the temporary customers (normal and urgent) coming at the booking period or last minute. In our study, the fraction of slots dedicated to contracted customers is 30 percent of a vessel's total capacity (Liu and Yang, 2015). The second type is normal customers, who book the slots during 9 days booking period. It is denoted in the formulation as a time interval from T=10 to T=2. Their proposed prices are not fixed but dynamically determined in terms of booking day, fill rate, number of demand and calculated marginal price through operational planning. The last type is urgent, in other words, last-minute customers who demand last day before the departure of the vessel. They are generally ready to pay more because they have a time constraint, approaching deadline to send their goods. Exploiting their high willingness-to-pay, MTP can increase their revenue by keeping the prices high. This high prices should be less than or equal to costs of trucking from origin to destination. In fact, trucking has higher external costs too besides the monetary costs.

We could not find enough real data to analyze and estimate the model parameters accurately. But with the little amount of available industrial data obtained from national MTPs, we produced demand data using examples from the previous studies. Poisson distribution (Lin, 2006) is widely found as an appropriate method to assume demand arrivals. In order to get rid of some well-known limitations of the Poisson distribution which are related to its mean and variance relationship as known as equidispersion, negative binomial distribution is used (Koenigsberg et al., 2008). Uniform demand (Zhang and Pel, 2016) is straightforward and gives us a chance to impacts of different demand sets representing a base demand set. Demand arrival rates in airline revenue management collected in previously conducted studies show an increasing trend of price in time while getting closing to the flight date (Koenigsberg et al., 2008). This linear trend can be applied also to the sea-rail multimodal transportation

Recognizing the customer classification, we decided to produce 3 different demand sets coming from 3 distributions: Uniformly distributed demand, demand from Poisson distribution and linearly increasing demand. The mean of these distributions is determined as 6 relying on the monthly data obtained from a national MTP. The aim of producing different demand sets, in other words, scenarios is to have a chance to compare the results and cover as much as possible situation with the dynamic pricing approach.

In the time and space diagram, each node in the physical base network (Figure 4.1) is represented by the number of mode type at each time period of the planning horizon. The physical base network is replicated at each time period in sequence (Figure 4.2). The duration of one time period is 6 hours (6h) since it is based on the link travel time for each mode and maximum frequency of a rail connecting route is four times a day, it means at least 6 hours-time interval. Also, it is small enough to express the amount of handling and waiting time on the transshipment links. Setting smaller time periods is also possible and it will lead more sensitive planning, but 6h time periods are sufficiently enough for our case. The movements of freights on a physical network over time are represented by the operation links in the time-space network. In the classical model, the total capacity is calculated by multiplying the capacity of a vehicle with the daily, weekly or monthly frequency according to the accepted time horizon. While using space-time network, we do not need extra calculations for the total capacity; the time period becomes smaller -6 hours in our case- and departure time changes for each frequency of a leg on the network at hand.

Our point of view, which is MTPs perspective, requires special attention to vessel shipment from the origin point. So, we choose to deal with the departure of a vessel having 240 freights capacity. The vessel has three types of the customer according to the arrival time of demands as mentioned above.

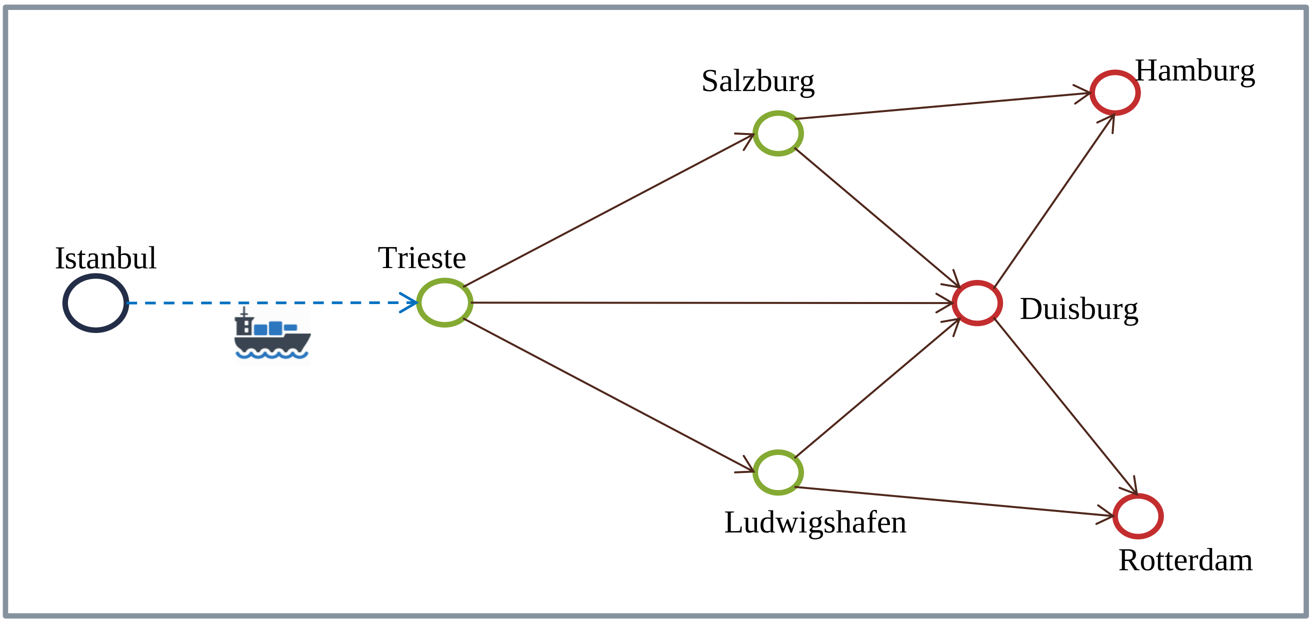

Figure 4.1: Designated Physical Base Network

If we had a larger network where multiple MTPs operate together and time period becomes smaller for example 1 hour instead of 6 hours, the problem will become more complex and time-consuming to solve. Under these circumstances, one will need to consult metaheuristics to cope with the complexity and the frequently used search algorithms are Tabu Search, Simulated Annealing and Adaptive Large Neighborhood Search (ALNS) (SteadieSeifi et al., 2017).

For the calculation of fixed price, in our case, the total cost divided by the capacity which is derived from the operational planning model plus the profit margin being 43 percent of this cost per slot from O to D. This profit margin is the currently used realistic margin, since the capacity of a vessel should be filled at least 70% in order to be profitable.

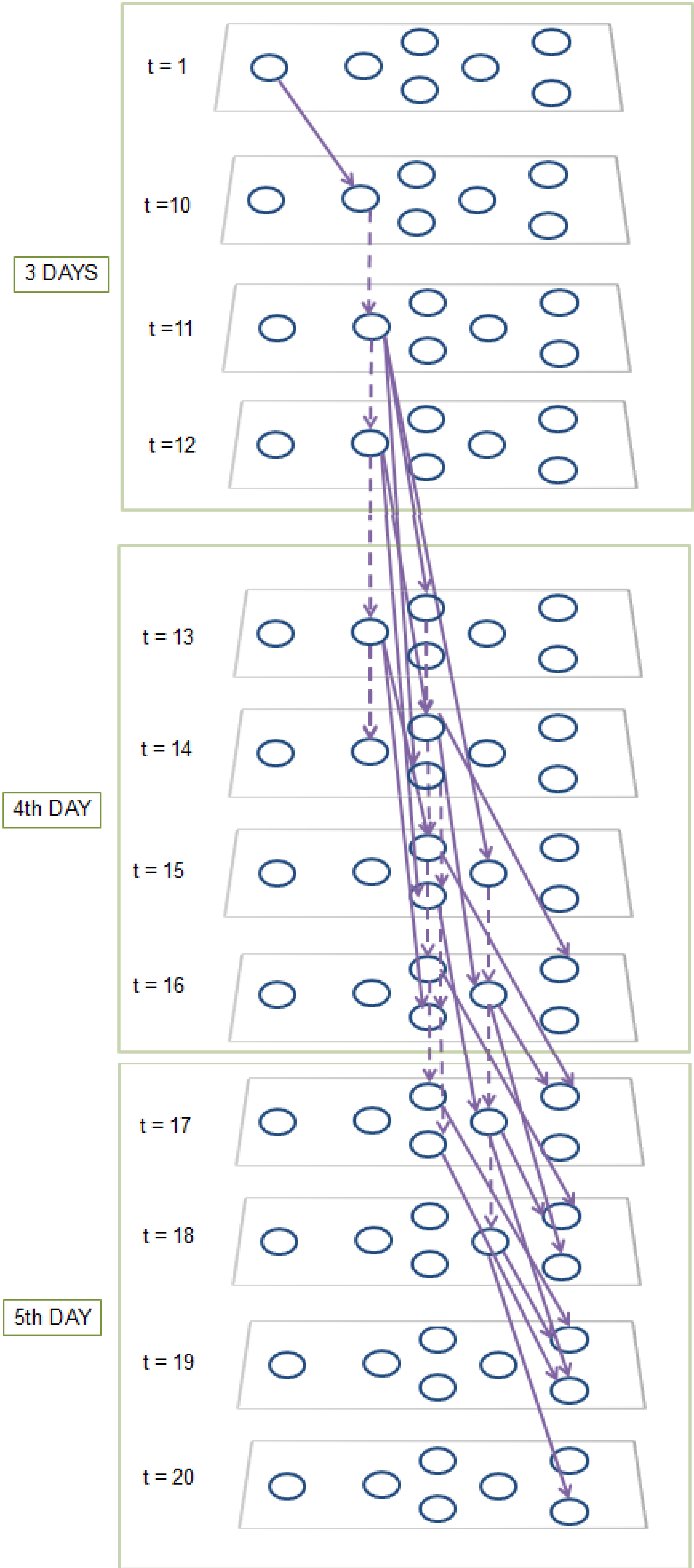

Figure 4.2: Designated Time-Space Network

To apply the dynamic pricing approach; it is necessary to determine meaningful model parameters α and β_k of the price function. For this reason, after several initial trials and tests concerning the industrial attitudes and literature outcomes, we tried to estimate the appropriate model parameters for online booking period, so to say, price offers for normal customers. Firstly we fixed α as the base price and determined five values for each parameter β_k.

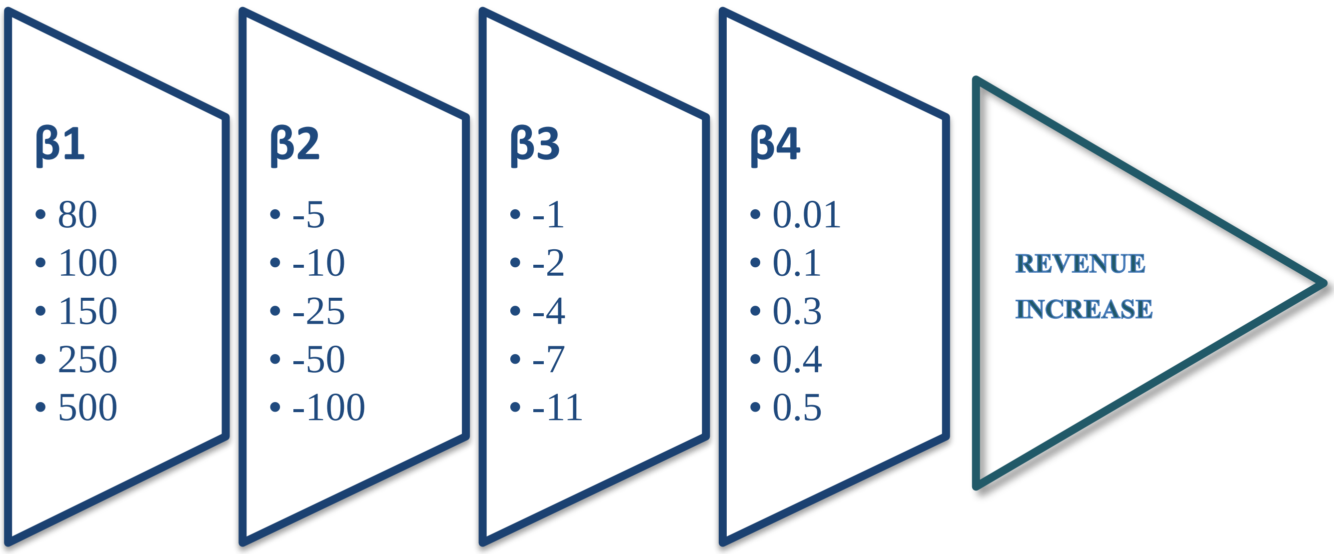

Figure 4.3: Scenarios of Model Parameters β_k

Firstly, we produced demand sets and integrate them one by one in the rolling horizon to the model. This operational planning model formulation has been implemented using IBM ILOG OPL modeling language and solved with CPLEX 12.6. After solving the model for each demand arrival, the marginal cost for each demand is obtained. This marginal cost together with other independent variables of fill rate, booking day and demand quantity. Next, in each scenario, only one β_k parameter changed and the other three parameters are kept unchanged (Figure 4.4).

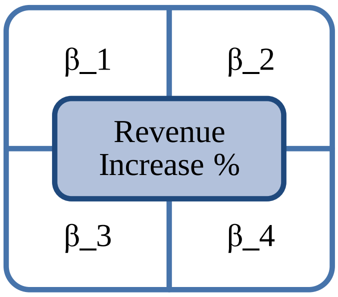

Figure 4.4: Principe of Dynamic Pricing Revenue Increase Rate Calculation

The 625 revenue increase percentages are calculated compared to the fixed price for one demand set obtained from one of the 3 distributions (Table 4.1, Table 4.2, Table 4.3, and Table 4.4). From these 625 values, it is necessary to determine the best parameter(s) for further usages. So, we have determined a percentage interval of revenue increase compared to fixed pricing strategy.

The upper limit of a price to offer a customer is trucking cost from the same origin to same destination. This total trucking cost is determined with the already demonstrated formula presented by Dong et al. (2017) and the maximum revenue increase rate is designated 10% in order to be competitive against unimodal road transportation by truck. As a lower increase rate 5% increase rate is accepted. This 5 % is determined in order to exceed the revenue increase rate which is already achieved in the literature.

Table 4.1: Scenarios of Linearly Increasing Demand while β_4 = 0.3

LINEAR	DEMAND	β4 = 0.3				
β1	**β2**	**β3 = -1**	**β3 = -2**	**β3 = -4**	**β3 = -7**	**β3 = -11**
80	**-5**	0.119	0.118	0.115	0.112	0.108
	-10	0.115	0.114	0.112	0.109	0.104
	-25	0.103	0.102	**0.098**	**0.096**	**0.092**
	-50	**0.088**	**0.087**	**0.085**	**0.081**	**0.077**
	-100	**0.054**	**0.053**	**0.050**	0.046	0.041
100	**-5**	0.121	0.120	0.118	0.114	0.110
	-10	0.118	0.116	0.114	0.111	0.106
	-25	0.105	0.104	0.102	**0.098**	**0.094**
	-50	**0.090**	**0.089**	**0.087**	**0.083**	**0.079**
	-100	**0.056**	**0.055**	**0.052**	0.048	0.043
150	**-5**	0.126	0.125	0.123	0.119	0.115
	-10	0.123	0.122	0.119	0.116	0.111
	-25	0.112	0.111	0.109	0.106	0.101
	-50	**0.095**	**0.094**	**0.092**	**0.088**	**0.084**
	-100	**0.061**	**0.060**	**0.057**	**0.053**	**0.048**
250	**-5**	0.137	0.136	0.133	0.130	0.125
	-10	0.133	0.132	0.130	0.126	0.122
	-25	0.123	0.122	0.120	0.116	0.112
	-50	0.106	0.105	**0.099**	**0.096**	**0.094**
	-100	**0.071**	**0.070**	**0.067**	**0.063**	**0.058**
500	**-5**	0.163	0.162	0.160	0.156	0.152
	-10	0.159	0.158	0.156	0.153	0.148
	-25	0.149	0.148	0.146	0.142	0.138
	-50	0.132	0.131	0.129	0.125	0.121
	-100	**0.098**	**0.096**	**0.094**	**0.091**	**0.086**

Table 4.2: Scenarios of Linearly Increasing Demand while β_4 = 0.4

LINEAR	DEMAND	β4 = 0.4				
β1	**β2**	**β3 = -1**	**β3 = -2**	**β3 = -4**	**β3 = -7**	**β3 = -11**
	-5	0.164	0.163	0.161	0.158	0.153
	-10	0.161	0.160	0.157	0.155	0.150
80	**-25**	0.151	0.150	0.147	0.144	0.139
	-50	0.133	0.132	0.130	0.127	0.122
	-100	**0.099**	**0.098**	**0.096**	**0.093**	**0.088**
	-5	0.166	0.165	0.163	0.160	0.155
	-10	0.163	0.162	0.159	0.157	0.152
100	**-25**	0.153	0.152	0.149	0.146	0.141
	-50	0.135	0.134	0.132	0.129	0.124
	-100	0.101	**0.100**	**0.098**	**0.095**	**0.090**
	-5	0.171	0.170	0.168	0.165	0.160
	-10	0.168	0.167	0.164	0.162	0.157
150	**-25**	0.158	0.157	0.154	0.151	0.146
	-50	0.140	0.139	0.137	0.134	0.129
	-100	0.106	0.105	0.103	**0.100**	**0.095**
	-5	0.182	0.181	0.177	0.175	0.171
	-10	0.178	0.177	0.174	0.172	0.167
250	**-25**	0.168	0.167	0.164	0.162	0.157
	-50	0.150	0.149	0.148	0.144	0.139
	-100	0.117	0.116	0.113	0.110	0.105
	-5	0.208	0.207	0.204	0.201	0.197
	-10	0.205	0.204	0.201	0.199	0.194
500	**-25**	0.195	0.194	0.191	0.189	0.183
	-50	0.177	0.176	0.174	0.171	0.166
	-100	0.143	0.142	0.140	0.137	0.132

Table 4.3: Scenarios of Poisson Demand while β_4 = 0.3

POISSON	DEMAND	β4 = 0.3				
β1	**β2**	**β3 = -1**	**β3 = -2**	**β3 = -4**	**β3 = -7**	**β3 = -11**
	-5					
	-10	0.108	0.107	0.104	**0.100**	**0.096**
80	**-25**	**0.094**	**0.093**	**0.091**	**0.087**	**0.082**
	-50	**0.071**	**0.070**	**0.068**	**0.064**	**0.059**
	-100	0.024	0.023	0.021	0.017	0.013
	-5					
	-10				0.104	**0.099**
100	**-25**	**0.096**	**0.095**	**0.093**	**0.089**	**0.084**
	-50	**0.073**	**0.072**	**0.070**	**0.066**	**0.061**
	-100	0.026	0.025	0.023	0.020	0.015

150	-5					
	-10					0.105
	-25	**0.102**	**0.101**	**0.100**	**0.095**	**0.090**
	-50	**0.079**	**0.078**	**0.076**	**0.072**	**0.067**
	-100	0.032	0.031	0.029	0.025	0.020
250	-5					
	-10					
	-25	0.113	0.112	0.109	0.106	0.102
	-50	**0.091**	**0.090**	**0.088**	**0.084**	**0.079**
	-100	0.044	0.043	0.040	0.037	0.032
500	-5					
	-10					
	-25	0.142	0.141	0.138	0.135	0.131
	-50	0.119	0.118	0.115	0.112	0.108
	-100	**0.072**	**0.071**	**0.068**	**0.065**	**0.061**

Table 4.4: Scenarios of Linearly Increasing Demand while β_4 = 0.3

UNIFORM	DEMAND	β4 = 0.3				
β1	β2	β3 = -1	β3 = -2	β3 = -4	β3 = -7	β3 = -11
80	-5					
	-10				**0.100**	**0.096**
	-25	**0.093**	**0.092**	**0.090**	**0.086**	**0.081**
	-50	**0.068**	**0.067**	**0.065**	**0.061**	**0.056**
	-100					
100	-5					
	-10				0.102	**0.098**
	-25	**0.095**	**0.094**	**0.092**	**0.088**	**0.083**
	-50	**0.07**	**0.069**	**0.067**	**0.063**	**0.058**
	-100					
150	-5					
	-10					
	-25	0.101	**0.100**	**0.098**	**0.094**	**0.089**
	-50	**0.076**	**0.075**	**0.073**	**0.069**	**0.064**
	-100					
250	-5					
	-10					
	-25	0.113	0.112	0.109	0.106	**0.100**
	-50	**0.087**	**0.086**	**0.084**	**0.080**	**0.075**
	-100	0.037				
500	-5					
	-10					
	-25	0.141	0.140	0.138	0.134	0.129
	-50	0.116	0.115	0.113	0.109	0.104
	-100	**0.066**	**0.065**	**0.062**	**0.058**	**0.053**

After producing results of all scenarios for each type of 3 demand distribution and best parameters that gives 10.0 % (or 9.9 %) increase rate are selected finally (Table 4.5). The final 9 parameters' performances are measured with calculations from scratch using newly produced sets of demand. The best parameter for each type of demand is nominated at the end of this process; these are shown in purple on Table 4.5. These selected parameters turn out dynamic prices for normal and urgent customers showing an increasing trend towards the end of the booking period (Figure 4.5). The horizontal axis of the chart represents the demand arrival during booking period from T=10 to T=1. Since customer type depends on the customer arrival during the booking period, the horizontal axis shows the customer types for one vessel. T= 11 is used as a dummy day in order to represent the contracted customers who sign a contract annually.

Table 4.5: Selected Best Working Parameters

Demand	β1	β2	β3	β4	β1	β2	β3	β4	β1	β2	β3	β4
Uniform	80	-10	-7	0.3	250	-25	-11	0.3	150	-25	-2	0.3
Linear	250	-50	-4	0.3	100	-100	-2	0.4	150	100	-7	0.4
Poisson	80	-10	-7	0.3	100	-10	-11	0.3	150	-25	-4	0.3

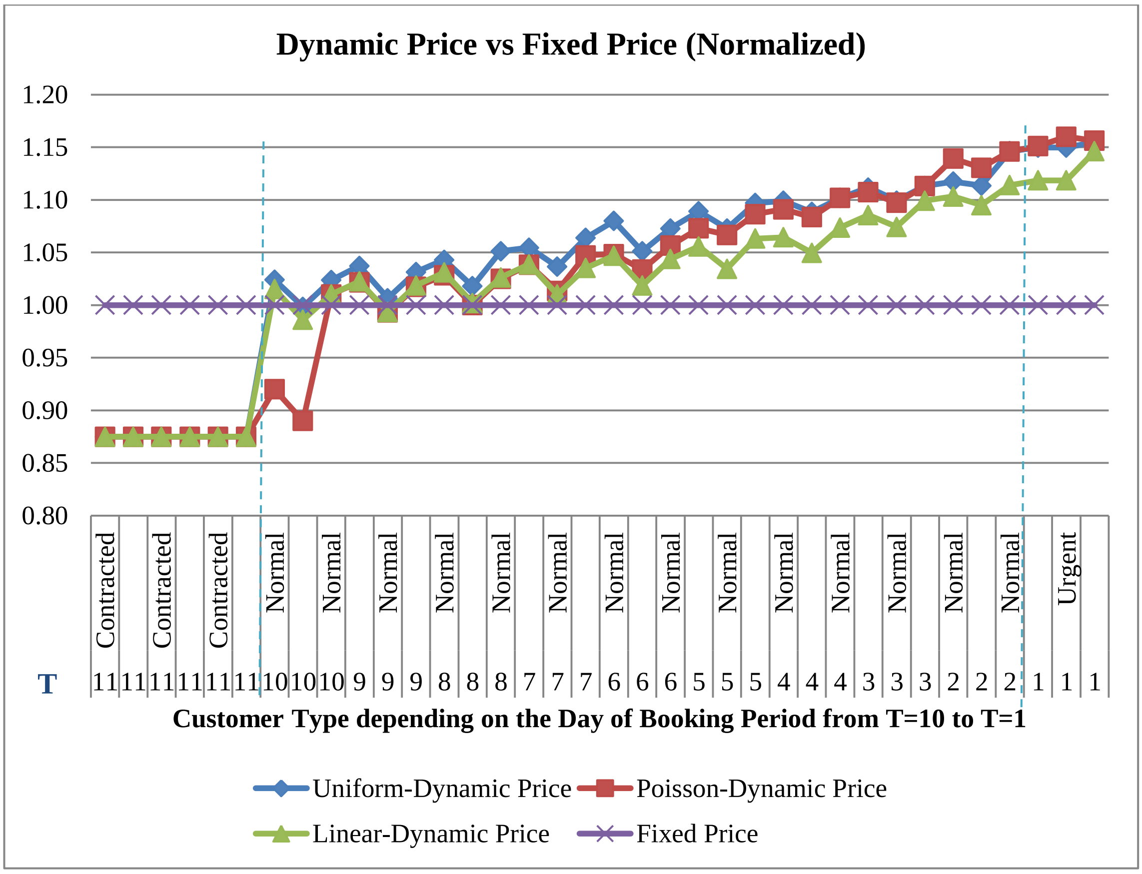

Figure 4.5: Dynamic Price vs Fixed Price (Normalized)

As a next step, we searched if we can finalize our calculations finding a unique parameter set by taking the average of these three best parameter sets (Table 4.6):

Table 4.6: Unified Dynamic Pricing Model Parameters

Demand	β1	β2	β3	β4
Unified	160	-30	-4	0.3

It is important to test the performance of this common parameter set and we accomplished this using two different demand set from 3 different distributions (Table 4.7). This unified parameter set almost conforms to the interval limits of revenue increase percentage and it is acceptable for further calculations.

Table 4.7: Performance Measurement Results for Unified Parameters

Demand Set	Poisson	Uniform	Linear
Demand_1	0.094	0.094	0.104
Demand_2	0.096	0.093	0.103

Let's measure the performance of chosen parameter sets on uniformly distributed demand regarding different scenarios of fill rate: full, early full (no slot for urgent customers), and not full (Table 4.8):

Table 4.8: Performance Measurement of Parameters on the Uniformly Distributed Demand

UNIFORM	Demand_1	Demand_2	Demand_3	Demand_4	Demand_5	Demand_6
160,-30,-4,0.3	9.3%	9.4%	6.1%	6.9%	8.4%	8.0%
150,-25,-2,0.3	10.0%	10.0%	6.7%	7.5%	8.9%	8.6%

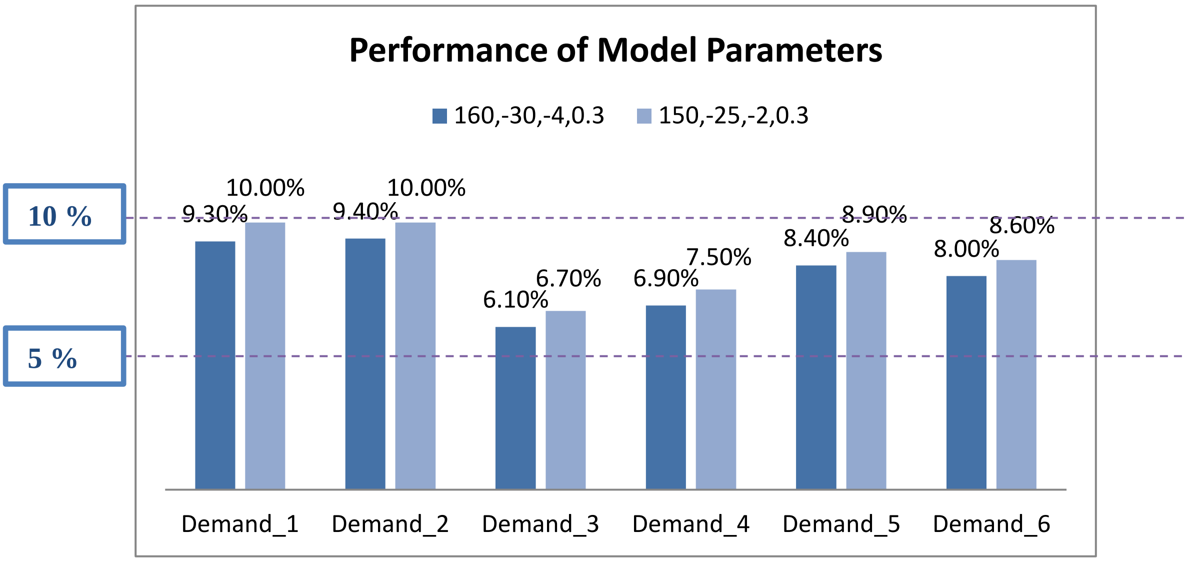

Figure 4.6: Graphic of Table 4.8

Table 4.8 and Figure 4.6 allows declaring that the estimated parameters are working well and do not fall down the determined lower level of revenue increase (5%) for the uniformly distributed demand sets. These demands sets also represent different scenarios because randomly produced demands can cause fulfillment of the capacity earlier than the end of booking period or lack of total capacity utilization. But the estimated parameters work well and stay within the determined limits of revenue increase rates 5% and 10%.

The dynamically changing prices fluctuate up and down by using estimated parameters; however, it is possible to restrict the decrease of price in time (Figure 4.7). But then again the increase in the revenue against fixed pricing strategy becomes 10.5 % which is only 0.5% higher than the proposed dynamic pricing model (Figure 4.5). This is also applicable; however, fluctuations are not problematic for this kind of dynamic pricing approach in various sectors.

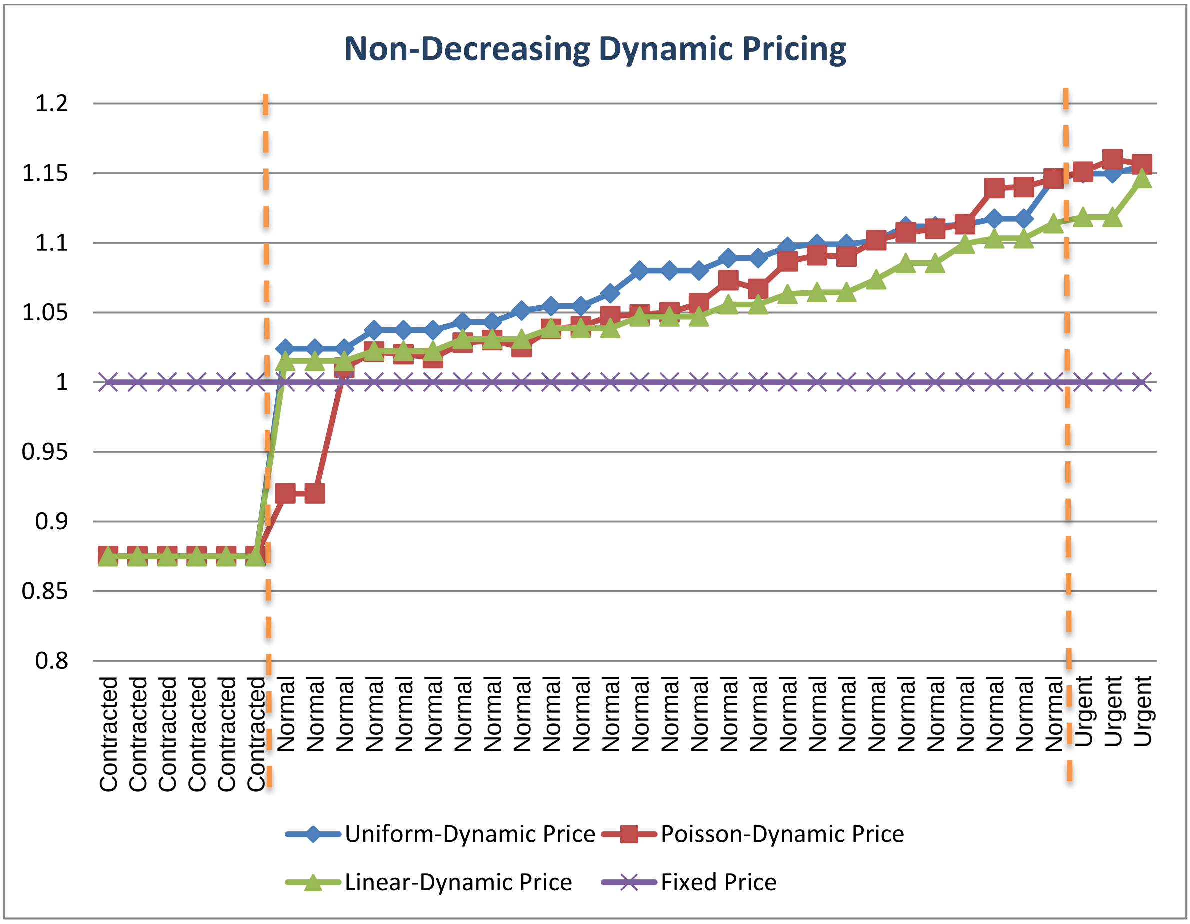

Figure 4.7: Non Decreasing Dynamic Prices

In sum, the dynamic pricing approach relies on the scenario-based parameter estimations and the performance of these estimated parameters demonstrated the success of the proposed approach. The overall process of dynamic pricing and slot allocation in the designated multimodal freight network is summarized in the following flowchart (Figure 4.8):

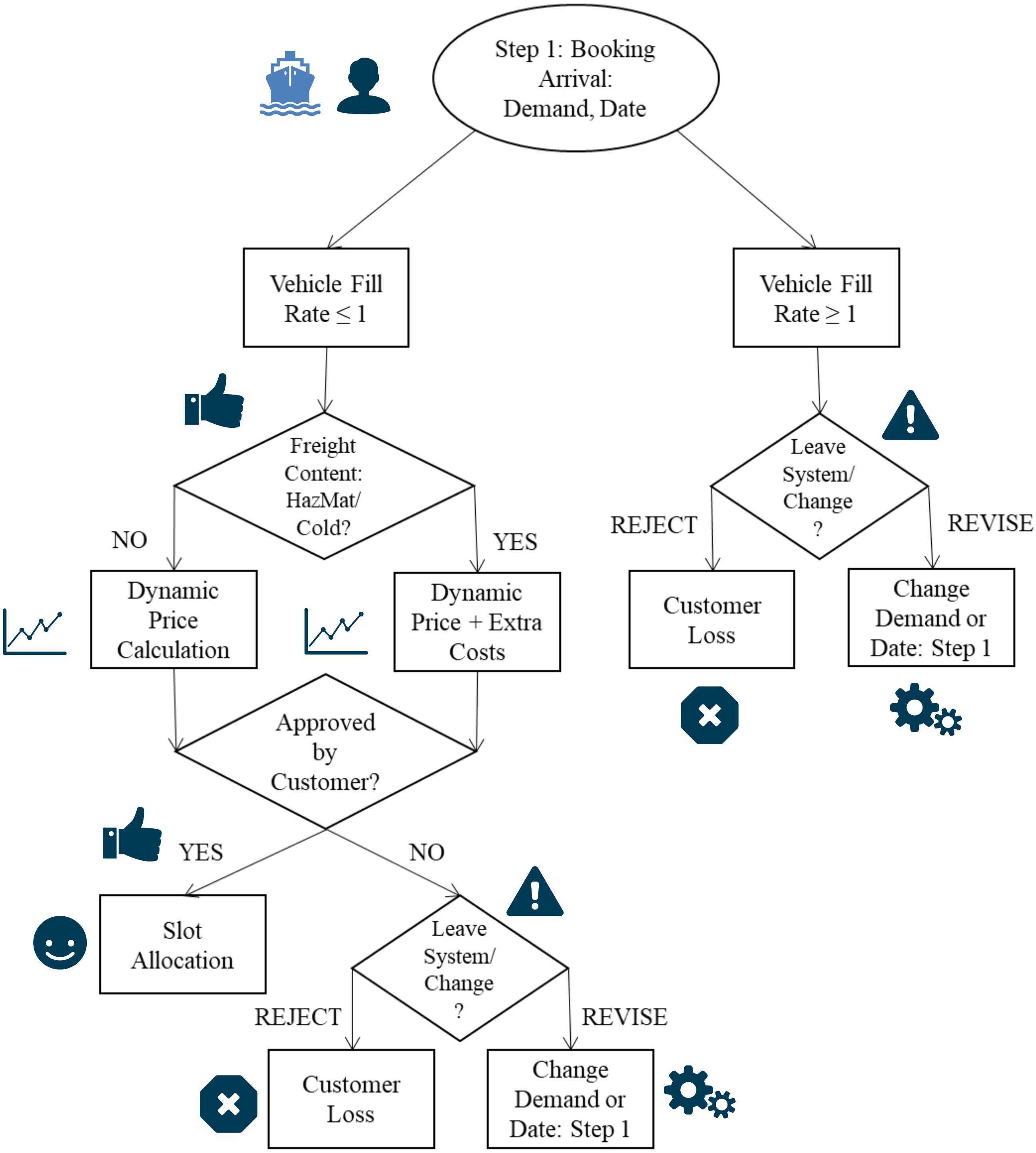

Figure 4.8: Flowchart of Dynamic Pricing and Slot Allocation in Multimodal Freight Network

Chapter 5

Conclusion and Future Studies

In this thesis, we proposed a dynamic pricing approach to be applied together with slot allocation from the MTPs perspective in order to increase their revenue, without exceeding customer's convenient willingness-to-pay for a slot, considering the different type of pre-defined customer classes and online booking system. Pursuing the slot allocation and marginal cost calculation, we developed a time-space diagram and formulate the sea-rail multimodal freight transportation problem as a linear network flow model. The variables of dynamic pricing equation are determined relying on the literature and discussion with national MTPs as influencing elements for price changes; parameters are estimated with scenario-based calculation and their performances are measured on different demand sets. Since the results of proposed dynamic pricing approach are promising in order to increase revenue and encourage MTPs to maintain their multimodal transport services, we can claim that this study provides managerial insights about the advantages of multimodality and dynamic pricing strategy.

As a future research direction, one can release some limitations and assumptions to elaborate deeply on the subject of dynamic pricing in multimodal transport management. To begin with, the testing of multilinear pricing strategies and achieving more accurate parameters of the dynamic pricing model in the multimodal transport sector has been very restricted due to the lack of available data, especially daily demand, and individual pricing because of confidentiality of the adequate data and continuation of traditional methods. As already applied in the airline industry, online reservation system –if established- will help to keep track of the demand and price changes and correlation between them. Collaboration between stakeholders and MTPs –if established- can release issue of confidentiality rights and this will precede common benefits between stakeholders of the same consortium thanks to transparent communication and fair revenue allocation parallel to service ratio. Thanks to this price transparency and past data accumulation; customer behaviors, willingness-to-pay, price changes, demand changes can be followed closely and learned in time. Possible extensions of this research include incorporating machine learning through an online reservation system to update demand, arrival rate, and price distributions over time. This system will allow empirical analysis to result in better coefficient predictions. By looking further, the focus of transportation and supply chain management is not only minimization of costs but also adding value to global supply chain via automation and robotization building hyper-connected networks. It is presumable that future studies will emerge as a collaboration of autonomous vehicles, terminals and online data keeping and mining systems. Users and providers will still be the ones who provide the destinations and system developments.

As an extension to existing problem setting, first, the current network is designed using real-life network being operated by national MTPs; however, it shows a small piece of the network in the world of sea-rail transportation. Hence, thanks to collaboration and agreements between various stakeholders, one can work on a larger and complex network which will be very interesting to implement further.

Secondly, the only freight type of semi-trailer limits the compatibility with real life application and it can be developed by adding containers as an alternative freight type and increasing the number of overall capacity since containers can be stacked on top of each other. The fraction of allowed containers in a vessel should be arranged accordingly to the capacity of trains afterward. Because the frequency of trains depends on the schedule of the whole network and containers can be only double-stacked on trains, mainly Ro-La.

Furthermore, the operational planning model can be extended adding due date index to demand to be arrived at the destined terminal; price and slot allocation scheme can be assigned in this direction. To illustrate, if the due date of some freights is too close; they need to allocated and transported directly while others can wait for the departure of the vessel the next day. This system will obviously influence the pricing strategy with the reason of urgency.

Moreover, allowing cancellation and overbooking will be a novelty to multimodal transportation and a new opportunity to increase revenue without upsetting the customers. Overbooking can increase revenue significantly due to high no-show rates. Increasing revenue strategies can merge with the objective of cost saving without reducing the reliability of operation.

Empty container reposition and allocation of round trips will also have a positive impact on capacity utilization rate and revenue maximization.

Next, our study assumes that there is no demand uncertainty by producing demand instances from different distributions; however, consideration of stochastic demand and arrival rates will be an interesting and real-life problem to direct the related research further.

As a final extension to dynamic pricing approach, the fact that the amount of increase in price when moving from BookingDay = 6 to BookingDay = 7 is equal to the increase when moving from BookingDay = 1 to BookingDay = 2 is a strong assumption and it is not realistic to follow in real life applications. This negative effect of this assumption can be prevented using interaction effects of two or more variables and it would be better if one can estimate varying parameters instead of fixed parameters for each demand arrival.

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Appendix

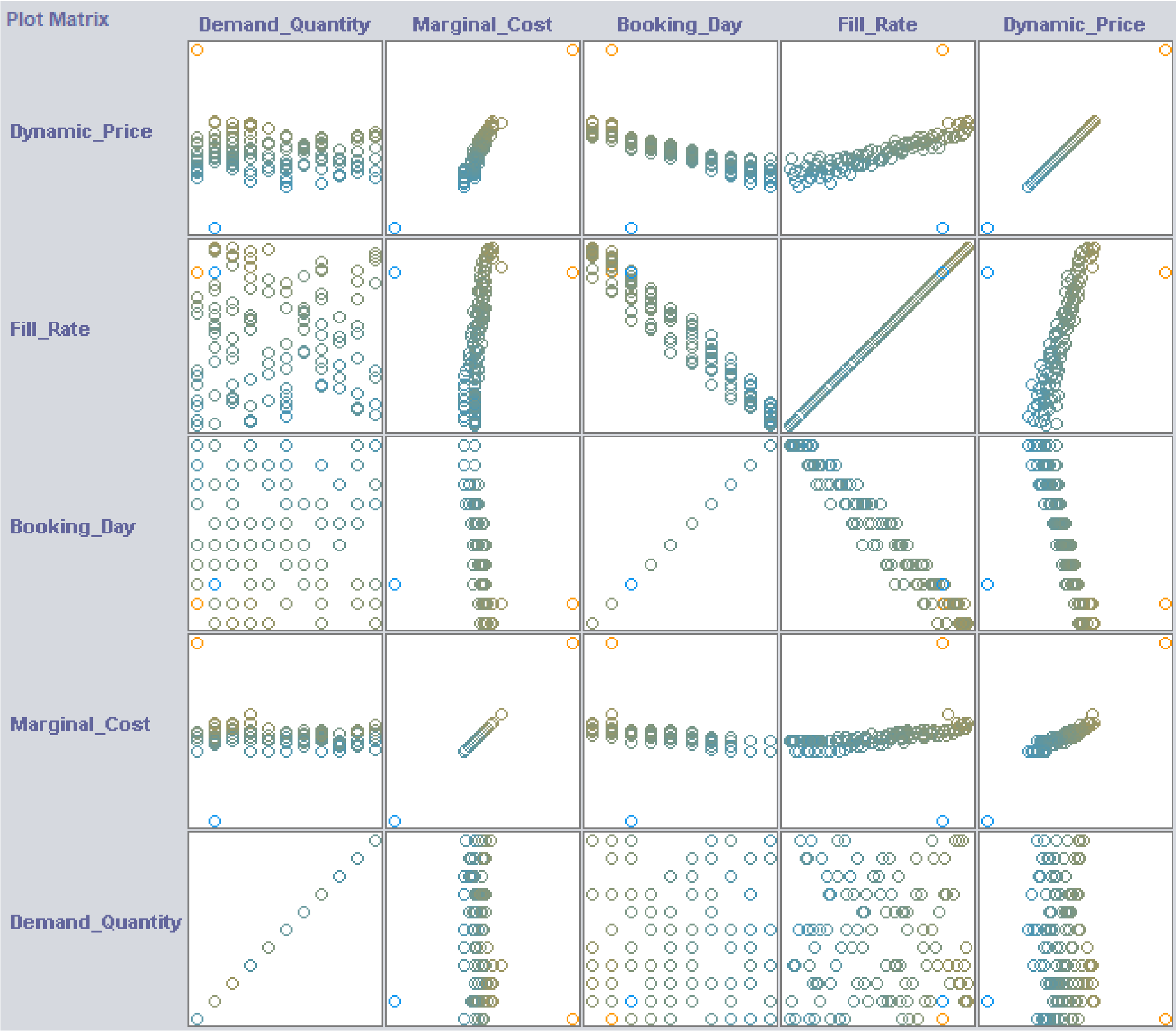

Figure A: The Plot of Data: Variables and Assigned Dynamic Prices