ABSTRACT

Title of Dissertation / Thesis: **PERFORMANCE AND ANALYSIS OF SPOT TRUCK-LOAD PROCUREMENT MARKETS USING SEQUENTIAL AUCTIONS**

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Competition in a transportation marketplace is studied under different supply/demand conditions, auction formats, and carriers' behavioral assumptions. Carriers compete in a spot truck-load procurement market (TLPM) using sequential auctions. Carrier participation in a TLPM requires the ongoing solution of two distinct problems: profit maximization problem (chose best bid) and fleet management problem (best fleet assignment to serve acquired shipments).

Sequential auctions are used to model an ongoing transportation market, where carrier competition is used to study carriers' dynamic vehicle routing technologies and decision making processes. Given the complexity of the bidding/fleet management problem, carriers can tackle it with different levels of sophistication. Carriers' decision making processes and rationality/bounded rationality assumptions are analyzed. A framework to study carrier behavior in TL sequential auctions is presented. Carriers' behavior is analyzed as a function of fleet

management technology, auction format, carrier bounded rationality, market settings, and decision making complexity.

The effects of fleet management technology asymmetries on a competitive marketplace are studied. A methodology to compare dynamic fleet management technologies is developed. Under a particular set of bounded rationality assumptions, bidding learning mechanisms are studied; reinforcement learning and fictitious play implementations are discussed. The performance of different auction formats is studied. Simulated scenarios are presented and their results discussed.

PERFORMANCE AND ANALYSIS OF SPOT TRUCK-LOAD PROCUREMENT MARKETS USING SEQUENTIAL AUCTIONS

By

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Chapter 1: Introduction

1.1. Motivation

Information and communication technologies (ICT) are transforming key market processes and the very architecture of the markets. The Internet and especially auctions have emerged as an effective catalyst to sell/buy through electronic marketplaces. Transaction time, cost and effort can be dramatically reduced, creating new markets and connecting buyers and sellers in ways that were not previously possible (Lucking-Reily, 2001). Inexpensive, ubiquitous, and reliable communication networks are allowing a physical decentralization of the decision making process while connecting market agents in real time.

Network business to business transactions have reached $2.4 trillion, fulfilling early growth forecasts (Mullaney, 2003). This growth is partly supported by the increasing use of private exchanges, where a company invites selected suppliers to interact in a real time marketplace, compete, and provide the required services. A report published in mid 2002 estimated that by June 2003, 15 percent of all Fortune 2000 companies would have set up private exchanges (Hoffman, 2002). Furthermore, the same source indicated that an additional 28 percent of all Fortune 2000 companies planned to implement a private exchange by the end of 2003. At the moment of writing (March 2004) these figures have not yet been confirmed, however the dominance of business to business transaction in United States (over 93%) has been recognized (UNCTD, 2003).

The changes that ICT could bring to companies' strategies and market structures have been examined from a broad perspective. As early as 1987, Malone et al. (1987) predicted that reducing coordination costs (while holding other factors constant) should increase the proportion of economic activity coordinated by the markets. Factors that favor electronic market systems include the simplicity of the product description, the adoption of common standards, and access to multiple potential suppliers in the marketplace.

Other authors suggest the opposite, namely that widespread availability of ICT will reduce the number of suppliers and foster long-term cooperative partnerships (Clemmons, 1993). These two opposite views respectively lead to the market model or to the emergence of hierarchies. Compromising views have also been suggested (Holland, 1994), specifically that organizations gain the benefits of a controlled and known hierarchy, while also retaining an element of market competition to gain efficiency.

The transportation and logistics sector has also been affected by the recent technological advances in ICT (Regan and Golob, 1999). Among many changes, it is only recently that ICT has started to modify the way contracts are negotiated, by enabling demand and supply to be matched dynamically through online market mechanisms. Important changes have been taking place in the structure of the transportation market, with the development of auction and load matching markets for transportation services, in the form of Internet sites that match shipments (shippers demand) and transportation capacity (carriers offer). The effect and impact of these changes on a 585 billion dollar industry (American Trucking Association, 2003) are still unraveling.

Transportation auctions are still a relatively recent phenomenon, characterized by rapid change and fast development. There is a large number and variety of online markets as detailed by Tankersley (2001) and Huff (2002). This type of market has not yet reached maturity as indicated by the significant number of start-ups, mergers, consolidations, and constant evolution and changes in the services offered to shippers and carriers. Appendix A contains a list of freight-matching services.

This dissertation explores how carriers compete in a transportation marketplace and studies the performance of a marketplace under different supply/demand conditions, auction formats, and carriers' behavioral assumptions. In this dissertation the type of marketplace where carriers compete is a spot truck-load (TL) procurement market using sequential auctions. Herein, for the sake of brevity this type of marketplace is referred as the TL procurement market (TLPM) problem or simply TLPM.

This chapter is organized as follows: section 2 positions the TLPM problem under study in the context of shipper-carrier procurement relations. It also surveys relevant literature. Section 3 provides a general definition of a TLPM. Section 4 presents the research context and general approach to tackle the TLPM problem. Section 5 details the research objectives and contributions. Section 6 explains the rational behind the dissertation organization. It also presents the outline of the dissertation. Section 7 delves into the notation convention to be used throughout this research.

1.2. Shipper-Carrier Procurement Structures

Online markets are just one way to organize trading and resource allocation among carriers and shippers. In the continuum from markets to vertical hierarchies (in which all activities are performed internally), shippers and carriers can meet under a wide array of relational structures. All these structures share a basic functionality: shippers can procure transportation services. The cost and characteristics of the provided services are dependent on the shipper procurement strategy and needs, how prices are negotiated, and the efficiency of the fleet operation.

The span of shipper/carrier relationships is depicted in Figure 1. The different structures range from vertical integration (on the left) to spot markets or public exchanges (on the right). Long term contracts and private exchanges are located between vertical and spot markets. While plethora of procurement arrangements between shippers, carriers, third party logistic (3PL) companies, and brokers are possible, the discussion is limited to the main four structures depicted in Figure 1.

Vertical integration takes place when the shipper uses a private fleet. Ownership's main advantage is total control over the fleet operation, therefore guarantying direct influence over equipment availability and service quality. However, ownership distracts resources from core activities and may result in high transportation costs due to excessive deadheading. Conversely, in a market, shippers must search for and transact with carriers interested in providing the demanded services.

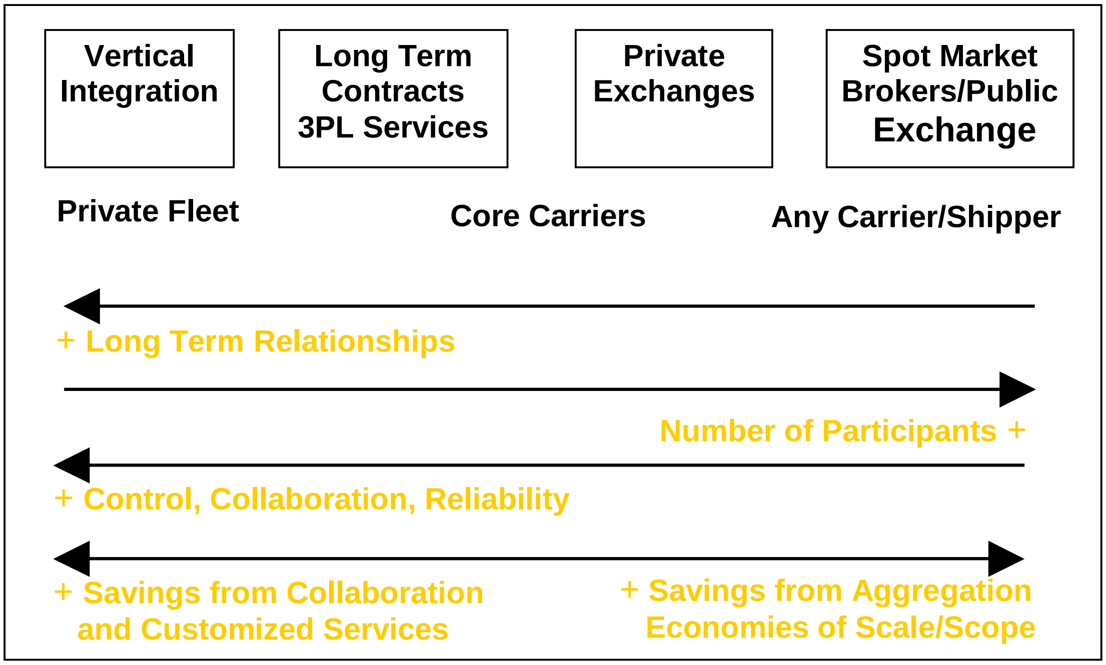

Figure 1 Spectrum of Shipper-Carrier procurement structures

Long term contracts with a carrier or a 3PL guarantee service while releasing the shipper from owing/managing the fleet. Less resources are distracted from the core company activities but control is somewhat relinquished. Service characteristics, prices, and payment mechanisms are usually detailed in a binding contract.

Private exchanges are usually owned and maintained by a single owner. It is a one-to-many environment, among a shipper and a small number of selected carriers or 3PLs. Negotiations are no longer bilateral, they take place in the private exchange, a private forum where carriers compete. Shipper and carriers participate in each transaction, which may range from a single shipment to a long term contract over a network lane/s. If several shipments or lanes are transacted simultaneously they are generally assigned using combinatorial auctions. Competition is increased but at the price of owning and maintaining the private exchange.

Public exchanges or markets connect many shippers and many carriers. They are usually owned by a trusted third party, acting as a connecting hub. Market reach is expanded, maintenance costs are spread out among many parties, but parties also relinquish control over operations and transaction formats.

Along the procurement spectrum, the number of self-interested agents involved in the market increases from one (integrated shipper-carrier) to many shippers/carriers buying/selling services in a market (public exchange). In a similar way, the lengths of the relationships shorten while the services provided are increasingly becoming a commodity.

The commoditization of services provided as well as the utilization of meaningful service standards are key factors in the development of public markets. Search and transaction time and cost are reduced while guarantying specified levels of service. Furthermore, bringing together many shippers and carriers creates a positive synergy as it allows for economies of scale and scope while keeping transaction costs low. Alternatively, if a shipper's product/service requirements are such that they cannot be met with standard equipment/operations, the shipper must negotiate with a carrier or manage its own fleet in order to customize services to meet his own special needs.

The changes and trends in shipper-carrier procurement strategies have received a great deal of attention in the transportation and logistics academic literature. This type of study specially flourished after legislation regarding motor carrier deregulation was passed by the United States Congress in the late 1970s and early 1980s. Crum and Allen (1990) report how Just In Time (JIT) inventory and production systems and economic deregulation have impacted carrier-shipper relations. These authors use survey data to show trends towards a reduction in the number of motor carriers utilized by individual shippers and towards long term contracting. A slightly different trend is reported by Lieb and Randall (1996). These authors report a trend, mainly among big companies, towards outsourcing transportation and logistics responsibilities to 3PLs. Crum and Allen (1997), after comparing survey data taken in 1990 and 1996, conclude that the trend in carrier-shipper relationships continues to move away from a transactional framework to a relational one (from a cost based procurement to a collaboration based procurement)

Technology has also spurred changes and transformation of transportation-logistics procurement structures. Shortly after deregulation legislation was passed, Electronic Data Interchange (EDI) started to become available. Williams (1994) studies and reports how EDI facilitates and fosters a seamless integration between a shipper and group of core carriers. The internet has been widely reported as a catalyst to foster integration of business processes in the supply chain, collaboration, and the usage of market mechanisms (e.g. auctions) (Garcia-Dastungue, 2003).

A survey study about the adoption and usage of Internet procurement tools by shippers was conducted by Lin et al. (2002). That survey indicated that 60% of the shippers use the internet to procure transportation services (phone usage was tallied at 90%). Load matching and transportation auctions were used by 15% of the shippers that used some transportation online service (2001 data). Another survey cited by Huff (2002) includes results from 373 for-hire-trucking companies. More than 90% of the respondents use phones to bid and accept loads, 40% use email, and 30% use freight boards or exchanges (data from December 2001). Song and Regan (2001) examine the potential benefits and costs of shifting from traditional 3PLs to online procurement markets.

Another line of work has focused on the study of new means of price discovery made possible by ICT advances and the advent of electronic marketplaces. A seminal work by Caplice (1996) studies combinatorial bidding over network lanes (long term contracts). Caplice's comprehensive work focuses mainly on the design of combinatorial auctions to reduce carriers' repositioning costs. Song and Reagan (2003) propose a fast and optimization-based bid construction strategy that carriers can use to evaluate transportation costs. Abrache et al. (2003) propose a bidding framework that seeks to simplify bidding complexities in combinatorial auctions while allowing bidders to express their preferences over sets of items. Sheffi (2004) reports on the benefits and practical applications of combinatorial auctions in the TL industry.

Most of the oldest and major online transportation marketplaces offer a combination of services that encompass a large portion of the procurement continuum (e.g. NTE (www.nte.com), BestTransport (www.BestTransport.com), and LeanLogistics (www.LeanLogistics.com)). As an example, the LeanLogistics Transportation Marketplace consists of three market formats: (1) ContracTender (1:1) electronically tenders a load to a core carrier, based on specific rules, with a previously negotiated contract rate attached. (2) Private Spot Market (1: Many) electronically tenders a load to the shipper's carrier base (or a subset) simultaneously. The shipper could use the contract rate as a base price and receive bids from core carriers. The Private Spot Market has a dynamic set of rules that can vary by product, by region, by division, and over time. (3) Exchange (Many: Many) electronically tenders loads from many shippers to many carriers for improved access to the best load opportunities and capacity available (expanded search capabilities).

Work in the area of electronic transportation procurement has so far focused on contracting issues and trends in the design and solution of combinatorial auctions. Even though the items being auctioned can range from long term contract services (over network lanes) to a sequence of one-time shipment auctions, issues related to spot markets or the usage of sequential auctions in a transportation context have not yet been explored. Furthermore, there appears to be no published work of a fundamental, scholarly or methodological nature specifically dealing with procurement of truckload (TL) services using sequential auctions (spot market).

In the context of the procurement spectrum (Figure 1) the range yet to be explored is the area between private exchanges and public marketplaces (especially with real time or sequential operation). This procurement range is characterized by short term and frequent transactions (spot market), two or more carriers offering transportation services, and one (private exchange) or several shippers (public exchange) requesting transportation services. Many types of procurement arrangements can be found in the described range. The next section will delineate the type of market to be studied herein.

1.3. ***Spot Truck-load Procurement Market using Sequential Auctions***

Many Internet-based transportation marketplaces have emerged to serve the transportation industry, each offering a wide variety of services. These services range from load posting boards, cargo matching, and auctions, to the procurement of transportation equipment, parts and systems for logistics and supply chain management (Wolfe, 1999).

The transportation marketplace to be studied enables the sale of cargo capacity, based mainly on price yet still satisfying customer level of service requirements (e.g. shipment time window).

A diversity of market timings may exist. In the cases where demand can be anticipated (days, weeks, or months ahead), forward markets are used. Forward markets allow for balancing of both power and storage equipment. This allows (a) shippers to hedge against demand/supply fluctuations and (b) carriers to increase fleet operational efficiency.

Spot markets are useful to deal with unanticipated demand or supply shocks. Unanticipated demand may be originated by the increasing number of companies (especially manufacturing) adopting customer-responsive, made-to-order manufacturing systems (Dell Computers exemplifies this trend). Though a diversity of market timings may coexist (i.e. the aforementioned LeanLogistics marketplace), the type of market to be studied herein is solely restricted to spot markets.

The market is comprised of a shipper (private exchange) or set of shippers (public exchange) that independently call for TL procurement auctions and the carriers that participate in them. Without loss of generality, it is assumed herein that shipments are generated independently by a set of shippers. Prices and allocations are determined using a reverse auction format (to be defined shortrly), where shippers post loads and carriers compete for them (bidding). A set of shippers generates a stream of shipments, with their corresponding attributes. Shipment attributes are defined as all the shipment characteristics that can affect the cost or likelihood of being serviced (e.g. arrival time, origin-destination, delivery time windows, reservation price, etc.).

Reverse auctions that comprise a buyer and several sellers are used in the TLPM. The term “auction” usually refers to the case that involves a seller and several buyers. The term “reverse” is added because sellers (carriers) bid instead of buyers (shippers); prices are bid down instead of up. In “reverse auctions” sellers have a production or service costs, while in “auctions” buyers have a valuation of the object/service to be purchased. Fortunately, models and intuition derived for most “auctions” can be easily reversed and applied to “reverse auctions” and vice versa (Rothkopf, 1994a). Throughout this dissertation, the words “value” or “valuation” imply the usage of an auction while the word “cost” imply the usage of a reverse auction.). Throughout this dissertation it is implicit the usage of reverse auctions when referring to or analyzing a TLPM.

Auctions are performed one at a time as shipments arrive to the auction market. It is assumed that auctions take place in a private exchange. Furthermore, a stable set of pre-screened or selected core carriers participate in each and every auction. Therefore, each and every carrier participates in a sequence of one shipment auctions. When an auction is called, carriers do not know with certainty, neither when the next auction will be called, nor the characteristics of the next shipment to be auctioned.

The auctions are assumed to operate in real time: transaction volumes and prices reflect the status of demand and supply. Auction announcement, bidding, and resolution take place in real time, thereby precluding the option of bidding on two auctions simultaneously (the likelihood of two auctions being called at the same time is zero).

The items to be auctioned in the market are restricted to TL shipments. A characteristic of TL carrier operations is that trucks do not follow regular routes. Trucks travel from shipment origin to destination without any intermediate stops (there is no shipment consolidation). A significant proportion of a carrier's costs is due to repositioning of empty vehicles (deadheading or empty distance) from the destination of one load to the origin of the next load to be served. Given that carriers operate in an uncertain and dynamic environment, deadheading costs are never known with certainty.

This type of TL sequential market is suitable for shippers who are required to interact with multiple carriers over time. The sequential nature of the auctions mirrors in some degree the demand for transportation services, which is a derived demand. This derived demand originates over time as shippers fulfill new orders or replenish stock.

Shippers are assumed to be non-strategic agents. This implies that they do not speculate on the arrival or reservation price of their market postings. Shippers are assumed to know the exact value of the reservation price (the highest price a shipper is willing to pay a carrier for serving a given shipment) of their shipment as a function of its attributes (origin-destination, commodity type, stock out costs, time window, etc.). Shippers achieve a profit (saving) when paying less than the reservation price. Shippers reject bids that exceed the reservation price.

The dynamic interaction among a stable set of carriers creates a public history and environment that enables learning, the evaluation of current actions' future consequences, and the implementation of evolving strategies. There is a rich gamut of possible carrier behaviors in the proposed TLPM. Different levels of rationality and cognitive capabilities are employed in this dissertation, which are specified as needed. Section 6 (in this chapter) broadly illustrates how these levels of rationality are used. Chapters 5 and 6 study carriers' behavior as a function of their cognitive and learning capabilities.

This section has defined the general characteristics of the market to be studied. The next section presents the research approach.

1.4. <u>Research Context and General Approach</u>

Markets, especially auctions, are a powerful social information-processing mechanism. They are useful for the social construction of value; they provide a formidable set of tools for price discovery. McAffee and McMillan (1987) define auctions as market institutions with an explicit set of rules determining resource allocation and prices, based on the bids from the market participants. In a more general way, auctions can be defined as any well defined set of rules for determining the terms of exchange of some good or service for money (Wurman, 2002).

The design of an auction requires the precise specification of a set of rules. These rules determine an auction model, the system by which bidding is conducted, how information is revealed, how communications are structured between buyers and sellers, and how allocations and payments are settled. The outcome of the auction strongly depends on the set of rules used. This study will not deal with the design of an auction, the details regarding how the process is conducted, or how information is processed. Rather, it will use existing standard auctions mechanisms (e.g. second price auction) and analyze their performance in a TLPM context as a function of information revealed. Considering a given set of rules (rules that include how information is revealed), this dissertation looks into how exogenous (to the TLPM) factors affect the performance of the system. The exogenous factors to be considered include supply/demand patterns, carriers' fleet assignment technologies, and carriers' behavior.

The decision problem that a carrier faces is strategic in nature due to the inter-dependency among competitors' bids, costs, and profits. Game theoretical analysis of auctions can be quite challenging and often intractable. In the proposed TLPM carriers face a highly complicated decision problem. Furthermore, sequential auctions with bidders with multiunit demand/supply curves, remains intractable (Krishna, 2002). However, this is not the only source of complexity. In the TLPM context, adequate fleet management and bidding entails estimating the shipment service cost and assigning shipments to vehicles. These are NP hard problems (vehicle routing problems with time windows). Additionally, in a dynamic environment, the decision-maker has to consider future impact of current decisions, and update policies or strategies as new information becomes available.

Closed analytical solutions for this complex carrier decision problem would require many simplifications that could compromise the validity of the results. Therefore, computational experiments and simulation are used as needed to enhance and extend simpler theoretical models. Furthermore, simulation is used to study the dynamics of carriers' behaviors and interactions in controlled and replicable experiments.

This dissertation deals with both the shippers and carriers' perspective. Shippers are concerned about service levels and prices available in an auction market. Carriers focus on maximizing profits, which is hindered by competition and by requirements to provide a suitable level of service. The two perspectives are strongly intertwined, and will be examined concurrently through the same conceptual framework.

This dissertation does not consider the market operator or auctioneer's perspective; i.e. the profits of the entity running the auction site, the profitability of the web site, etc. Similarly, the organizational aspects of delivering the auction web site are not of primary concern. The latter might be an industry effort, a partnership, or a third party -- these issues are only relevant to the extent that they might affect the rules of the transactions and hence the resulting service levels and prices to shippers.

1.5. ***Research Objectives and Contributions***

The properties or performance of a spot TL transportation market are not evident a priori; nor are approaches to study them. A primary contribution of this dissertation is to initiate the study carriers' behavior in an ongoing competitive environment. Sequential auctions are the framework chosen to model and study carrier competition. This research examines TLPM markets using sequential auctions under different demand/supply conditions, carriers' fleet management technologies, and behavioral assumptions.

The specific goals of this research are as follows:

1. Model a competitive spot market for TL procurement using sequential auctions;
2. Analyze characteristics and complexity of sequential TL procurement auctions;
3. Formulate the bidding problem for TLPM using sequential auctions as an equilibrium and decision theory problem;
4. Define a benchmark to compare the efficiency of sequential transportation marketplaces;
5. Provide a methodology to compare carriers' fleet assignment asymmetries;
6. Evaluate the competitive performance of vehicle routing technologies with different degrees of sophistication under different demand patterns;
7. Propose a framework for carrier behavior in sequential auctions for transportation procurement, where behavior is shaped by learning and cognitive capabilities;

8. Develop a market simulation framework to get insights into complex dynamic aspect of the TL spot market using sequential auctions; and
9. Study the influence auction format and data disclosure on learning (fictitious play and reinforcement learning), market performance, and technological advantages.

1.6. Dissertation Organization

In TLPM markets, it is possible to identify two layers of interdependent allocations. The first layer is a public allocation, the auction layer, which is an allocation from the set of carriers to the set of shipments (the set of shippers). There is an exchange of services and money (dynamic pricing through auctions) and a first allocation process. The second layer, a private allocation, constitutes allocation of shipments to vehicles as determined by the carriers' fleet management technology. While the first layer (auctions) performance is best described by economic indicators (e.g. prices, efficiency of allocations, etc.), the second (fleet management) is best described by engineering indicators (empty distance, fleet utilization, etc.).

From a carrier's point of view, these layers represent two distinct problems: (1) profit maximization problem (choose best bidding policy) and (2) cost minimization (best fleet assignment to serve acquired shipments). The set of skills and capabilities (i.e. problem solving skills, software, technology, human resources, etc.) that a carrier requires to excel in each layer are distinct, though both are indispensable for a successful operation. Given the complexity of the bidding/fleet management problem, carriers can formulate and solve the bidding/fleet management problem using different approaches and levels of sophistication. Three distinct approaches are: game theoretical (several decision makers, strategic rationality), decision theory (one decision maker, non-strategic rationality), and bounded rationality (non-optimal decision maker, can be strategic or non-strategic).

These concepts (allocation layers and approaches) are used to provide the structural organization of this dissertation (see Figure 2). After introducing the topic, chapter 2 examines relevant auction theory, mainly considering strategic issues that arise in sequential auctions (game theoretic approaches). Chapter 3 formulates the entire bidding-fleet management problem still using a game theoretic approach. The complexity and characteristics of the problem are analyzed. Chapter 4 assumes the existence of an ideal market where bidding best policy equals marginal cost bidding. Under this assumption, fleet management technologies are the only source of competitive advantage. Chapter 5 relaxes the full rationality assumption of chapters 2 and 3 and presents a framework for learning and boundedly rational behavior in the analyzed market. Chapter 6 looks at competition under different boundedly rational behaviors.

A more detailed outline of the chapters follows. Chapter 2 presents a review of auction theory and its relation to the present research. The chapter begins presenting an archetypical (though highly idealized) auction model and comparing it to TL sequential auction. Relaxations of the archetypical model are discussed, specifically models dealing with sequential auctions.

Chapter 3 formulates the complete decision problem as an equilibrium problem, using a game theoretical approach. The characteristics and complexity of this approach are analyzed. Additionally, the validity of a full rationality assumption and market efficiency measures are proposed. The chapter ends with an introduction to the simulation framework and experiment design.

Chapter 4 is dedicated to studying the effect of fleet management technology asymmetries in a competitive market. Algorithm analysis and vehicle routing technologies literature are surveyed and discussed. The bidding problem is formulated using non-strategic approach. A methodology to compare dynamic fleet management technologies is introduced. Simulation results are presented and analyzed.

Chapter 5 presents a framework to study carrier behavior in TL sequential auctions. Carriers' decision making processes and bounded rationality are analyzed. Behavior is also analyzed in relation to the auction information disclosed and decision making complexity.

Chapter 6 analyzes the market performance under different carrier behavioral assumptions. Reinforcement learning and fictitious play implementations are discussed. The performance of different auction formats is studied. Simulated scenarios are presented and their results discussed.

The last chapter presents a summary of the main findings and results as well as suggested avenues for future research.

1.7. Notation Convention

This section presents the notation convention that is used throughout this dissertation. Unless explicitly stated otherwise, this is the convention used:

- Superscripts are used for carriers (players). The letter "i"is preferably used to refer to any carrier; "$-i$"refers to the set of all carriers but carrier "i", that is, the opponents of carrier "i".
- When the superscript is a number within parentheses, it is referring to the carrier that occupies that position in an ordered set (e.g. an ordered set of bids). For example arranging the bids from lowest to highest, $b^{(k)}$ is the kth lowest submitted bid, then $b^{(1)} \leq b^{(2)} \leq ... \leq b^{(n)}$.
- Subscripts are used for shipments and time, j or k are the letters preferably used to refer to any shipment/arrival time.
- N and n are used to denote the number of objects for sale on a sequential auction (sequential auction length) and the number of participating bidders, respectively.
- Variables and constants are formatted in italics while functions are not. For example b^i is the bid of carrier i (a real number) while b^i is the bidding function of carrier i.
- The letter $\Im$ is used for the set of carriers, then $b^{\Im} = \{b^1, ..., b^n\} = \{b^i, b^{-i}\}$ denotes the set of carriers' bids, similarly $\mathrm{b}^{\Im}$ denotes the set of carriers' bidding functions.

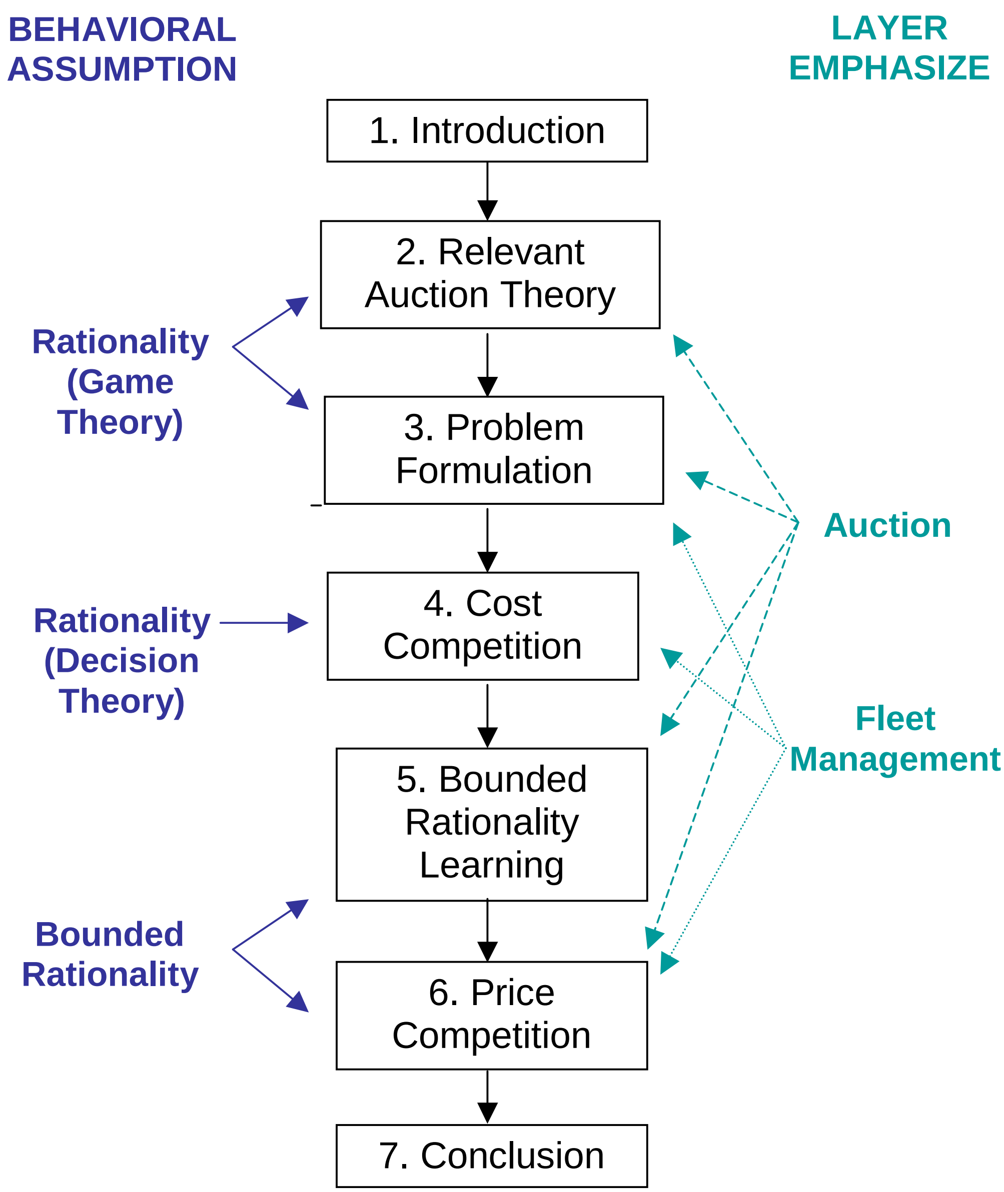

Figure 2 Outline Structure

Chapter 2: Game Theoretic Auction Literature Survey

This chapter reviews relevant game theoretic auction equilibrium models and presents characteristics of TLPM markets. Special attention is given to sequential auction models. This chapter focuses on literature and models that are fundamentally game theoretical, i.e. with strategic rational players. This chapter does not include boundedly rational models of auctions and bidding (chapter 5 deals with boundedly rational behavior; this chapter contains a survey of bounded rationality models).

Section 1 describes auctions as pricing mechanisms. Section 2 reviews some basic auction terminology and notation that is used throughout this dissertation. Section 3 discusses the assumptions of an archetypical auction model. Section 4 presents solutions to the archetypical model. Section 5 discusses the characteristics of TL sequential auctions, characteristics that are also compared to the ones of the archetypical model. Section 6 reviews relaxations of the archetypical model. Section 7 summarizes results and insights presented in the chapter.

2.1. Auctions as a pricing mechanism

Economic markets can be defined as "a set of products, a set of buyers, a set of sellers, and a geographic area in which the buyers and sellers interact and determine prices for each product." (Church, 2000, page 601) Typical means of price discovery are fixed pricing, haggling, and auctions. In traditional markets, where buyers and sellers physically meet, market participants can haggle with each other directly (even over fixed prices) or use an auction to reach a price. In an electronic marketplace, participation is physically decentralized but linked through communications and computing processes. Auctions and fixed prices are the most ubiquitous transaction methods used in electronic marketplaces. Fixed pricing reduces transaction time cost but decreases flexibility and allocation efficiency when compared to auctions (Sashi, 2002).

Auctions are specially useful and practical when there is uncertainty about an object (or service) value. In such cases, an auction mechanism is used to “extract” buyers’ or sellers’ valuations. If there were no uncertainty, the seller/buyer would just transact with the buyer/seller that had the highest valuation. Speed and simplicity are two other auction advantages, which are clearly essential in a transportation spot market where transaction resolution time could be a significant constraint in real time markets. These advantages are increasingly important as the difference between the shipments’ delivery time deadline and their posting time decreases. In the case of transportation auctions, where participating shippers and carriers are physically decentralized but linked through the market, auction simplicity facilitates communication and transaction completion.

Non-cooperative game theory studies the behavior of agents in situations where each agent’s optimal choice may depend on his forecast of the choices of his opponents. From a modeling perspective, game theory formulations of auctions formally capture market competition and strategic interactions. These auction models recognize that individuals’/companies’ behaviors are affected by the presence of competition. Auction models try to replicate the behavior of real world companies and decision makers (ideally successful ones), who formulate strategies with a keen awareness of their market competition, and react proactively to potential competitive responses.

Game theory makes explicit and highly restrictive assumptions about the behavior of agents in a game (in this dissertation, bidders in an auction). These assumptions include the rationality of the players, common knowledge, and unbounded computational resources. Agents' rationality (typically) follows the von Neumann-Morgenstern (1953) preference axioms. Something is common knowledge if all game players know this information; know that the other players are aware of this information; and so on ad infinitum. This "something" could be a bidding strategy, the structure of the game, agents' characteristics, etc. Any strategy has to go through this process to reach equilibrium. Unbounded computational resources are necessary in games where a player perfectly needs to simulate his own behavior at the same time as he simulates that of his opponents, ad infinitum.

Despite these limitations, game theoretical analysis provides insightful models in a wide variety of strategic situations, ranging from nuclear deterrence (international relations) and voting in Congress (political science), to labor-labor management relations and auctions (McMillan, 2001).

2.2. Basic Auction Terminology and Concepts

Different auctions produce different outcomes. There are two main quantitative performance measures used to evaluate auctions: (a) revenue and (b) efficiency. Revenue is the expected price or income that a seller would obtain or the expected price that a buyer would pay (reverse auctions). Efficiency does not explicitly consider prices but rather how the object/service is allocated. An auction is efficient if it allocates the object/service to the buyer/seller with the highest/lowest valuation/cost. While the first performance parameter takes into account the buyer/seller point of view, the second performance parameter takes into account society's point of view.

The relationship among buyers' valuations (auctions) or among sellers' costs (reverse auctions) has important strategic implications. This relationship is commonly used to classify auction models. Two extreme and opposite relationships among bidders' valuations exist: these are usually called private values and common values assumptions, introduced in the auction literature by Friedman (1956) and Capen et al. (1971) respectively.

Bidders have private values (costs) when each bidder knows its own value (cost) of the object at the time of bidding (other bidders' valuations does not influence its value or cost). This value (cost) is the utility (disutility) that the bidder itself obtains from the consumption, use, possession or service of the auctioned item.

Bidders have common values (costs) when each bidder (by itself) does not know the value (cost) of the object at the time of bidding because other bidders' valuations and quality assessments influence its own valuation. Furthermore, the object has a unique true value. An archetypical common value example is the auction of underground oil property rights where (a) each bidder has an estimate of some sort (i.e. expert's estimate or tests results); (b) the other bidders posses extra information (additional estimates or different test results) that affect the value that a bidder attaches to the object; (c) the true value of the object is the same for all bidders (the amount of oil to be extracted is the same for all bidders). Another classic example is the auction of an object which is bought with the intention of reselling it shortly after the auction (i.e. stock in the stock market)

Intermediate cases between private and common values (costs) assumptions are called interdependent values (costs) assumption. The relationship among buyers' valuations (or sellers' costs) can be expressed in mathematical terms. Let $\Im = \{1, 2, \ldots, n\}$ be the set of bidders and θ^i denote the private information that buyer (seller) i possesses about the value (cost) of the item being auctioned. Then, the cost c^i for bidder i is a function of:

$c^i = \mathrm{f}(\theta^i)$ (Private costs assumption)

$c^i = \mathrm{f}(\theta^1, \ldots, \theta^n)$ (Interdependent cost assumption)

$c^i = c^j = \mathrm{f}(\theta^1, \ldots, \theta^n) \ \ \forall i, j \in \{1, 2, \ldots, n\}$ (Common cost assumption)

2.2.1. Strategic Equivalence among Auctions

In the ascending English auction, the auctioneer raises the bids until all bidders but the winner are eliminated. The winner pays the price of the last bid. In the Dutch auction the auctioneer lowers the bids until a bidder claims the object. The winner pays the price of the last announced bid.

In first and second price sealed bid auctions, all bidders submit a sealed bid. In both cases the highest bidder gets the object. However, in the first price auction the winner pays the amount of his bid, while in the second price auction the winner pays the amount of the second highest bid.

The strategic equivalence between the Dutch and first price auctions can be easily established. In both auctions the bidder decides how much to bid for or claim the object *without* receiving any signal from the other bidders. At the moment of bidding, the bidder does not know competitors' already submitted/about to be submitted bids. If a bidder knows a competitor's bid it implies that the auction is already over. If the strategy space as well as the information available to the bidders is the same in both auctions, the payoff functions and equilibrium outcomes are equivalent.

The English auction and the second price auctions have in common the fact that the winner pays the second best bid. This is explicit in the second price sealed bid auction. In the English auction it is implicit. In this auction bidding stops at the price set by the second best bidder. Therefore, in either case the price paid by the winner is exclusively determined by rivals' bids. However, prices paid in each auction are not always equivalent. In the interdependent or common value (cost) case the two auctions are not strategically equivalent.

Two conditions must be met to have dissimilar outcomes: (a) bidders have interdependent or common values, and (b) in the English auction bidders can observe prices at which bidders drop out. Outcomes are dissimilar because competitors' bids carry relevant information about the object valuation. However, in both cases, bidders have the (weakly) dominant strategy to bid up (down) to an amount equal to the *current* best estimation of their own true valuation (cost). The fact that there is information revelation in English auctions may help to explain why they are so widely used. Bidders have a chance to update their valuations as the auction evolves, which in turn may drive bids up (Krishna, 2002).

Outcomes and auctions are always equivalent in the private value case. English auctions with static proxy bidding are also strategically equivalent to second price sealed auctions. Proxy bidding occurs when an automated bidding agent bids on behalf of the bidder, as prices go up (down), up to the bidder's reservation price. In static proxy bidding the bidder sets his reservation price before the auction starts (reservation prices cannot be updated during the auction).

The auction formats used in this dissertation are limited to first price sealed bid auctions and second price sealed bid auctions. Given the strategic equivalence discussed in this chapter, the results obtained automatically extend to Dutch and English auctions with static proxy bidding respectively.

2.3. <u>The Symmetric Independent Private Values Model</u>

This section reviews the assumptions and solution of the symmetric independent private values (SIPV) model, which is one of the simplest and most comprehensively studied auction models (Wolfstetter, 1999). This model is usually used as a benchmark in auction theory. In this dissertation this model is useful to illustrate the working of game theory in auctions and to serve as a starting point to characterize TL procurement sequential auctions.

2.3.1. Model Assumptions

The first six assumptions are exclusive to the SIPV model. The rest are implicitly used or assumed in the subsequent game theoretic formulation and solution of the model. This is a list of the main assumptions of the SIVP model:

1. One indivisible object is being auctioned;
2. Several bidders (more than one) compete for the object;
3. Complete symmetry among bidders (all bidders are identical);
4. A bidder’s valuation (cost) is only known to himself (private value);
5. Bidders’ valuation (costs) are identically independently distributed (iid);
6. Bidders’ and seller are risk neutral;.
7. There is a symmetric Nash equilibrium in increasing bidding functions;
8. Valuations (costs) are drawn from continuous and differentiable distributions;

The following items are all common knowledge:

9. Bidders are rational (rationality assumption);
10. The rules of the auction;
11. Private information probability distribution functions;
12. Fixed number of bidders;
13. There is no uncertainty about bidders’ participation;
14. Seller’s reservation price is zero;
15. No fees or participation costs, losers do not pay anything;
16. No budget constraints;
17. Bidders have no uncertainties about their private values; and

18. Time is not an issue (time at which the auction takes place or resolution time does not affect results or valuations).

2.3.2. Game Theoretic Solution to the SIPV Model

Since valuations are private information and bidders are assumed to behave strategically, the SIPV model is formulated as a non-cooperative game under incomplete information.

There are $n > 1$ potential buyers and an object for sale. Let $\Im = \{1, 2, ..., n\}$ be the set of bidders and θ^i denote the private information that buyer i possesses about the value of the item being auctioned. If bidders' valuations $\{\theta^1, ..., \theta^n\}$ are identically independently distributed (iid) and uniformly distributed on the support [0,1] then there is a unique symmetric equilibrium bid functions $\mathrm{b}^* : [0,1] \to \mathrm{R}^+$

$$\mathrm{b}^*(\theta) = \left(1 - \frac{1}{n}\right)\theta \qquad \text{(Dutch and first price sealed bid auction)}$$

$$\mathrm{b}^*(\theta) = \theta \qquad \text{(English and second price sealed bid auction)}$$

2.3.2.1. First Price and Dutch Auctions

The solution to the first price auction presented here is adapted from Wolfstetter (1999). Suppose bidder i bids the amount b^i, and each and every competitor bidder bids according to the strictly monotonic increasing equilibrium strategy $\mathrm{b}^*(\theta)$. The inverse bidding function is denoted $\beta(b) = \beta(\mathrm{b}^*(\theta)) = (\mathrm{b}^*(\theta))^{-1}$.

Using the symmetry assumption, bidder i wins the auction if and only if all rivals' valuations are below $\beta(b^i)$ .Ties have zero probability (continuous valuation distributions and $\mathrm{b}^*(\theta)$ is strictly monotone increasing).

The probability density function of the private value distribution is denoted $\mathrm{f}(x)$, the cumulative density function is $\mathrm{F}(\theta) = \int_{x\in[0,\theta]} \mathrm{f}(x)\,dx$. The probability of winning when bidding an amount b and competitors play bidding equilibrium function $\mathrm{b}^*(\theta)$ is $p(b) = \mathrm{F}((\mathrm{b}^*)^{-1}(b))^{n-1} = \mathrm{F}(\beta(b))^{n-1}$ (if the bidding function is reversible and private values are iid).

In equilibrium, the bid b^i must maximize the expected utility:

$\pi(b^i,\theta^i) = \mathrm{p}(b^i)(\theta^i - b^i)$. The first order condition (FOC) is:

$\frac{\partial}{\partial b}\pi(b^i,\theta^i) = \mathrm{p}'(b^i)(\theta^i - b^i) - \mathrm{p}'(b^i) = 0$ (differentiability and concavity assumptions). Due to symmetry the superscript can be dropped. Replacing $\theta = \beta(b)$ (by definition) and $\beta(0) = 0$ (border condition):

$$(n-1)\,\mathrm{f}(\beta(b))(\beta(b) - b)\beta'(b) - \mathrm{F}(\beta(b)) = 0$$

In the uniform distribution is assumed for the private values:

$\mathrm{F}(\beta(b)) = \beta(b)$, then,

$$(n-1)(\beta(b) - b)\beta'(b) - \beta(b) = 0$$

This differential equation has the solution $\beta(b) = [n/(n-1)]b$, solving for the optimal bidding function:

$$\mathrm{b}^*(\theta) = \left(1 - \frac{1}{n}\right)\theta$$

The equilibrium expected price can be easily obtained by introducing the highest order statistic of the entire sample of n valuations in the bidding function. Then,

$$\theta^{(k)} = \frac{k}{n+1} \quad \text{(k}^{\text{th}}\text{ order statistic uniform distribution with support [0,1])}$$

$$E[\mathrm{b}^*(\theta^{(n)})] = \frac{n-1}{n+1}$$

2.3.2.2. Observations of First Price Auction Solution

The equilibrium bidding strategy and prices are dependent on the amount of competition in the market. As expected, when the number of bidders grows the expected price fetched in the auction also grows. Therefore, a seller benefits while the buyers are worse off with competition.

On the technical side, the derivation of a closed analytical equilibrium bidding formula has several essential requirements: a well behaved probability density function (continuity, differentiability, and easy to work with and few parameters), an increasing bidding function, and a solvable differential equation. Game theoretic models of auctions are in general very difficult to solve mathematically. This mathematical complexity usually leads to the formulation of models that make extremely strong simplifying assumptions (Rothkopf, 2001).

On the behavioral side, the symmetry, rationality, and common knowledge assumptions made about the bidder are extremely restrictive. Symmetry implies that no bidder is known to have an advantage. Furthermore, no bidder believes that he is in an advantageous or disadvantageous position with respect to the other bidders.

Common knowledge implies that every bidder possesses exactly the same public information about the others. All bidders model other bidders' private values (costs) in exactly the same way and analyze the strategic situation in the same rational way; rationality that leads to a Nash-Bayes equilibrium.

2.3.2.3. Second Price and English Auctions

In a second price sealed bid or English auction with private values truthful bidding is a weakly dominant strategy. In mathematical terms: $b^*(\theta) = \theta$

This bidding strategy survives the elimination of weakly dominated strategies as shown first by Vickrey (1961). It is easy to show that a bid equal to the valuation of the object weakly dominates any other bid. As in the previous auction, let's assume that a bidder has a valuation θ. The best of the competitors' bid or value is denoted as "s". Let "b" denote any possible bidding value such that $b \neq \theta$. Then

(a) Assume $b > \theta$

IF	Profit obtained from bidding b	θ
$s < \theta < b$	$(\theta - s) > 0$	$(\theta - s) > 0$
$\theta < s < b$	$\underline{(\theta - b) < 0}$	**Zero**
$\theta < b < s$	Zero	Zero

(b) Assume $b < \theta$

IF	Profit obtained from bidding b	θ
$s < \theta < b$	$(\theta - s) > 0$	$(\theta - s) > 0$
$\theta < s < b$	**zero**	$\underline{(\theta - s) > 0}$
$\theta < b < s$	zero	Zero

In the first case, overbidding may result in having a negative profit (underlined). Bidding the value of the object profits cannot be negative. In the second case, underbidding may result in a profit of zero; bidding the value of the object results in a positive profit (underlined). There are cases where the profits are equivalent, either $(\theta - s) > 0$ or zero. This is why bidding the true value *weakly* dominates other values.

The expected equilibrium price is equal to the $n-1$ order statistic of the given sample. This sample consists of n realizations from the uniform distribution with support on [0, 1]. The expected price is equal to the one obtained in the Dutch-first price auction:

$$E[\mathrm{b}^*(\theta^{(n-1)})] = E[\theta^{(n-1)}] = \frac{n-1}{n+1}$$

However it is not the only equilibrium, there are a multiplicity of asymmetric equilibria (Wolfstetter, 1999). For example:

$$\mathrm{b}^i(\theta) = 1,\ \mathrm{b}^k(\theta) = 0 \ \textit{for}\ k \neq i\ \textit{and}\ i,k \in \{1,2,\ldots,n\}$$

2.3.2.4. Observations of Second Price Auction Solution

As in the other auctions (Dutch and first price) the equilibrium bidding strategy and price are dependent on the amount of competition in the market. As expected, when the number of bidders grows the expected price fetched in the auction also grows. Therefore, the seller benefits while the buyers are worse off with competition.

In general, sealed second-price and English auction bidding functions are conditional expectations (i.e. interdependent values), which can yield closed-form expressions for sufficient simple underlying distributions (Rothkopf, 1994b). The SIPV model, with values being uniformly distributed, provides an unusually simple equilibrium bid function.

Behaviorally, the rationality requirements for this type of auctions are less restrictive than in the Dutch or first price auction. This is plainly evident in the private value (costs) case, where bidders are required to just estimate and bid their best estimation of their values (costs). Competitors' beliefs or value (cost) distributions are not relevant in SIPV model. Unfortunately this characteristic does not apply in multi-unit sequential auctions (Sandholm, 1996).

It was shown that there exists an asymmetric equilibrium. In this case it is easy to rule out the "plausibility" of this type of asymmetric equilibrium. However, it is not so easy in more complex models. A strong criticism of game theory is directed specifically at its inability to reach a unique equilibrium. In many games where multiple equilibria may exist, how can theory convincingly explain how players would agree on playing just one out of the possible equilibria? This and other criticisms to game theory are revisited in chapter 5, as part of the motivation for proposing a bounded rationality approach.

A notable result is that the four auction types lead to the same level of expected revenue and efficiency. This is usually called the "revenue equivalence" principle, which does not usually hold outside the SIPV model.

2.3.3. A Reverse Auction Model

This section shows the results of a reverse auction model, with one buyer and several sellers. The notation and assumptions used are all the same as in the previous SIPV model but the reservation price of the buyer is known to be equal to one. In the Dutch-first price auction the equilibrium bidding function is:

$$\mathrm{b}^*(\theta) = \left(1 - \frac{1}{n}\right)\theta + \frac{1}{n}$$

The expected price reached is:

$$E[\mathrm{b}^*(\theta^{(1)})] = \frac{2}{n+1}$$

As expected, this is the reverse case of the analyzed SIPV model with one seller and several buyers. The sum of the expected prices in the first price auction and reverse auction models sums to one, for any number of bidders (i.e. with two bidders expected prices are respectively $1/3$ and $2/3$ respectively). More competition leads to more aggressive bidding which leads to lower bids. This simple model can be viewed as a link to oligopoly theory (Wolfstestter, 1999). The structure of the model is similar to an incomplete information Bertrand oligopoly game with inelastic demand and $n \geq 2$ identical firms. A Bertrand game where each firm has constant unit costs θ^i (which is private information) and unlimited capacity. If it is common knowledge that companies' unit costs are iid uniformly distributed with support $[0,1]$, then the oligopoly game is similar to a Dutch auction (lowest price wins the market).

2.3.4. Extension to Price-elastic Demand

If the reservation price of the seller (denoted as r) follows a uniform distribution with support $[0,1]$, then the equilibrium bidding in the Dutch-first price auction is as if there was an extra bidder:

$$\mathrm{b}^*(\theta) = \left(1 - \frac{1}{n+1}\right)\theta + \frac{1}{n+1}$$

Intuitively, pricing is more aggressive if demand responds to price. Of course if the auction were second price, bidding would not be affected, since $b^*(\theta) = \theta$ independently of how many bidders there are.

In this case first price auction leads to lower expected prices, however it also leads to inefficiency. With positive probability there are valuations where $\theta^{(1)} \leq r$ (where $\theta^{(1)}$ is the lowest of the cost realizations) and

$$\theta^{(1)} \leq r < \left(1 - \frac{1}{n+1}\right)\theta^{(1)} + \frac{1}{n+1}$$

This is an inefficient outcome that would be avoided using a second price auction. It is clear that maximum efficiency and lowest expected cost for the buyer cannot be obtained using the same auction type. This simple example shows that a slight departure from the SIPV model leads to contradictory results. Unfortunately, this is a common characteristic in auction theory, where minor relaxations of a model can lead to unexpected or suspiciously dissimilar results (Rothkopf, 1994b).

2.4. <u>Characteristics of Spot TL Procurement Market using Sequential Auctions</u>

The most influential (and obvious) characteristic is the "sequential" aspect, which introduces a new dimension (time). In general, the sequential aspect has four distinct impacts (a) bidding is affected by the auction data already disclosed (i.e. carriers form expectations (beliefs) based on past data, such as bids, allocations, etc.); (b) the current bid or action will affect the future evolution of the bidding process; (c) unlike a single object auction, in TL sequential auctions, the cost of serving one shipment is uncertain and in general this cost cannot be correctly estimated without considering the other shipments already auctioned or to be auctioned; and (d) carrier available capacity is neither static nor unlimited. Section 3.3 in chapter 3 deals with the complexity of the auction-fleet assignment problem; it further analyzes how the fact of being "sequential" aspect affects the complexity of the problem.

Anther important characteristic of a TLPM is that carriers do not know the characteristics of the shipments to come. In this sense the problem can be defined as "sequential online", where it is uncertain not only whether a carrier will serve future shipments but also what the characteristic of the yet unrealized future shipments will be. A "sequential offline" problem is one where all the shipments to be auctioned are known before the auction starts.

Other characteristic of a TLPM are listed below:

1. Shipments being auctioned are usually heterogeneous objects (i.e. some shipment characteristics, such as origin-destination or the arrival-delivery time for example, always differ).
2. Transportation services are perishable, non-storable commodities. Therefore the timing and ordering of the auction is important.
3. Transportation supply/capacity/infrastructure is limited and highly inelastic (at least in the short term).
4. Demand and supply are not only geographically dispersed but also uncertain over time and space.
5. Each shipment has no standard value; auctions facilitate the price discovery process.
6. Strong complementarities exist among the items auctioned (the value of an item is a function of the acquisition of other items).
7. An item's value (shipment) is not only strongly dependent upon the acquisition of other items (e.g. nearby shipments) but also highly dependent on current spatial and temporal deployments of the fleet.
8. Penalties/costs associated with late deliveries or no delivery might be several times higher than the cost of transportation per se.

It was already mentioned that the SIPV model is a widely studied model. TL procurement auctions dramatically differ from the SIPV model. A detailed comparison of the two models, using the assumptions of the SIPV model as a base, is presented in Table 1.

An important common element is that in both models the values and costs are private. Why does a carrier have private costs in a TLPM? The reasoning is simple: the cost of servicing a shipment is not dependent on competitors' private information. A carrier's private information encompasses all the information regarding its assignment and cost functions, fleet status and deployment, as well as the shipments waiting to be fully serviced (this broad definition of a carrier's private information is used in chapter 3 to formulate the problem). Let θ^i and c^i be the private information and the cost of serving a given load by carrier i respectively, then $c^i = \mathrm{f}(\theta^i) \neq \mathrm{f}(\theta^1, ..., \theta^n)$.

Competitors' fleet deployment and status do not affect $i's$ cost of servicing a load. They can certainly affect the profit or probability of winning that load (more or less competitive bids) but not the cost (the number of empty and loaded miles that carrier $i's$ fleet have to travel to serve that load). In other words, whether or not the carrier i knows his competitors' private information may affect his bid but not his cost.

Table 1 indicates many differences between the TLPM and SIPV model. Though models in the literature cannot cover them all, relevant relaxations of the SIPV model are described and analyzed in the next section with a twofold purpose: (a) describe the state of art in sequential auctions and (b) gain intuition about the TL auction problem.

2.5. ***Extensions to the SIPV Model***

The following extensions of the SIPV model are all sequential offline auction models. Therefore, the characteristics of all the objects being auctioned are known before the auction starts, and the auction timing does not affect bidders' valuations. Another important distinction is between two period models and $N > 2$ period models. The former type of models assumes bidders with a two-unit demand function, while the latter type of models assumes bidders with a unit-demand function. Models with three or more objects, bidders with multiunit demands, and incomplete information about competitors' costs remain intractable (Krishna, 2002).

This section reviews game theoretic sequential auction literature. The literature is divided in two classes (a) papers that study expected revenue, efficiency, and equilibrium of a given model; and (b) papers that optimize either seller choice of auction mechanism or bidder strategies in a given auction environment. The formed are named "Economic Models" since they are mostly formulated by economists, while the later are called "Operations Research Models" (OR models) since they are studied primarily by operation research and computer science researchers.

ASSUMPTION SIPV Model	ASSUMPTION TL Sequential Auctions
One object	NO. Many shipments in a sequence of auctions.
Several bidders	Idem
Complete symmetry among bidders	NO. Carriers are inherently asymmetric (different fleet deployment and history)
A bidder's valuation is only known to himself (private value)	Idem. A carrier's private cost is a function of his own deployment only
Bidders' valuation are identically independently distributed	NO. Carriers may have different cost distributions (i.e. asymmetric fleet management technologies)
Bidders' and seller are risk neutral.	Idem
There is a symmetric Nash equilibrium in increasing bidding functions	NO. Asymmetries and binary variables impede it.
Valuations (costs) are drawn from continuous and differentiable distributions	NO. Asymmetries and binary variables impede it.
The following items are all common knowledge:	
Bidders are rational (in game theoretical terms)	Assumption hard to support. If rationality is relaxed, how competitors should be modeled?
The rules of the auction	Idem
Private information probability distribution functions	Assumption hard to support in a competitive environment. Companies' proprietary information.
Fixed number of bidders	Idem. A private market is assumed.
There is no uncertainty about bidders' participation	Idem. A private market is assumed.
Seller's reservation price is zero	Shippers' reservation price may not be necessarily known
No fees or participation costs, losers do not pay anything	Idem.
No budget constraints	NO. There are capacity constraints that affect strategic interactions among carriers and costs
Bidders have no uncertainties about their private values	NO. There are capacity constraints that affect strategic interactions among carriers and costs
Time is not an issue	NO. Timing of auctions affect carries costs and capacity.

Table 1 Comparing the SIPV and TLPM model

2.5.1. Economic Models

The first game theoretic model of sequential auctions to be published (Weber, 1983 and Milgrom, 2000) analyzes a model of sequential identical "*N*" auctions with unit demand bidders. This model introduces just one relaxation to the SIPV model: more than one object is for sale. However, this model assumes that bidders have unit demands, therefore if they win one object they do not participate in the subsequent auctions. Equivalently, a bidder's marginal value for the rest of the objects (after securing one) is zero or negative. It is shown that expected prices follow a martingale, i.e. bidders expected prices will remain constant on average throughout the sequence of auctions. The prices remain constant on average because there are two opposite forces at work as objects are being sold (1) less demand -- a reduction in competition (fewer buyers) drives prices downward, and (2) less supply – an increment in competition (fewer objects) drives prices upward.

The problems posed by the repeated interaction of bidders in multiunit auctions in business to business (B2B) online markets led to a revival of sequential auction theory in recent years. Branco (1997) finds equilibrium in an example of a two unit sequential ascending auction where there are two types of bidders: some bidders have unit demand functions and some bidders have super-additive demand functions. The equilibrium is in pure strategies. In equilibrium the expected price declines from the first to the second auction.

The importance of information transmission is studied by Jeitschko (1998), who presents a model with two identical objects. These objects are auctioned in sequence to three bidders. Each bidder has a unit-demand function and his valuations can be of two possible types, low or high (valuation). Bidders have an ex-ante probability of having a high valuation α, which is common knowledge. Ties are broken with the roll of a dice. The auction format is a first price sealed bid auction in which only the winning bid is announced. After the conclusion of the first auction, bidders use this information to update their expectations (beliefs) regarding the types of their opponents. The remaining bidders perform Bayesian updating of their expectations about the competitors' values after the result of the first auction is revealed. The model shows that bidders who are aware of informational effects place lower bids on average and hence have higher payoffs. Regardless of the outcome of the first auction, the second price is expected to be equal to the first price.

The first model with two-unit demand bidders is formulated by Katzman (1999), who establishes the efficiency of second price auctions when the seller is auctioning two homogeneous objects in a sequence. Katzman uses an auction model of incomplete information where bidders' valuations are determined by two independent draws from a twice differentiable, atomless distribution. These two draws are ranked as high (H) and low (L). The study finds a symmetric equilibrium where the bidding function $b^*(H)$ is strictly increasing and generates a bid shaded below the high valuation.

The primary obstacle faced when introducing multi-unit bidder demands into a model of sequential auctions is asymmetry of bidder expectations (beliefs), even if expectations are ex ante symmetric. Any symmetry is broken after the first auction, since one bidder has won and the rest have lost. Katzman avoids this problem using a second price auction and backward induction. The second and final auction can be viewed as a one-shot auction. It was shown that in a one object second price auction, bidders have a weakly dominant strategy of bidding their valuation for the object. Therefore, by limiting the auctions to two the asymmetry problem has been avoided.

Jeitschko (1999) analyses sequential auctions when the supply is unknown ex ante. There are $n>2$ bidders and an unknown number of identical objects to be auctioned sequentially. Bidders have unit demands, and their valuations are independent random variables drawn from a continuous distribution. Objects are auctioned in a sequence of second price auctions. Jeitschko presents two scenarios. In the first scenario, whether an object will be auctioned does not become known until immediately before the auction for the item is about to commence. In this case, given the supply uncertainty, prices decline as more items are put for sale. In the second scenario, information regarding whether there are either one or two further objects for auction becomes available before each auction. As expected, if good news is announced (two more objects are for sale), prices decline.

Jeitschko concludes that prices depend on information regarding supply: uncertain supply reduces the 'option value' and yields declining prices as more objects are put for sale. However, prices increase if it becomes known that supply falls short of expectations.

Menezes and Monteiro (1999) consider the sale of two homogenous objects using two second price sequential auctions. They consider that bidders have synergies (or super-additive demand functions). Buyers' valuations are iid; the positive synergy for owing two objects is modeled as a positive continuous increasing function of one object value. Synergies can be positive (the two objects are worth more as a bundle than as separate objects) or negative (the two objects are worth less as a bundle than as separate objects). In presence of positive synergies, prices in the first auction include a premium and prices decline in the second auction. The opposite effect is found in presence of negative synergies.

Jeitschko and Wolfstetter (2002) study a two object sequential auction with two bidders, where economies of scale can be present. Prior to the first auction each bidder privately observes his valuation for the first object, but not for the second. There are two possible valuations for the objects: high and low. In the first auction, both bidders have the same probability "τ" of having a high valuation. After the winner is announced, bidders privately observe their valuation for the second auction. The winner of the first auction has a probability σ of having a high valuation (for the 2^{nd} object) while the loser has a probability τ (with economies of scale: $\sigma > \tau$, with diseconomies of scale: $\sigma < \tau$). Jeitschko and Wolfstetter show that economies of scale give rise to higher bids in the first auction, where as the converse is not true. Moreover, first and second price auctions are not revenue equivalent. With economies of scale second price auctions have higher revenues, whereas the revenue equivalence is preserved in the case of diseconomies of scale.

Unlike previous models, the last "economic" model to be reviewed is one of *complete* information and budget constraints. This implies that the values of the objects and the bidders' budgets are common knowledge. With complete information the SIVP model becomes trivial; Benoit and Krishna (2001) introduce bidders with budget constraints in a sequential auction. They examine the revenue generated by the sale of two heterogeneous objects under a complete information setting under sequential and simultaneous auctions. Depending on the nature of the relationship between the two objects (i.e., whether they are complements or substitutes) and the difference in their values, the optimal sequencing of the auctions may change.

An appealing insight of Benoit and Krishna's paper is that when multiple objects are auctioned in the presence of budget constraints, it may be advantageous for a bidder to bid aggressively on one object in order to raise the price paid by his rival. This high price may diminish his competitor's budget so that the second object may then be obtained at a lower price. The same idea can be applied to a reverse auction, with one buyer and several capacity-constraint service providers. To illustrate how this intuition can be applied to the problem studied in this dissertation, three examples have been adapted from Benoit and Krishna's paper.

Example 1: Assume two shipments (A and B) sold sequentially by means of two successive English Auctions. Two carriers compete for the shipments; both carriers have the same costs: $C_A = 40$ and $C_B = 50$. The shipper has a reservation value of 100 for each shipment. Carrier 1 can serve both shipments while carrier 2 can serve either shipment but not both. Suppose that the object sell in the order A followed by B.

Analysis: Being a game of complete information, the game can be solved with backward induction (assuming that weakly dominated strategies are not played). In a descending English auction without capacity constraints the buyer (shipper) would have paid only $90 for having both A and B served. The profit for both carriers would have been zero.

With capacity constraints it is an equilibrium for carrier 1 to let carrier 2 win the first auction with a bid of \$41 (or \$40+ε, without loss of generality natural numbers are used), then carrier 1 can win shipment B for \$100 (carrier 2 cannot compete after wining shipment A). In this way carrier 1 has a profit of \$50 and carrier B a profit of \$1. The shipper pays \$141 for both shipments.

It is obvious that carrier 1 is using its market power to drive up its profits. The order of sale is important too. If the order of the auctions is reversed, i.e. B followed by A, the shipper would pay \$151, carrier 1 would have a profit of \$60 and carrier B a profit of \$1.

Example 2: This example is similar to the preceding one, but with different costs: $C_A^1 = 40$, $C_B^1 = 50$, and $C_{AB}^1 = 90$ for carrier 1. Costs for carrier 2 are: $C_A^2 = 60$, $C_B^2 = 30$, and $C_{AB}^2 = \infty$. The shipper still has a reservation value of 100 for each shipment. Carrier 1 can serve both shipments while carrier 2 can serve either shipment but not both. Suppose that the object sell in the order A followed by B.

Analysis: with capacity constraints it is an equilibrium for carrier 1 to let carrier 2 win the first auction with a bid of \$61 and then to win shipment B for \$100 (carrier 2 cannot compete after wining shipment A). In this way carrier 1 has a profit of \$50 and carrier B a profit of \$1. The shipper pays \$161 for both shipments.

It is obvious that the assignment is completely inefficient from a "society" point of view. The shipments are allocated to the carriers with the highest cost. Social wealth is \$90 = \$40 + \$50. However, inverting the auction order, first B, followed by A, social wealth is \$130 = \$60 + \$70. Therefore, the ordering of the auctions affects the efficiency of the allocations.

Example 3: $C_A^1 = 40$, $C_B^1 = 50$, and $C_{AB}^1 = \infty$ for carrier 1. Costs for carrier 2 are the same as for carrier 1. The shipper still has a reservation value of 100 for each shipment. Neither carrier has capacity to serve both shipments. Suppose that the objects sell in the order A followed by B.

Analysis: In equilibrium carriers go down to $90 for the first object. The second object is sold for $100. In this equilibrium both carriers get a profit of $50 and are indifferent about what shipment they serve.

It was shown in the examples that capacity constraints provide incentives for carriers to exercise market power and capacity rationing. This is possible because a particular bidder's payoff is affected by the remaining capacity of the competition. Obviously, this is only possible when more than one shipment is sold sequentially.

On the technical side, if the assumption of complete information about capacities is relaxed, one should not expect the bidding strategy in the incomplete information setting to be monotonically increasing. It was shown in example two that there is no decreasing equilibrium regardless of the auction order. Benoit and Krishna indicate that typical differential equation techniques used to determine equilibrium strategies do not work under these conditions.

2.5.2. Operations Research Models

Oren and Rothkopf (1975) study optimal bidding in sequential auctions. Their model has a distinctive (unique to the author's best knowledge) characteristic: the opponents explicitly adapt to the competition level. The competition level is characterized by a scalar. A reaction function relates bids to changes in the state of the competition level. The base model is a common value model where bidders draw their valuations from a Weibull distribution. The bidders develop a dynamic programming approach to find the best bidding policy. However, the bidding policy is not updated as the sequential auction evolves, ipso facto the model has become static in nature. Since the bidders account for the future impact of their bids, as the competitive reaction increases (competition responds harshly) bids and expected profits increase too. A similar effect takes place when the discount factors and the number of periods increase. The results are similar to those obtained using game theoretic models in oligopoly theory (for example Maskin (1988), and Philips (1995))

More recently, Friedman and Parkes (2002) describe the challenges associated with the design of an online sequential auction mechanism to allocate computational resources among consumers. They specifically analyze the challenges of designing an auction mechanism to allocate internet bandwidth when the arrival of customers is uncertain.

Chaky et al. (2002) use sequential auctions to optimize the allocation of (homogenous) computational resources among users. They are interested in designing a fast and simple (from a computational standpoint) auction mechanism that guarantees equilibrium where users (agents) report their true valuation. They propose a mechanism that distributes users into auction pools and match them with the available resources using sequential auctions.

Vulcano et al. (2002) try to optimize the revenue for a seller with C homogeneous items. The seller uses a sequential auction, in which a seller faces a sequence of buyers separated into T time periods. Each group of buyers has independent, private values for a single unit. The number of buyers in each period as well as the individual buyers' valuations is random. In this setting they prove that revenues are higher in dynamic versions of the 1st and 2nd price auctions than a selling mechanism using prices set as a function of time and remaining capacity.

The previous model is the game theoretical equivalent of traditional revenue models in OR. A seller with limited products or capacity tries to maximize his revenue using auctions. The analysis is greatly simplified by assuming that customers appear in just one period, therefore customers do not learn/speculate about prices. Likewise, buyers do not return to the system if they lose one auction. Furthermore, buyers have unit demand functions.

Elmaghraby (2003) studies what ordering is optimal in a sequential procurement auction of two heterogeneous jobs. The set suppliers (two or more) have capacity constraints and two different technological costs that are assumed to be distributed over $[0,1]$. Because any supplier can win just one auction, the sequence of the auctions affects their behavior (similar idea to what was already examined in Benoit and Krishna's paper). The ability of the buyer to select the efficient suppliers is complicated by the presence of asymmetry in information (each supplier's technology type is private information) and supplier capacity constraints. While the buyer does not know the types of the suppliers competing in the auction, the buyer assumes that knows their suppliers' common distribution function, as well as their cost functions for each job.

2.6. Summary

This chapter describes characteristics of TL procurement auctions, which are compared to a basic auction model widely studied in the game theoretic auction literature, the SIPV model. Basic auction terminology is introduced, as well as the strategic equivalence between Dutch and first price auctions, and the strategic equivalence among English, proxy bidding English, and second price auctions.

Relevant relaxations of the SIVP model are presented. It is clear from the literature review that no game theoretical model provides a realistic representation of the TLPM under study. However, they provide useful insights. Capacity constraints affect carriers bidding behavior and introduce speculation in the market. Furthermore, the models presented indicate that in general supply/demand variations affect market prices, even in the simple SIPV model. Links between results in auction theory and oligopoly theory also confirm these results.

The relationship among bidders and objects valuations is also important. The presence of economies of scale (or positive synergies) tends to increase the price of the first object being auctioned. The opposite can be said when there are diseconomies of scale or negative synergies. Intuition that agrees with results obtained in chapter 4 when analyzing fleet management technologies.

The SIPV model solution is explained in detail to show the number of assumptions that are necessary to develop a mathematically simple and solvable auction model. Relaxed SIPV models introduce new elements, but usually at the cost of introducing more simplifying assumptions that make the relaxation tractable.

This chapter provides the necessary background to formulate and analyze the complexity of the whole bidding-fleet assignment problem in chapter 3. The intuition developed from the presented models will also be useful in chapter 6 when the results of competition among boundedly rational carriers are analyzed.

This chapter focused on literature and models that are fundamentally game theoretical, i.e. with strategic rational players. This chapter does not include boundedly rational models of auctions and bidding. Chapter 5 deals with boundedly rational behavior and contains a survey of bounded rationality models. Chapter 4 deals with technology based competition in a TLPM, a survey of relevant literature regarding technology and algorithms analysis is presented in chapter 4. .

Chapter 3: Conceptual Formulation

The focus of this chapter is on providing the specific context and formal definition of the problem addressed in this dissertation. Section 1 introduces the problem context. The overall bidding-fleet management problem for a TLPM problem is formulated as an equilibrium problem in section 2. This formulation is used to illustrate the game theoretic approach to the problem. Section 3 analyzes the complexity and behavioral assumptions of this approach. Section 4 introduces the simulation framework and parameters that are used throughout this dissertation. Section 5 formally introduces the concept of auctions as mechanisms. The mechanism approach is used to define market performance measures and to introduce the concept of truthful mechanisms that is used in chapter 4. Section 6 ends the chapter with a summary.

3.1. Problem Context

The elements that constitute a TLPM using sequential auctions were broadly defined in chapter 1. The specifics of the problem are defined in this section.

Shippers are assumed to procure TL services using sequential auctions. A fixed set of carriers bid on each announced auction. The auctioneer's role (marketplace) is limited to setting the auction rules, as well as specifying and monitoring allowable communication among carries and shippers. Rules and settings do not change once auctions have started. A TLPM is a spot market, where auctions for shipment service requests are taken or rejected on the fly; it is not possible to book or reserve capacity without buying it. Future markets are not allowed (no bidding allowed on shipments that cannot be served immediately). Carries cannot resale already won shipments.

Shippers announce to the market time-sensitive shipment service requests and call for auctions as needed on a continuous basis. Shipments have time windows that must be strictly satisfied (hard time windows). Once the auction announcement has been made, changes in the auction call or to the shipment service request characteristics are not possible.

Given that all service quality (i.e. time windows) elements of the request are met, a shipper pre-selects the carrier with the lowest bid. The time windows are always respected since (a) deterministic service (travel) times are assumed, and (b) carriers are assumed to meet the shippers' request (check for feasibility) before submitting a bid. If the payment that the lowest bid carrier should receive is less than the shipper's reservation value, the shipper selects the lowest bid carrier and the transaction is completed. Otherwise, the shipper uses an alternative system to obtain transportation services (long term contractor, own fleet, etc. paying the shipment reservation value). Shipments that are not successfully matched do not return to the market.

Carriers' fleet management decisions are binding in the sense that past decisions affect future costs and even constrain whether future shipments can be served. Each carrier has a constant fleet size. Carriers serve the secured shipments by picking up the loads at their origins and delivering them to the destinations within their specified time-windows. Loads are not combined as part of a tour (truckload operation).

Carriers bid on just one shipment auction at a time, in the same order (first in, first out) as these are arriving. The possibility of two or more requests arriving at the same time or composed requests (one order that involves several distinct shipments) is ruled out. The auction process, announcement, bidding, and resolution are done in real-time.

In order to deal with this dynamic problem a carrier has to make two kinds of decisions: (a) bidding decisions (i.e. decide how much to bid), and (b) demand-truck assignment decisions for the accepted demands (i.e. when and which trucks serve the accepted demands within specified time-windows).

The main objective of the carriers is to maximize profits while managing the fleet to satisfy the service quality requirements (time windows). This objective may run against other performance parameters, such as serving high number of loads, market share, or highest efficiency (low empty distance). The revenue from a secured auction is the auction payment. The primary operating costs are proportional to the haul-length and the distance traveled by a truck to serve it (loaded and empty distance respectively). Fixed costs are considered already sunk and therefore not considered.

3.2. Formulation of a TLPM problem as a Game (Equilibrium Formulation)

This section describes the notation and theoretical concepts required to describe (a) the strategic issues involved in bidding, and (b) the dynamic fleet management aspects. A sequential auction belongs to the class of dynamic games of incomplete information. Its characterization as a dynamic game refers to the fact that players (carriers) face each other at different stages that are usually associated with different time periods. Sequential auctions are also characterized by incomplete information since players do not know with certainty the private information that affects competitors' costs.

A sequential auction game is defined by the auction rules (allocation/payment functions), a set of players (carriers), a set of feasible actions (bids), a set of sequential auctions (stages), and a set of bidders' private signals about its costs. In addition, TLPM requires the definition of shipment characteristics, carriers' endowments (fleet size, vehicle routing technology, cost functions, etc.), and the market/demand geographic and temporal boundaries and characteristics.

It is assumed that stages are identified with shipment arrival epochs. More precisely, each stage or auction is fully identified by the arrival of the shipment to be auctioned. In the previous chapter, it was noted that the auction literature by and large assumes that costs are drawn from a stationary probability distribution. This is not the case in a TLPM problem, in which history and fleet management decisions affect future cost probability distributions. The TLPM formulation distinguishes itself from other auction formulations in several aspects: (a) the description of items to be auctioned (shipments) require a multi-attribute characterization; (b) costs are functions of carriers' status and vehicle routing technologies (carriers' private information); (c) history affects costs; (d) capacity constraints are linked to private information and shipments characteristics; (e) bidding strategies are dependent on public and private history; (f) timing of auctions is important; and (e) it is an online sequential auction.

The formulation presented below is intended for the strategic situation where the operational information is private. Consequently, a carrier has full knowledge about its fleet status (vehicles and shipments) and its technology (how the carrier determines the routing and costing of vehicles and shipments). However, a carrier has uncertainty about its competitors' fleet status or technology. The formulation follows the notation convention adopted in chapter 1, section 7.

3.2.1. Players (carriers)

There are n carriers competing in the sequential auction market place, each carrier $i \in \Im$ where $\Im = \{1, 2, ..., n\}$ is the finite set of players.

3.2.2. Stages/Auctions

Let the shipment/auction arrival/announcement epochs be $\{t_1, t_2, ..., t_N\}$ such that $t_i < t_{i+1}$, where $N \in \boldsymbol{N}$ (set of natural numbers). Let $\{s_1, s_2, ..., s_N\}$ be the set of arriving shipments. Let t_j represent the time when shipment s_j arrives and is auctioned. Each shipment has an associated reservation value, denoted v_j, that is only known to the shipper. There is a one to one correspondence between each t_j, s_j, and v_j for any $j = 1, 2, ..., N$ (i.e. for each t_j there is just one s_j and v_j).

The subset of the first $j = 1, 2, ..., N$ arrival times is denoted as T_j where $T_j = \{t_1, ..., t_j\}$, the corresponding subsets of shipments and reservation values are denoted S_j and V_j where $S_j = \{s_1, ..., s_j\}$ and $V_j = \{v_1, ..., v_j\}$ respectively. The subset of last shipments is denoted as $S_{j...N} = \{s_j,...,s_N\}$ ($T_{j...N}$ and $V_{j...N}$ are defined in a similar way).

3.2.3. History and Public Information

In an auction for shipment s_j, each carrier $i \in \Im$ simultaneously bids a monetary amount $b_j^i \in R$. A set of bids $b_j^{\Im} = \{b_j^1,...,b_j^n\}$ generates publicly observed information y_j. The public information at the beginning of the auction for shipment s_j is $h_j = (h_0, y_1, y_2,..., y_{j-1})$, where h_1 denotes information publicly known to all carriers before bidding for shipment s_1. The elements and corresponding attributes of y_j and h_1 may greatly vary with the auction type and rules; therefore they will be specified on a case-by-case basis (when analyzing a particular auction). Once the game is over, all the information revealed to the carriers is contained in h_N. The set of all possible histories up to time t_j (not including auction information for shipment s_j) is H_j.

3.2.4. Private Information

Each carrier also has private information. Private information embodies any information that is relevant to a player's decision making without being common knowledge for all carriers (Fudenberg, 1991). This private information is generally called (in game theory) the "type" of a player. In this formulation a carrier's "type" includes, in addition to its status, its cost and assignment functions. Denote this private information for each carrier $i \in \Im$ at time t_j by θ_j^i.

In general, a “type” may include not only what a carrier believes about other carries’ cost functions, routing technology, and current status, but also its expectations (beliefs) about what other carriers expect (belief) its expectations (beliefs) are, and so on.

The fleet status of carrier i when shipment s_j arrives is denoted as z_j^i, which comprises two different sets:

S_j^i: set of shipments acquired up to time t_j

V_j^i: set of vehicles in the fleet of carrier i (vehicle status updated to time t_j)

The elements of these sets have the following attributes:

For each $s | s \in S_j^i$, attributes of shipment s are:

Location of origin of shipment s, denoted $o(s)$

Location of destination of shipment s, denoted $d(s)$

Earliest pickup time of shipment s, denoted $ept(s)$

Latest pickup time of shipment s, denoted $lpt(s)$

Status of shipment s at time t_j (served or not served), denoted $sts(s, t_j)$

For each $v | v \in V_j^i$, attributes of vehicle v are:

Current location of vehicle v at time t_j, denoted $loc(v, t_j)$

Status of vehicle v at time t_j (empty or loaded with a shipment s), denoted $sts(v, t_j)$

Locations belong to a subset of R^2 and times belong to a subset of R^+. At time t_0 each carrier i has an initial status of his fleet denoted as z_0^i (vehicles are not necessarily empty or idle at time t_0).

There is a state or assignment function such that the status of carrier $i \in \Im$ when shipment s_j arrives is $z_j^i = \mathrm{a}^i(t_j, h_j, z_{j-1}^i)$. It is assumed that the fleet status at a given time is a function of time, previous fleet status, and history of play up to the previous epoch. The estimated cost of serving shipment s_j by carrier $i \in \Im$ of type z_j^i is denoted $\mathrm{c}^i(s_j, z_j^i)$. The sets of possible assignment and cost functions are denoted by A and C respectively, then for each $i \in \Im$ it follows that $\mathrm{a}^i \in \mathrm{A}$ and $\mathrm{c}^i \in \mathrm{C}$.

The private information or type for carrier at time t_j is $\theta_j^i = \{\mathrm{z}_j^i, \mathrm{a}^i, \mathrm{c}^i\}$. In a game of incomplete information each player (bidder) has expectations (beliefs) about the competitors' private values. Following Harsanyi's (1967) modeling of games of incomplete information, players' types $\theta_j^{\Im} = \{\theta_j^i\}_{i=1}^n$ are drawn from some probability density function $\mathrm{p}(\theta_j^1, ..., \theta_j^n)$ where types θ_j^i belong to a space Θ^i. The conditional probability about his opponents' types $\theta_j^{-i} = \{\theta_j^1, ..., \theta_j^{i-1}, \theta_j^{i+1}, ..., \theta_j^n)$ given his own type θ_j^i is denoted $\mathrm{p}(\theta_j^{-i} \mid \theta_j^i, h_{j-1})$. This is what characterizes and complicates the solution of a dynamic game of incomplete information. Since the players do not know the competitors' types at the start of each auction, they have to update these conditional probabilities (beliefs about the competitors' status) as public information is revealed and the game evolves.

3.2.5. Bidding, Payment and Profit functions

The set of feasible actions is the same in all the auctions. Each and every carrier must participate in each action (submit a bid) and bids are restricted to the set of real numbers. A bidding strategy is a contingent plan on how to bid in each auction given current private information and a possible history.

Let $\mathrm{b}^i : S, H, \Theta^i \to R$ be the bidding function. Carrier $i's$ bid for shipment s_j, given history h_j, and type θ_j^i is equal to $b_j^i = \mathrm{b}^i(s_j, h_j, \theta_j^i)$. Denote by $\mathrm{b}^{-i} = \{\mathrm{b}^1, ..., \mathrm{b}^{i-1}, \mathrm{b}^{i+1}, ..., \mathrm{b}^n\}$ the set of bidding functions of all carriers but carrier i. Denote by $b_j^{\Im} = \mathrm{b}^{\Im}(s_j, h_j, \theta_j^{\Im}) = (\mathrm{b}^i \circ \mathrm{b}^{-i})(s_j, h_j, \theta_j^{\Im}) = \{b_j^1, ..., b_j^n\}$, where the set of all carriers' bids is denoted $b_j^{\Im}$. For each carrier $i \in \Im$ the set of all possible bidding functions is denoted B^i. The set of all possible bids for all carriers is denoted $B^{\Im}$. Arranging the bids from lowest to highest, $b_j^{(k)}$ is the k$^{\text{th}}$ lowest submitted bid for serving shipment s_j, then $b_j^{(1)} \leq b_j^{(2)} \leq ... \leq b_j^{(n)}$.

Let q_j^i be the probability that carrier i wins shipment s_j. Let q be the auction assignment function that given the set of bids $b_j^{\Im}$ determines the probability that a carrier wins shipment s_j. Then, $\mathrm{q}(b_j^{\Im}) = q_j^{\Im} = \{q_j^1, ..., q_j^n\} \in [0,1]^n$ and $\sum_{i \in \Im} q_j^i = 1$.

Ties are solved with the roll of a dice or any other random device. Let I_j^i be the indicator variable for carrier i for shipment s_j, such that $I_j^i = 1$ if carrier i secured the auction for shipment s_j and $I_j^i = 0$ otherwise. The set of indicator variables is denoted $I_j^{\Im} = \{I_j^1, ..., I_j^n\}$ and $\sum_{i \in \Im} I_j^i \leq 1$.

Let m be the auction payment function, then $m_j^{\Im} = \mathrm{m}(b_j^{\Im}, q_j^{\Im})$, where $m_j^{\Im} = \{m_j^1, ..., m_j^n\} \in R^n$ is the set of corresponding expected payments (ex-ante). Replacing $q_j^{\Im}$ by $I_j^{\Im}$ the realized payments (ex-post) are indicates by $m_j^{\Im} = \mathrm{m}(b_j^{\Im}, I_j^{\Im})$.

Let $m_j^i = \mathrm{m}^i(b_j^{\Im}, q_j^{\Im})$, where m^i is the auction payment function that returns the expected payment for carrier *i*. Replacing $b_j^{\Im}$ and $q_j^{\Im}$:

$$m_j^i = \mathrm{m}^i(b_j^{\Im}, q_j^{\Im}) = \mathrm{m}^i((\mathrm{b}^i \circ \mathrm{b}^{-i})(s_j, h_j, \theta_j^{\Im}), \mathrm{q}((\mathrm{b}^i \circ \mathrm{b}^{-i})(s_j, h_j, \theta_j^{\Im})))$$

This is the expected payment obtained by carrier i for shipment s_j when (a) using bidding function (strategy) b^i (b) the other players are using bidding functions (strategies) b^{-i} (c) history of play is h_j, and (e) the private information of all players is $\theta_j^{\Im}$.

Let π_j^i be the expected profit for carrier i for shipment s_j, then:

$\pi_j^i = m_j^i - c^i[s_j, \theta_j^i] q_j^i$, replacing terms:

$$\begin{aligned}\pi_j^i = {} & \mathrm{m}^i((\mathrm{b}^i \circ \mathrm{b}^{-i})(s_j, h_j, \theta_j^{\Im}), \mathrm{q}((\mathrm{b}^i \circ \mathrm{b}^{-i})(s_j, h_j, \theta_j^{\Im}))) - \\ & - c^i[s_j, \theta_j^i] \mathrm{q}^i((\mathrm{b}^i \circ \mathrm{b}^{-i})(s_j, h_j, \theta_j^{\Im})))\end{aligned}$$

$$\pi_j^i = \pi^i(\mathrm{m}^i, \mathrm{q}^i, \mathrm{b}^i, \mathrm{b}^{-i}, s_j, h_j, \theta_j^i, \theta_j^{-i}, c^i[s_j, \theta_j^i])$$

Therefore, a carrier's profit is affected by the auction payment and allocation rules, by its bidding function as well as the competitors' bidding functions, by the characteristics of the shipment, by the history of play, by the private information of all carriers, and by its own cost function and fleet status.

3.2.6. Equilibrium Formulation

The problem is to find a bidding function b^{*i} for each carrier $i \in \Im$ such that the set of functions $\{\mathrm{b}^{*1},...,\mathrm{b}^{*n+1}\} = \{\mathrm{b}^{*i},\mathrm{b}^{*-i}\}$ form a Bayes-Nash Equilibrium for each carrier, possible auction, history of play, and possible set of private information. In mathematical terms:

$$\mathrm{b}^{*i} \in \arg\max \sum_{s_j \in S_{j...N}} \sum_{\theta_j^i} \sum_{\theta_j^{-i}} p(\theta_j^i,\theta_j^{-i}) \;\; \pi^i(\mathrm{m}^i,\mathrm{q}^i,\mathrm{b}^i,\mathrm{b}^{*-i},s_j,h_j,\theta_j^i,\theta_j^{-i},c^i[s_j,\theta_j^i])$$
$$\mathrm{b}^i \in \mathrm{B}^i \qquad \forall i \in \Im, \forall s_j \in S_N, \forall h_j \in H_j, \forall \theta_j^{\Im} \in \Theta^{\Im} \qquad (3.1)$$

In the spirit of the auction models studied in chapter 2, the following concepts are common knowledge among carriers: their rationality, the space of private information and the corresponding probability density function, the auction rules, and the set of bidding functions.

This equilibrium assumes that before the game starts, players (carriers) have already simulated all possible game paths and have selected a bidding strategy that satisfies equation (3.1). In game theory, this type of formulation is called “normal form game,” equilibrium. An alternative approach for dynamic games is the “agent form” equilibrium, This approach requires that the agent (player) finds the best bidding strategy for each and every possible decision point in the game. Then, if the agent based approach is taken, the formulation becomes:

$$\mathrm{b}^{*i} \in \arg\max \sum_{s_j \in S_{j...N}} \sum_{\theta_j^i} \sum_{\theta_j^{-i}} p(\theta_j^i,\theta_j^{-i}) \, \pi^i(\mathrm{m}^i,\mathrm{q}^i,\mathrm{b}^i,\mathrm{b}^{*-i},s_j,h_j,\theta_j^i,\theta_j^{-i},c^i[s_j,\theta_j^i])$$
$$\mathrm{b}^i \in \mathrm{B}^i \qquad \forall i \in \Im, \forall s_j \in S_N \mid h_j,\theta_j^i \qquad (3.2)$$

3.2.7. Online TLPM

The previous formulation assumes that the sets T_N and S_N are known before bidding starts (offline sequential auction).

In general, arrival times and shipments will not be known in advance. The arrival instants $\{t_1, t_2, ..., t_N\}$ will follow some general arrival process. Furthermore, arrival times and shipments are assumed to come from a probability space $(\Omega, \mathcal{F}, \mathcal{P})$, with outcomes $\{\omega_1, \omega_2, ..., \omega_N\}$. Any arriving shipment s_j represents a realization at time t_j from the aforementioned probability space, therefore $\omega_j = \{t_j, s_j\}$.

If the TLPM problem is considered online, the equilibrium formulation will need to be reformulated. In the spirit of a Markof Perfect Equilibrium (MPE) (Fudenberg, 1991) and agent based formulation, in equilibrium, a carrier bidding function has to maximize current period plus expected future profits, given the competitors equilibrium bidding functions, and the current state of the system (private information). A carrier's profit function becomes:

$$\begin{aligned}\pi^i_{j,...,N}(\mathrm{m}^i, \mathrm{q}^i, \mathrm{b}^i, \mathrm{b}^{-i}, s_j, h_{j-1}, \theta^{\Im}_j, c^i[s_j, \theta^i_j]) &= \pi^i(\mathrm{m}^i, \mathrm{q}^i, \mathrm{b}^i, \mathrm{b}^{-i}, s_j, h_{j-1}, \theta^{\Im}_j, c^i[s_j, \theta^i_j]) \\ &+ E_{(\omega_{j+1},...,\omega_N)}[\sum_{k=j+1}^{N} \pi^i(\mathrm{m}^i, \mathrm{q}^i, \mathrm{b}^i, \mathrm{b}^{-i}, s_k, h_{k-1}, \theta^{\Im}_k, c^i[s_k, \theta^i_k])]\end{aligned}$$

The profit function has been expressed as the sum of current period profits plus expected future profits ($E_{(\omega_{j+1},...,\omega_N)}$ is the expectation of the future shipment arrivals). Calling $\pi^i_{j,...,N}$ the current plus expected future profits function, the equilibrium formulation becomes:

$$\mathrm{b}^{*i} \in \arg\max \sum_{\theta_j^i} \sum_{\theta_j^{-i}} p(\theta_j^i, \theta_j^{-i}) \; \pi^{\,i}_{j,..,N} \, (\mathrm{m}^i, \mathrm{q}^i, \mathrm{b}^i, \mathrm{b}^{*-i}, s_j, h_j, \theta_j^{\Im}, c^i[s_j, \theta_j^i])$$

$$\mathrm{b}^i \in \mathrm{B}^i \qquad \forall i \in \Im \,|\, s_j, h_j, \theta_j^{\Im} \qquad (3.3)$$

Equation (3.3) it is not a MPE, since the whole history of play is used to estimate the current distribution of the competitors' private information or carriers' "belief" about the competitive status of the competition. A MPE is a relaxation of equation (3.3), where h_j is replaced by y_{j-1} (i.e. the hole history is replaced by the information provided by the last bid only).

3.3. <u>Sources of Complexity Analysis</u>

This section deals with the complexity of the formulated equilibrium problem. The literature review in chapter 2 illustrated that the state of the art sequential auction models are fairly rudimentary compared to the problem described in the previous section. There are many factors that contribute to the intractability of TLPM game theoretic models. In this section these factors are divided into two groups: (a) technical problems – characteristics that impede reaching a closed analytical solution or even any solution for real-life problems and computational resources, and (b) conceptual problems – characteristics that go against the appropriateness of game theory to describe the strategic interaction among carriers.

3.3.1. Technical Problems

1. Even with extremely simple assumptions, the number of paths to be evaluated grows dramatically quickly. Assuming ten auctions, two carriers, two valuations (high-low), and two possible bids (high-low bids), the number of possible game paths is 2^{40}.
2. There is no possible symmetry among carriers. Even if carriers start in identical conditions, symmetry is broken in round two (there is only one winner and many losers). The differential equation approach used in the SIPV model is not possible. Furthermore, asymmetries are what make the problem interesting. Each carrier has essentially the same information about the nature of the shipment but a different opportunity cost of completing it. Whenever the existence of asymmetries is common knowledge, the problem is asymmetric (Maskin, 2000).
3. The accurate estimation of service costs may involve the solution of NP-hard problems (multi-vehicle-multi-shipment routing problem with time windows)
4. Updating the beliefs about competitors' private information (competition status conditioned on the public information revealed) might be a very complex problem.
5. The cost functions $c[s_j, \theta_j^i]$ are neither convex, nor differentiable, nor continuous (presence of binary variables in the routing problem).
6. The online problem is characterized by stochastic arrival times and unknown origins and destinations of future shipments. Finding the expected profit function is not a trivial task.

3.3.2. Conceptual Problems

1. It was mentioned that large game theoretic problems usually have a multiplicity of solutions. If several equilibria are possible, how do carries agree on what unique equilibrium is played?
2. The lack of equilibrium uniqueness is exacerbated in dynamic problems. Several equilibrium refinements exist (perfect equilibrium (Selten, 1975), Nash refinements (Myerson, 1978), sequential equilibrium (Kreps, 1982), etc.) that try to eliminate the set of "unreasonable equilibria". However, these refinements are not guaranteed to provide the same set of equilibria or even to eliminate all but one equilibrium (Fudenberg, 1991).
3. The use of equilibrium refinements to reduce the number of equilibria assume some kind of "super-rationality" (Aumman, 1997), necessary to solve the indeterminacy of beliefs at decision points that follow unexpected actions.
4. The two ways of formulating the offline problem (Equation 3.1 and Equation 3.2) are both compatible with the concept of rationality, though they may provide different equilibrium sets even in simple games (Fudenberg, 1991).
5. What information is common knowledge? What information is not common knowledge? Who knows what others know? How is this common knowledge obtained?
6. How is learning taken into account by bidders? How is the potential information transmission and signaling taken into account by rational players?
7. The presence of capacity constraints introduces complex considerations into multi-object sequential auctions. Can bidders estimate all the implications?

Real-life computational resources and bidding time limitations preclude exceedingly complex approaches. It seems impossible to conciliate a full game theoretic analysis and its real-life implementation. However, the game theoretic approach provides an ideal and useful reference point. This reference point is used in subsequent chapters to introduce simplifying assumptions about carriers' behavior; simplifying assumptions that try conciliate both, implementation feasibility and some degree of rationality (i.e. bounded rationality).

3.4. Simulation Framework

The complexity of the TLPM problem calls for the use of computational simulation. Although all models (even simulation models) necessarily abstract from some aspects of reality, simulation is indispensable given that closed analytical solutions for these complex dynamic systems would require many simplifications that could compromise the validity of the results. This is especially important in auction models, where relaxation of assumptions can lead to unexpected results. As expressed by Rothkopf and Harstad (1994b, page 374): "... auction models have shown a striking tendency for the answers to change as enrichments to their realism are introduced. This tendency should discourage attempts to derive general answers in abstract models. Attempts to enrich mainstream models with a view toward relevance to practice are still a small part of the bidding theory literature, but they suggest that result reversals may be common."

Roth (2002) argues that the complications of an auction marketplace require new tools to supplement the traditional analytical toolbox of the theorist. He argues that experimental and computational economics are natural complements to game theory in the task of designing marketplaces.

A realistic market experiment may require a large amount of economic resources. The analysis of actual market data could provide important insights into the behavior of a given TL marketplace. However, companies' cooperation and willingness to fully disclose proprietary and competitive information is unlikely at best, if not impossible. Simulation enables the computational study of interactions among carriers by means of controlled and replicable experiments. In a wide spectrum of scenarios allowed by the many potential market settings it is also possible to explore and systematically test changes in key market parameter values.

This section introduces the framework used to simulate a TLPM and section five describes the simulation performance measures. The simulation framework presented in this section simplifies real-world TL markets but still provides useful insights about their performance – mainly to freight transportation researchers and practitioners. A discrete-event simulation (DES) framework is employed. The backbone of any DES is a set of events that take place at a specific time (Law, 1991). In this framework there are auction and fleet management related events. The former includes posting, bidding, and resolution of an auction. The latter includes demand arrival, pick up, and delivery.

Simulations are used to compare how auction types, behavioral assumptions, and demand patterns affect the performance of the market (performance measures are defined in the next section). In order to correctly compare the results, each run has a unique set of random number seed generators. Simulation results are obtained from ten runs of one thousand auctions each. The same random number generator sets are used across all experiments.

The auction events are assumed to take place in real time. Computation times or delays are not taken into account, therefore the computationally efficiency or speed of different bidding/fleet management strategies are not compared. Shipment service times are taken into account in order to simulate dynamic truckload pickup-and-delivery situations (dynamic multi-vehicle routing problems with time-windows). It is assumed that pick-ups and deliveries are instantaneous, i.e. the time spent at origins and destinations is negligible relative to travel times; vehicles are assumed to travel at a constant speed in a Euclidean two-dimensional space. Shipments and vehicles are fully compatible in all cases; there are no special shipments or commodity specific equipment (for example, just tractors and trailers).

The results obtained reflect the steady state operation of the simulated system. This is obtained using an adequate warm-up period - in all cases set to one hundred auctions; a warm up length that is more than adequate for the fleet sizes and shipment time windows considered.

3.4.1. Market Geographic Area

The shipments to be auctioned are circumscribed to a bounded geographical region. The simulated region is a 1 by 1, square area. Trucks travel from shipment origins to destinations at a constant unit speed (1 unit distance per unit time). The carriers do not know information concerning the precise origin and destination of the shipments in advance. Shipment origins and destinations are uniformly distributed over the region; the average loaded distance for an auctioned shipment is approximately 0.52 units.

There is no explicit underlying network structure in the chosen origin-destination demand pattern. Alternatively, it can be seen as a network with infinite number of origins and destinations (basically each point in the set [0,1]x[0,1]) and the infinite number of corresponding links. Each and every link possesses an equal infinitesimal probability of occurrence.

This geographical demand pattern creates a significant amount of uncertainty for fleet management decisions such as costing a shipment or vehicle routing. Since the degree of deadheading is unknown, any fleet management decision should hedge for this uncertainty.

3.4.2. Time-Windows

A time-window constraint represents the time sensitivity of the shipment and limits the fleet capacity to accommodate and feasibly route present and future shipments. In the present framework, shippers alone specify the time windows before calling an auction. In a general depiction, long time windows are characteristic of push inventory systems based on order and transportation economies of scale, while short time windows are a characteristic of pull inventory systems based on lean, just-in-time (JIT) inventory and production control systems (Hopp, 2000).

A growing trend in the TL market is the increase of Time-Definite Freight (TDF) (FHWA, 2001), defined as any shipment that is required to arrive within very tight time windows. Late and early arrivals are penalized with hefty fines. TDF is a standard requirement in most JIT manufacturing environments.

From the carrier's point of view, the ratio between shipment time window lengths and service time duration (or trip length) affects how many shipments can be accommodated in a vehicle's route. In general (not always true), the more shipments that can be accommodated, the lesser the deadheading (or average empty distance). A low ratio indicates that few shipments can be accommodated, either due to short time windows (time sensitive shipment) or long trips (for example intercity operation) or both. A high ratio indicates that many shipments can be accommodated, either due to long time windows (no-time sensitive shipment) or relatively short trips (for example city deliveries) or both.

Given the importance of this ratio in carriers' operations and as a characterizer of shipper/geographic demand patterns, three different TW length/shipment service duration ratios are simulated. These ratios are denoted short, medium, and long, making reference to the average time window length. The different Time Window Lengths (TWL) for a shipment s, where $\mathrm{ld}(s)$ denotes the function that returns the distance between a shipment origin and destination, are:

- $\mathrm{TWL}(s) = 1(\mathrm{ld}(s) + 0.25) + \mathrm{uniform}[0.0, 1.0]$ (*short*)
- $\mathrm{TWL}(s) = 2(\mathrm{ld}(s) + 0.25) + \mathrm{uniform}[0.0, 2.0]$ (*medium*)
- $\mathrm{TWL}(s) = 3(\mathrm{ld}(s) + 0.25) + \mathrm{uniform}[0.0, 3.0]$ (*long*)

In the simulated market, vehicle speeds are a unit, the average shipment length is ≅0.52, and the average empty distance may range between [0.2, 0.3]. Average empty distance changes with arrival rate, time window length, and carrier fleet management technology.

3.4.3. Arrival Rates

It was seen in chapter 2 that the ratio between demand and supply influences auction prices. In the simulated market, different demand/supply ratios are studied. Arrival rates range from low to high. At a low arrival rate, all the shipments can be served (if some shipments are not serviced it is due to a very short time window). At a high arrival rate carriers operate at capacity and many shipments have to be rejected.

Changing demand/supply ratios can be caused by increases/decreases in economic activity and the lagging response of the supply (new vehicle orders/vehicle retirement). Changing ratios can also reflect temporal patterns (peak hourly demand, time of day, etc.). It is assumed that the auction announcements are random and that their arrival process follows a time Poisson process. The expected inter-arrival time is normalized with respect to the market fleet size. The expected inter-arrival times are $1/2$ arrivals per unit time per truck, $2/2$ arrivals per unit time per truck, and $3/2$ arrivals per unit time per truck (low, medium, and high arrival rates respectively).

3.5. Performance Measures - Auction Mechanisms

This section defines the performance measures used to compare TL markets. The concept of auction mechanisms is first introduced. This concept is necessary to define truthful mechanisms, which are used as a market performance benchmark and to define carriers' behavioral assumptions in chapter 4. The section ends defining performance measures for carriers and shippers.

3.5.1. Auction Mechanisms

Auctions were defined in chapter 1 as market institutions with an explicit set of rules determining resource allocation and prices on the basis of bids from the market participants (McAffee, 1987). The design of an auction requires the precise specification of a set of rules. These rules determine an auction model, the system by which bidding is conducted, how information is revealed, and how communications are structured between buyers and sellers. The outcome of the auction strongly depends on the set of rules used. This section defines auctions in a general way, abstracting away from the details of any particular bidding format.

There are three indispensable elements in an auction: (a) rules needed to allocate the resource – allocation rules, (b) rules to determine prices and payments – payment rules, and (c) bids from the auction participants – a set of possible bids.

Using notation previously defined, the auction mechanism $\mathcal{A} = (\mathrm{q}, \mathrm{m}, B^{\Im})$ has all three elements: an allocation rule, a payment rule, and a set of possible bids.

3.5.2. Direct and Truthful Mechanisms

If the set of possible bids $B^{\Im}$ is equal to the set of possible values (costs), the mechanism is called *direct*. If the mechanism is direct, and it is an equilibrium strategy for each player to bid his own value (cost), the mechanism is called *truthful*. Myerson (1979) established the *revelation principle,* which states that: given an auction mechanism and equilibrium for that mechanism, there exists a truthful mechanism in which the outcome is the same as in the given equilibrium of the original mechanism. Two sets of conditions must be met to guarantee the existence of a truthful mechanism. Each bidder must satisfy two conditions called (a) incentive compatibility, and (b) individual rationality constraints.

In the TLPM let $\mathrm{m}(\cdot)=\{\mathrm{m}^1(\cdot),\dots,\mathrm{m}^n(\cdot)\}$ and $\mathrm{q}(\cdot)=\{\mathrm{q}^1(\cdot),\dots,\mathrm{q}^n(\cdot)\}$. Without loss of generality, the next discussion is limited to one shipment, therefore the subscript j is dropped. Using previous notation $c^i=\mathrm{c}^i(s,z^i)$ will be the cost of serving shipment s_j when the status of the carrier is z^i. The set of all bidders' costs is $c^{\Im}=\{c^1,\dots,c^n\}$.

3.5.3. Incentive compatibility

A direct mechanism is said to be incentive compatible (IC) for a carrier i if:

$$\sum_{(\theta^i,\theta^{-i})\in\Theta^{\Im}}(m^i(c^{\Im})-q^i(c^{\Im})c^i)\ p(\theta^{-i}\,|\,\theta^i)\geq\sum_{(\theta^i,\theta^{-i})\in\Theta^{\Im}}(m^i(a^i,c^{-i})-q^i(a^i,c^{-i})c^i)\ p(\theta^{-i}\,|\,\theta^i)\tag{3.4}$$

Where the carrier's cost is c^i and a^i is any other possible cost (in our case $a^i \in R$). Incentive compatibility makes bidding the true cost a weakly dominated strategy. Any other bid achieves equal or less profit. Alternatively, a bidder's unilateral deviation from the truthful mechanism is a weakly dominated strategy.

3.5.4. Individual Rationality

A direct mechanism is said to be individually rational (IR) for a carrier *i* if:

$$\sum_{(\theta^i,\theta^{-i})\in\Theta^{\Im}} (m^i(c^{\Im}) - q^i(c^{\Im})c^i)\ p(\theta^i,\theta^{-i}) \geq 0 \qquad (3.5)$$

This guarantees voluntary participation of risk-neutral bidders, since a non-negative utility is guaranteed. Again, participating in the auction is a weakly dominant strategy. The second price auction in the SIPV model is an example of a truthful mechanism. From the behavioral point of view, a truthful mechanism simplifies bidding for rational carriers, which are only required to estimate their cost of serving the load. In chapter 4 competition is assumed to take place under a truthful mechanism.

3.5.5. Efficient Mechanism

In auction theory a reverse auction mechanism is said to be "price efficient"[1] if its allocation rule q^* is such that:

$$\mathrm{q}^*(c^{\Im}) \in \arg\min \sum_{i\in\Im} \mathrm{q}^i(c^{\Im})\, c^i \qquad (3.6)$$

When there are no ties, a price efficient allocation rule allocates the shipment to the carrier with the lowest cost of service. If there are ties, only the carriers with the lowest cost may have a positive probability of obtaining the shipment. A second price auction of one object is an example of a "price efficient" auction. The value of social welfare obtained with a price efficient auction mechanism is defined as:

$$W(c^{\Im}) = v - \sum_{i\in\Im} \mathrm{q}^{*i}(c^{\Im})\, c^i$$

However, this is not the system optimal welfare outcome, which would usually imply more than allocating the load to the lowest cost carrier (for example a system optimal allocation may require swapping shipments among different carriers.) The allocation that maximizes social welfare or generates the most wealth is denoted:

$$W(z^{\Im}) = v - \sum_{i\in\Im} \mathrm{c}^i(\mathrm{a}(\mathrm{z}^{\Im}))$$

where "a" is the optimal assignment function (i.e. the assignment function that minimizes costs), which assigns shipments to carriers, thus $W(z^{\Im}) \geq W(c^{\Im})$.

The TLPM defines a new class of problem, for which there is no standard or agreed upon performance measures. The social welfare of a price efficient auction

[1] A mechanism that satisfies (3.6) is called in auction theory simply "efficient", in this report it is called differently to differentiate from allocations that minimize system wide costs.

mechanism is used as a benchmark to compare the efficiency of a marketplace. This is a market-wide measure of how much wealth is generated using auctions. Specific measures for shippers and carriers are detailed next.

3.5.6. Carrier and Shipper Performance Measures

It was already stated in the equilibrium problem formulation that profit maximization is the primary objective of carriers. Other important performance measures include: (a) number of shipments secured – which is closely related to carriers' market share and (b) average empty distance – a measure of how efficient the fleet assignment is. Shippers' performance measures include: (a) number of shipments served – which is closely related to the likelihood of being served and (b) shippers' consumer surplus – which indicates how much money shippers would have saved if the alternative was to serve the shipments by a contract carrier, at a rate equal to the reservation prices.

Carriers' costs are composed of a fixed and variable part. Fixed costs are assumed sunk since they are mainly linked to fleet size, which cannot be modified in the short run. Variable costs are incurred through the total traveled distance (including loaded and empty movements).

The set of auctioned shipments is $S_N = \{s_1, s_2, ..., s_N\}$. Let $s_j, s_k \in S_N$ and let $x^i_{jk} \in \{0,1\}$ be a binary variable. Let $x^i_{jk} = 1$ if carrier i has served shipment s_k immediately after serving shipment s_j, $x^i_{jk} = 0$ otherwise. Let $\mathrm{ed}(s_j, s_k)$ be the function that returns the distance between the destination of shipment s_j and the origin of shipment s_k.

The number of shipments secured by carrier i is:

$$\mathrm{ns}^i(S_N) = \sum_{s_j \in S_N} I_j^i$$

The empty distance traveled by fleet i is:

$$\mathrm{ed}^i(S_N) = \sum_{s_j, s_k \in S_N} \mathrm{ed}(s_j, s_k)\, x_{jk}^i$$

The average empty distance of carrier i is:

$$\mathrm{aed}^i(S_N) = \frac{\sum_{s_j, s_k \in S_N} \mathrm{ed}(s_j, s_k)\, x_{jk}^i}{\sum_{s_j \in S_N} I_j^i}$$

The revenue secured by carrier i is:

$$\mathrm{r}^i(S_N) = \sum_{s_j \in S_N} I_j^i\, b_j^{(1)} \qquad \text{(1}^{\text{st}}\text{ price auction)}$$

$$\mathrm{r}^i(S_N) = \sum_{s_j \in S_N} I_j^i\, b_j^{(2)} \qquad \text{(2}^{\text{nd}}\text{ price auction)}$$

Assuming unit costs per unit distance, the profit secured by carrier i is:

$$\pi^i(S_N) = \sum_{s_j \in S_N} I_j^i\, b_j^{(1)} - \sum_{s_j, s_k \in S_N} \mathrm{ed}(s_j, s_k)\, x_{jk}^i - \sum_{s_j \in S_N} I_j^i\ \mathrm{ld}(x_j) \quad \text{(1}^{\text{st}}\text{ price auction)}$$

$$\pi^i(S_N) = \sum_{s_j \in S_N} I_j^i\, b_j^{(2)} - \sum_{s_j, s_k \in S_N} \mathrm{ed}(s_j, s_k)\, x_{jk}^i - \sum_{s_j \in S_N} I_j^i\ \mathrm{ld}(x_j) \quad \text{(2}^{\text{nd}}\text{ price auction)}$$

The number of shipments served by the market is:

$$\mathrm{ns}(S_N) = \sum_{i \in \Im} \mathrm{ns}^i(S_N) = \sum_{i \in \Im} \sum_{s_j \in S_N} I_j^i$$

The shippers' consumer surplus is:

$$\text{cs}(S_N) = \sum_{i \in \Im} \sum_{s_j \in S_N} I_j^i \,(v_j - b_j^{(1)}) \qquad \text{(1}^{\text{st}} \text{ price auction)}$$

$$\text{cs}(S_N) = \sum_{i \in \Im} \sum_{s_j \in S_N} I_j^i \,(v_j - b_j^{(2)}) \qquad \text{(2}^{\text{nd}} \text{ price auction)}$$

It was already mentioned that the loaded distance is a constant associated to each shipment. Carriers can easily estimate the variable cost component associated to the loaded distance. Assuming that all carriers have the same cost per loaded mile, adding/subtracting a constant to/from all the bids does not alter the ranking of bids. Then, if all carriers include the loaded distance in their bids, that term cancels out when computing profits (the payment or second bid and the winner's cost include the same constant: the shipment loaded distance).

Herein, it is assumed that carriers' bids take into account solely empty distance costs (correspondingly, shippers' reservation values have also discounted the corresponding loaded distance). This is done for two reasons: (a) it does not alter the order of bids or profits, and (b) it emphasizes the fact that estimating the empty distance costs is the complex part of costing shipments. Carriers' profits can now be expressed as:

$$\pi^i(S_N) = \sum_{s_j \in S_N} I_j^i \, b_j^{(1)} - \sum_{s_j, s_k \in S_N} \text{ed}(s_j, s_k)\, x_{jk}^i \qquad \text{(1}^{\text{st}} \text{ price auction)}$$

$$\pi^i(S_N) = \sum_{s_j \in S_N} I_j^i \, b_j^{(2)} - \sum_{s_j, s_k \in S_N} \text{ed}(s_j, s_k)\, x_{jk}^i \qquad \text{(2}^{\text{nd}} \text{ price auction)}$$

3.6. ***Summary***

This chapter presented the conceptual and theoretical framework to define and measure the performance of a TLPM. The problem was formulated as a dynamic game of incomplete information. Section three analyzed the complexity of the problem. The intractability of the problem raises serious questions about the validity and feasibility of a game theoretic approach to model real life TLPM.

Simulation is a viable and helpful tool to tackle the study of TLPM. Section four described the simulation framework that is used to evaluate demand/supply patterns, fleet assignment technologies, and carriers' behavioral assumptions. Demand/supply patterns are described by the relation among time window lengths, arrival rates, and the market geographic area.

Section five describes the performance measures used to evaluate TLPM; the notation and formulas needed to define them are also introduced. In addition, this section introduces the concept of truthful mechanisms. This type of mechanism is very appealing for two reasons: (a) it considerably reduces the complexity of the problem from the carrier perspective (b) if there is an auction winner; a carrier with the smallest submitted bid always wins the auction. This type of mechanism is assumed in chapter 4 where it can be used to evaluate carriers' fleet assignment technologies.

Chapter 4: Technology Based Competition

The focus of this chapter is on technology based competition. A crucial chapter assumption is that a cost truth telling strategy (marginal cost bidding) is the only dominant strategy. Section one analyses the relevance of cost competition and technological adequacy in the TL industry. Existing approaches to evaluate carriers' Dynamic Vehicle Routing (DVR) technologies and algorithms are reviewed in section two. Section three explores the difficulties and shortcomings of applying existing approaches to the TLPM problem. Section four presents a methodology based on second price auctions (auction analysis of algorithms) to evaluate online DVR technologies. The relationships between the new methodology and other vehicle routing problems are presented in section five. Section six compares auction analysis of algorithms with competitive analysis of algorithms. In section seven the auction methodology is applied to the study of three different DVR technologies while section eight applies the auction methodology to compare auction and vertical TL market structures. The chapter summary is presented in section nine.

4.1. <u>Industry competition, Costing, and DVR Technologies</u>

This chapter emphasizes the importance of the DVR aspects of the TLPM market. In this research a carrier's DVR technology determines the estimated cost of servicing a shipment and the manner in which vehicle routes are constructed. The DVR technologies to be studied in this chapter are reduced to algorithms, when simulated; however, their real life implementation may require inherently different communication and decision support systems, software, computational power, qualified personnel, as well as an understanding of the nature and complexity of the DVR problem. As such, the terms *algorithm* and *technology* are used interchangeably throughout this chapter.

Estimating the cost of serving a shipment is not a trivial task; it depends on all the other loads being served and the fleet deployment as well as on the future loads to be served. The auction models presented in chapter 2 assumed that any bidder knows the value of the object being auctioned. However, in a TLPM market the value or cost of servicing a shipment is not only unknown but also difficult to estimate for three main reasons: (a) the number of potential schedules increases exponentially with the number of trucks and shipments (NP hard problem); (b) there always exists uncertainties about next arriving load characteristics and timing; and (c) prices (payments) are not only uncertain but also strongly dependent on the level of competition. The algorithmic complexity and analytical tractability of the problem may impede the evaluation of all potential schedules for carries with bounded computational resources and hard bid submission deadlines. The uncertainties surrounding the problem (points b and c) affect the cost of serving a shipment because the carrier must cover or hedge for future deadheading and opportunity costs. The service of a shipment can affect both, the empty distance of servicing follow-on shipments and the revenue (or payment) that can be obtained servicing those follow-on shipments.

Adequate costing and routing is especially important in a highly competitive environment such as the truckload industry. The Truckload Carriers Association of America (TCA) provides a set of suggested financial benchmarks for trucking companies. The TCA offers the following breakdown of operating ratios (operating expenses divided by operating revenues) to measure a company's performance (TCA, 2002):

0.90 to 0.91 - Excellent

0.92 - 0.95 - Average

Above 0.96 - Poor

An operating ratio of 0.95 allows 5 cents per dollar earned to cover fixed costs, interest cost, and return to owners/taxes. The intense competition in the trucking industry can be explained by a highly deregulated environment, low capital constraints to entry (especially in the TL sector), and the high number of trucking companies (Coyle, 2000).

In such a tight and competitive environment, TL companies must constantly search for ways to increase revenues and/or decrease costs. Revenues and market share are influenced by many external factors that cannot be directly controlled by managers; while operating costs can be decreased as the result of efficient management practices and technological improvements. Therefore, a carrier's constant consideration of new means to improve efficiency and competitiveness is a prerequisite for survival. Such competitive environment requires methodologies to evaluate the performance and advantage of DVR technological upgrades.

In a complex environment, such a methodology to evaluate technological competitiveness would provide the necessary insights and tools needed to make sound decisions. DVR researchers and developers (not just TL company's managers) could use such a methodology to test and compare their DVR solutions. In addition to looking at cost competition and comparing different DVR technologies this chapter also develops and analyzes a methodology to compare DVR technologies in a competitive environment.

Performance measures and evaluation of algorithms (i.e. technologies in the broader characterization used in this research) have been extensively studied in computer science and operations research. However, the emphasis has not been on the evaluation of algorithms in competitive market situations. The next section reviews related contributions of the computer science and operations research literature.

4.2. <u>Classical and Competitive Approaches to Analyze Algorithms</u>

The main objective of the study of algorithms is to characterize the quality of the solution they compute and the resources (computer time or elementary computing operations) needed to reach those solutions. "Classical" computational complexity analysis of algorithms assumes complete information about the problem under study, while "competitive" analysis of algorithms assumes incomplete or partial information of the problem. A thorough introduction to the former type is presented by Cormen et al. (1991); Borodin and El-Yaniv (1998) present a comprehensive introduction to competitive analysis and online computation.

Under complete information (also called "static" or "off-line" problems), algorithms that provide optimal solutions are compared in terms of the worst case number of computations necessary to reach a solution. Algorithms that do not always provide optimal solutions (heuristics) are compared on the number of computations and their performance ratio. The performance ratio is defined as the ratio between the worst case behavior of the algorithm (measured in units of the objective function, e.g. cost in a minimization problem) on a problem instance and the behavior of the optimal algorithm in the same problem instance (for profits or maximization problems the definition of the performance ration is inversed). Employing worst case analysis is not the only option; a different ordering of algorithms could be obtained using average case analysis. For this type of analysis it is necessary to make some assumptions on the input distribution or problem instances. Both measures could be problematic. Worst case analysis could be overly pessimistic, while average case analysis requires the specification of a "typical" or "representative" distribution. The latter could be problematic since the performance of algorithms may depend on the distribution assumed; thus such a comparison does not impose a unique ordering in the quality of the algorithms.

Competitive analysis of algorithms assumes incomplete or partial information about the problem. This type of analysis is especially helpful for a problem where information is progressively revealed over time; this type of problem is also commonly called an "online" problem. Worst case and average analysis can be applied to this type of problem. A major issue inherent to online problems is that incomplete knowledge of the problem may lead an algorithm to perform very poorly.

Another important consideration is the computational complexity of an algorithm, particularly when the algorithm operates in a real time environment and response time is a factor that affects the quality of the solution.

Typically, a distinction is made between problem parameters and the problem instance of online problems. This distinction refers to what is known to the algorithm in advance, i.e., the problem parameters, and what is not known ahead of time, i.e. the problem instance. An on-line algorithm is said to be *c-competitive* if at each instance its performance is within a factor of, at most, *c* of the performance of the optimal off-line algorithm for the same instance (Boroding, 1998. This would be characterized as a worst-case measure since it is valid on every instance. Competitive analysis assumes that the online algorithm being analyzed faces the competition of a *powerful adversary* that begets the worst sequence of tasks in order to maximize the competitive ratio; while the online algorithm makes decisions with partial information.

Boroding and El-Yaniv (1998) distinguish three types of powerful adversaries: (a) an *oblivious* adversary constructs the whole sequence of tasks in advance and compares the resulting cost or profit of the online algorithm with the result obtained with an optimal offline algorithm; (b) an *adaptive-online* adversary chooses the next task based on the online algorithm's actions so far and compares the resulting cost to the performance obtained by the adversary's online algorithm (which has the advantage of knowing the future sequence of tasks); and (c) an *adaptive-offline* chooses the next request based on the online algorithm's actions so far and compares the resulting cost to the performance obtained by the optimal off-line algorithm.

It is not surprising that with such powerful adversaries, worst case analysis can be overly pessimistic (Karlin, 1998). Karlin attributes this to the fact that real life studies of task/demand/request records/logs for different classes of online problems (from computer paging to message network routing) have indicated that there exists usually a “structure” underlying the task sequences. However, each case or application may have a particular input structure. Therefore, it is impossible to make any detailed or general assumption about the input distribution.

Fiat and Woeginger (1998) suggest that the competitive approach does provide insight into the underlying online problem. They also acknowledge that in many cases, meaningful information about the actual quality of an algorithm is lost. The loss of meaningful quality information occurs mainly when the worse case that can be forced (by the powerful adversary upon the online algorithm) is abnormally (pathologically) bad. Randomization is a recourse used successfully by many online algorithms to decrease their competitive ratio. Randomizing over the set of possible answers, allow the online algorithm to partially deceive the powerful adversary; it introduces uncertainty about the worst possible sequence of future tasks. When the competitive results are trivial even with randomization, researchers have suggested limiting the power of the online adversary, either reducing their resources such as memory in the paging problem (Awerbuch, 1996) or limiting an adversary’s computing speed in scheduling problems (Phillips, 1997). Another approach to limit the relative power of the online adversary is the diffuse adversary model proposed by

Koustupias and Papadimitriou (1974). In the diffuse adversary model the online algorithm is empowered since it is given the information that the request sequence belongs to a specific class of distributions (in competitive analysis the online algorithm knows nothing about the future request sequence).

Competitive analysis is an active area of current research. Nissan and Ronen (2001) study algorithmic problems in distributed settings (the internet for example, where each computer is a self-interested agent). In this environment, agents can manipulate the central or scheduling algorithm by lying or hiding information. This is an extension of the mechanism design problem, presented in chapter 3, to algorithms. In the type of problems studied by Nissan and Ronen the algorithm designer should ensure in advance that the agents' best interest lies in behaving correctly (i.e. reporting the truth would be the agent's best strategy). Ajtai et al. (2003) try to extend competitive analysis to distributed algorithms. Distributed algorithms are several sub-algorithms or agents that act based on local (as opposed to global) information. They propose to compare distributed algorithms to the best distributed algorithm in any given input (instead of comparing against the best global algorithm), effectively reducing the power of the adversary.

Competitive analysis has also been applied to transportation problems. Ausiello et al. (1995) study competitiveness of algorithms for the online traveling salesman problem (TSP). In their study of the single vehicle TSP, a vehicle has to service (in an order to be determined) a sequence of requests that are presented in a metric space in an on-line fashion. After serving all the requests the vehicle must return back to the departure point. For the multi-vehicle dynamic traveling repair problem, Lu et al. (2002) present an asymptotic performance study.

Paepe (2002) studies the online TSP where the online salesman moves at no more than unit speed and starts and ends his work at a designated origin. The objective of the online algorithm is to find a routing which finishes as early as possible. Paepe reduces the power of the adversary, assuming the existence of a "non-abusive adversary", who is not allowed to move in a direction where there is no request waiting to be served.

The limitations of competitive analysis (or even hind sight advantage) have been recognized when applied to real-time dynamic routing and scheduling problems. Powell et al. (1995) claim that comparing against hind sight solutions does not provide a fair evaluation of real time fleet management strategies. The lack of systematic evaluation methodologies has led researchers to compare algorithms performance using simulation and under the same strings of randomly generated demands, as in Kim (2003).

Since the problems faced by carriers in a TLPM can be described as online problems, the next section describes the advantages and difficulties that arise when applying competitive analysis of algorithms to a TLPM problem.

4.3. Applying Competitive Analysis to TLPM Problems

Applying competitive analysis to the TLPM market would result in a competition among two carriers; one denoted O for "ordinary" and one denoted P for "powerful" (the adversary). The carrier O possesses a given fleet assignment and bidding functions, has uncertain information about the future (only knows the parameters of the demand function, not the future instances), and knows with certainty his private information. Carrier O falls along the general description of a carrier in chapter 3. The carrier P possesses a given fleet assignment and bidding functions, determines the sequence of future shipment arrivals (the future instances), and knows with certainty his private information as well as O's private information. The objective of P is to maximize the competitive ratio ($\max[\pi^P(S_N)/\pi^O(S_N)]$) while the objective of O is to minimize the competitive ratio:

$$\min[\pi^P(S_N)/\pi^O(S_N)] = \max[-\pi^P(S_N)/\pi^O(S_N)] \ .$$

These perfectly conflicting objectives determine a zero sum game between carriers O and P.

Under the previous assumptions competitive analysis would provide trivial results; i.e. the adversary P is so powerful that the competitive ratio would not sufficiently distinguish among DVR technologies otherwise of distinct quality. If carrier P determines the sequence and characteristics of shipment arrivals, these can be easily chosen to minimize his fleet empty distance. If carrier P knows carrier O's private information, P also knows O's bids. With this information, carrier P can bid in a way that completely minimizes carrier O's profits in a first or second price auction, even if P does not determine the shipment arrivals. In a second price auction, P can bid O's bid *plus* a non negative negligible amount in order to limit O's revenues. In a first price auction, P can maximize his revenues bidding O's bid *minus* a non negative negligible amount.

The assumptions of competitive analysis go against standard notions of fair market competition and operation. Firstly, in a procurement marketplace the sequence and characteristics of arrivals are determined by the shippers' needs, carriers cannot determine those needs. Secondly, assuming that just *one* carrier has full and precise knowledge about competitors' private information (deployment, assignment, costing, and bidding functions), the information asymmetry provides such an advantage in the bidding process that it conceals any qualitative difference among carriers DVR technologies. Thirdly, competitive analysis assigns the adversary P with an *off-line* technology (since P has full information) and limits O to have an *online* technology. The two carriers are not even "competing" in the same kind and problem instance.

From a behavioral perspective, the competitive analysis of algorithms cannot capture the objectives and goals of TLPM agents. It is in the best interest of shippers to foster competition and efficiency in the markets, therefore advocating for auction, data disclosure rules, and carrier behaviors that do not foster monopolistic or anticompetitive practices. Carriers are not willing to relinquish sensitive information about their fleet management strategies and status that could compromise their profits. It was already mentioned that operating ratios in the TL industry are fairly high (0.95 is good, 0.90 is excellent). Therefore it is more realistic to analyze the performance of DVR technologies in a market environment characterized by cut-throat competition and perfect information symmetry than in a market characterized by one dominant player and extreme information asymmetry. The next section describes the attempt proposed in this research to create an environment and procedure to analyze DVR technologies in a level playing field.

4.4. Auction Analysis of Algorithms

The proposed methodology to analyze DVR technologies in a market environment utilizes a sequence of second price auctions. Carriers are symmetric in all aspects but in their DVR technology. Therefore the DVR technologies and results can be compared ceteris paribus. Shipments or auctions are generated by a demand function that is representative of the shippers demand arrivals and characteristics. As in chapter 3, arrival times and shipments are assumed to arise from a probability space $(\Omega, \mathcal{F}, \mathcal{P})$, with outcomes $\{\omega_1, \omega_2, ..., \omega_N\}$. Any arriving shipment s_j represents a realization at time t_j from the aforementioned probability space, therefore:

$\omega_j = \{t_j, s_j\}$.

Two carriers compete for each and every shipment $s_j \in S_N$. Sequential second price auctions are used to allocate the shipment to the carrier with the lowest bid (if the lowest bid is less than the shipment reservation value). The winner is paid the minimum between the second lowest bid and the shipment reservation value. Therefore prices and payments are generated *endogenously* as a result of the interaction between carriers and their environment. The carriers know the parameters and functional form of the probability space but not the future demand realizations. The only public information revealed after the auction is the price paid to the winner, if any. Simulation is used to estimate the performance of DVR technologies.

It is assumed that each carrier bids his best estimation of his marginal cost given his DVR technology and current status. As mentioned in section two, estimating the marginal cost of serving a shipment is not a trivial task given the complexity of the problem and the uncertainties about future arrivals and payments. It was noted in the game theoretic auction literature review (chapter 2) that, in a one-item second price auction, bidding the items value (cost) is the dominant strategy. However this generally does not hold true for several items and bidders with multi-unit demand functions. Nevertheless, marginal cost bidding may be reasonable or even a dominant strategy in a particular setting. For example, a setting where a carrier believes that is being randomly matched with a group of carriers drawn from a large population (in each and every auction). If the chances of meeting the same competitors are negligible, a carrier may safely ignore any inter-temporal link between his current bid and the opponents' future bids.

If the carriers' problem is completely outstripped of their strategic considerations, carriers model market prices or payments as a random process that is not influenced by their own actions (bids). Therefore, the problem is similar to a one-item second price where competitors' behavior can be ignored and the dominant strategy is marginal cost bidding. In the notation introduced in chapter 3, this is similar to assuming that competitors are playing $\mathrm{b}^{-i}(\xi) = \mathrm{f}(\xi)$ or simply $\mathrm{b}^{-i}(\xi) = \xi$, where ξ is a random process that is not linked in any way to carrier $i's$ bidding, capacity/deployment, or history of play. It can also be interpreted that $\mathrm{b}^{-i}(\xi) = \xi$ reflects the degree of competition in the market or represents different fractions of customers' reservation prices. However, with uncertainty about the prices (since prices are not revealed until the auction is completed), the problem is still best described as an auction. If the reservation price is known immediately before the auction takes place, the carrier's problem is better described as an acceptance/rejection decision given a fix posted price.

4.4.1. Shipment Cost Function

In a one-item second price auction, the value of the item (to a particular bidder) is equivalent to the bid that maximizes the bidder's profit. Applying the same logic, the value of a shipment to a carrier is equal to the bid that maximizes the carrier's profit – in the assumed procurement marketplace and given the carrier's technological endowment and status. In mathematical terms, the cost of serving shipment s_j for carrier i is equal to b_j^{*i}, where:

$$b_j^{*i} \in \arg\max_{b \in \mathrm{R}} E_{(\xi)}[(\xi - c^i(s_j, z_j^i))I_j^i + \pi^i_{j+1,..,N}(s_j \mid I_j^i = 1)I_j^i + \pi^i_{j+1,..,N}(s_j \mid I_j^i = 0)\ (1 - I_j^i)] \qquad (4.1)$$

$$\pi^i_{j+1,..,N}(s_j \mid I_j^i = 1) = E_{(\omega_{j+1},...,\omega_N)}[\sum_{k=j+1}^{N} E_{(\xi)}[\pi^i(\xi, c^i, s_k, z_k^i \mid I_j^i = 1)]] \qquad (4.2)$$

$$\pi^i_{j+1,..,N}(s_j \mid I_j^i = 0) = E_{(\omega_{j+1},...,\omega_N)}[\sum_{k=j+1}^{N} E_{(\xi)}[\pi^i(\xi, c^i, s_k, z_k^i \mid I_j^i = 0)]] \qquad (4.3)$$

$$E_{(\xi)}[\pi^i(\xi, c^i, s_k, z_k^i)] = E_{(\xi)}[(\xi - c^i(s_{k+1}, z_{k+1}^i))\, I_k^i \mid b_k^{*i}] \qquad (4.4)$$

$$I_k^i = 1 \quad if \quad \xi > b_k^i \quad and \quad I_k^i = 0 \quad if \quad \xi \le b_k^i \qquad (4.5)$$

$$z_k^i = \mathrm{a}^i(t_k, h_j, z_{k-1}^i) \qquad (4.6)$$

The value of the shipment s_j in equation (4.1) is the value of the bid that maximizes the expected sum of present plus future profits conditional on bidding a real number b. In equation (4.1) there are two kinds of profits: (a) present expected profit – estimated as if shipment s_k is the last shipment to be auctioned – and (b) future expected profits – depending on whether the auction for s_k is won or not. The former type of profit expressed is by $(\xi - c^i(s_j, z^i_j))$ and the latter is expressed by $\pi^i_{j+1,..,N}(s_j \mid I^i_j = 1) + \pi^i_{j+1,..,N}(s_j \mid I^i_j = 0)$.

Equation (4.4) shows the recursive nature of the problem while equation (4.6) is the "rule" to be applied to obtain a carrier's status when a new shipment arrives (given a history of outcomes and the previous fleet status – this could include repositioning of vehicles and projection of a schedule into the future). The cost provided by $\mathrm{c}^i(s_j, z^i_j)$ is the change in distance traveled by incorporating s_j to the carrier schedule when his status is z^i_j (change estimated using the carriers assignment function a^i). This change in distance traveled is estimated at time t_j as if s_j is the last shipment to be acquired in the marketplace and the vehicles do not have to return to the depot. Equation (4.5) simply states that an auction is won by the carrier if his bid is lower than the competitors' bids or the realized shipment price.

4.4.2. Solving for the Optimal Bid

Neither equation (4.2) nor equation (4.3) are affected by the bid value for shipment s_j, they are simply conditioned on the outcome of the auction for s_j. The expected value of the present plus future profits for any bid $b \in R$ can be expressed as:

$$E_{(\xi)}[(\xi - c^i(s_j, z_j^i))I_j^i + \pi^i_{j+1,..,N}(s_j \mid I_j^i = 1)I_j^i + \pi^i_{j+1,..,N}(s_j \mid I_j^i = 0)\ (1 - I_j^i)] = \qquad (4.7)$$

$$= \int_b^\infty (\xi - c^i(s_j, z_j^i))\, p(\xi)\, d(\xi) + \int_b^\infty \pi^i_{j+1,..,N}(s_j \mid I_j^i = 1)\ p(\xi)\, d(\xi) +$$
$$+ \int_{-\infty}^b \pi^i_{j+1,..,N}(s_j \mid I_j^i = 0)\ p(\xi)\, d(\xi)$$

The first two integrals are evaluated in the interval [b, ∞] because they are not zero only if the bid b is smaller than the competitors' bids $(b < \xi)$, or equivalently, if the auction for s_j is won. The last integral is evaluated in the interval [-∞, b] because it is not zero only when the bid b is bigger than the competitors' bids $(b > \xi)$, or equivalently, if the auction for s_j is lost. Grouping terms in (4.7):

$$\int_b^\infty (\xi - c^i(s_j, z_j^i) + \pi^i_{j+1,..,N}(s_j \mid I_j^i = 1) - \pi^i_{j+1,..,N}(s_j \mid I_j^i = 0))\, p(\xi)\, d(\xi) +$$
$$+ \int_{-\infty}^\infty \pi^i_{j+1,..,N}(s_j \mid I_j^i = 0)\ p(\xi)\, d(\xi)$$
$$= \int_b^\infty (\xi - c^i(s_j, z_j^i) + \pi^i_{j+1,..,N}(s_j \mid I_j^i = 1) - \pi^i_{j+1,..,N}(s_j \mid I_j^i = 0))\, p(\xi)\, d(\xi) +$$
$$+ \ \pi^i_{j+1,..,N}(s_j \mid I_j^i = 0) \qquad (4.8)$$

The term

$$- c^i(s_j, z_j^i) + \pi^i_{j+1,..,N}(s_j \mid I_j^i = 1) - \pi^i_{j+1,..,N}(s_j \mid I_j^i = 0)$$

does not depend on the realization of ξ or the value of b. Denoting $c_j^{*i} = c^i(s_j, z_j^i) - \pi^i_{j+1,..,N}(s_j \mid I_j^i = 1) + \pi^i_{j+1,..,N}(s_j \mid I_j^i = 0)$ and replacing in (4.8):

$$E_{(\xi)}\{\,[(\xi - c^i(s_j, z_j^i)) + \pi^i_{j+1,..,N}(s_j \mid I_j^i = 1) + \pi^i_{j+1,..,N}(s_j \mid I_j^i = 0)\,] \mid b_j^i = b\} \quad =$$

$$= \pi^i_{j+1,..,N}(s_j \mid I_j^i = 0) + \int_b^{\infty} (\xi - c_j^{*i})\, p(\xi)\, d(\xi) \qquad (4.9)$$

Then, (4.9) is strategically equivalent to a second price auction, where ξ is the distribution of the best competitors' bids and c_j^{*i} is the carrier $i's$ value. The bid that maximizes equation (4.9) is simply c_j^{*i}, the proof that c_j^{*i} is optimal parallels the proof given in chapter 2 for the one-item second price auction. Assuming $b > c_j^{*i}$ then:

$$\int_b^{\infty} (\xi - c_j^{*i})\, p(\xi)\, d(\xi) \le \int_b^{\infty} (\xi - c_j^{*i})\, p(\xi)\, d(\xi) + \int_{c_j^{*i}}^{b} (\xi - c_j^{*i})\, p(\xi)\, d(\xi)$$

since all the elements in the last integral are equal or bigger than zero. Assuming $b < c_j^{*i}$ then:

$$\int_{c_j^{*i}}^{\infty} (\xi - c_j^{*i})\, p(\xi)\, d(\xi) \ge \int_{c_j^{*i}}^{\infty} (\xi - c_j^{*i})\, p(\xi)\, d(\xi) + \int_{c_j^{*i}}^{b} (\xi - c_j^{*i})\, p(\xi)\, d(\xi)$$

since in the last integral the term $\xi - c_j^{*i}$ is negative while the other the elements are equal or bigger than zero. Therefore, equation (4.9) is maximized when $b = c_j^{*i}$. Therefore, the optimal bid for a shipment s_j^i is:

$$c_j^{*i} = \quad c^i(s_j, z_j^i) - \pi^i_{j+1,..,N}(s_j \mid I_j^i = 1) + \pi^i_{j+1,..,N}(s_j \mid I_j^i = 0) \quad (4.10)$$

4.4.3. Optimal Bid Analysis

Equation (4.10) represents the value of the best bid given a carrier's assignment technology a^i and estimated price function $\mathrm{b}^{-i}(\xi)$. Therefore, a carrier with a different technology or estimated price function may have a different value for the optimal bid (even if the both carriers have the same fleet status).

The intuition behind (4.10) is fairly straightforward. The first term represents the "static marginal cost" of serving shipment s_j as if it was the last shipment to arrive. The other two terms are linked to the future and are best interpreted together. If the difference $\pi^i_{j,\ldots,N}(s_j \mid I^i_j = 0) - \pi^i_{j,\ldots,N}(s_j \mid I^i_j = 1)$ is:

a) $\pi^i_{j,\ldots,N}(s_j \mid I^i_j = 0) - \pi^i_{j,\ldots,N}(s_j \mid I^i_j = 1) > 0$

Having to serve s_j decreases the future profits since the carrier is better off without serving s_j. The carrier must hedge against the expected decrease in future profits increasing the static marginal cost by the positive difference. This increase may not be only due to the increase in the probability of deadheading but also due to the carrier's operation at or near capacity levels (serving the present shipment may preclude serving a more profitable shipment in the future)

b) $\pi^i_{j,\ldots,N}(s_j \mid I^i_j = 0) - \pi^i_{j,\ldots,N}(s_j \mid I^i_j = 1) = 0$

Having to serve s_j does not change future profits. The carrier must not hedge any value.

c) $\pi^i_{j,\ldots,N}(s_j \mid I^i_j = 0) - \pi^i_{j,\ldots,N}(s_j \mid I^i_j = 1) < 0$

Having to serve s_j increases future profits since the carrier is better off serving s_j. The carrier must bid more aggressively for shipment s_j decreasing the static marginal cost by the negative difference. This last case may seem counterintuitive at first glance. However, if a vehicle is located in a "sink" area (a lot of trips are attracted and few are generated) and s_j originates in a "sink" and goes to a "source" (a lot of trips are generated and few are attracted), it is absolutely plausible that future expected profits with s_j are greater than without s_j.

The true cost of serving shipment s_j is equal to the payment that carrier i has to receive in order to make him indifferent between serving the shipment or not, this payment is c_j^i. Therefore, paying the exact value of the shipment makes the bidder indifferent between winning and losing the auction.

4.4.4. Optimal Bid Complexity

Analyzing the complexity of (4.10) helps to put in perspective the complexity of equation (3.1) or equation (3.3), where carriers not only have to estimate their own and competitors' costs but to find equilibrium in bidding strategies. The expectation over the sums of expected profits can be an insurmountable task since it involves several random variables: arrivals, shipment characteristics, and prices. Furthermore, equation (4.10) contains an exponential number of future histories. Even assuming, for the time being, that $S_{j+1,\ldots,N}$ is known at time t_j, since each auction can be won or lost, the corresponding decision tree has $2^{|S_{j+1,\ldots,N}|} = 2^{N-j}$ end nodes and possible future histories. Furthermore, the potential NP hard complexity of the underlying VRP is present every time $c^i(s_k, z_k^i)$ has to be estimated.

The intricacies do not stop there. The profitability of each history is linked to the value of future costs (which are unknown when going forward). The value of future costs are known when moving backwards, but not the carrier's status at the time (a carrier's status is dependent on the previous history).

Therefore, in general, equation (4.1) cannot be solved on one pass, neither going forward or backward, nor by brute force enumeration or simulation. Some kind of iterative process becomes necessary (if convergence were possible) to break the circular process where the future depends on the present. It is important to note that future deployment depend on the present bid and its probability of winning. At the same time, the present depends on the future, the present bid depend on the future profits and future fleet statuses.

4.5. Relaxations of Auction Analysis

Auction analysis can be seen as a general methodology to evaluate algorithms, which is closely linked to two well known problems. Under special demand and auction settings, auction analysis can be reduced to (a) the acceptance/rejection problem and (b) optimal DVR assignment and average analysis of the DVR.

4.5.1. Acceptance/Rejection Online Problem

Assume a carrier has a fleet assignment technology a^i and a static cost function c^i. Assume also a demand arrival rate that exceeds carrier capacity (i.e. the carrier cannot satisfy all the arriving shipments without violating time windows constraints). As in the general problem, the carrier does not know the timing or characteristics of future shipment arrivals. However, when a shipment arrives, the carrier is told the shipment reservation price, denoted P. No auction is held. The shipper fixes a price and the carrier has to either accept or reject it.

It is trivial to show that accepting a load is equivalent to bidding less than P and rejecting a load is equivalent to bidding more than P. Then, there are two possible decisions: accept or reject the shipment. The problem can be formulated as:

$$b_j^{*i} \in \underset{b \in R}{\arg\max} \{ (P - c^i(s_j, z_j^i))I_j^i \mid b + \pi^i_{j+1,..,N}(s_j \mid I_j^i = 1) + \pi^i_{j+1,..,N}(s_j \mid I_j^i = 0) \}$$

while the other formulas (4.2), (4.3), (4.4), and (4.5) remain unchanged. Then, shipment s_j is accepted if:

$$P - c^i(s_j, z_j^i) + \pi^i_{j+1,...,N}(s_j \mid I_j^i = 1) \geq \pi^i_{j+1,...,N}(s_j \mid I_j^i = 0) \qquad (4.11)$$

Shipment s_j is rejected otherwise. This is the best acceptance/rejection policy given carrier's assignment technology a^i and static cost function c^i, under the assumed arrival and shipment probability space $(\Omega, \mathcal{F}, \mathcal{P})$ and estimated price function for future arrivals $\mathrm{b}^{-i}(\xi) = \xi$.

4.5.2. Average Case Analysis of DVR Technologies

Assuming a situation similar to the acceptance/rejection problem but now assuming that (a) the reservation price P is constant (b) the cost of serving a shipment never exceeds the reservation price (c) the arrival rate is such that the carrier can serve all the arriving shipments. Then, equation (4.4) becomes:

$$E_{(\xi)}[\pi^{i}(\mathrm{b}^{-i}(\xi), c^{i}, s_k, z_k^{i})] = P - c^{i}(s_k, z_k^{i})$$

Equation (4.2) becomes:

$$\pi^{i}_{j+1,..,N}(s_j \mid I_j^{i} = 1) = E_{(\omega_{j+1},\ldots,\omega_N)}[\sum_{k=j+1}^{N} P - c^{i}(s_k, z_k^{i})] = (N-j)P - E_{(\omega_{j+1},\ldots,\omega_N)} \sum_{k=j+1}^{N} c^{i}(s_k, z_k^{i})$$

Since all shipments can be served and the prices are always greater than the costs, no shipment is ever rejected. Therefore $I_j^{i} = 1$ always holds, while $I_j^{i} = 0$ never takes place. Then, the expected profit function for shipments $S_{j...N}$ given a current status z_j^{i} becomes:

$$\begin{aligned}
&E_{(\xi)}\{ P - c^{i}(s_j, z_j^{i})) + (N-j)P - E_{(\omega_{j+1},\ldots,\omega_N)} \sum_{k=j+1}^{N} c^{i}(s_k, z_k^{i}) = \\
&= P - c^{i}(s_j, z_j^{i}) + (N-j)P - E_{(\omega_{j+1},\ldots,\omega_N)} \sum_{k=j+1}^{N} c^{i}(s_k, z_k^{i}) \\
&= (N-j+1)\ P - c^{i}(s_j, z_j^{i}) - E_{(\omega_{j+1},\ldots,\omega_N)} \sum_{k=j+1}^{N} c^{i}(s_k, z_k^{i})
\end{aligned}$$

This expected profit is a function of a carrier's assignment technology a^{i} and static cost function c^{i}. Since bidding is trivial under the conditions assumed (all shipments must be accepted), a carrier maximizes profits when has the best assignment function:

$$\mathrm{a}^{*i} \in \arg\max\{\ (N-j+1)\ P - \mathrm{c}^i(s_j, z_j^i) - E_{(\omega_{j+1},\ldots,\omega_N)} \sum_{k=j+1}^{N} \mathrm{c}^i(s_k, z_k^i)\ \} \quad (4.12)$$

$$\begin{aligned} \mathit{subject\ to}:\ & z_k^i = \mathrm{a}^i(t_j, h_{j-1}, z_{j-1}) \\ & \mathrm{a}^i \in \mathrm{A} \end{aligned}$$

Taking out $(N-j+1)\ P$, since it is a constant, and multiplying by -1:

$$\mathrm{a}^{*i} \in \arg\min\{\ \mathrm{c}^i(s_j, z_j^i) + E_{(\omega_{j+1},\ldots,\omega_N)} \sum_{k=j+1}^{N} \mathrm{c}^i(s_k, z_k^i)\ \}$$

$$\begin{aligned} \mathit{subject\ to}:\ & z_k^i = \mathrm{a}^i(t_j, h_{j-1}, z_{j-1}) \\ & \mathrm{a}^i \in \mathrm{A} \end{aligned}$$

Under the current assumptions, profit is maximized choosing the assignment function a^{*i} which minimizes expected operating costs (present and future expected operating costs). For any assignment function a^i, the average cost for the assumed arrival and shipment probability space $(\Omega, \mathcal{F}, \mathcal{P})$ is:

$$E_{(\omega_1,\ldots,\omega_N)} \sum_{k=j+1}^{N} \mathrm{c}^i(s_k, z_k^i)$$

Therefore, average case competitive ratio c for the assignment function and shipment probability space $(\Omega, \mathcal{F}, \mathcal{P})$ is equal to:

$$c = \frac{E_{(\omega_1,\ldots,\omega_N)} \sum_{k=1}^{N} \mathrm{c}^i(s_k, z_k^i \mid \mathrm{a}^i)}{E_{(\omega_1,\ldots,\omega_N)} \sum_{k=1}^{N} \mathrm{c}^i(s_k, z_k^i \mid \mathrm{a}^{*i})}$$

When the demand surpasses the capacity of the carrier the problem becomes an acceptance/rejection problem. With high demand, the optimal assignment policy is the one that maximizes profits using equation (4.11) to accept or reject shipments.

4.6. ***Comparing Competitive and Auction Analysis of Algorithms***

Competitive and auction analysis are both suitable methodologies to analyze the performance of online algorithms; however the similarities among them stop there. Competitive analysis is a form of worst case scenario; auction analysis is closer in spirit to average case analysis (as it was shown in section 4.5**)**.

Competitive analysis is fundamentally asymmetrical. A powerful adversary has control (not just knowledge) over the yet unknown (to the algorithm under analysis) future tasks. Auction analysis strives for symmetry, aiming at comparing two different technologies ceteris paribus in a level playing field. No competitor controls the future, and rewards and prices are a result of technological interaction; not even the researcher has control over them. Prices are determined online; they do not follow a preset function. In auction analysis both competitors have the same knowledge, however a technological (algorithmic) attribute is precisely how well and to what degree it takes advantage of that knowledge – ranging from ignoring the future and past to completely accounting for it.

Competitive analysis is mainly an analytical approach. Auction analysis is a simulation based approach; which has some pros and cons. Simulation allows the analysis of richer and complex environments that could never be fully addressed analytically. For example, the incorporation of real time limits to evaluate trade offs between solution quality and technology complexity (execution speed). However, with simulation is not possible to obtain close solutions or to prove general theorems or results.

Semantically, the name "competitive" for the worst case competitive analysis methodology was not wisely chosen. The Merriam Webster Online dictionary (www.m-w.com), defines *competitive* as "1. Relating to, characterized by, or based on competition". *Competition*, in turn is defined as "1 **:** the act or process of competing as **a :** the effort of two or more parties acting independently to secure the business of a third party by offering the most favorable terms **b :** active demand by two or more organisms or kinds of organisms for some environmental resource in short supply".

Paraphrasing definition **a**, auction analysis wants to distinguish how the effort (the cost determination) of two parties (technologies/algorithms) – acting independently to secure the business of a third party by offering the most favorable terms (bid) – affect the parties' profits. Paraphrasing definition **b**, auction analysis wants to replicate the active demand by two or more organisms (algorithms or transportation companies) or kinds of organisms for some environmental resource (tasks/shipments that is) in short supply.

Concluding, auction analysis aspires to construct an environment that rewards low cost or more efficient technologies. In that environment, auction analysis measures the relative performance of two technologies. Competitive analysis also measures the performance of technologies (algorithms), but, first comparing them to some imaginary all powerful adversary, which are simply a technical aid to allow absolute worst case comparisons.

4.7. <u>Applying the Proposed Methodology</u>

It was mentioned in chapter 1 that carriers and shippers are increasingly using private exchanges, where a company invites selected suppliers to interact in a real time marketplace, compete, and provide the required services. Carriers have to keep in mind the cost for each transaction, especially in a sequential auction that implements a truth revealing mechanism. Even though carriers may compete in the same market in a level playing field, they are "endowed" with inherently different resources ranging from physical assets, such as fleets and facilities, to communication and decision support systems. Furthermore, the adoption of communication technology and expertise by carriers may vary greatly (Regan, 1999).The purpose of auction analysis of algorithms is to evaluate ceteris paribus the impact of a DVR technology on carriers' market performance.

4.7.1. Formulations and Solutions of the DVR Problem

A review of the main formulations and solutions, proposed up to date, for the DVR problem is presented in this section. The DVR problem is a relaxation of the static vehicle routing problem, where information about the demand or shipments to be served unfolds over time. Stochastic arrival times and shipment characteristics differentiate the DVR problem from the vehicle routing problem. Stochasticity transforms a NP hard combinatorial optimization problem (with complete information) into a decision making problem under uncertainty (partial information), while preserving all the intricacies associated with the original NP hard problem. Powell et al. (1995) present an extensive discussion of dynamic network modeling problems that arise in logistics and distribution systems, including a-priori optimization and on-line decision policies for stochastic routing problems.

Regan et al. (1996a, 1996b, and 1998) analyze the opportunities and challenges of using real time information for fleet management. They also formulate and evaluate (using simulations) various heuristics for the dynamic assignment of vehicles to loads under real-time information. Subsequent work by Yang et al. (1999 and 2002) introduces a static optimization-based approach and tests it against the previously developed heuristic rules. Their approach solves static snapshots of the DVR problem with time windows using an exact mathematical programming formulation (which is the basis for two of the technologies studied in this paper). As new input occurs, static snapshot problems are solved repeatedly, allowing for a complete reassignment of trucks to loads at each arrival instance. Mahmassani et al. (2000) and Kim et al. (2002) study DVR strategies for fleet size operations, where computational and response times are important constraints. They also study strategies for DVR under high arrival rates and “priority” loads.

A growing body of work focuses on the solution of the stochastic DVR problem. Powell proposes a formulation based on a Markov decision process and several formulations using stochastic programming (1986a, 1986b, 1987, and 2000). Gendreau et al. (1999) and Ichoua et. al. (2000) use tabu search to solve a DVR problem with soft time windows. Gendreau et al. (1999) suggest the use of information about future requests to solve the DVR problem. This paper delves further into this idea, presenting a methodology that uses information about future requests to estimate the cost of servicing a new load. More recently, Larsen et al.

(2002) study the DVR problem with different degrees of dynamism (defined as the percentage of demands that carriers typically do not know in advance).

4.7.2. Static Cost of Serving a Shipment

Chapter 3 defines how a carrier's performance is evaluated. These definitions can be applied after the market has closed and the whole sequence of shipments has been auctioned and served. Additional notation is necessary to describe the costing of shipments while the market is operating. This notation is also going to prove helpful to describe carrier technologies and analyze results.

As before, let I_j^i be the indicator variable for carrier i for shipment s_j, such that $I_j^i = 1$ if carrier i won the auction for shipment s_j and $I_j^i = 0$ otherwise. The set of acquired shipments up to time t_k by carrier i is S_k^i. Let the set of acquired shipments up to time t_k by carrier i which are not yet served be $\breve{S}_k^i$ and the set of the set of acquired shipments up to time t_k by carrier i which have been already served be $\widehat{S}_k^i$, then $\widehat{S}_k^i + \breve{S}_k^i = S_k^i \subseteq S_k \subseteq S_N$. A shipment is considered to be served if it has been already delivered at its destination point; a shipment is considered to be yet to be served otherwise.

Let $s_j, s_k \in \widehat{S}_k^i$ and let $\widehat{x}_{jk}^i \in \{0,1\}$ be a binary variable. Let $\widehat{x}_{jk}^i = 1$ if a carrier $i's$ vehicle has *already* picked up and served shipment s_k immediately after serving shipment s_j, $\widehat{x}_{jk}^i = 0$ otherwise. Similarly, let $s_j, s_k \in \breve{S}_k^i$ and let $\breve{x}_{jk}^i \in \{0,1\}$ be a binary variable. Let $\breve{x}_{jk}^i = 1$ if a carrier $i's$ vehicle is going to deliver shipment

s_k (not *yet* delivered) immediately after serving shipment s_j, $\breve{x}^i_{jk} = 0$ otherwise. However, while $\widehat{x}^i_{jk}$ is a constant, $\breve{x}^i_{jk}\ (z^i_t)$ is a binary variable that is dependent on the carrier's status z^i_t at time t. The carrier's status can be in turn obtained as a function of the carrier's assignment function, history of play, and time $z^i_k = \mathrm{a}^i(t_k, h_{k-1}, z^i_{k-1})$. To clearly distinguish the different statuses whether the auction is won or not, the following notation is used:

(a) $z^i_k \mid (I^i_k = 0) = \mathrm{a}^i(t_k, h_k \mid I^i_k = 0, z^i_k) = \mathrm{a}^i(t_k, h_{k-1}, z^i_{k-1})$ to indicate the status immediately *before* the auction for shipment s_k or the status immediately *after* the auction for shipment s_k if the auction is *lost*.

(b) $z^i_k \mid (I^i_k = 1) = \mathrm{a}^i(t_k, h_k \mid I^i_k = 1, z^i_k)$ to indicate the status immediately *after* the auction for shipment s_k if the auction is won.

Any set of binary variables $\{\breve{x}^i_{jk}(z^i_t)\}$ that constitute a complete fleet schedule is assumed to satisfy all the time windows and flow constraints of a Mixed Integer Programming (MIP) formulation of the corresponding vehicle routing problem. The base MIP formulation used in this research is based on the work of Yang et al. (2002).

Let $\mathrm{ed}(s_m, s_n)$ be the function that returns the distance between the destination of shipment s_m and the origin of shipment s_n. When a new shipment s_k is posted (the next auction after shipment s_j has been auctioned) the total *estimated* distance needed to serve S^i_j, at time t_k, is:

$$\sum_{s_j, s_{j'} \in \widehat{S}_k^i} \mathrm{ed}(s_j, s_{j'})\, \widehat{x}_{jj'}^i + \sum_{s_j \in S_k^i} \mathrm{ld}(s_j) + \sum_{s_j, s_{j'} \in \breve{S}_k^i} \mathrm{ed}(s_j, s_{j'})\, \breve{x}_{jj'}^i (z_k^i \mid I_k^i = 0) +$$
$$+ \sum_{s_j \in \widehat{S}_k^i, s_{j'} \in \breve{S}_k^i} \mathrm{ed}(s_j, s_{j'})\, \breve{x}_{jj'}^i (z_k^i \mid I_k^i = 0) \qquad (4.13)$$

The first term represents the empty distance *already traveled* by the fleet; the second term represents the sum of the acquired shipments loaded distance; and the third and fourth term represents the empty distance that *is going to be traveled* by the fleet according to the current schedule at time t_k. This schedule changes if shipment s_k is acquired; otherwise it remains the same if s_k is not acquired since the status of the carrier has not changed. The second term includes the loaded distance of both already served and going to be served shipments since a shipment loaded distance does not change over time.

If carrier i wins the auction for shipment s_k, the estimated distance needed to serve the acquired shipments so far (including s_k) is:

$$\sum_{s_j, s_{j'} \in \widehat{S}_k^i} \mathrm{ed}(s_j, s_{j'})\, \widehat{x}_{jj'}^i + \sum_{s_j \in S_k^i} \mathrm{ld}(s_j) + \sum_{s_j, s_{j'} \in \breve{S}_k^i} \mathrm{ed}(s_j, s_{j'})\, \breve{x}_{jj'}^i (z_k^i \mid I_k^i = 1) + \qquad (4.14)$$
$$+ \sum_{s_j \in \widehat{S}_k^i, s_{j'} \in \breve{S}_k^i} \mathrm{ed}(s_j, s_{j'})\, \breve{x}_{jj'}^i (z_k^i \mid I_k^i = 1)$$
$$+ \mathrm{ld}(s_k) + \sum_{s_j \in S_k^i} \mathrm{ed}(s_j, s_k)\, \breve{x}_{jk}^i (z_k^i \mid I_k^i = 1) + \sum_{s_j \in S_k^i} \mathrm{ed}(s_k, s_j)\, \breve{x}_{kj}^i (z_k^i \mid I_k^i = 1)$$

The first two terms are the same as in equation (4.13). The third and fourth represent the empty distance that *is going to be traveled* by the fleet to serve S_k^i given the new schedule; the fourth term is the loaded distance of s_k; the fifth term represents the empty distance that *is going to be traveled* to pick up s_k; and the sixth term represents the empty distance that *is going to* be traveled (if any) after serving s_k to pick up a shipment that belongs to S_k^i.

The cost of serving shipment s_k (at the time of its auction and as if s_k is the last shipment to arrive) is the difference between equation (4.14) and equation (4.13). Let $\mathrm{c}^i(s_k, z_k^i)$ be the cost of shipment s_k for carrier i when his status is z_k^i, then:

$$
\begin{aligned}
\mathrm{c}^i(s_k, z_k^i) = & \sum_{s_j, s_{j'} \in \breve{S}_k^i} \mathrm{ed}(s_j, s_{j'})\, \breve{x}_{jk}^i(z_k^i \mid I_k^i = 1) - \sum_{s_j, s_{j'} \in \breve{S}_k^i} \mathrm{ed}(s_j, s_{j'})\, \breve{x}_{jk}^i(z_k^i \mid I_k^i = 0) + \\
& + \sum_{s_j \in \widehat{S}_k^i, s_{j'} \in \breve{S}_k^i} \mathrm{ed}(s_j, s_{j'})\, \breve{x}_{jj'}^i(z_k^i \mid I_k^i = 1) - \sum_{s_j \in \widehat{S}_k^i, s_{j'} \in \breve{S}_k^i} \mathrm{ed}(s_j, s_{j'})\, \breve{x}_{jj'}^i(z_k^i \mid I_k^i = 0) \\
& + \sum_{s_j \in S_k^i} \mathrm{ed}(s_j, s_k)\, \breve{x}_{jk}^i(z_k^i \mid I_k^i = 1) + \sum_{s_j \in S_k^i} \mathrm{ed}(s_k, s_j)\, \breve{x}_{kj}^i(z_k^i \mid I_k^i = 1) + \mathrm{ld}(s_k)
\end{aligned}
\tag{4.15}
$$

The first two terms in equation (4.14) and equation (4.13) cancel each other out. The conditions $I_k^i = 1$ and $I_k^i = 0$ indicate the current schedule with and without s_k respectively. The sum of the two differences represents the *change* in empty distance for the shipments in S_k^i that are not yet serviced. The cost of serving a shipment according to equation (4.15) does not depend on the cost of the already served shipments, which have already been “sunk”.

The previous formulation assumes that vehicles are always located at the destination of some shipment, which is compatible with assumptions taken for the technologies studied in this chapter. However, if real time diversion and repositioning is used, equation (4.15) is still valid if, for each vehicle a dummy shipment is added to $\widehat{S}_k^i$.

4.7.3. Technologies

In the rich spectrum of DVR technologies, three inherently distinct and archetypical approaches are evaluated. These three technologies require different levels of sophistication in communication capabilities, static optimization, and the evaluation of opportunity costs. In real time situations, cost evaluation is a difficult task when optimal decision-making involves the solution of larger NP hard problems and the necessity of taking into account the stochastic nature of future demands. The three technologies are presented in an order that shows an increasing and distinct level of sophistication.

4.7.4. Base or Naïve Technology

This type of carrier simply serves shipments in the order they arrive. If the carrier has just one truck, it estimates the marginal cost of an arriving shipment s_j simply as the additional empty distance incurred when appending s_j to the end of the current route. If the carrier has more than one truck, the marginal cost is the cost of the truck with the lowest appending cost. This technology does not take into account the stochastic or combinatorial aspect of the cost estimation problem and is considered one of the simplest possible. Each vehicle acts as if it were an independent carrier; in fact, the auction and fleet assignment results are not altered if each vehicle submits its own bid. Communication and coordination overheads are reduced to a minimum. Nonetheless, this technology provides a useful benchmark against which to compare the performance of more complex and computationally demanding technologies.

The first technology is such that the schedule for the yet not served shipments in $\breve{S}_k^i$ does not change. The first four terms of equation (4.3) cancel each other out since the schedule for the "old shipments" is not changed. The last term of equation (4.3) is zero since the "new shipment" is appended at the end of a carrier's vehicle route. Then:

$$\mathrm{c}^i(s_k, z_k^i) = \mathrm{ld}(s_k) + \sum_{s_j \in S_k^i} \mathrm{ed}(s_j, s_k)\ \breve{x}_{jk}^i(z_k^i \mid I_k^i = 1)$$

For each $v | v \in V_{k+1}^i$, let denote by $\mathrm{ls}(v)$ the last shipment in vehicle v current route if any or vehicle v current location otherwise. If the auction is won, shipment s_{k+1} is allocated to the vehicle v^* that:

$$v^* \in \underset{v \in V_k^i}{\arg\min}[\,\mathrm{ed}\,(\mathrm{ls}(v), s_k)]$$

Therefore, the marginal cost of serving shipment s_{k+1} is:

$$\mathrm{c}^i(s_k, z_k^i) \approx \mathrm{ed}\,(\mathrm{ls}(v^*), s_k) + \mathrm{ld}(s_k) \qquad (4.16)$$

Finally, in terms of equation (4.10), it is clear that equation (4.16) is simply a heuristic that approximates the optimal static cost.

4.7.5. Static Fleet Optimal (SFO)

This carrier optimizes the static vehicle routing problem at the *fleet* level. The marginal cost is the increment in empty distance that results from *adding* s_j to the *total pool of trucks and loads* yet to be serviced. Communication and coordination capabilities are needed to feed the central dispatcher with real time data and to communicate altered schedules to vehicle drivers.

If the problem were static, this technology would provide the optimal cost. Like the previous technology, it does not take into account the stochastic nature of the problem. This technology roughly stands for "the best" a myopic (as ignoring the future but with real time information) fleet dispatcher can achieve. A detailed mathematical statement of the MIP formulation used by SFO is given in Yang et al. (2002).

Using this technology, the set of $\breve{x}^i_{jk}(z^i_k \mid I^i_k = 1)$ must be such that they minimize equation (4.15) given the current status of the fleet and the current schedule. If $\mathrm{ld}(s_k)$ and $\breve{x}^i_{jk}(z^i_k \mid I^i_k = 0)$ are constant expressions, the set of $\breve{x}^i_{jk}(z^i_k \mid I^i_k = 1)$ that minimize (4.15) must also minimize:

$$\min\{ \sum_{s_j, s_{j'} \in \breve{S}^i_k} \mathrm{ed}(s_j, s_{j'})\ \breve{x}^i_{jk}(z^i_k \mid I^i_k = 1) + \sum_{s_j \in \hat{S}^i_k, s_{j'} \in \breve{S}^i_k} \mathrm{ed}(s_j, s_{j'})\, \breve{x}^i_{jj'}(z^i_k \mid I^i_k = 1)$$
$$+ \sum_{s_j \in S^i_k} \mathrm{ed}(s_j, s_k)\ \breve{x}^i_{jk}(z^i_k \mid I^i_k = 1) + \sum_{s_j \in S^i_k} \mathrm{ed}(s_k, s_j)\ \breve{x}^i_{kj}(z^i_k \mid I^i_k = 1) \} \quad (4.17)$$

Using this technology, the marginal cost of serving shipment s_k is equal to the empty distance needed for best possible schedule including load s_k minus the previous schedule (which does not include s_k and that is still "optimal" if it was the best schedule at time t_k and travel times are deterministic).

Finally, in terms of equation (4.10), it is clear that equation (4.17) approximates the real cost of serving a shipment as $c^{*i}_j \approx c^i(s_j, z^i_j)$ -- the opportunity costs are completely ignored.

4.7.6. 1- step-look-ahead Fleet Optimal Opportunity Cost (1FOOC)

As the previous carrier, this carrier optimizes the static vehicle routing problem at the fleet level. This provides the *static cost* for adding s_j. However, this carrier also knows the distribution of load arrivals over time and their spatial distribution (it is not discussed in this research how the carrier has acquired this information). This type of carrier also has an estimation of the endogenously generated prices or payments. Hence, the carrier can assess whether and how much winning s_j affects his future profits. This is the *opportunity cost* of serving s_j. Unlike previous types, this carrier takes into account the stochasticity of the problem to estimate the opportunity costs of serving s_j as if there is just one more auction after the auction for s_j (one step look ahead). Limiting the "foresight" to just one step into the future has two advantages: (a) it considerable eases the estimation and (b) it provides a first approximation (as in the first term of a Taylor series) about the importance of opportunity costs in a given competitive environment.

Unlike the previous technologies, this one is not function or parameter free. Estimation opportunity cost requires the knowledge of arrival, shipment, and price distributions. In addition, there is the computational burden of estimating the opportunity costs. On the other hand, this type of carrier can adapt to changing conditions in the marketplace – his price is truly "dynamic" and "flexible", in the sense that future consequences are evaluated and that the shipment and price distribution can be estimated online. In the present research, this type of carrier estimates the price function as a normal function, whose mean and standard deviation are obtained from the whole sample of previous prices.

4.7.7. One Step Look-ahead

The previous formulation implicitly assumes that acquiring shipment s_k does not affect the marginal cost of future loads (i.e. s_{k+1}, s_{k+2}, ..., s_N). However this is not entirely correct since acquiring a new load (a) temporarily reduces carriers' capacity (capacity defined as the ability to serve additional shipments at a point in time) and (b) changes the current schedule and therefore possibly changes fleet deployment at the time of the next shipment auction. The only exception to this takes place in the final auction (shipment s_N) and there are no repositioning costs (trucks do not return to depot).

As stated in Chapter 3, in general, arrival times and shipments will not be known in advance. The arrival instants $\{t_1, t_2, ..., t_N\}$ will follow some general arrival process. Furthermore, arrival times and shipments are assumed to come from a probability space $(\Omega, \mathcal{F}, \mathcal{P})$, with outcomes $\{\omega_1, \omega_2, ..., \omega_N\}$. Any arriving shipment s_j represents a realization at time t_j from the aforementioned probability space, therefore $\omega_j = \{t_j, s_j\}$. Therefore, at time t_{k+1}, the sets $T_{k+2,...,N}$ and $S_{k+2,...,N}$ are unknown before bidding for s_{k+1} starts.

The carrier is also assumed to know the parameters of the function $\mathrm{b}^{-i} = \mathrm{f}(\xi)$ --reservation price or competition function. It has already been discussed the complexity of estimating the value of the bid that maximizes equation (4.1). However, the estimation of the cost of serving s_k is greatly simplified if it is assumed that shipment s_{k+1} is the last shipment to ever arrive at the marketplace.

Using backward induction, the cost of serving s_{k+1} has to be estimated first. This cost would be simply $c^i(s_{k+1}, z^i_{k+1})$; however s_{k+1} and z^i_{k+1} are still unknown at time t_k. Equation (4.2) for this special case becomes:

$$\pi^i_{j,k}(s_j \mid I^i_j = 1) = E_{(\omega_k)}[E_{(\xi)}[\pi^i(\mathrm{b}^{-i}(\xi), c^i, s_k, z^i_k \mid I^i_j = 1)]] =$$
$$= E_{(\omega_k)}[E_{(\xi)}[(\mathrm{b}^{-i}(\xi) - b^i_k \mid I^i_j = 1) I^i_k]] = E_{(\omega_k)}[E_{(\xi)}[(\xi - c^i(s_{k+1}, z^i_{k+1} \mid I^i_j = 1)) I^i_k]]$$

Similarly, equation (4.3) becomes:

$$\pi^i_{j,k}(s_j \mid I^i_j = 0) = E_{(\omega_k)}[E_{(\xi)}[\pi^i(\mathrm{b}^{-i}(\xi), c^i, s_k, z^i_k \mid I^i_j = 0)]] =$$
$$= E_{(\omega_k)}[E_{(\xi)}[(\mathrm{b}^{-i}(\xi) - b^i_k \mid I^i_j = 0) I^i_k]] = E_{(\omega_k)}[E_{(\xi)}[(\xi - c^i(s_{k+1}, z^i_{k+1} \mid I^i_j = 0)) I^i_k]]$$

In this report $\pi^i_{j,k}(s_j \mid I^i_j = 1)$ and $\pi^i_{j,k}(s_j \mid I^i_j = 0)$ are estimated using simulation. Then the optimal bid value is:

$$c^{*i}_j \approx c^i(s_j, z^i_j) - \pi^i_{j,k}(s_j \mid I^i_j = 1) + \pi^i_{j,k}(s_j \mid I^i_j = 0) \qquad (4.18)$$

This result coincides with the theoretical analysis of auctions surveyed in chapter 2. In the presence of synergies or economies of scale the first bid is increased (decreased in reverse auctions); conversely, in the presence of negative synergies or diseconomies of scale the first bid is decreased (increased in reverse auctions).

4.7.8. Assumptions

Response or solution time is a key consideration in real time applications. However, given that the objective of this paper is to analyze how much can be gained using different technologies, it is assumed that carriers have enough computational power to submit a bid before another request comes in.

In all cases it is assumed that a carrier bids only if a feasible solution has been found. If serving s_j unavoidably violates the time window of a previously won shipment, the carrier simply abstains from bidding or submits a high bid that exceeds the reservation price of s_j. Simulation experiments are conducted to evaluate the performance of these strategies under alternative specifications and parameter values.

The loaded distance is not included in the final cost because it is assumed that all carriers have the same cost per mile, therefore adding/subtracting a constant to/from all the bids (e.g. the loaded distance of an arriving shipment) does not alter the ranking of bids. Besides, if all carriers include the loaded distance in their bids, that term cancels out when computing profits (the payment, in this case the second bid, and the winner's cost include the same constant: the shipment loaded distance). Shippers' reservation prices do not include the loaded distance either. However, loaded distance of all shipments is included when estimating the opportunity costs in (4.18), since loaded distance is a key factor that can affect a carrier's capacity.

Another assumption is that once a vehicle is loaded with a shipment (i.e. at its origin), it travels directly to the shipment destination before picking up another demand. Therefore, the possibility of shipment consolidation at a terminal or load exchanges among vehicles (in-route load swap) is precluded. It is also assumed that a vehicle that is moving empty to pick up a shipment cannot be rerouted before completing the service of that shipment. It is further assumed that, a vehicle does not move empty unless they are going to pick up a load (no repositioning).

The simulations settings are as described in chapter 3 unless stated otherwise. Auction analysis of technologies was applied to compare naïve vs. static fleet optimal (SFO) and to compare static fleet optimal vs. 1-step-look-ahead fleet optimal opportunity costs (1FOOP). All the figures presented and analyzed in this chapter were obtained with a carriers' fleet size of two vehicles.

4.7.9. Analysis of Results

Figures 3, 4, 5, and 6 compare the performance of the SFO vs. naïve technology. Figures 3 and 5 are absolute changes in profits and shipments served respectively; while Figures 4 and 6 are percentage changes in profits and shipments served respectively.

The results obtained for the less sophisticated carrier (naïve carrier in Figures 3, 4, 5, and 6) are used as the base line. Therefore, any positive difference (indicated in red) in the first four graphics demonstrates that the more sophisticated carrier (SFO carrier in Figures 3, 4, 5, and 6) has either obtained more profits or served more shipments than the less sophisticated carrier; a native difference (indicated in blue) would demonstrate the opposite.

As expected, a more sophisticated technology outperforms the naïve one. However, relative performance critically depends on the arrival rate and time windows. Figures 3 and 4 show how SFO outperforms naïve in profit levels, for the most part with wider time windows and medium arrival rates. A similar behavior can be observed in Figures 5 and 6 with respect to the number of shipments served.

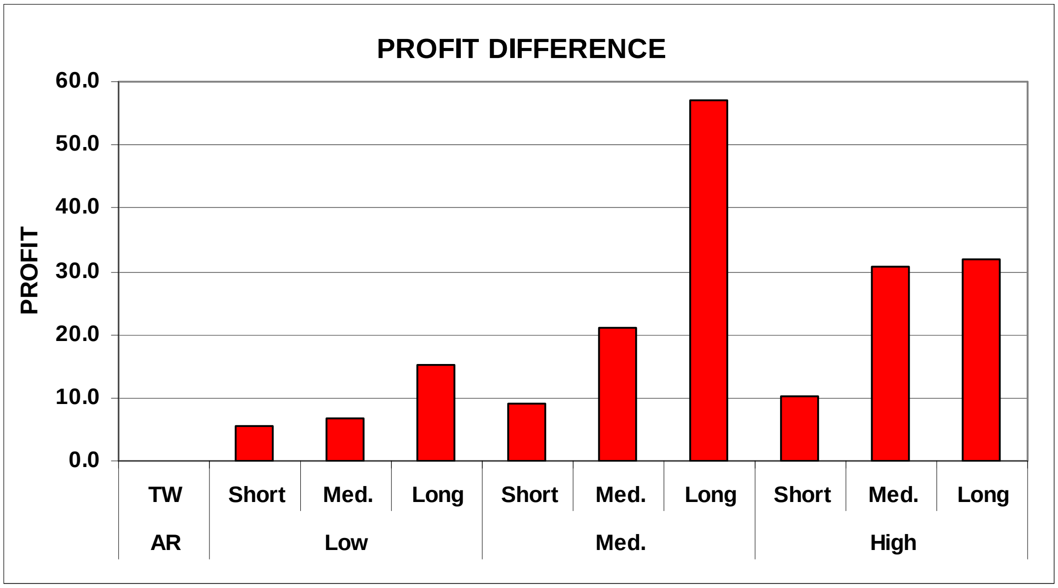

Figure 3 Profit Difference SFO vs. Naïve Technology

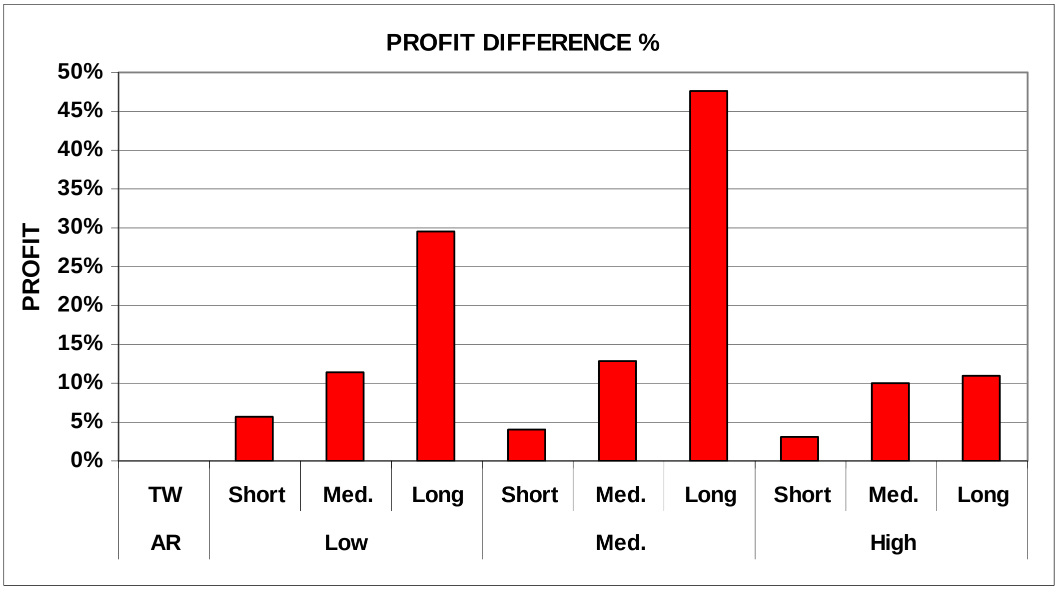

Figure 4 Profit % Difference SFO vs. Naïve Technology

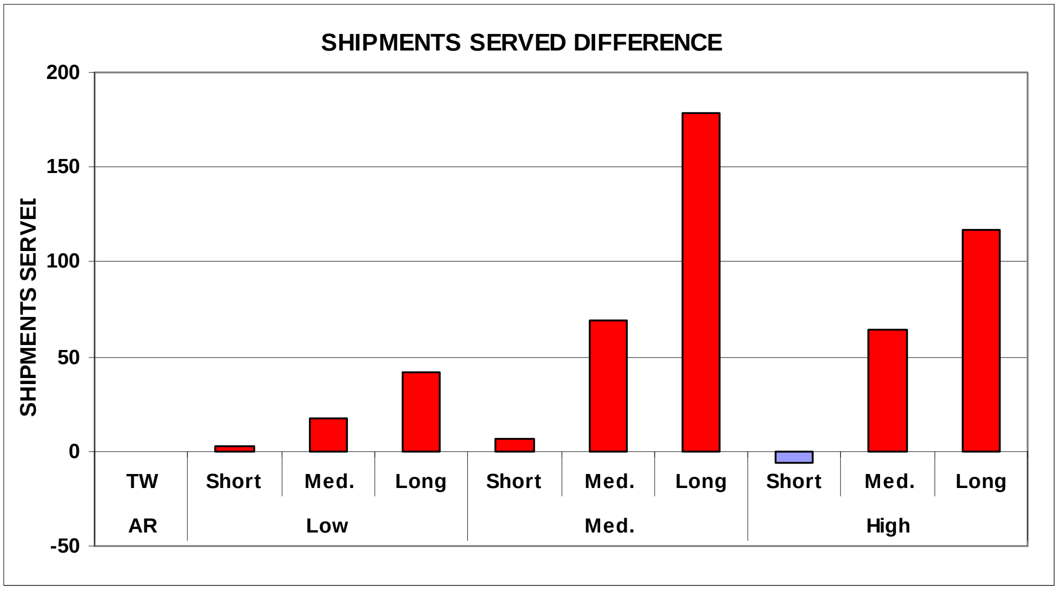

Figure 5 Shipments Served Difference SFO vs. Naïve Technology

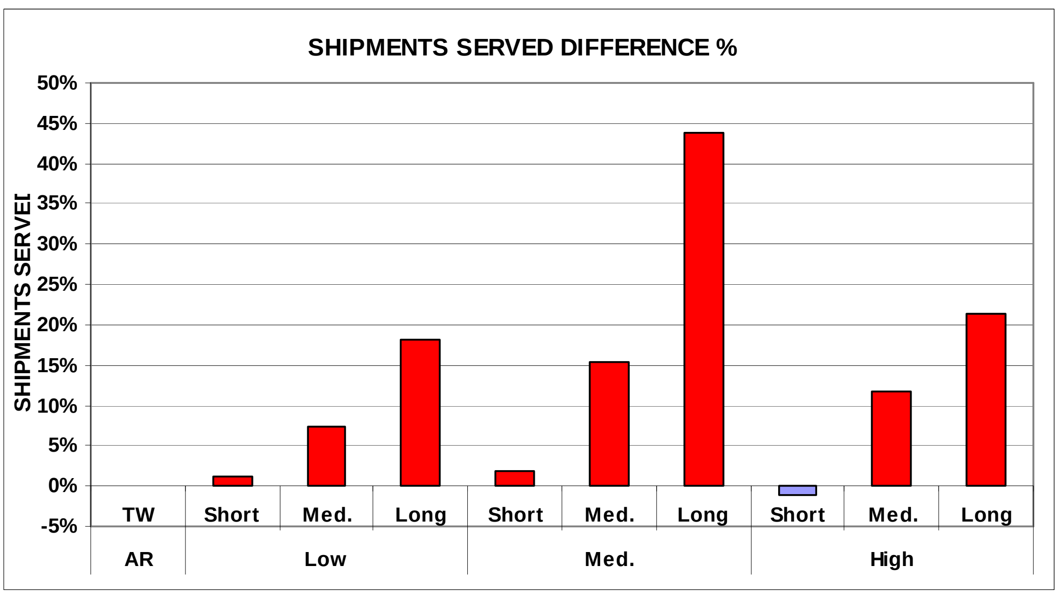

Figure 6 Shipments Served % Difference SFO vs. Naïve Technology

To understand why the SFO technology outperforms the naïve one, it is useful to look at how they estimate the cost of serving a shipment. Assuming for a moment any carrier i with a fleet status z_k^i, bidding for shipment s_k, the marginal cost obtained with equation (4.16) is bigger or equal than the marginal cost obtained with equation (4.17) since the former is special case of equation (4.15) – search over a subset of feasible solutions set – and the latter is the result of minimizing equation (4.15) – search over the whole feasible solution set. Comparing both marginal costs and simplifying the constant loaded distance:

$$
\begin{aligned}
\mathrm{ed}(\mathrm{ls}(v^*), s_k) \geq & \sum_{s_j, s_{j'} \in \breve{S}_k^i} \mathrm{ed}(s_j, s_{j'})\ \breve{x}_{jk}^i(z_k^i \mid I_k^i = 1) - \sum_{s_j, s_{j'} \in \breve{S}_k^i} \mathrm{ed}(s_j, s_{j'})\ \breve{x}_{jk}^i(z_k^i \mid I_k^i = 0) + \\
& + \sum_{s_j \in \hat{S}_k^i, s_{j'} \in \breve{S}_k^i} \mathrm{ed}(s_j, s_{j'})\ \breve{x}_{jj'}^i(z_k^i \mid I_k^i = 1) - \sum_{s_j \in \hat{S}_k^i, s_{j'} \in \breve{S}_k^i} \mathrm{ed}(s_j, s_{j'})\ \breve{x}_{jj'}^i(z_k^i \mid I_k^i = 0) + \\
& + \sum_{s_j \in S_k^i} \mathrm{ed}(s_j, s_k)\ \breve{x}_{jk}^i(z_k^i \mid I_k^i = 1) + \sum_{s_j \in S_k^i} \mathrm{ed}(s_k, s_j)\ \breve{x}_{kj}^i(z_k^i \mid I_k^i = 1)
\end{aligned}
$$

Any schedule that assigns the new shipment to the end of a vehicle route results in a strict *equality*. This is:

$$
\mathrm{ed}(\mathrm{ls}(v^*), s_k) = \sum_{s_j \in S_k^i} \mathrm{ed}(s_j, s_k)\ \breve{x}_{jk}^i(z_k^i \mid I_k^i = 1) \qquad (4.19)
$$

Any "optimal static" schedule that does not assign the new shipment to the end of a vehicle route results would generally result in a strict *in*equality (though ties are theoretically possible they are not very likely). This is:

$$
\begin{aligned}
\mathrm{ed}(\mathrm{ls}(v^*), s_k) > & \sum_{s_j, s_{j'} \in \breve{S}_k^i} \mathrm{ed}(s_j, s_{j'})\ \breve{x}_{jk}^i(z_k^i \mid I_k^i = 1) - \sum_{s_j, s_{j'} \in \breve{S}_k^i} \mathrm{ed}(s_j, s_{j'})\ \breve{x}_{jk}^i(z_k^i \mid I_k^i = 0) + \\
& + \sum_{s_j \in \hat{S}_k^i, s_{j'} \in \breve{S}_k^i} \mathrm{ed}(s_j, s_{j'})\ \breve{x}_{jj'}^i(z_k^i \mid I_k^i = 1) - \sum_{s_j \in \hat{S}_k^i, s_{j'} \in \breve{S}_k^i} \mathrm{ed}(s_j, s_{j'})\ \breve{x}_{jj'}^i(z_k^i \mid I_k^i = 0) + \\
& + \sum_{s_j \in S_k^i} \mathrm{ed}(s_j, s_k)\ \breve{x}_{jk}^i(z_k^i \mid I_k^i = 1) + \sum_{s_j \in S_k^i} \mathrm{ed}(s_k, s_j)\ \breve{x}_{kj}^i(z_k^i \mid I_k^i = 1) \qquad (4.20)
\end{aligned}
$$

Let denote the former type of schedule (4.19) as "appending" and the latter (4.20) as "inserting". Formally, inserting takes place any time:

$$\sum_{s_j \in S_k^i} \text{ed}(s_k, s_j)\ \breve{x}_{kj}^i(\, z_k^i \mid I_k^i = 1) > 0\,,$$

while appending takes place when $\sum_{s_j \in S_k^i} \text{ed}(s_k, s_j)\ \breve{x}_{kj}^i(\, z_k^i \mid I_k^i = 1) = 0$.

The "appending" technique has at most a polynomial number of solutions. The two DVR techniques provide the same costs when they search over the same set of feasible solutions. Intuitively, if time windows constraints are very tight, the only feasible solutions may be to append the arriving shipment to the end of existing routes. The initial status of the carrier $(\, z_k^i \mid I_k^i = 0)$ does not provide "enough room" to insert arriving shipments. A very low arrival rate would have a similar effect. If all vehicles are idle, the two technologies would provide the same cost. The cardinality of $\breve{S}_k^i$ must be equal or bigger than one for an insertion to be possible.

However, the greedy polynomial approach is in serious disadvantage when "inserting" is possible, especially if it results in near zero or even negative marginal costs. Inserting it is facilitated when time windows are wide enough to accommodate the service of several shipments. As the cardinality of $\breve{S}_k^i$ and the time windows width grow linearly, the set of feasible solutions can have an exponential growth.

While the cost of appending is always bigger or equal than zero, the cost of inserting could be negative. The best case scenario is when the arriving shipment s_k "fits" perfectly on an existing route. In this case the marginal cost is negative and equal to $-\text{ld}(s_k)$.

Time-windows have a significant impact on the carriers' ability to serve shipments. All things equal, a SFO carrier's capacity increases as the shipments' time-windows increase since the carrier (a) has more flexibility to "insert" a shipment and (b) can hold more shipments in a queue (shipments waiting to be served) which increases exponentially the number of possible schedules and therefore the number of opportunities to insert loads and reduce average deadheading. On the other hand, a naïve carrier can only "append" shipments at the end of the route. Therefore, any increase in queue length of shipments waiting to be served cannot be utilized to improve the previous schedule.

Arrival rates also have a significant impact on the number of carriers' shipments waiting to be served (queue length). All things equal, a carrier's queue length tends to increase as the arrival rate increases -- up to a limit determined by the average time windows length. At the arrival rate where that queue length limit is reached, the advantage of the SFO carrier over the naïve carrier is maximized. Under very high arrival rates, all the carriers' fleets are fully utilized irrespectively of their intrinsic technology or efficiency. On the other hand, if the demand arrival rate is low, such that the queue length is close to zero, a repositioning policy of moving idle vehicles to geographic areas that are "sources" (demand generating areas) may provide a competitive edge (specially with short time windows).

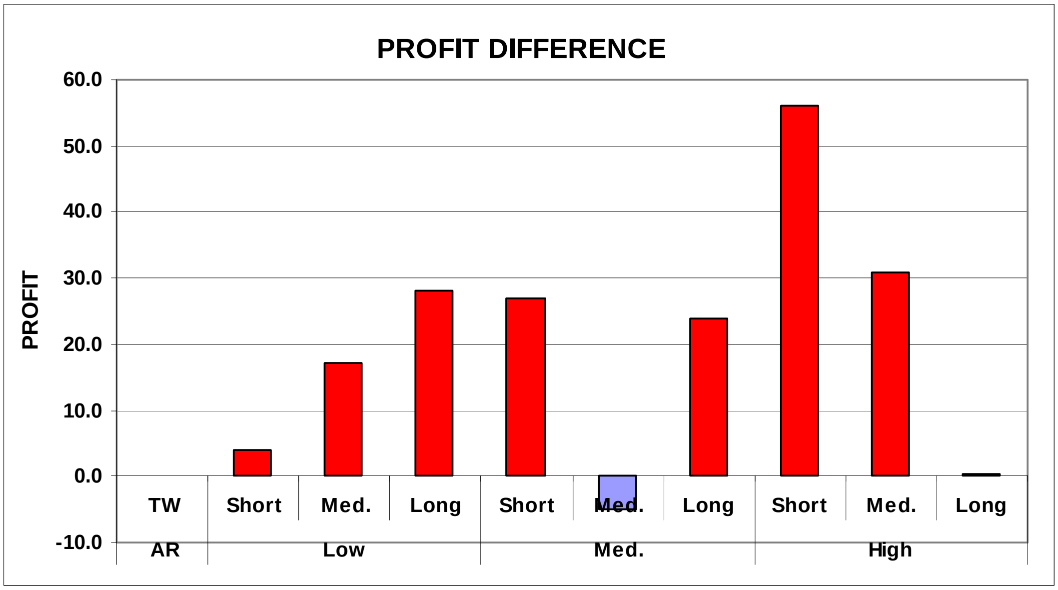

Figure 7 Profit Difference 1FOOC vs. SFO Technology

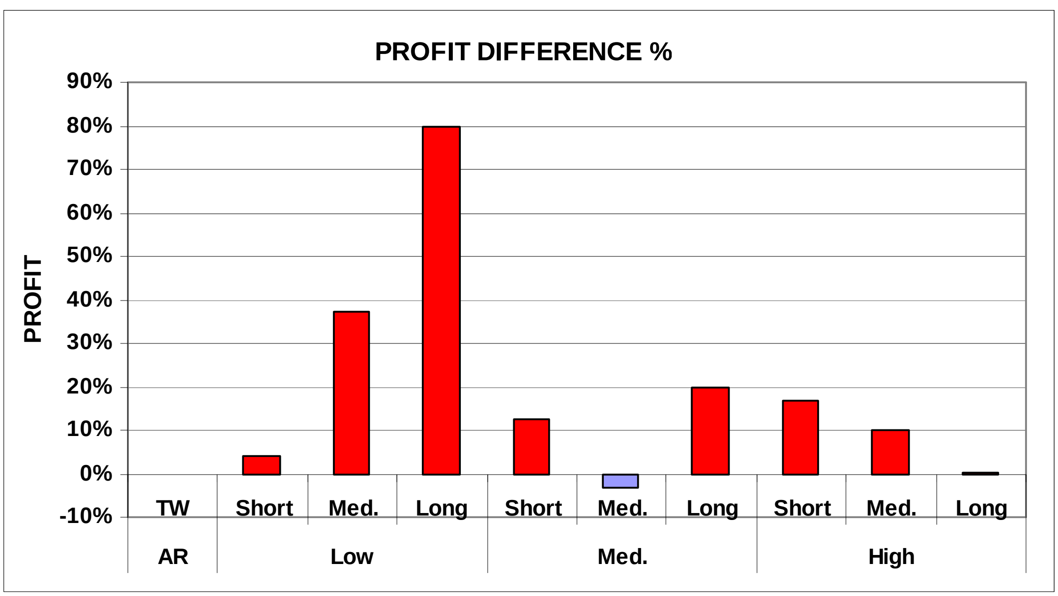

Figure 8 Profit Difference % 1FOOC vs. SFO Technology

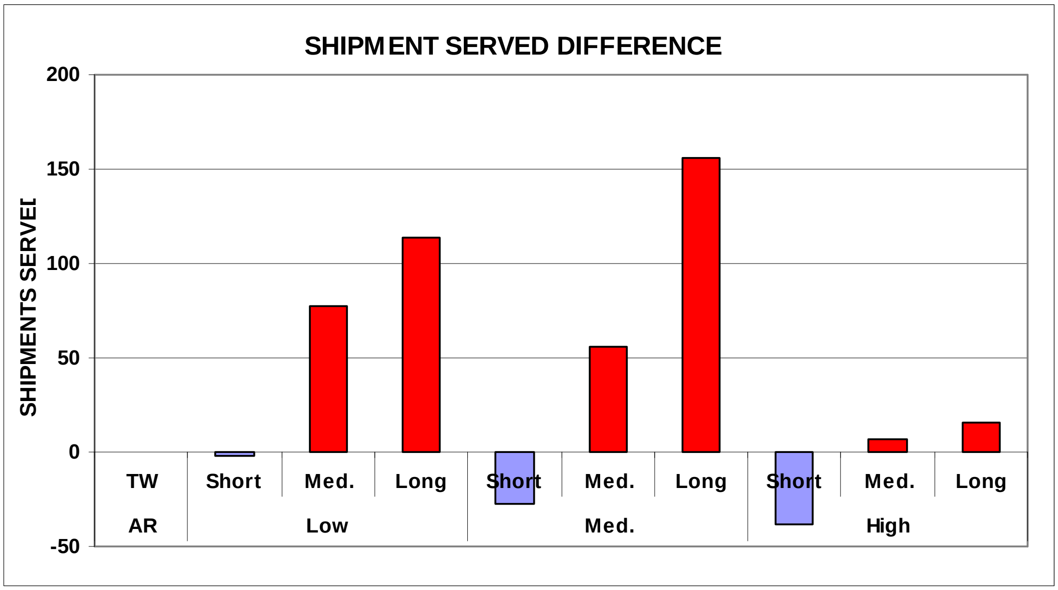

Figure 9 Shipments Served Difference 1FOOC vs. SFO Technology

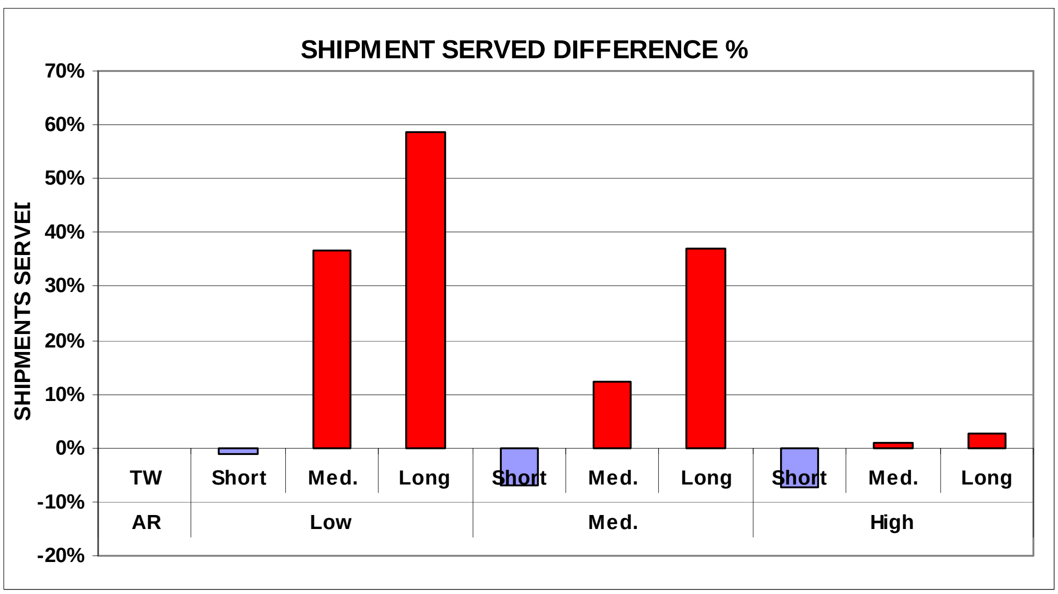

Figure 10 Shipments Served % Difference 1FOOC vs. SFO Technology

Figures 7, 8, 9, and 10 compare the performance of the 1FOOC vs. SFO technology. Figure 7 and 9 are absolute changes in profits and shipments served respectively; while Figure 8 and 10 are percentage changes in profits and shipments served respectively. The results obtained for the less sophisticated carrier (SFO carrier in Figures 7, 8, 9, and 10) are used as the base line. The color convention remains unchanged.

Unlike the previous results, the more sophisticated technology does not outperform less sophisticated technology across the board. Profit-wise, the 1FOOC carrier obtains higher or equal profits than the SFO, yet no clear pattern emerges from Figures 7 and 8.

Regarding shipments served, the 1FOOC carrier tends to serve fewer shipments when the time windows are short. However, 1FOOC carrier tends to serve more shipments for medium and long time windows. Arrival rates affect these differences, because as arrival rates decrease the positive changes increase. However, as arrival rates increase the negative changes decrease.

To understand why the 1FOOC technology outperforms the OFS, it is useful to look at how they estimate the cost of serving a shipment. Assuming for a moment any carrier i with a fleet status z_k^i, bidding for shipment s_k, the marginal cost obtained with technology SFO differs from the result obtained with 1FOOC technology by the term:

$$-\pi^i_{j,k}(s_j \mid I^i_j = 1) + \pi^i_{j,k}(s_j \mid I^i_j = 0)$$

As previously mentioned, this term measures the opportunity cost of winning the current auction. The influence of the opportunity cost on carrier 1FOOC bids can be seen in Figures 11 and 12 which depict the percentage change in winning and losing bids. The 1FOOC carrier sets bids values more aggressively (bids lower) when, the time windows are not short, and the arrival rate is not too high. The 1FOOC carrier bids less aggressively (bids higher) when the time windows are short and the arrival rate is high. There are two distinct forces operating in the market: time windows and arrival rates. An increase in arrival rates increases the bid values (therefore the opportunity cost has increased). A decrease in time windows lengths increases the bid values (therefore the opportunity cost has increased).

Short time windows affect the ability of carriers to "insert" new shipments, therefore limiting carriers' capacity, which increases the opportunity cost of serving a shipment. The arrival rate effect on opportunity costs follows the universally accepted economic laws of demand, supply, and prices. From the fleet management perspective, it can be reinterpreted as a consequence of decreasing returns of scale, where scale is measured by the number of shipments to be served or the length of the queue. All things equal, having more having more shipments in the queue increases exponentially the number of possible schedules and therefore the number of opportunities to insert loads. Therefore, at low arrival rates and with a short queue length, the opportunity cost may be negative. However, the number of possible and feasible schedules starts to decrease if the queue keeps growing. Effectively, adding an extra shipment (especially if the static marginal cost is high) precludes servicing other future more profitable shipments, which increases the opportunity cost.

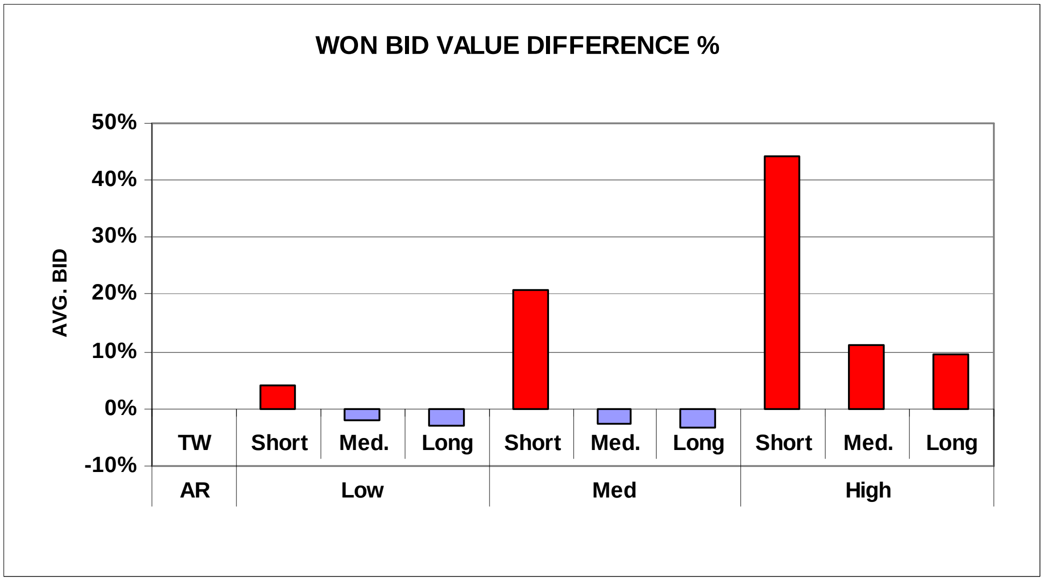

Figure 11 Won Bid Values % Difference 1FOOC vs. SFO Technology

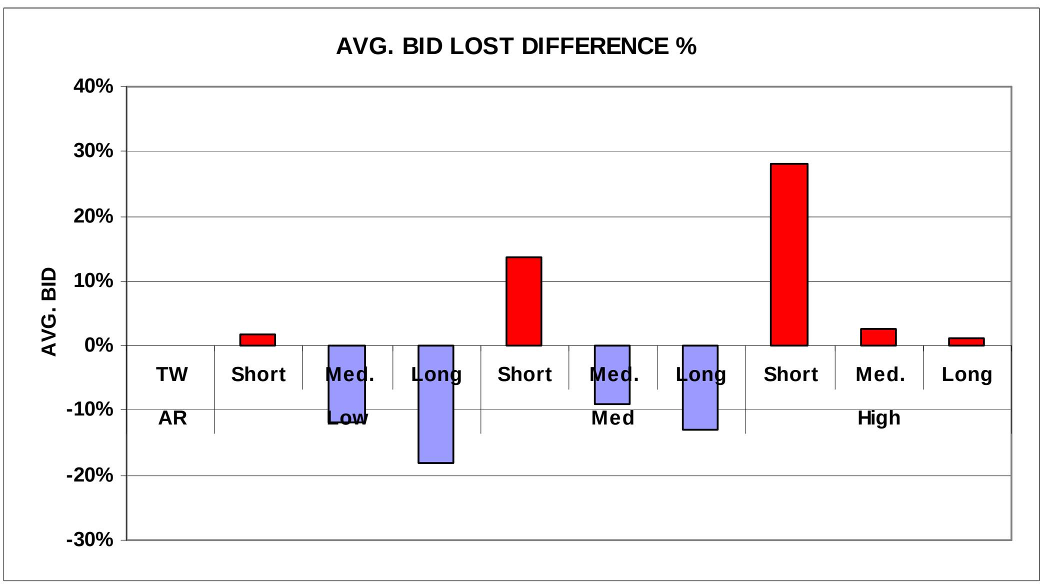

Figure 12 Lost Bid Values % Difference 1FOOC vs. SFO Technology

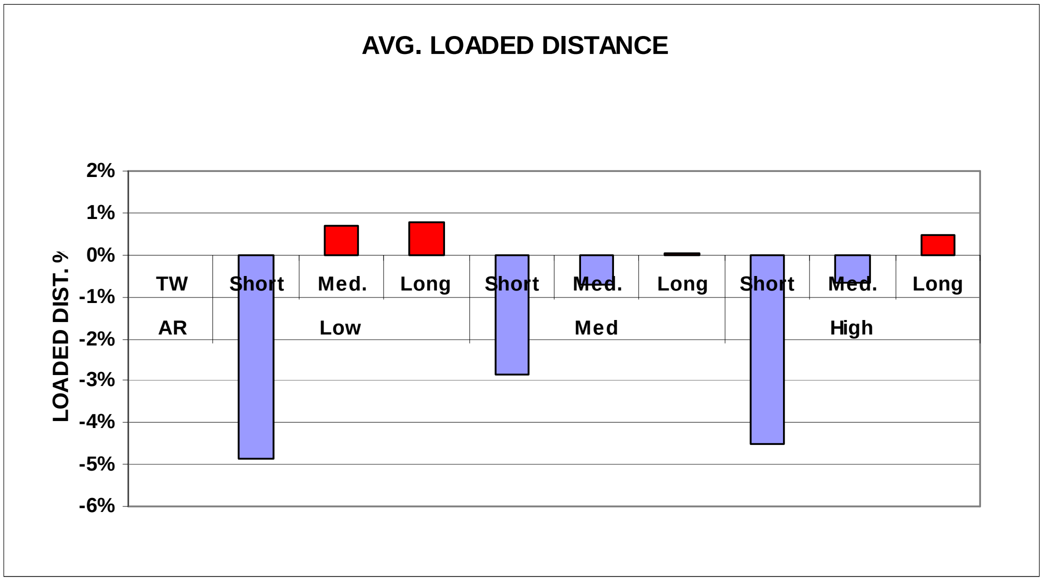

Figure 13 Loaded Distance % Difference 1FOOC vs. SFO Technology

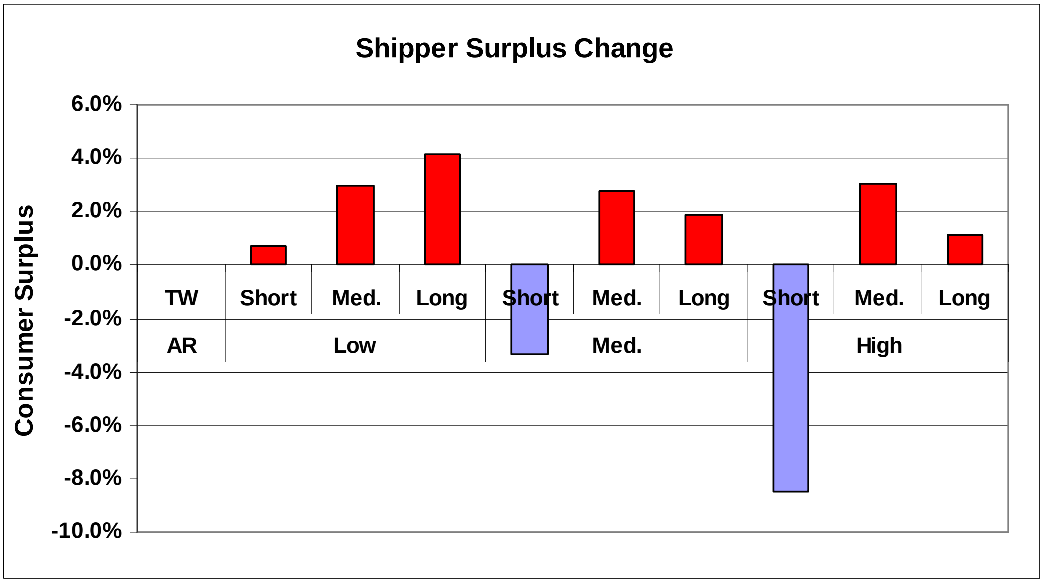

Figure 14 Shipper Surplus % Difference 1FOOC vs. SFO Technology

Another effect of adding opportunity costs can be seen in Figure 13 which depicts the change in average loaded distance per shipment served. Carrier 1FOOC tends to serve shorter shipments when the time windows are short. This indicates that the opportunity cost of a shipment increases with its loaded distance when time windows are small, since inserting or even appending new shipments becomes more difficult. Finally, Figure 14 points out what changes can be expected by shippers when opportunity costs are incorporated. Shippers should expect prices to go up when shipments have short time window and arrival rates are moderate to high. However, prices should go down as time windows widen. Clearly, prices are adjusted to reflect the difficulty or opportunity cost to serve them.

4.8. Private Fleets vs. Procurement Markets

It was mentioned in chapter 2 that in one-item auctions, truth revealing auction mechanism like a second price auction, optimizes social welfare since the item is acquired by the bidder with the highest value (lowest cost in a reverse auction). In TLPM markets, a truth revealing auction mechanism, like the proposed auction analysis, allocates each shipment to the carrier with the lowest expected cost. Such mechanism cannot be guaranteed to optimize social welfare. However it is still incentive compatible and guarantees that the shipment is handed to the carrier with the lowest expected cost, therefore the mechanism is ex-ante efficient.

It was mentioned in chapter 1 that vertical integration takes place when each shipper uses a private fleet. Equipment availability and service quality is guaranteed but at the cost of excessive deadheading. Conversely, in a market, shippers must search for and transact with carriers interested in providing the demanded services. Auction analysis can be used to approximate what can be gained by "society", in terms of extra-generated wealth, when an ex-ante efficient marketplace is implemented.

4.8.1. Assumptions and Results

Figures 15, 16, 17, 18, 19, and 20 show the changes in average empty distance, total number of served shipments, and total wealth generated when a marketplace is implemented. The original market consists of four shippers with private fleets of two vehicles each. Shipments are assigned to each carrier as follows:

carrier one serves shipments $\{s_1, s_5, ..., s_{997}\}$,

carrier two serves shipments $\{s_2, s_6, ..., s_{998}\}$,

carrier three serves shipments $\{s_3, s_7, ..., s_{999}\}$, and

carrier four serves shipments $\{s_4, s_8, ..., s_{1000}\}$.

The TLPM consists also of four shippers and four carriers, however, shipments are assigned to the carrier with the lowest cost. All carriers are implementing the same SFO (static fleet optimal) fleet management strategy.

Figure 15 and 17 indicate that deadheading is reduced considerable across the board, improvements range from 24% to almost as high as 50%. The number of served shipments increased considerably with short time windows and at high arrival rates. The increases indicate that in a competitive market, the cost of serving a shipment provides a competent tool to allocate supply and demand.

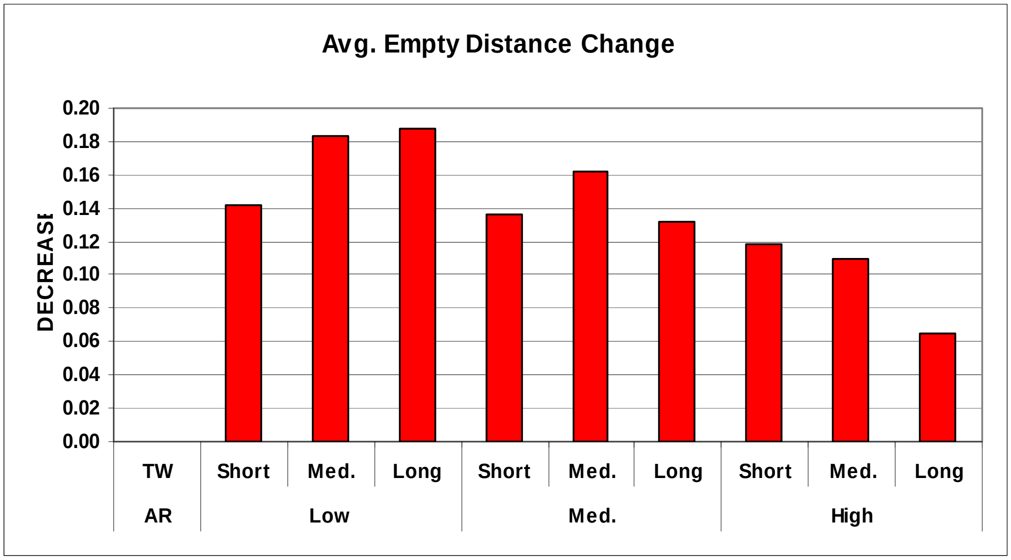

Figure 15 Empty Distance Difference Resale Market vs. Private Fleets

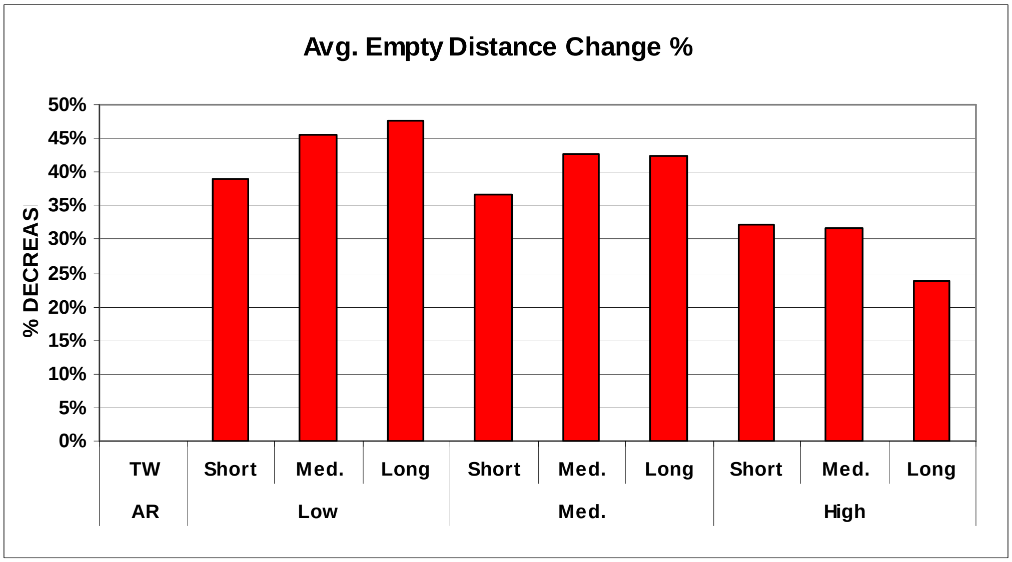

Figure 16 Empty Distance % Difference Resale Market vs. Private Fleets

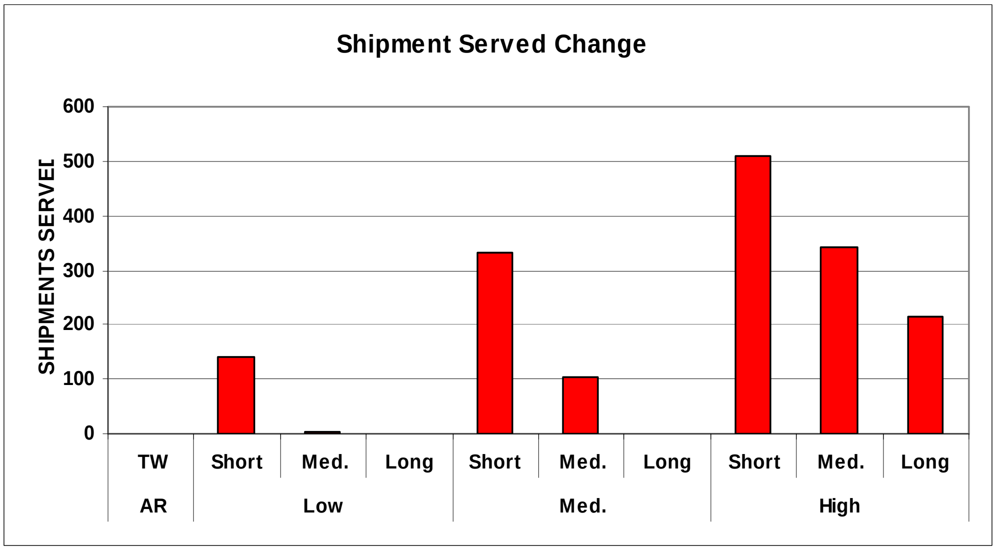

Figure 17 Shipments Served Difference Resale Market vs. Private Fleets

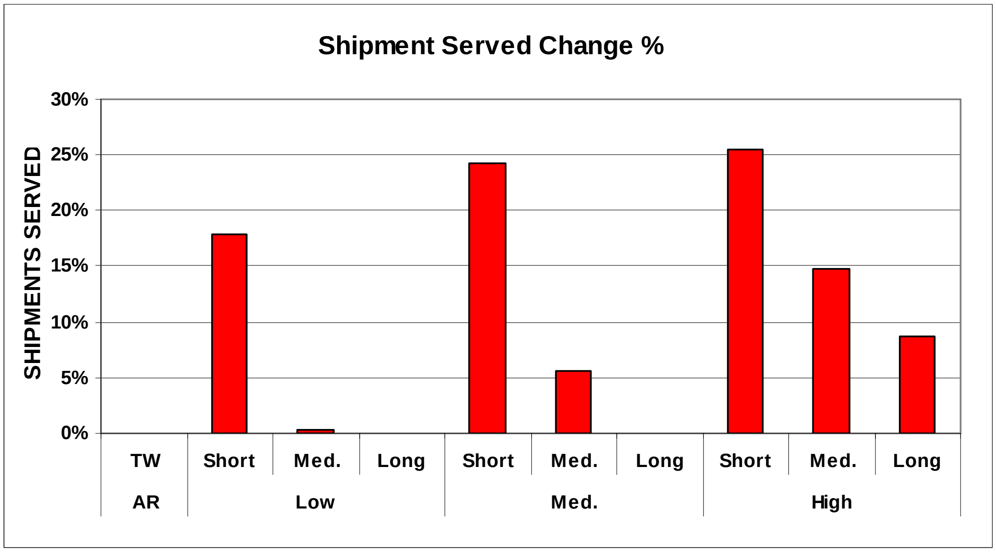

Figure 18 Shipments Served % Difference Resale Market vs. Private Fleets

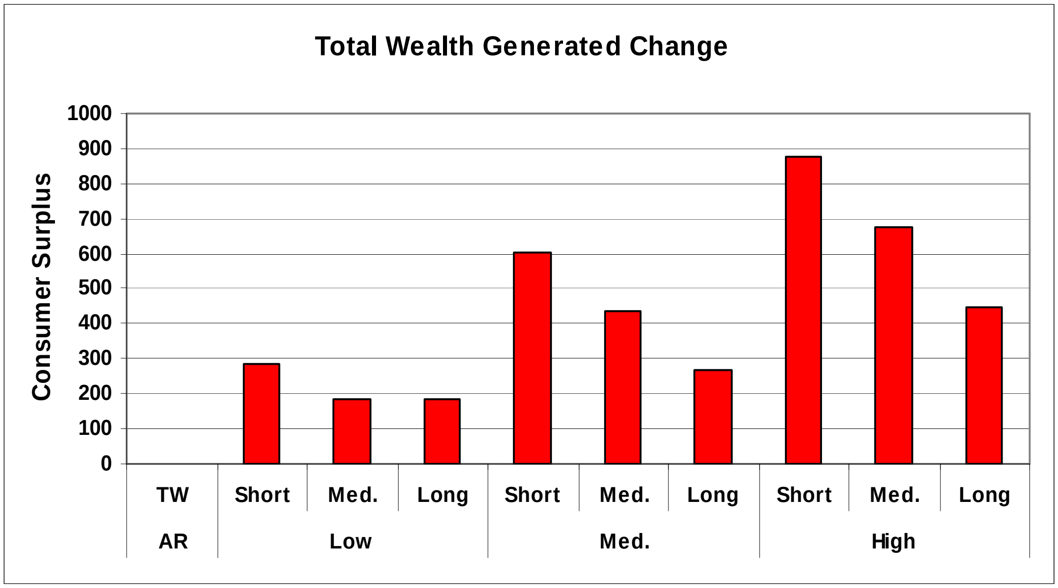

Figure 19 Total Wealth Generated Difference Resale Market vs. Private Fleets

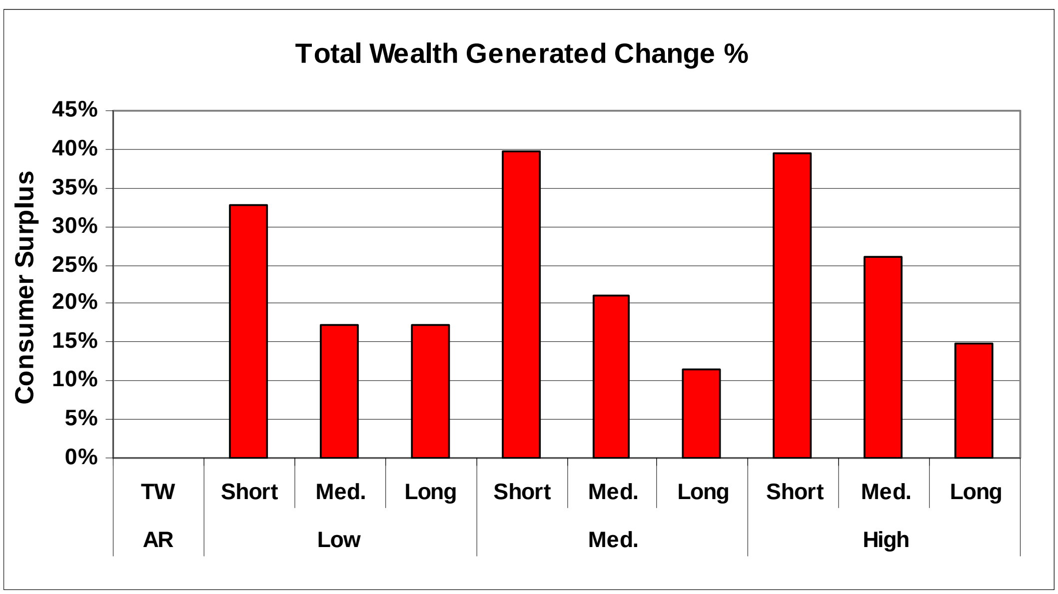

Figure 20 Total Wealth Generated % Difference Resale Market vs. Private Fleets

The market system clearly generates more wealth than a system of independent shipper-carrier pairs. In absolute terms, the additional wealth that is generated by the marketplace increases with the arrival rate (see Figures 19 and 20). However, percentage-wise, the major increases correspond to short time windows and, in a lesser degree, to high arrival rates. Results that reflect the influence of the additional shipments served (see Figures 17 and 18).

4.8.2. Resale TLPM

The benefits of a TLPM can be reached even if each carrier has signed a private contract with a shipper (dedicated carrier situation). The carriers can set up their own private "resale" marketplace. When a carrier, called A for "assigned" carrier, is handed a shipment s_j, the carrier estimates his cost of serving s_j, denoted c_j^A. Then, carrier A calls for a second price auction for shipment s_j with secret reservation price c_j^A. If the lowest bid, denoted $c_j^{(1)}$, is less than the reservation price ($c_j^{(1)} < c_j^A$), the lowest cost carrier is handed shipment s_j and is being paid an amount equal to $\min(c_j^{(2)}, c_j^A)$.

The implementation of such a resale TLPM clearly benefits carriers and could be the basis for cooperation and partnership agreements. The benefits to the carriers are clearly independent of the level of the originally contracted payment in the carrier-shipper agreement. Furthermore, the same allocations and payments are obtained with a private marketplace and with private contracts plus resale marketplace, independently of marketplace carriers or demand characteristics. Market forces are providing a decentralized matching of supply and demand – matching which is ex-ante efficient – in an incentive compatible environment.

4.9. __Summary__

This chapter studies a TLPM based on cost competition. In this environment a general framework to evaluate DVR technologies was introduced. The proposed methodology to test DVR technologies seems more adequate to evaluate competitive performance than traditional analysis of algorithms; especially in logistics and transportation problems embedded in dynamic stochastic environments and supporting e-commerce marketplaces and activities.

The auction methodology was successfully applied to evaluate the competitiveness of three distinct DVR technologies. It was shown that under certain demand condition auction analysis of algorithms is similar to average cost analysis. It was shown that the estimation of opportunity costs in an online marketplace provides a competitive edge. However, an exact calculations of these opportunity cost can be quite challenging. A simplified approach (1-step-look-ahead) to estimate opportunity costs was developed and applied successfully. Cost competition was also utilized to demonstrate the advantages of a market structure over a set of independent fleets.

In this chapter it was assumed that carriers' best strategy was cost bidding. Chapter 5 presents a framework to study carrier behavior in TL sequential auctions. Under that framework, cost bidding is considered a particular case that can arise under determined auction and informational settings.

Chapter 5: Boundedly Rational Behavior in a TLPM

This chapter lays out the basis for a conceptual framework that facilitates the study of behavioral aspects of carriers participating in TLPM. The behavioral assumptions used in chapter 3 and 4 are special cases of this general framework. An important chapter objective is to link a carrier's behavior to the auction and competitive setting as well as the carrier knowledge and problem solving capabilities.

Section one introduces the concept of bounded rationality. Section 2 presents a literature review of boundedly rational behavior in auctions and marketplaces (in chapter 2 a game theoretic auction literature review was presented). Section 3 defines bounded rationality in the TLPM context. Section 4 identifies and analyzes the sources of bounded rationality. Two of the identified sources, knowledge acquisition and problem solving capabilities are analyzed in sections 5 and 6 respectively. Section 7 evaluates different bidding problems from a complexity point of view. Similarly, section 8 compares the complexity of first and second price auctions in an array of different bidding problems. Section 9 defines the factors that are used to classify carriers' behavior. Section 10 summarizes the chapter.

5.1. The Genesis of Boundedly Rational Behavior

Competition in a TLPM is an ongoing and sequential process, and thus naturally represented as an extensive-form game. The standard notion of rationality (for economists at least) requires that agents automatically solve problems that may in fact lay beyond the capabilities of any agent (Colinsk, 1996). Chapter 3 presented the game theoretical formulation of the sequential auction TLPM problem. Unfortunately, the problem is intractable and well beyond the conceptual and computational abilities of ordinary humans or decision support systems. In addition, response time limitations, framing effects, and cognitive limitations of the human mind impede bidders' ability to strictly adhere to precepts of economic rationality. The framing and cognitive limitations of human judgment and decision making have been widely studied and reported (Camerer, 1995; Kagel, 1995), mainly in the psychology and behavioral economics literature. Therefore, the basic motivation for studying models of bounded rationality in TLPM environments stems from the need to inject a dimension of behavioral realism in situations where perfect rationality may be implausible.

When the complexity of the auction problem precludes bidders from implementing optimal solution strategies, computational agents (or human beings with the help of decision support systems) need to simplify or modify the original decision problem. Boundedly rational behavior, as studied in this research, is born out of these simplifications or alterations to the original intractable problem. This chapter provides a behavioral framework to represent how carriers might tackle the overwhelming complexity of the problems they face in a TLPM (complex detailed histories, numerous current options, future infinite contingent options, and the potential consequences).

Boundedly rational bidders solve a less complex problem than fully rational bidders. The type of problem they solve is directly influenced by available response time, existing computational/material resources, and their own cognitive/decision-making process. Although the result of boundedly rational deliberation would not necessarily be an equilibrium solution, the boundedly rational response would likely have greater relevance to how ordinary carriers would act in sequential auction TLPM. The introduction of boundedly rational decision makers radically alters the notion of equilibrium and decision making. The next section reviews the bounded rationality literature in auctions, marketplaces, and freight transportation.

5.2. <u>Relevant Background Review and Concepts</u>

This section reviews the large body of research that deals with boundedly rational behavior in auctions, with special emphasis on those contributions that are relevant to sequential auctions and TLPM's. Contributions are mainly classified according to the disciplinary approach taken or the academic background of the authors.

5.2.1. Operations Research and Computer Science

The first contribution of operations research to auction theory is attributed to Friedman (1956), who presented a method to determine optimal bids in a first price-sealed bid auction. Actually, the first Ph. D. in Operations Research (OR) was granted to Friedman for his work on auctions (Rothkopf, 2001). Friedman's idea was to estimate the probability distribution of the best competitive bid on the basis of previous bidding data/records. The distribution of competitors' bids could then be used to estimate the bid that maximizes expected profits in a first price sealed auction.

In a reverse auction, calling B the set of feasible bids, c the cost of producing or serving the auction item, and $p(b)$ the probability that bid $b \in B$ is the lowest bid, the optimal bid b^*, according to Friedman's model is:

$$b^* \in \underset{b \in B}{\arg\max}\,(b-c)\,p(b)$$

Friedman's approach did not seek equilibrium among rational bidders. It presented the best response of a bidder that model competition as a probability distribution.

Extensive literature in OR and technical journals took Friedman's approach and tailored it to practical bidding applications in the construction, timber, and petroleum industries. Stark and Rothkopf's (1979) comprehensive bibliographical review contains hundreds of references to the aforementioned literature. Friedman's approach is appealing for a boundedly rational bidder seeking a good bidding strategy rather than a presumed equilibrium.

The description, evolution, and usage of a real-life bidding system is presented by Keefer et al. (1991). The purpose of the bidding system was to provide decision support and insight to Gulf Oil Corporation managers. The bidding system combined techniques from decision analysis, statistics, and nonlinear optimization. The system was used in the early 1980's to bid for U.S. offshore oil and gas leases, an auction environment characterized by considerable uncertainty from multiple sources and many interrelated decisions. The system was used as a decision tool in Gulf's bids that totaled over $1.5 billion. Equilibrium was not analyzed nor considered in the model; rather the emphasis was on estimating the probability of winning (based on past data), allocating the limited budget to the most promising oil exploration blocks, and on forecasting and performance models for oil production and future oil prices.

The emergence of electronic commerce and auction marketplaces in the mid/late 1990's stimulated boundedly rational auction research. Larson and Sandholm (2002) study optimal strategies for computationally bounded agents. The agents face uncertainty in their valuations; however the accuracy of the valuations can be improved by spending more computational resources. Agents are free to compute on any valuation problem including their opponents'. Larson and Sandholm distinguish two types of computation (deliberation): (a) strong, if an agent uses part of its deliberation resources to compute another agent's valuation problems, and (b) weak, if an agent does not use part of its deliberation resources to compute on another agent's valuation problems. If the computational power is bounded and free, agents only estimate their own valuation in second price auctions (weak). However, this does not hold in first price auctions where agents have an incentive to use resources to estimate competitors' valuations (strong); therefore not obtaining their own best achievable valuation. These results cannot be generalized to multiple objects (Larson, 2002) or when computations are costly (Sandholm, 2000).

Part of the computer science community retook the OR auction tradition but incorporated a multi-agent system perspective, agent learning, and simulation flavor to it. Richter (1998) uses genetic algorithms to improve bidding strategies in an environment where electric companies buy and sell power via double auctions. Boutilier et al. (1999) provides a Markov Decision Process (MDP) formulation of the bidder's problem in sequential auction of objects with complementarities as an alternative to combinatorial auctions. The MDP model does not allow for strategic interaction, the bidding agent takes the expected prices as given and does not compute the impact of his bids on his competitors' behavior. Agents update its bidding policies based on past price observations. Kephart et al. (2000) use simulation to study search and pricing by computational agents (shop-bots). Walsh et al. (2002) propose a model for analyzing complex games with repeated interactions, for which a full game-theoretic analysis is intractable, using simulation and evolutionary selection of strategies, and finally perturbation analysis to determine the most plausible equilibria.

Zhu and Wurman (2002) simulates the market interaction of boundedly rational bidders in a first price sequential auction, with several identical items for auction, where bidders are interested in just one item and have independent private values. They assume that players use fictitious play to model opponents' bidding behavior. It is assumed that after each auction, a bidder gets to see all competitors' bids. Tesauro and Bredin (2002) develop a dynamic programming formulation that can be used to formulate agent bidding strategies in double auctions with sequential bidding, continuous clearing, and buyer/seller agents. States are represented by an agent's holding, and transition probabilities are estimated from the market event history. The model uses a belief function (about price formation), combined with a forecast of how it changes over time, as an approximate state transition model in the DP formulation. With a similar approach, Hattori et al. (2001), develop a DP formulation for agents with quasi-linear utilities and budget constraints in a first price auction.

A common theme in the reviewed papers is a predominantly non-strategic approach to auctions and market interactions, following Friedman's model. Despite the non-strategic approach, simplifications are still necessary in order to obtain tractable problems (for example, sufficiently compact state-spaces for DP formulations); the auction problems have to be solvable. In repeated auctions learning is an issue that it is mostly ignored, except for the simple updates of the state transition function as the game is played or auctions are resolved.

5.2.2. Economics -Learning and Experimental Game Theory

The concept of bounded rationality economic agents was first fully articulated by Simon (1955 and 1956). There are two main sources of objections to the traditional rational model of the economic man. First, many researchers are uneasy about the fundamental assumptions of rationality and game theory that are inconsistent with evidence about human decision-making. Secondly, there is widespread documentation of anomalies observed in the outcome of laboratory experiments (i.e. rationality does a poor job explaining the outcomes). A survey of those objections can be found in Camerer (1995) and Kagel and Roth (1995) respectively.

These incompatibilities between theory and experiments led empirical economics researchers (econometricians) to search for models that better fit their observations. A family of models that has close ties to discrete choice modes of behavior arises when the perfect rationality assumption of game theory is relaxed (introducing some noise into rational behavior, mostly via a logit probabilistic choice functions).

In a seminal work, McKelvey and Palfrey (1995) propose a model of stochastic choice in finite games. McKelvey and Palfrey interpret the agent or player underlying decision processes and knowledge of the game as rational with the addition of noise (an error term). A logit formulation can be used. One of the most appealing features of this formulation is that it is parameterized in a way that is intuitive for interpretation from a bounded rationality perspective. As one parameter varies from zero to infinity, the choice behavior of the agent varies from being random to rational. Further, different players can exhibit different degrees of rationality. The logit equilibrium is a generalization of the Nash equilibrium, which incorporates decision error and links the likelihood of a deviation from a best response to the cost of such a deviation.

Chen et al. (1998) add conditions that in repeated games lead to a convergence to equilibrium. They explicitly introduce learning in their model structure, assuming a population of players who repeatedly play the same game, and model the dynamic learning through fictitious play (Brown, 1951). Under fictitious play, players' beliefs concerning the other players' choice probabilities are given by the frequency of observed past behavior. Anderson et al. (1999), extend the use of the logit equilibrium to a continuous set of actions. Rather than limiting the game to a discrete set of actions, the action set is an interval of the real line. This type of game is easily found in economic situations anytime prices or bids are assumed to be continuous. Since there is a continuous set of possible actions (decisions) the equilibria are characterized by a probability density function over the space of actions.

Other learning models are based on reinforcement. Archetypal examples of this type of models include Arthur (1993) and Erev and Roth (1996) models of learning. The agent keeps track of a cumulative utility index and chooses an action with a proportional probability, where ratios of choice probabilities for two decisions depend on ratios of the cumulated payoffs for those decisions.

Fictitious play (Brown, 1951), has already been mentioned. With fictitious play, the agent chooses at each period the best response to his present conjecture on others' strategies. But he acts more or less myopically, since he re-optimizes at each step, not only on a limited horizon, but without considering that his beliefs or conjunctures will change. The standard fictitious play assumes that the probability of an opponent's next action equals its frequency in the past. A weighted sum giving more importance to the last actions can also be employed.

Fudenberg and Levine (1998) thoroughly detail the convergence properties of fictitious play. An application of this type of learning to auction is done by Hon-Snir and Monderer (1998). They study repeated first price auctions, where bidders have a discrete distribution of private values. Bidders are boundedly rational, they use learning with bounded recall and fictitious play, and each player's private value is determined before the first auction and does not vary with time. Hon-Snir and Monderer find that after a sufficient amount of time the players play the one shot auction equilibrium in which players' types are common knowledge, i.e. the player with the highest valuation wins the object and pays the second-highest valuation. In the long run a repeated first price auction yields the outcome of a one-shot second-price auction. The results are sensitive to the tie-breaking rule used, a caveat of discrete models.

McCabe et al. (1999) argue for the simultaneous use of game theory and laboratory experimentation to guide auction design. Olson et al. (1999) document a series of controlled experiments in the trading of wholesale electricity using cash motivated students. The experiments aim to compare the performance of two systems: a day-ahead sealed bid trading and a simultaneous continuous double auction (up to the hour of delivery).

5.2.3. Economics - Agent based Computational Economics

Agent based Computational Economics (ACE), studies the economics of the self-organization of boundedly rational agents (Tesfatsion, 2001). The approach relies heavily on simulating the interaction of heterogeneous agents among each other and with the environment on the basis of their behavior and experience. Agents continually adapt and experiment new rules of behavior. Usually, once initial conditions are set, all subsequent events can be initiated and driven by agent-agent and agent-environment interactions without further outside intervention.

Work done in ACE that closely relates to this research includes the simulation of auctions in the electric power marketplace (Bower, 2001). Andreoni and Miller (1995) use bidders represented by genetic algorithms in first and second price auctions. The authors suggest that such a simple adaptive learning process provides a lower bound on the potential impact of learning in auction systems. Among their main findings, Andreoni and Miller report that auctions are very problematical environment for genetic based learning. Independent values and first price auctions tend to make learning even harder.

The approach of ACE is somewhat similar to the one used later in this research. After defining and analyzing different types of carrier bounded rationality, simulation is used to study the interaction of carriers among each other and with the environment on the basis of their behavior and experience.

5.2.4. Automata Models and Machine Learning

Another more theoretical path of research about boundedly rational agents is found in the area of automata and machine learning models. From the strategic point of view these models tend to be more sophisticated than the previously mentioned. These machines believe that other machines are also learning or speculating and may try to anticipate how these other machines are going to change before deciding what to do.

Binmore (1987, 1988) proposes the replacement of perfectly rational players by machines. These machines can be represented in games as Turing machines. Each machine has in itself some approximate idea of what the other players (machines) may look like. When these machines play a repeated game they are limited to using mixtures of pure strategies, each of which can be programmed on a finite automaton with an exogenously fixed number of states.

Stahl and Wilson's "players' models of other players" (1995) where players truncate an internal simulation of the model of the other players is an example of this type of cognitive process. Stahl uses this model to explain how people play games (in controlled experiments). This model admits players with different types or levels of rationality, from a zero level (no modeling of the opponents) to the n-level player (can compute the expectations and play of the competitors up to n-1 levels of best or optimal responses).

When the game players' reasoning becomes limited to n-common knowledge (crossed probabilistic expectations truncated at finite level n), and all the agents are of this type they give origin to a "rationalizable equilibrium," a weaker equilibrium notion than Nash Equilibrium (Walliser, 1998). In this equilibrium, each player chooses a best response to their competitors' expected strategies estimated in a recursive loop up to some common level.

Modeling players' model of other players in the machine learning context is done by Vidal and Durfee (1995). Wellman and Hu (1998) study the equilibrium of multiagent learning, when all agents (machines) are simultaneously optimizing and learning in a double auction. Vidal and Durfee (2003) try to predict the expected behavior of agents that learn about other agents; however the task is highly complex unless extreme simplifying assumptions are taken.

5.2.5. Bounded Rationality in Freight Transportation

Unfortunately, empirical or theoretical work dealing with carriers' cognitive process or bounded rationality is practically nonexistent. Even in the travel behavior research community the behavioral dimensions of freight demand has received limited attention (Mahmassani, 2001). Part of the vehicle routing literature deals with the implementation of online computerized routing and scheduling optimizers, for example Bell et al. (1983), Powell et al. (1988). More relevant work from the boundedly rational point of view is presented by Gelfand et al. (1998) and Powell et al. (2002).

Gelfand et al. (1998) describe pattern learning in a motor carrier scheduling system. The scheduling system is based on a dynamic programming formulation; however the formulation does not include all possible states of the system. Human dispatchers experience and patter recognition abilities are used to improve the performance of dynamic programming based scheduling system. Basically, human dispatchers can recognize states that computational decision support system can't. It is the first reported contribution of systematic human-computer system learning in freight transportation scheduling.

Powell el al. (2002) discusses the challenges faced over a two years implementation of a dispatching decision support system. From a boundedly rational perspective, their work is noteworthy in that it compares the decision making process followed by humans and mathematical programs. Powell el al pointed out that a major difficulty for implementing effective computerized dispatching systems is the information transmission process among different agents: drivers, dispatchers, and the decision support system.

Summarizing, this section has presented a survey of relevant literature in bounded rationality with applications to auctions, bidding, and freight transportation. Given the breadth of topics covered, the survey does not intend to be exhaustive;

rather it aims at highlighting important references. Different research approaches are pointed out to better frame this research in the existing body of research.

5.3. Modeling Bounded Rationality

The literature review revealed the variety of approaches that could be used to model boundedly rational bidders. Bounded rationality is borne out of simplifying a (complex) problem or the cognitive/material limitations of the decision maker (or decision support system). Therefore, bounded rationality is always associated with the notion of deficiency or insufficiency of a positive quality (of a rational player). Though bounded rationality as a research topic is not new, it was first proposed by Simon (1955), many modeling issues surrounding boundedly rational decision making have not yet been fully addressed.

Bounded rationality and learning in games are currently very active areas of research; however general and comprehensive models that integrate how agents (or humans) acquire, process, evaluate, search for information, and make decisions are still mostly open. As expressed by highly respected game theorist Robert Aumman, "there is no unified theory of bounded rationality, and probably never will be." (Aumman, 1997, page 4).

Rationality assumptions are very convenient from a modeling point of view. The self-referential nature of rationality (coupled with common knowledge in games) imposes astringent limitations on how a rational agent (player in a game) foresees his competitors' behavior and how the competitors foresee other players' behavior. Bounded rationality come with an embarrassment of riches in terms of the number of possible deviations from a fully "rational" model. When boundedly rational behavior appears, it may take on many different forms. Boundedly rational decision makers do not necessarily choose equally, even when having the same knowledge or information. Furthermore, there may be many "plausible" boundedly rational models that can explain a given social or economic phenomenon. Correspondingly, the many possible ways a boundedly rational bidder can model his competition, and vice versa, adds a class of uncertainty not found were players are perfectly rational.

Determining the bounded rationality of a carrier is crucial since it is equivalent to determining how the carrier bids (i.e. his bidding function) in a TLPM. Similarly, determining that all carriers are rational is equivalent to determining how the carriers bid (i.e. their bidding function) in a SIPV setting. A bidding function, as understood in this research, is a process, whose inputs are a carrier's private information and his knowledge about the auction and competitors, and whose output is a bid.

Given the plethora of games and decision problems, boundedly rational behavior is hard to define, classify, and model in general terms. When the restrictions of rationality are lifted, any general assumption about the behavior of the bidders that is not properly justified, introduces a strong sense of arbitrariness. In order to avoid this kind of arbitrariness, the discussion of bounded rationality is limited to the TLPM context. Furthermore, departures from the rationality model are analyzed and connected to carriers' cognitive and problem solving processes.

5.4. <u>*Sources of Bounded Rationality in a TLPM*</u>

Bounded rationality can stem from different cognitive and computational/physical limitations, in the TLPM context, the following classification of sources is proposed:

- Bounded Recall and Memory: a carrier has limited memory (physical capacity) to:
  - record and keep past data/information
  - simulate and record data of all future possible paths in the decision tree
- Processing Speed: time is valuable in a dynamic setting. Most practical problems have a limited response time that may limit the solution quality or decrease the effectiveness of a delayed response.
- Data Acquisition and Transmission: data acquisition and processing is usually costly. Furthermore, the transmission of data among agents can be noisy. In a world with bounded resources (budget/memory/attention), deciding how, how much, and what type of information should be acquired, kept, transmitted, or analyzed can lead to complex decision problems.
- Knowledge Acquisition: in a dynamic strategic situation, as data is being revealed or obtained, carriers have the potential to acquire knowledge (truths about competitors or the environment) from logical and sound inferences. In particular, the decision maker may have limited ability to discover

competitors' behavior, which may involve modeling and solving complex logical and econometrics problems.

- Problem Solving: as a carrier participates in a TLPM market, it is required to make decisions (bidding or fleet management decisions). These decisions may lead the carrier to formulate and solve complex optimization problems. In particular, the decision maker may have limited ability to predict or model the impact of his own actions on future fleet operational costs or on his competitors' behavior.

Although the five aspects of bounded rationality are somewhat interrelated, this research focuses on the knowledge acquisition and problem solving aspects. Memory and processing speed are physical limitations. It is assumed carriers have enough material resources and response time/speed to implement bidding and fleet management strategies with different degrees of sophistication. Carriers have limitations to formulate and elucidate knowledge acquisition problems. Similarly, carriers have limitations to formulate and solve complex optimization problems. The data available to carriers is only limited to data publicly and freely disclosed after each auction, which renders the data acquisition problem trivial. No transmission losses or alterations are considered.

The focus of this research is on the knowledge acquisition and problem solving aspects, as they capture how carriers can frame and solve TLPM problems. Therefore, the emphasis is on the more "mental" processes that determine behavior rather than on the "physical" limitations. Knowledge acquisition and problem solving in a TLPM are analyzed in the next two sections.

5.5. Knowledge Acquisition in a TLPM

In a TLPM, each carrier is aware that his actions have significant impact upon his rival's profits, and vice-versa. In the perfect rational model, common knowledge and logical inferences allow the estimation of the impact of a carrier's actions on competitors' profits and vice-versa. It is implicit that a rational bidder bids as a rational bidder. In a boundedly rational model, a carrier faces two basic types of uncertainties regarding the competition: (a) an uncertainty relative to the private information of his opponents, and (b) a strategic uncertainty relative to bounded rationality type of the others players.

The first type of uncertainty, using the notation developed in chapter 3, is about $\theta_j^{-i} = \{z_j^{-i}, \mathrm{a}^{-i}, \mathrm{c}^{-i}\}$ for a carrier $i \in \Im$ at time t_j, the private information regarding competitors' fleet status, assignment, and cost functions. This type of uncertainty is also present in most game theoretic auction models (games of incomplete information). The second type of uncertainty is about the bidding strategies that the competitors use, $\mathrm{b}^{-i} = \{\mathrm{b}^1, ..., \mathrm{b}^{i-1}, \mathrm{b}^{i+1}, ..., \mathrm{b}^n\}$ the set of bidding functions of all carriers but carrier i. It is implicit that a boundedly rational bidder bids accordingly, i.e. as a boundedly rational bidder. However, it is not evident for the competition to determine what "type" of bounded rationality a carrier has. This type of uncertainty is not present in game theoretic auction models.

Depending on a carrier's ability to elucidate uncertainties (a) and (b), two extreme cases may take place:

1. No knowledge acquisition. The carrier cannot form a useful model of competitors' behavior that links their private information and their bids. In this situation, the "best" a carrier can do is to observe market prices and estimate them as the result of a random process. In the notation introduced in chapter 4, this is similar to assuming that competitors are playing $\mathrm{b}^{-i}(\xi) = \mathrm{f}(\xi)$ or simply $\mathrm{b}^{-i}(\xi) = \xi$, where ξ is a random process that is not linked in any way to carrier $i's$ bidding, capacity/deployment, and history of play or to the competitors private information $\theta_j^{-i} = \{z_j^{-i}, \mathrm{a}^{-i}, \mathrm{c}^{-i}\}$.

2. Full knowledge acquisition. The carrier knows $\theta_j^{-i} = \{z_j^{-i}, \mathrm{a}^{-i}, \mathrm{c}^{-i}\}$ and also $\mathrm{b}^{-i} = \{\mathrm{b}^1, ..., \mathrm{b}^{i-1}, \mathrm{b}^{i+1}, ..., \mathrm{b}^n\}$, therefore carrier i is able to precisely foresee what the competition is going to bid for shipment s_j. However, carrier i still has uncertainties about the future bids, simply because carrier i does not know the future realizations of the demand. Nevertheless, carrier i can estimate future prices not just as a stationary random process but as a function of shipment arrival distribution, shipment characteristics distribution, competitors' behavior, and competitors' private information. This is $\xi = \mathrm{f}(\Omega, \theta_j^{-i}, \mathrm{b}^{-i})$.

In game theoretic terms the former case is not possible since there is no game if players cannot speculate about the competitors' actions. The latter case corresponds to a game of perfect and complete information *if all the players are rational* and the private information is common knowledge. Knowledge states in between the two extreme cases correspond to games of imperfect information, *if all the players are rational* and there is uncertainty about the players' private information (as in chapter 3, the uncertainty can be expressed as $p(\theta_j^{-i} \mid \theta_j^i, h_{j-1})$).

The two extreme cases have already been analyzed in chapter 4. The no-knowledge case corresponds to the general competitive situation described under auction analysis while the asymmetric full-knowledge case (one carrier has complete knowledge and the others have no-knowledge) corresponds to an acceptance/rejection problem. Therefore, the value of full knowledge acquisition in a TLPM or any other competitive situation, for a given player can be defined as the difference in profits between the full-knowledge and no-knowledge cases. A definition that is fairly similar (at least in spirit) to the definition used in stochastic programming for the value of the stochastic solution.

Acquiring knowledge about the competitors' private information and bounded rationality type poses a potentially highly complicated econometric/logical problem. A carrier's behavior is likely to be affected by his own history and how the carrier perceives and models the strategic situation. From the public information (revealed after each auction) and its own private information a carrier needs to build a model of the private information and bounded rationality type of his competitors.

Even in simple auctions, the econometric models can quickly become extremely complex and data are usually not rich enough to successfully estimate those structurally complex models (Laffont, 1997). Furthermore, the complexity of the underlying DVRP adds hurdles to the problem. However, the most challenging obstacle may come from the competitors, which may be "sophisticated" enough to realize that they are bidding against other bidders who are also learning and may adjust their behavior accordingly, in order to obstruct the process of knowledge acquisition. This type of sophistication is particularly important when the fact that the same carriers interact repeatedly is common knowledge.

In most game theoretic models, a simple private value probability distribution, symmetry, rationality, and common knowledge assumptions permit a closed analytical solution. In equilibrium bidders know the competitors' bidding function, however, they do not know the realization of the competitors' private value, therefore they do not know the competitors' actual bid. Conversely, in a TLPM, private values are not random but correlated, the status of a carrier at time t_j provide useful information to estimate the status of the carrier at time t_{j+1}. A bidder may potentially obtain information about competitors' private values and bidding functions if the bidder invests resources to infer them. Market settings, such as auction data disclosed and number of competitors, strongly affect the difficulty of the inference process.

Summarizing, repeated interaction can lead to learning and knowledge acquisition. This research distinguishes among the two. Learning takes place in the no-knowledge case; the carrier does not get to know the competitors' behavioral processes just the price function as a random process. Learning is superficial, it is merely phenomenological. In the full knowledge case, the carrier acquires knowledge about the competitors’ behavioral processes. Knowledge acquisition is deeper; it is causal.

5.6. Problem Solving in a TLPM

The previous section focused on “what can be learnt or known” about the competition. This section specifically contemplates “how carriers come up” with a bid or decision given what has been learnt or what knowledge has been acquired about a problem. Usually, models in which decision makers are assumed rational do not explain the procedures by which decisions are taken, rational procedures are implicitly embedded in the answer or approach. Furthermore, economic models pay no or little attention to how hard it is to make decisions. Conversely, boundedly rational decision maker models detail the procedural aspects of decision making. Those detail procedures are the essence of a boundedly rational decision making model. The degree of intricacy of the decision making procedure is used in the last part of this chapter to classify boundedly rational behaviors.

As a carrier participates in a TLPM market, it is required to make decisions, to choose among alternative future paths. Each decision poses a problem that the carrier has to solve (not necessarily optimally). The rest of this section analyzes, in this order, the type of decision a carrier faces in a TLPM and how bounded rationality can appear in the steps of a decision making process.

5.6.1. Carriers Decisions in a TLPM

From the carriers' point of view, the choice problems that take place in a TLPM are either bidding or operational (fleet management) decisions. Bidding decisions may carry a strategic value since they directly affect competitors' profits. Bidding decisions are also the result of a boundedly rational decision process, a carrier's choice and therefore can reveal or transmit information about a carrier's decision making process or intentions.

Operational (fleet management) decisions mostly affect a carriers' own fleet status (private information). Therefore, operational decisions are considered non-strategic and take place as new information arrives: auctions are won or shipments are served. This type of decision, for example, includes the estimation of a shipment value or service cost, the rerouting of the fleet after a successful bid, the reaction to unexpected increase in travel times, etc.

In this research, a strategic decision is defined as the investment of resources, for the purpose of learning about or influencing competitors. The ultimate goal of a strategic decision is to improve future profits but somehow linked to future the behavior or reaction of the competitors. In an environment where bidders know that competitors are also learning about the marketplace environment, strategic decisions can be sub-classified as identifying or manipulative.

Identifying decisions are characterized by attempts to identify or discover a competitor's behavior – the second type of uncertainty dealt with in the knowledge acquisition section. Those labeled manipulative are decisions that aim to control competitors’ future behavior – i.e. use the behavioral knowledge acquired to improve future profits.

Whether a carrier can bid strategically or not it is an important characteristic that is used to classify bounded rationality behavior in section 7. The analysis of the decision making process from a bounded rationality perspective will be discussed next.

5.6.2. Bounded Rationality and Decision Making

Given a decision maker and a decision problem, a rational decision maker, as assumed in economic theory, chooses an alternative after inquiring (Rubinstein, 1997) what can be done, how to evaluate, and what to choose given alternatives and values. This procedural description is expanded in order to fully dissect the relevant steps of decision making in a TLPM. In this research a rational decision maker chooses an alternative after inquiring and answering correctly:

0. What is the decision/problem?
1. What are the feasible alternatives?
2. What is desirable in an alternative?
3. How desirable is each feasible alternative?
4. What is the best alternative given the answers to questions 0,1, 2, and 3?

Boundedly rational problem-solving arises if any of the previous questions are not answered completely and flawlessly given the available data and knowledge about the problem. Defining the problem or decision correctly is essential, hence numbered as zero – needless to say that generally an optimal answer for the wrong problem is not useful unless it is used to slyly misguide competitors. Problem definitions can be quite challenging in real life decision making (as well as in research projects).

The first question is associated to a search problem. Applying the concept to the DVR technologies analyzed in chapter 4, it is clear that the naïve technology is boundedly rational since the search for alternatives is incomplete. Even the MIP based SFO is boundedly rational because it does not include repositioning of idle vehicles. In more general terms, the search problem may involve what and where to search under time or budget constraints.

The second question is associated to defining the objective function. In the case of the DVR technologies analyzed in chapter 4, the alternatives are simply evaluated as a function of their profitability. If there were more than one objective (i.e. profits and market share), the comparison of alternatives is not trivial as the decision maker has to define a preference relation function for each possible pair (i.e. {profit, market share}).

The third question is associated to the evaluation of each objective. In the case of the DVR technologies analyzed in chapter 4, from a fleet management perspective, the alternatives selected by the technologies SFO and 1FOOC are the same (the best static assignment). However, the difference among the two technologies resides in the evaluation of the scheduling change cost or value. In the DVR realm, a technology like 1FOOC can be improved in two ways: (a) evaluating more alternatives – the problem is how to select good candidates, and (b) improving the evaluation itself, for example increasing the foresight to two, three, or more steps in the future.

The fourth question is associated with putting it all together, in the vein of a mathematical program or algorithm. The same type of analysis can be applied to bidding decisions, which is done in the next section.

5.7. ***Bidding Problem Complexity***

There are several factors that contribute to the complexity of biding in a TLPM. These factors are: competitors bounded rationality, knowledge about the competitors, look-ahead depth, and the type of auction utilized. This section analyzes the first three factors while the next section analyzes the latter.

It was mentioned in the literature review that sophisticated boundedly rational players have a "model" of the other players. In the work of Stahl and Wilson (1995) and Vidal and Durfee (1995), players model other players' cognitive process and decision rules up to a finite number of steps of iterated thinking. The number of iterations that a player can perform is a measure of the sophistication of a player. A zero level player does not model his opponents, it simply ignores the fact that other agents exit. Reinforcement learning is an example of this type of agent sophistication. A one level agent models only the frequency or another statistic that represents other players' actions. Fictitious play is an example of this type of agent sophistication. A two level agent can simulate the other agents' internal reasoning process (i.e. a model of level zero or level one agents) and take an action by taking into account how the other players (of level zero or one) are going to play. A level three agent can build models, simulate them, and act in response to the behavior of players up to level two. Recursively, a level four agent can model the actions of level three agents and so on. Perfectly rational agents can follow the recursion to an infinite level. Then, if the level of rationality of a player is denoted by L^i, then that player can model the most sophisticated of his competitors up to a level $L^{-i} = L^i - 1$.

Section 5.6 dealt with the level of knowledge about the competition. A player with no-knowledge about the competition can only implement a level zero or level one type of player since it cannot link his actions (bids) to the consequences that his actions have. A player with full knowledge could possibly foresee (if it could only solve the corresponding problems) the behavior of any player type. However, the complexity increases as the level type to be implemented increases, i.e. as the competitors bounded rationality sophistication increases.

The carrier with full-knowledge knows $\theta_j^{-i} = \{\mathrm{z}_j^{-i}, \mathrm{a}^{-i}, \mathrm{c}^{-i}\}$ about the competition and also $\mathrm{b}^{-i} = \{\mathrm{b}^1, ..., \mathrm{b}^{i-1}, \mathrm{b}^{i+1}, ..., \mathrm{b}^n\}$. Therefore, carrier i can compute precisely what the competition is going to bid for shipment s_j. However, carrier i still has uncertainties about the future bids, simply because carrier i does not know the future realizations of the demand. Nevertheless, carrier i can estimate future prices, not just as a random process but as a function of shipment arrival and characteristics distribution, competitors' behavior and competitors' private information.

When the knowledge is imperfect, complexity further increases since there is a probability distribution over the competitors' private information space. Furthermore, the probability distribution is a function of the history of play and the competitors' fleet management strategies. In mathematical notation, the probability distribution of competitors' future private information is $\mathrm{p}(\theta_N^{-i} \mid h_N)$.

The third factor is the look-ahead depth. In a sequential auction setting like a TLPM, bids affect future auctions profits. The look-ahead depth is the number of future auctions that are taken into account when estimating how a bid may affect future auctions profits. A zero step look-ahead (or myopic) analysis does not consider future auction profits, just the profit for the current auction. A one-step look-ahead analysis considers one future auction, current plus the following auction profits. Similarly, a m-step look-ahead analysis considers m future auctions, current plus the following m auction profits.

When the analysis is myopic, shipment s_j is known and the uncertainties are reduced to a minimum. Projecting one step into the future, the arrival time (t_{j+1}) and characteristics of shipment s_{j+1} are uncertain. Furthermore, if the link between bidding and future prices ξ_{j+1} is incorporated, the optimal bid for shipment s_j takes into account its impact on competitors' bids (prices) in the next auction. Then, for shipment s_{j+1} the price function at time t_{j+1} is a function of the previous bids and the unknown previous arrival $\xi_{j+1}(s_j, b_j^{*i})$.

In the one-step problem, the arrival and characteristics of s_{j+1} are uncertain, but the future history h_{j+1} is a function of the already known s_j. Projecting two steps into the future, the estimation of the future price function ξ_{j+2} becomes more complex. The price function ξ_{j+2} for shipment s_{j+2} is a function of the yet unknown s_{j+1} and the two previous bids $\{b_j^{*i}, b_{j+1}^{*i} \mid h_{j+1})$. Moving one extra step into the future increases the problem complexity significantly. For shipment s_{j+2} the price function at time t_{j+2} is a function of the previous bids and the unknown previous arrival $\xi_{j+2}(s_j, s_{j+1}(t_j, \Omega), b_j^{*i}, b_{j+1}^{*i} \mid h_{j+1})$. Calculation of future price functions is increasingly difficult as uncertainties and dependencies on earlier (but not yet realized) bids and shipments accumulate. When the look ahead is up to shipment s_N, the number of decision variables $B^{*i} = \{b_j^{*i}, ..., b_N^{*i} \mid h_N\}$ to be estimated is

$$\sum_{k=0}^{N-j} p^k \; .$$

When the number of players (bidders) is n, after each auction there are n possible outcomes and future histories. If backward induction is used, for each possible history it is necessary to estimate an optimal bid, the total number of decision variables increases exponentially with the number of future look-ahead steps. Let denote by $\Sigma = \{s_j, s_{j+1}(t_j, \Omega)..., s_N(t_{N-1}, \Omega)\}$ the set of shipments to be analyzed. Then, the future price function when earlier bids affect future prices and the carrier has imperfect information is a function of $\xi_N = \mathrm{f}(b_j^{*i}, ..., b_{N-1}^{*i}, \Sigma, \mathrm{p}(\theta_N^{-i} \mid h_N))$.

Table 2 puts the three factors together. The table is set up in such a way that the complexity of the price function ξ increases, moving downward or rightward. With higher levels of competitors' bounded rationality, the complexity of the problem increases exponentially with the number of iterations and players to be simulated. The symbol $\langle\cdot\rangle^{nL^{-i}}$ is used to denote the number of iterations as a function of the number of players and the highest level of iterations that the competition can sustain. Table 2, is very general and accommodates all bidding and pricing problems seen so far. Auction analysis of chapter 4 is a special case of the no-knowledge case (with second price auctions). The acceptance rejection problems of chapter 4 are special cases of the full-knowledge case.

The equilibrium formulation of chapter 3, is a special case of the imperfect knowledge case when all players are rational and $L^{-i} \to \infty$. In the game theoretic case, it is common knowledge that all the bidders are simultaneously foreseeing and simulating each others bids and decisions at infinitum. Each cell of Table 2 is a different decision theory problem that can potentially be expressed as a mathematical program or algorithm. It was mentioned that the complexity increases moving downward or rightward.

The problem solving capabilities of the carrier determines the type of problem the carrier solves. For example, a carrier may have imperfect information about the competitors; however, problem solving limitation may force him to solve a myopic problem assuming no-knowledge about the competition. When cost or time limitations are added to the problems, carriers can choose to ignore part of his knowledge in order to get a reasonable answer in a reasonable time, in the spirit of the "satisfying" rule, originally proposed by Simon (1982). According to Simon, economic agents do not always optimize fully, they optimize up to a satisfying level. Level that depends on personal characteristics and circumstances.

Know-ledge Level	Own Type L^i	Type L^{-i}	**Look-Ahead Depth**		
			Myopic $\Sigma = \{s_j\}$ $B^{*i} = \{b_j^{*i}\}$	**1-step** $\Sigma = \{s_j, s_{j+1}(t_j, \Omega)\}$ $B^{*i} = \{b_j^{*i}, b_{j+1}^{*i} \mid h_{j+1}\}$	**Multi-step** $\Sigma = \{s_j, ..., s_N(t_{N-1}, \Omega)\}$ $B^{*i} = \{b_j^{*i}, ..., b_N^{*i} \mid h_N\}$
NO	$L^i = 0$	-	Reinforcement Learning	-	-
	$L^i = 1$	-	Fictitious Play Stationary ξ	Fictitious Play Stationary ξ	Fictitious Play Stationary ξ
FULL	$L^i = 1$	-	Acceptance Rejection	Acceptance Rejection Stationary ξ	Acceptance Rejection Stationary ξ
	$L^i \geq 2$	$L^{-i} \leq 1$	Acceptance Rejection	Optimal Pricing Non-stationary $\xi_{j+1} = \mathrm{f}(b_j^{*i}, \Sigma)$	Optimal Pricing Non-stationary $\xi_N = \mathrm{f}(b_j^{*i}, ..., b_{N-1}^{*i}, \Sigma)$
	$L^i = m$	$2 \leq L^{-i}$ $L^{-i} < m$	Iterated Acceptance Rejection	Iterated Optimal Pricing Non-stationary $\xi_{j+1} = \left\langle \mathrm{f}(b_j^{*i}, \Sigma) \right\rangle^{nL^{-i}}$	Iterated Optimal Pricing Non-stationary $\xi_N = \left\langle b_j^{*i}, ..., b_{N-1}^{*i}, , \Sigma \right\rangle^{nL^{-i}}$
IMPER-FECT	$L^i = 1$	$L^{-i} \leq 1$	Fictitious Play $\xi_j = \mathrm{f}(\mathrm{p}(\theta_j^{-i} \mid h_j))$	Acceptance Rejection Stationary $\xi_{j+1} = \xi_j$	Acceptance Rejection Stationary $\xi_N = ... = \xi_{j+1} = \xi_j$
	$L^i \geq 2$	$L^{-i} \leq 1$	Fictitious Play $\xi_j = \mathrm{f}(\mathrm{p}(\theta_j^{-i} \mid h_j))$	Optimal Pricing Non-stationary $\xi_{j+1} = \mathrm{f}(b_j^{*i}, \Sigma, \mathrm{p}(\theta_{j+1}^{-i} \mid h_{j+1}))$	Optimal Pricing Non-stationary $\xi_N = \mathrm{f}(b_j^{*i}, ..., b_{N-1}^{*i}, \Sigma, \mathrm{p}(\theta_N^{-i} \mid h_N))$
	$L^i = m$	$2 \leq L^{-i}$ $L^{-i} < m$	Iterated Fictitious Play $\xi_j = \left\langle \mathrm{f}(\mathrm{p}(\theta_j^{-i} \mid h_j)) \right\rangle^{nL^{-i}}$	Iterated Optimal Pricing Non-stationary $\xi_{j+1} = \left\langle \mathrm{f}(b_j^{*i}, \Sigma, \mathrm{p}(\theta_{j+1}^{-i} \mid h_{j+1})) \right\rangle^{nL^{-}}$	Iterated Optimal Pricing Non-stationary $\xi_N = \left\langle b_j^{*i}, ..., b_{N-1}^{*i}, \Sigma, \mathrm{p}(\theta_N^{-i} \mid h_N) \right\rangle^{nL^{-i}}$

Table 2 Bidding Complexity as a function of price function (ξ) complexity

Simplifying (downgrading complexity) the problem due to boundedly rational limitations is always possible. In terms of the problem solving steps of section 5.6 the bidding limitations stem mainly from step number three. It can be interpreted that each problem type (each cell) of Table 2 is a different way of measuring how desirable each possible bid is, for a given DVR technology. Step number one (feasible alternatives) is determined partly by the DVR technology. Step number two is trivial, since profits are the only objective.

In section 5 the value of knowledge was defined as the profit difference that a carrier can obtain going from the no to full knowledge assumption. That definition can be complemented by the value of computational power. The value of computational power is the profit difference that a carrier can obtain from solving a more complex problem due to the increased performance of his computational resources.

Summarizing, based on their knowledge level and problem solving capabilities, agents differ in the type of problem they can solve. Next section analyzes the complexity of first and second price auctions.

5.8. Auction Mechanisms and Complexity

This section compares the complexity of first and second price auctions for boundedly rational agents in TLPM bidding problems. Chapter 4 developed the optimal bidding formulae for second price auctions and stationary price function. This section develops a similar bidding function for first price auctions, compares the complexity of both types of auctions, and finally points out problems where both auctions have similar complexity.

In a sequential first price auction, the best bid for serving shipment s_j for carrier i is equal to b_j^{*i}, where:

$$b_j^{*i} \in \arg\max_{b \in R} \; E_{(\xi)}\{[(b - c^i(s_j, z_j^i))\, I_j^i + \pi^i_{j+1,..,N}(s_j \mid I_j^i = 1)\, I_j^i + \pi^i_{j+1,..,N}(s_j \mid I_j^i = 0)(1 - I_j^i)]\} \qquad (5.1)$$

$$\pi^i_{j+1,..,N}(s_j \mid I_j^i = 1) = E_{(\omega_{j+1},\dots,\omega_N)}[\sum_{k=j+1}^{N} E_{(\xi)}[\pi^i(b_k^{*i}, c^i, s_k, z_k^i \mid I_j^i = 1)]] \qquad (5.2)$$

$$\pi^i_{j+1,..,N}(s_j \mid I_j^i = 0) = E_{(\omega_{j+1},\dots,\omega_N)}[\sum_{k=j+1}^{N} E_{(\xi)}[\pi^i(b_k^{*i}, c^i, s_k, z_k^i \mid I_j^i = 0)]] \qquad (5.3)$$

$$E_{(\xi)}[\pi^i(b_k^{*i}, c^i, s_k, z_k^i)] = E_{(\xi)}[(b_k^{*i} - c^i(s_k, z_k^i))\, I_k^i] \qquad (5.4)$$

$$I_k^i = 1 \quad if \quad \xi > b_k^{*i} \quad and \quad I_k^i = 0 \quad if \quad \xi \le b_k^{*i} \qquad (5.5)$$

$$z_k^i = \mathrm{a}^i(t_k, h_k, z_{k-1}^i) \qquad (5.6)$$

In the first price formulation, the profit at each period is the difference between the optimal bid and the cost of serving the corresponding shipment. Accordingly, either b or b_k^{*i} has to be added in equations (5.1), (5.2), (5.3), and (5.4) – replacing ξ by the bid value is the only difference between the first and second price auctions formulations.

5.8.1. One Step Look-ahead for First Price Auctions

If acquiring shipment s_j does affect the marginal cost of serving future loads (i.e. s_{j+1}, s_{j+2}, ..., s_N), this must be taken into account. In a first price auction, it still holds that a new load (a) temporarily reduces carriers' capacity (capacity defined as the ability to serve additional shipments at a point in time) and (b) changes the current schedule and therefore possibly changes fleet deployment at the time of the next shipment auction. The only exception to this takes place in the final auction (shipment s_N) if there are no repositioning costs (for example, trucks do not return to a central depot).

The estimation of the best bid for shipment s_k is greatly simplified if it is assumed that shipment s_{k+1} is the last shipment to ever arrive at the marketplace. The solution of the one step problem for the second price auction is in chapter 4, section 7. This section presents the equivalent analysis for the first price auction.

Using backward induction, the optimal bid, b^{*i}_{k+1} for shipment s_{k+1} has to be estimated first. This bid would be simply:

$$b^{*i}_{k+1} \in \underset{b \in R}{\arg\max}\ E_{(\xi)}[(b - c^i(s_{k+1}, z^i_{k+1} \mid I^i_k))I^i_{k+1}] \qquad (5.7)$$

$$I^i_{k+1} = 1 \quad if \quad \xi > b^{*i}_{k+1} \quad and \quad I^i_{k+1} = 0 \quad if \quad \xi \le b^{*i}_{k+1}$$

Since there are two possible values for I^i_k, two optimal bids must be estimated for shipment s_{k+1}. One bid is for the case where the auction for shipment s_k is won $(I^i_k = 1)$), the other bid is for the case where the auction for shipment s_k is lost $(I_k^i = 0)$. The last equation (5.7) assumed that the value of the shipment s_{k+1} is known. The expected profits obtained with the optimal bids are respectively:

$$\begin{aligned}\pi_{k+1}^i(s_k \mid I_k^i = 1) &= E_{(\omega_{k+1})}[E_{(\xi)}[\pi^i(b_{k+1}^{*i}, c^i, s_{k+1}, z_{k+1}^i \mid I_k^i = 1)]] = \\ &= E_{(\omega_{k+1})}[E_{(\xi)}[(b_{k+1}^{*i} - c^i(s_{k+1}, z_{k+1}^i \mid I_k^i = 1))\, I_{k+1}^i]]\end{aligned}$$

$$\begin{aligned}\pi_{k+1}^i(s_k \mid I_k^i = 0) &= E_{(\omega_{k+1})}[E_{(\xi)}[\pi^i(b_{k+1}^{*i}, c^i, s_{k+1}, z_{k+1}^i \mid I_k^i = 0)]] = \\ &= E_{(\omega_{k+1})}[E_{(\xi)}[(b_{k+1}^{*i} - c^i(s_{k+1}, z_{k+1}^i \mid I_k^i = 0))\, I_k^i]]\end{aligned}$$

Then, the optimal bid for shipment s_k is the bid that maximizes this function:

$$b_k^{*i} \in \arg\max\ E_{(\xi)}[(b - c^i(s_k, z_k^i))I_k^i + \pi_{k+1}^i(s_k \mid I_k^i = 1)\, I_k^i + \pi_{k+1}^i(s_k \mid I_k^i = 0)(1 - I_k^i)]$$

$$b \in R \tag{5.8}$$

$$I_k^i = 1 \quad if \quad \xi > b_k^{*i} \quad and \quad I_k^i = 0 \quad if \quad \xi \le b_k^{*i}$$

Using backward induction, the values of $b_{k+1}^{*i} \mid I_k^i = 1$, $b_{k+1}^{*i} \mid I_k^i = 0$, $\pi_{k+1}^i(s_k \mid I_k^i = 1)$, $\pi_{k+1}^i(s_k \mid I_k^i = 0)$, and b_k^{*i} are to be estimated in that order. In general, solving equation (5.8) or even equation (5.5) can lead to a nonlinear optimization problem (even assuming that the random process ξ corresponds to a simple distribution such as the uniform distribution). In order to estimate (5.8) three optimizations are needed, one for each possible bid. In general, for $N-k$ steps into the future, the number of nonlinear optimizations to be performed is:

$$\sum_{l=1}^{N-k} 2^l + 1$$

In comparison, the second price auction requires solving equation (4.18) instead.

$$c_k^{*i} \approx \quad c^i(s_k, z_k^i) - \pi_{k+1}^i(s_k \mid I_k^i = 1) \;+ \pi_{k+1}^i(s_k \mid I_k^i = 0) \qquad (4.18)$$

$$\pi_{k+1}^i(s_k \mid I_k^i = 1) \;= E_{(\omega_{k+1})}[E_{(\xi)}[(\xi - c^i(s_{k+1}, z_{k+1}^i \mid I_k^i = 1))\, I_{k+1}^i]]$$

$$\pi_{k+1}^i(s_k \mid I_k^i = 0) \;= E_{(\omega_{k+1})}[E_{(\xi)}[(\xi - c^i(s_{k+1}, z_{k+1}^i \mid I_k^i = 0))\, I_{k+1}^i]]$$

In order to estimate (4.18) two expected profits have to be estimated. In general, for $N-k$ steps into the future, the number of expected profits to be estimated is:

$$\sum_{l=1}^{N-k} 2^l$$

Paralleling the results obtained in chapter 2 for the SIPV model, the complexity of the first price auction is higher than the complexity of the second price auction. For each possible decision node, the corresponding first price auction optimal bid is the result of an optimization over the expected profits given the level of competition ξ. This adds an exponential number of nonlinear optimizations to be performed. Even assuming, for the time being, that $S_{k+1,\dots,N}$ is known at time t_k, the number of additional nonlinear optimizations to be performed in the first price auction is of order $o(2^{N-k})$.

5.8.2. Minimum and Maximum Complexity Gap -- First vs. Second Price Auctions

As in the SIPV model, the complexity gap stems from the fact that in second price auctions the best bid is just the value/cost of the item regardless of the competitors' bid distribution functions. With complete information (no uncertainty), one item auction, a first price auction bidder does not need to optimize since he knows the highest (lowest) value that the competitors are going to bid.

In the Table 2, there is no uncertainty about competitors' bids only in the myopic case with full knowledge. In this case, a first price auction bidder does not need to optimize since he knows the lowest value that the competitors are going to bid. It is simply an acceptance rejection problem.

Looking ahead into the future introduces uncertainty about the competitors' bids simply because the carrier (even with full-knowledge) cannot control when and what shipments are going to arrive next. Bidding using reinforcement learning ignores the existence of competitors; in this case also the bidding complexity is similar for first and second price auctions. In the problems where the complexity gap is zero, the complexity stems only from estimating the cost of serving the shipment, i.e. the complexity of the DVR technology.

The complexity gap between first and second price auctions is expected to grow with the number and intricacy of the non-linear optimizations to be performed in each decision node. More uncertainty is found with imperfect information and multi-steps. Furthermore, the number of optimizations grows exponentially with the number of steps, the level of bounded rationality, and the number of players. In Table 2 this corresponds to the problems found at the bottom rightmost cells.

The implications of this complexity analysis are important. With constrained and similar computational resources and similar setting, a second price bidder may look further into the future since it is solving a simpler problem. Similarly, there are cases where full knowledge about the competition is less significant for second price bidder (for example the myopic case). This analysis presents some similarities to the findings of Larson and Sandholm (2002), where the second price bidders use more resources to estimate their true costs than first price bidders.

5.9. <u>Determinants of Carrier Behavior</u>

Carrier behavior is defined as a sequence of bids taken by a carrier. This section looks into the elements or factors that determine carrier behavior. These factors are: carrier technology, bounded rationality, information availability, and strategic setting. Though all the factors are somewhat related, the first two are prominently intrinsic to the carriers' own characteristics, while the last two are predominantly linked to environmental or somewhat extrinsic factors. Some of the factors have been already extensively analyzed, for these factors the discussion is limited to highlight the link between them and carrier behavior.

5.9.1. Carrier Technology

Carrier technology or DVR technologies, as defined and explained in chapter 4, has an important role in bidding. In the bidding decision making process the carrier technology determines the number of feasible schedules to be evaluated. Therefore, unsophisticated DVR technologies serious limit the quality and quantity of alternatives that could be evaluated.

5.9.2. Auction Rules - Information Revelation

It has already been illustrated in the previous section that different auction payment rules lead to different bidding functions. Information revelation rules can also play a significant role.

The information that is revealed (before bidding begins or after each auction) can influence how, how much, and how fast carriers can learn or acquire knowledge about the strategic setting and competitors' behaviors. The information that could be available after auctions are resolved includes: bids placed, number of carriers participating, links (names) between carriers and bids, and payoffs. The information that could be available before bidding begins includes: some carriers' individual characteristics (e.g. fleet size or previous performance/profits from public financial reports), information about who knows what, information asymmetries, or common knowledge about previous items. Private information (as defined in chapter 3) is not included since it involves proprietary information that usually is to the best interest of the carrier to keep private.

Two extreme information scenarios can be defined: maximum and minimum. A maximum information environment is defined as an environment where all the information, mentioned in the previous paragraph, is revealed. On the other hand, an environment where no information is revealed is called a minimum information environment.

These two extreme scenarios can approximate two realistic situations: maximum information would correspond to a real time internet auction where all auction information is equally accessed by participants; minimum information would correspond to a shipper telephoning carriers for a quote. The shipper calls back just the selected carrier (if any is selected).

5.9.3. Strategic Setting

In this chapter, it has been tacitly assumed that a carrier operates in an environment determined by the other carriers' behaviors; a carrier uses a model of the behavior of the other carriers as an input to his decision problem. Under this interpretation a carrier's bidding function suits a carrier's best interest, assuming that competitors bidding functions pursues competitors' best interests. This is defined as a competitive strategic environment.

A diametrically different environment is a collusive or collaborative environment. One danger of auctions is the possibility that buyers/sellers who repeatedly participate in the same auctions could engage in collusive behavior. This topic is of primordial importance in the field of Industrial Organization – general references to this area include the work of Tirole (1989) and Martin (1993). As a general rule, the more information is revealed, the easier collusion becomes.

Even in minimum information settings collusion is possible. Blume and Heidhues (2003) study collusion in repeated first-price auctions under the condition of minimal information release by the auctioneer. In each auction a bidder only learns whether or not he won the object. Bidders do not observe other bidder's bid, who participates or who wins in cases in which they are not the winner. Even under these restrictive assumptions, for large enough discount factors, collusion can nevertheless be supported in the infinitely repeated game. Nevertheless, it may entail complicated inferences and full monitoring among them. Marshal and Marx (2002) analyze bidder collusion in first and second price auctions and SIPV assumptions.

The two environments, competitive and collusive, are nonetheless connected since underlying every negotiation or agreement there is a game-like component (Raiffa, 2002). From each carrier's individual perspective, the incentives (and legal or market risks) of collaborating with competitors has to prevail over the profits that can be obtained when each party acts separately (competitive environment).

5.9.4. Bounded Rationality

Bounded rationality limitations affect a) the knowledge that a carrier is able to acquire, and b) the bidding problem that the carrier can solve. Given the carrier's rational limitations, fleet technology, information available, and a competitive strategic setting the carrier ends up solving a bidding problem that best represent his interests in Table 2

5.9.5. Framework for Carrier Behavior

After analyzing carriers' decisions, learning, knowledge acquisition, problem solving processes, and bounded rationality we possess all the necessary elements to present a framework for studying carriers' behavior. Figure 21 presents a schematic overview of the process that brings about carriers' behavior.

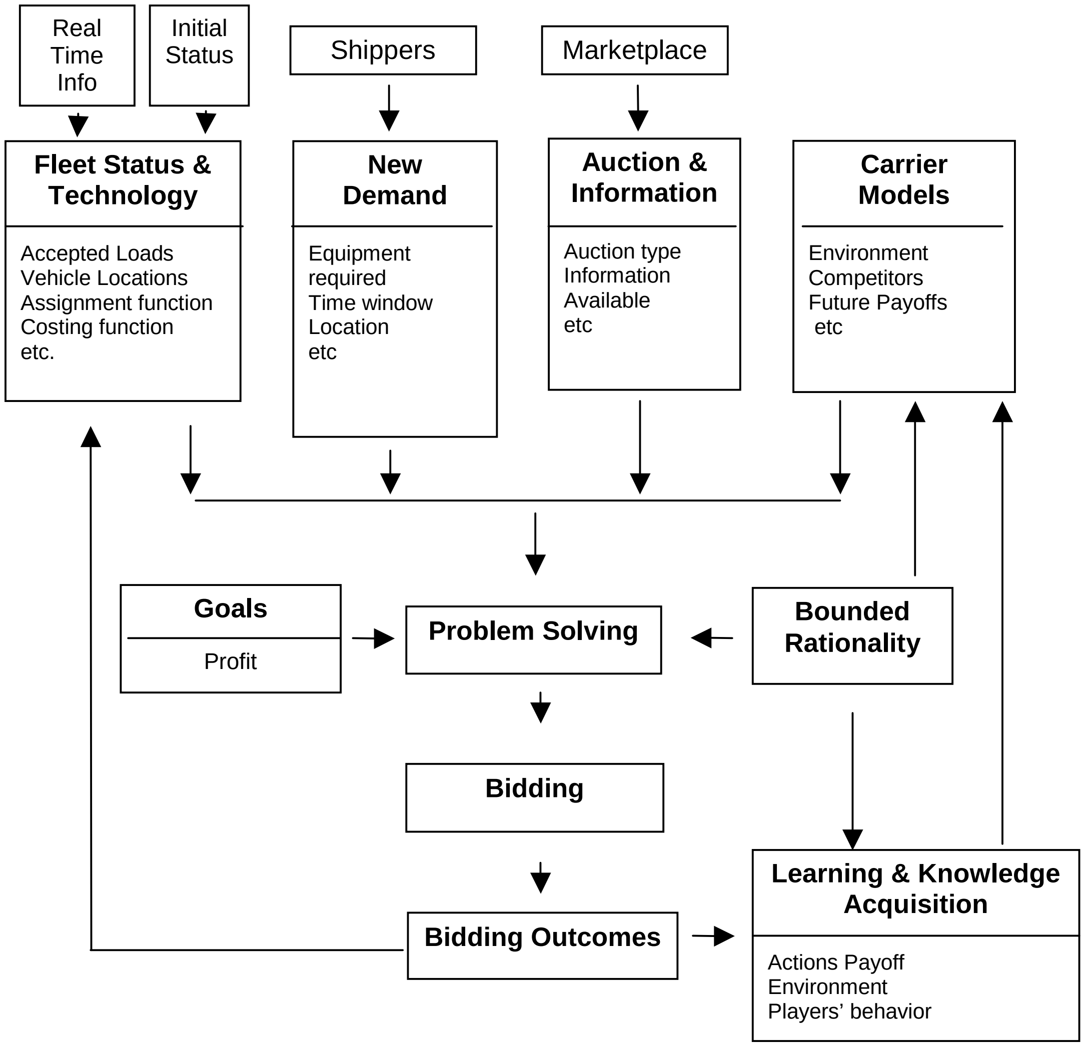

Figure 21 Carrier behavior in a sequential auction marketplace

A shipper's decision to post a shipment in the auction market initiates an auction. Carriers respond to auctions postings. Carriers attempt to maximize profits by adjusting their behaviors in response to interactions with other carriers and their environment. Bounded rationality limitations and pervasive and affect how a carrier models, evaluates, and optimizes his action as indicated by the arrows in Figure 21. Carriers also must abide by the constraints and the physical feasibility specified by their assignment strategies and pool of awarded shipments.

In this framework, carriers' learning and knowledge about other competitors' behavior types evolve jointly over time and their strategies at a given moment are contingent on interactions that have occurred or will occur in a path-dependent time line. Past decisions are binding and limit the future actions of carriers, therefore behavioral rules are state-conditioned and the carriers co-adapt their behavior as the marketplace evolves over time.

Carriers' internal events are the assignment, pickup, and delivery of loads, mostly operational decisions. Carriers repeatedly engage in bidding interactions modeled as noncooperative games. However these repeated bidding interactions are also the only means of communication for a carrier to "identify" or "manipulate" other competitors.

5.10. <u>Summary</u>

This chapter dealt with bounded rationality in a competitive TLPM setting. After reviewing the relevant literature, bounded rationality was approached analyzing its likely sources in the context of carriers' decision making process. Given the complexity of the bidding/fleet management problem, carriers can tackle it with different levels of sophistication. Carriers' decision making processes and bounded rationality were analyzed. The complexity of the different bidding problems that a boundedly rational carrier can be faced with was analyzed and classified. A framework to study carrier behavior in TL sequential auctions was presented.

The provided framework is general enough to accommodate problems already seen in previous chapters such as the game theoretic formulation of chapter 3 and the auction analysis of chapter 4. In the framework presented in this chapter, sequential auctions can be used to model an ongoing transportation market, where the effect of carrier competition, knowledge and information availability, dynamic vehicle routing technologies, computational power, and decision making processes can be studied.

Auction type influences the complexity of TLPM bidding. It was shown that second price auctions can be equally or less demanding computationally than first price auctions. It was also shown that bidding problems are less demanding computationally if no-knowledge conditions are assumed. Chapter 6 studies learning and behavior of carriers in a competitive TLPM under no-knowledge conditions.

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Chapter 6: Non-Strategic Boundedly Rational Competition

Chapter 6 studies the bidding behavior of carriers in a competitive setting where carriers are unable to use causal models of competitors' behaviors. This competitive setting corresponds to the no-knowledge assumption and non-strategic environments (defined in chapter 5 sections 5.5 and 5.6 respectively). Chapter 4 assumed that cost truth telling strategy was a dominant strategy, therefore carriers were limited to bid their marginal cost. In this chapter that assumption is relaxed; carriers bid trying to maximize their profits but limited by their boundedly rational limitations.

In this competitive setting (no-knowledge assumption, non-strategic environment, and no cost truth telling limitations) three different auction formats are compared using computational experiments. These auction formats are second price auctions, first price auction with minimum information disclosure, and first price auctions with maximum information disclosure.

Section 1 describes the properties and behavioral assumptions of carriers competing in the no-knowledge and non-strategic environment. Section 2 describes learning in a no-knowledge environment. Two widely used forms of learning that do not attempt to model competitors' behavior directly are discussed in section 3 and 4; these learning methods are reinforcement learning and fictitious play, respectively. Section 5 compares a carrier's behavior with the behavior of a machine. Reinforcement learning and fictitious play can be seen as either human or machine behavior. Sections 6 to 8 present different computational experiments aimed at studying the properties of different auction settings and learning methodologies. Section 9 presents a chapter summary.

6.1. ***Competition in a Non-Strategic Environment***

The high complexity of acquiring and using knowledge about competitors' behaviors was discussed in chapter 5, even in a TLPM market that has been streamlined to its very basic elements. Knowledge acquisition and its use can be considerably more complex in a more complete model where other critical constraints and variables are added (for example, getting drivers home, variation in travel times, delays incurred while unloading the truck, etc). Furthermore, noisy information transmission, as reported by Powell et al. (2002), even among agents that respond to the same carrier (i.e. drivers, dispatchers, decisions support systems), seem to sustain the notion that perfect knowledge about competitors' private information and behavior could only be possible in a flight of the imagination. Imperfect knowledge is possible, but at the cost of even higher complexity.

Given the high level of complexity of full or imperfect knowledge assumptions, it is methodologically sensible to first focus on behaviors and settings which are more plausible for implementation in real-life TLPM marketplaces. The first tool that bounded-rational agents use to cope with insurmountable complexity is simplification. In this chapter it is assumed that acquiring or using knowledge about the competitors' behavior causality (bounded rationality) is so complex that carriers make no attempt to acquire this knowledge about competitors. Rather, carriers learn about the distribution of past market prices or the relationships between realized profits and bids.

6.1.1. Behavioral Assumptions

In a TL transportation company, scheduling decisions can be made by a human being, a computerized decision support system, or a hybrid human/machine dispatcher. Powell et al. (2002) indicates that most carriers still rely heavily on human dispatchers, though large carriers have already implemented or are in the process of implementing more computerized decision support systems.

It is assumed that humans, as well as computerized systems, follow a set of rules or programs whose ultimate goal is to maximize carrier's profits. Therefore, boundedly rational behavior, as understood in this research, is not chaotic or absurd. Carriers try to evaluate the possible consequences of their actions; carriers prefer outcomes that yield higher expected profits. Furthermore, carriers' decisions must be related to the deployment of the carrier's assets or fleet status. It is also assumed that decisions are based on the possible consequences of the choices made.

The previous set of behavioral assumptions are needed to ensure that the steps of rational decision making, described in section 5.6, are at least followed. Though the steps of rational decision maker are followed different boundedly rational imperfections can arise when implementing any given step. The objective of the mentioned assumptions is to screen out carriers' behaviors that could not be expected from any thriving carrier in a TLPM.

The goal of this chapter is not to find the "optimal" rules or procedure that lead to the best possible boundedly rational reasoning or machine (with the no-knowledge assumption), a la Descartes (i.e. setting out to conjecturally discover general rules for proper reasoning). Rather, the idea is to define plausible boundedly rational procedures that carriers can implement in a TLPM. These carriers are then engaged in competition in simulated TLPM markets. The next section discusses plausible learning and behavioral models.

6.2. __Learning__

The learning literature mainly takes an experience based learning approach. In an auction context, learning methods look for good bidding strategies by approximating the behavior of competitors. Most learning methods assume that competitors' bidding behavior is stable. This assumed bidding stability is like believing that all competitors are in a strategic equilibrium.

Learning in this environment is based on the belief that experience is important and can improve carriers' profits. Such past experience can not only help players to avoid dominated (poor) strategies but it can also lead them to play the most successful strategies. Given that learning is phenomenological rather than causal, learning can be based on false backward-looking procedures that: a) make forecasts about other players' behaviors and b) select a response to these forecasts. Therefore, since learning can be fundamentally based on false premises, learning does not guaranty good performances. Nevertheless, this may not be a problem in an environment where all players share the same level of sophistication (i.e. all players are type zero or type one level). In other words, no other competitor can exploit their boundedly rational weaknesses. Still, poor performance may take place if carriers' bids get attracted to an undesirable "equilibrium" or attractor point.

Walliser (1998) distinguishes four distinct dynamic processes to play games. In a decreasing order of cognitive capacities they are: eductive processes, epistematic learning (fictitious play), behavioral learning (reinforcement learning), and evolutionary process. An eductive process requires knowledge about competitors' behavior, such as the n-level player theory where players simulate each others behavior. Epistemic and behavioral learning are similar to fictitious play and reinforcement learning, they are studied in this chapter in sections 3 and 4. In the evolutionary process, a player has (is born with) a given strategy, after playing that strategy the player dies and reproduces in proportion to the utilities obtained (usually in a game where it has been randomly matched to another player).

This chapter studies the two intermediate types of learning. It was already discussed in the first section that eductive-like type of play requires players (carriers) that are assumed too smart (to be possible). On the other hand, evolutionary model players seem too simplistic: they have no memory, and simply just react in response to the last result. Furthermore, the notion that a company is born, dies, and reproduces with each auction does not fit well behaviorally in the defined TLPM. Ultimately, neither extreme approach is practically or theoretically compelling in the TLPM context. Carriers that survive competition in a competitive market like TL procurement cannot be inefficient or simply dumb. They are just limited in the strategies they can implement. Carriers would like to implement the strategy (regardless of its complexity) that ensured higher profits, but they are restricted by their boundedly rational limitations.

6.2.1. Learning Initial Assumptions

In practical and theoretical applications, the process of setting learning initial beliefs has always been a thorny issue. Implemented learning models must specify what agents initially know. Ideally, how or why these initials assumptions were built should always be reasonable justified or explained. In this aspect, solely restricting the research to the TLPM context has clear advantages.

It was mentioned in chapter 4 that normal operating ratios in the TL industry range from 0.90 to 0.95. It is expected that operating ratios in a TLPM do not radically differ from those in the mentioned range. If prices are too high shippers can always opt out, abandon the marketplace and find an external carrier. Prices cannot be substantially lower because carriers would run continuously in the red, which does not lead to a self-sustainable marketplace. Obviously, operating ratios fluctuations in a competitive market are expected, which reflects natural changes in demand and supply. However, these fluctuations should be in the neighborhood of historical long term operating ratios unless the market structure is substantially changed.

Another practical consideration is the usage of ratios or factors in the trucking industry. Traditionally, the trucking industry has used numerous factors and indicators to analyze a carrier's performance, costs, and profits. It seems natural that some carriers would obtain a bid after multiplying the estimated cost by a bidding coefficient or factor. Actually, experimental data show that the use of multiplicative bidding factors may be quite common in bidding as (Paarsch, 1991). Learning coupled with the usage of bidding factors is studied in section 7. In chapter 5 it was mentioned that there are two distinct information levels. The next two sections describe a suitable learning method for each level.

6.3. <u>Reinforcement Learning</u>

In this learning method the required knowledge about the game payoff structure and competitors behavior is extremely limited or null. From a single carrier's perspective the situation is modeled as a game against nature; each action (bid) has some random payoff about which the carrier has no prior knowledge.

Learning in this situation is the process of moving (in the action space) in a direction of higher profit. Experimentation (trial and error) is necessary to identify good and bad directions.

6.3.1. Stimulus Response Model with Reinforcement Learning

Let M be the ordered set of real numbers that are multiplicative coefficients $\mathrm{M} = \{mc_0, ..., mc_K\}$, such that if $mc_k \in \mathrm{M}$ and $mc_{k+1} \in \mathrm{M}$, then $mc_k < mc_{k+1}$. Using multiplicative coefficients the profit obtained for any shipment s_j, when using the multiplicative coefficient mc_k is equal to:

$$\pi_j^i(mc_k) = (mc_k\, c_j^i - c_j^i) I_j^i = c_j^i\, I_j^i\, (mc_k - 1) \qquad (6.1a)$$

$$\pi_j^i(mc_k) = (b_j^{(2)} - c_j^i) I_j^i \qquad (6.1b)$$

The first equation (6.1a) applies to first price auctions while the second equation (6.1b) applies to second price auctions. Adapting the reinforcement model to TLPM bidding, the probability $\varphi_j^i(mc_k)$ of carrier i using a multiplicative coefficient mc_k in the auction for shipment s_j is equal to:

$$\varphi_j^i(mc_k) = (1-\lambda\,\pi_{j-1}^i(mc_k))\varphi_{j-1}^i(mc_k) + I_{j-1}^i(mc_k)\,\lambda\,\pi_{j-1}^i(mc_k) \qquad (6.2)$$

To use equation (6.2), each bidder only needs information about his bids and the result of the auction. To use this model the profits $\pi_{j-1}^i(mc_k)$ must be normalized to lie between zero and one so that they may be interpreted as probabilities. The indicator variable $I_j^i(mc_k)$ is equal to one if carrier i used the multiplicative coefficient mc_k when bidding for shipment s_j, the indicator is equal to zero otherwise. The parameter λ is called the reinforcement learning parameter, it usually vary between $0 < \lambda < 1$.

The stimulus response model with reinforcement had its origin in the psychological literature and has been widely used to try to explain human and even animal behavior. Some computer science literature calls this model the learning automaton. Narenda and Tatcher (1974) showed that a players' time average utility, when confronting an opponent playing a random but stationary strategy, converges to the maximum payoff level obtainable against the distribution of opponents' play. The convergence is obtained as the reinforcement parameter λ goes to zero.

The reinforcement is proportional to the realized payoff, which is always positive by assumption. Any action played with these assumptions, even those with low performance, receives positive reinforcement as long as it is played (Fudenberg, 1998). Furthermore, in an auction context there is no learning when the auction is lost since $\pi^i_{j-1}(mc_k) = 0 \quad \forall\, mc_k \in \mathrm{M}$ if $I^i_{j-1} = 0$

Borgers and Sarin (1996) propose a model that deals with the aforementioned problems. In this model the stimulus can be positive or negative depending on whether the realized profit is greater or less than the agent's "aspiration level". If the agent's aspiration level for shipment s_j is denoted ρ^i_j and the effective profit is denoted $\tilde{\pi}^i_{j-1}(mc_k) = \pi^i_{j-1}(mc_k) - \rho^i_j \quad (6.3)$, then

$$\varphi^i_j(mc_k) = (1-\lambda\,\tilde{\pi}^i_{j-1}(mc_k))\varphi^i_{j-1}(mc_k) + I^i_{j-1}(mc_k)\,\lambda\,\tilde{\pi}^i_{j-1}(mc_k) \qquad (6.4)$$

When $\rho^i_j = 0$, the equation (6.4) provides the same probability updating equation as (6.2). Borgers and Sarin explore the implications of different policies to set the level of the aspiration level. These implications are clearly game dependent. A general observation applies for aspiration levels that are unreachable. In this case equation (6.3) is always negative; therefore the learning algorithm can never settle on a given strategy, even if the opponent plays a stationary strategy.

These learning mechanisms were originally designed for games with a finite number of actions and without private values (or at least for players with a constant private value). In the TLPM context, the cost of serving shipments may vary significantly. Furthermore, even the "best" or optimal multiplier coefficient can get a negative reinforcement when an auction is lost simply because the cost of serving a shipment is too high. This negative reinforcement for the "good" coefficient creates instability and tends to equalize the attractiveness of the different multiplicative coefficients. This problem worsens as the number of competitors is increased, causing a higher proportion of lost auctions, i.e. negative reinforcement.

This research proposes a modified version of the stimulus response model with reinforcement learning that better adapts to TLPM bidding. Each multiplicative coefficient m_k has an associated average profit value $\overline{\pi}_j^i(m_k)$ that is equal to:

$$\overline{\pi}_j^i(m_k) = \frac{\sum_{t\in\{1,\ldots,j\}} \pi_t^i(s_t)\ I_t^i(m_k)}{\sum_{t\in\{1,\ldots,j\}} I_t^i(m_k)}$$

The aspiration level is defined as the average profit over all past auctions:

$$\overline{\rho}_j^i = \frac{\sum_{t\in\{1,\ldots,j\}} \pi_t^i(s_t)\ I_t^i}{j}$$

Therefore the average effective profit is defined as $\overline{\pi}_{j-1}^i(mc_k) = \overline{\pi}_{j-1}^i(mc_k) - \overline{\rho}_j^i$. Probabilities are therefore updated using equation (6.5).

$$\varphi_j^i(mc_k) = (1-\lambda\,\overline{\pi}_{j-1}^i(mc_k))\varphi_{j-1}^i(mc_k) + I_{j-1}^i(mc_k)\,\lambda\,\overline{\pi}_{j-1}^i(mc_k) \qquad (6.5)$$

With the latter formulation (6.5), a "good" multiplicative coefficient does not get a negative reinforcement unless its average profit falls below the general profit average. At the same time, there is learning even if the auction is lost.

6.3.2. Observations of the Reinforcement Learning Model

Stimulus-response learning requires the least information (a minimum information setting as described in chapter 5 section 5.9) and can be applied to both first and second price auctions. The probability updating equations (6.2), (6.4), and

(6.5) are the same for first and second price auctions. Therefore the application of the reinforcement learning model does not change with the auction format that is being utilized in the TLPM. Using this learning method, a carrier does not need to model neither the behavior nor the actions of competitors. The learning method is essentially myopic since it does not attempt to measure the effect of the current auction on future auctions. The method clearly fits in the category of no-knowledge/myopic carrier bounded rationality.

Since the method is myopic, for the first price auction the multiplicative coefficients must be equal or bigger than one, i.e. $mc_0 \geq 1$. A coefficient smaller than one, generates only zero or negative profits. In a second price auction the multiplicative coefficients can be smaller than one and still generate positive profits since the payment is dependent on the competitors' bids.

In both types of auctions it is necessary to specify not just the set of multiplicative coefficients but the initial probabilities. If equation (6.4) is used it is also necessary to set the aspiration level. If equation (6.5) is used it is necessary to set the level of the initial profits but not the aspiration level. A uniform probability distribution is the classical assumption and indicates a complete lack of knowledge about the competitive environment.

Summarizing, in reinforcement learning, the agent does not consider strategic interaction. The agent is unable to model an agent play or behavior but his own. This agent is informed only by their past experiences and is content with observing the sequence of their own past actions and the corresponding payoffs. Using only his action-reward experience, he reinforces strategies which succeeded and inhibit strategies which failed. He does not maximize but moves in a utility-increasing direction, by choosing a strategy or by switching to a strategy with a probability positively related to the utility index.

6.4. Fictitious Play

Fictitious play came about as an algorithm to look for Nash equilibrium in finite games of complete information (Brown, 1951). It is assumed that the carrier observes the whole sequence of competitors' actions and draws a probabilistic behavioral model of the opponents' actions. The agent does not try to reveal his or her opponents' bounded rationality from their actions although the agent may eventually know that opponents learn and modified their strategies too. The agent models not behavior but simply a distribution of opponents' actions. Players do not try to influence the future play of their opponents. Players behave as if they think they are facing a stationary, but unknown, distribution of the opponents' strategies. Players ignore any dynamic links between their play today and their opponents' play tomorrow. These assumptions are similar to the ones applied in chapter 4.

A player that uses a generalized fictitious play learning scheme assumes that his opponents' next bid vector is distributed according to a weighted empirical distribution of their past bid vectors. The method cannot be straightforwardly adapted to games with an infinite set of strategies (for example the real numbers in an auction). Two ways of tackling this problem are: a) the player divides the set of real numbers into a finite number of subsets, which are then associated with a strategy or b) the player uses a probability distribution, defined over the set of real number to approximate the probabilities of competitors play. In either case, the carrier must come up with a estimated stationary price function ξ. If a second price auction format is used in the TLPM, equation (4.1) from chapter 4 is used.

$$b_j^{*i} \in \arg\max_{b \in R} E_{(\xi)}\{[(\xi - c^i(s_j, z_j^i))I_j^i + \pi^i_{j+1,\ldots,N}(s_j \mid I_j^i = 1)I_j^i + \pi^i_{j+1,\ldots,N}(s_j \mid I_j^i = 0)(1 - I_j^i)]\} \quad (4.1)$$

If a first price auction format is used in the TLPM, equation (5.1) from chapter 5 is used.

$$b_j^{*i} \in \arg\max_{b \in R} E_{(\xi)}\{[(b - c^i(s_j, z_j^i))I_j^i + \pi^i_{j+1,\ldots,N}(s_j \mid I_j^i = 1)I_j^i + \pi^i_{j+1,\ldots,N}(s_j \mid I_j^i = 0)(1 - I_j^i)]\} \quad (5.1)$$

The look-ahead depth is limited by the problem solving capabilities of the carrier. When the look-ahead depth is zero (myopic case) the fictitious play model of learning is similar to a repeated version of Friedman's model of bidding (described in chapter 5 section 5.2).

6.5. Automaton Interpretation

The two previous sections have described reinforcement learning and fictitious play models of learning. In section 2 it was mentioned that in a TL company, scheduling decisions can be made by a human being, a computerized decision support system, or a hybrid human/machine dispatcher. Reinforcement learning and fictitious play were originally conceived as human methods of learning.

However, they can also be used by machines or computerized systems. This section tries to link both views.

An automaton is a self operating machine or mechanism. In a game context, an automaton is meant to be an abstraction of the process by which a player *implements* a given bounded rationality behavior. Rubenstein (1998) replaces the notion of a strategy with the notion of a machine called finite automaton. In Rubenstein's model a finite automaton that represents player i is a four-tuple $(Z^i, \mathrm{z}_0^i, \mathrm{b}^i, \mathrm{a}^i)$, where Z^i is a finite set of machine states (from this constraint the adjective "finite"), z_0^i is the initial state for carrier i, $\mathrm{b}^i : Z^i \to A$ is an output function that produces an action (given the state of the automaton), and $\mathrm{a}^i : Z^i \times A^{-i} \to Z^i$ is a transition function that updates the state of the automaton (given the actions taken by the competitors in the previous period). The set of possible actions is denoted by A.

Adapting these concepts to this research, a TLPM automaton can be defined as an abstraction of the process by which a carrier implements a given boundedly rational behavior in a TLPM. A TLPM automaton can be defined by the eight-tuple $(Z^i, \mathrm{z}_0^i, \Xi, \xi_0^i, S, \mathrm{b}^i, \mathrm{u}^i, \mathrm{a}^i)$ comprised by:

Z^i the set of possible states (private information states) ;

z_0^i the initial state for carrier i;

Ξ the set of possible price functions;

ξ_0^i the initial price function for carrier i;

$s_j \in S$ the stimulus sent by marketplace;

$\mathrm{b}^i : Z^i \times \Xi \times S \rightarrow R$ the bidding (output) function;

$\mathrm{u}^i : h \times \Xi \rightarrow \Xi$ the update function (updates the price function $\xi \in \Xi$) ; and

$\mathrm{a}^i : Z^i \times S \rightarrow Z^i$ the assignment function (assignment if an auction is won).

A TLPM automaton would work in the following way: the initial state and price function are z_0^i and ξ_0^i respectively, the automaton chooses a bid $\mathrm{b}^i(z_0^i, \xi_0^i, s_1)$ when the first shipment arrives. If carrier i wins, the assignment function updates the carrier's status $\mathrm{a}^i(z_0^i, s_1)$. The price function is updated based on the information revealed after the auction $\mathrm{u}^i(h_1, \xi_0^i)$. When the second shipment arrives the same process is repeated but starting with the new state and price function z_1^i and ξ_1^i respectively. Once the initial conditions are set, the transitions, bidding, and updating are set by the arrival of shipments. A TLPM automata game takes place when a player cannot change the working of his machine during the course of the game.

The two learning approaches described in this chapter, reinforcement learning and fictitious play, can be interpreted as the work of an automaton (which is valid in general for any learning strategy that seeks or uses no knowledge about the competitors' behavior). Therefore, the simulation results presented in this or previous chapters can also be interpreted as the interaction or competition of TLPM automata (which may represent the behavior of human, computerized, or hybrid dispatchers).

A boundedly rational behavior connects the status of the carrier and the system with the action or decision that the carrier takes. It is assumed in this research that for a given status, price function, and stimulus, an action has the same probability of being played; as if the decision process is *wired-up* and cannot change (data and information can change over time, but not the decision-making process). This is consistent (in the short-medium term) with the industry experience (Powell, 2002).

6.6. Bidding Factors and Marginal Cost Pricing in Second Price Auctions

In chapter 4, it was assumed (in auction analysis of algorithms) that carriers bid their best cost estimation. In chapter 2, it was shown that a significant characteristic of one-item second price auction is also value/cost bidding. That characteristic cannot be necessarily maintained in multiunit sequential auctions setting such as the TLPM marketplace. Actually, it was shown in chapter 4 that the static marginal cost is not an optimal strategy (adding or subtracting the opportunity costs using the 1FOOC technology provides better results).

This chapter deals with boundedly rational learning in competitive no-knowledge settings. Of the two learning methods proposed, only reinforcement learning can be applied to second price auctions[2]. In the TLPM context, the objective of reinforcement learning is to "learn" what the best bidding coefficient is; the bidding coefficient that maximizes a carrier's profits.

The reminder of this section addresses the following question: in a TLPM second price auction environment can carriers be better off by using bidding factors?

[2] Fictitious play in a second price auction coincides with marginal cost bidding. Regardless of the price distribution, the expected profit is always optimized with marginal cost bidding.

This question is answered using computational experiments. The auction settings utilized herein are similar to those described in chapter 3 and used in chapter 4. For consistency, all the simulations results shown in this chapter are obtained for shipments with medium time window width.

In order to answer the question put forward earlier, the following simulation experiment is carried out. Two carriers using the same type of technology compete against each other using the same simulation setting used in chapter 4. However, while one carrier bids the marginal cost (called MC carrier) the other bids the marginal cost multiplied by a bidding factor (called BF carrier). Eleven different bidding factors are utilized, ranging from 0.5 to 1.5. The impact of these factors on carrier BF's profits are depicted in FigureFigure 22. The profit levels of a BF carrier when the bidding factor is equal to 1.0 are used as the reference or base level – they correspond to 100% level. Both carriers are using the SFO technology (defined in chapter 4, section 4.7).

The results depicted in Figure Figure 22 show that for low arrival rates the best bidding factor is 1.0, corresponding to simply bidding the marginal cost. For medium arrival rates the best bidding factor is 1.1. For high arrival rates the best bidding factor is 1.3. Regardless of the arrival rate level, the "curve" is quite flat around the "optimal". Furthermore, if the profits are connected the resulting curve is concave-shaped.

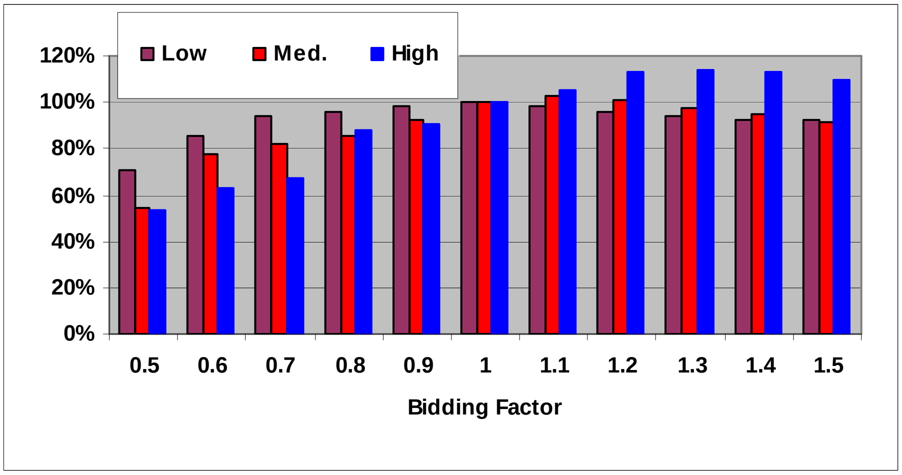

Figure 22 Profit Level for a BF Carrier

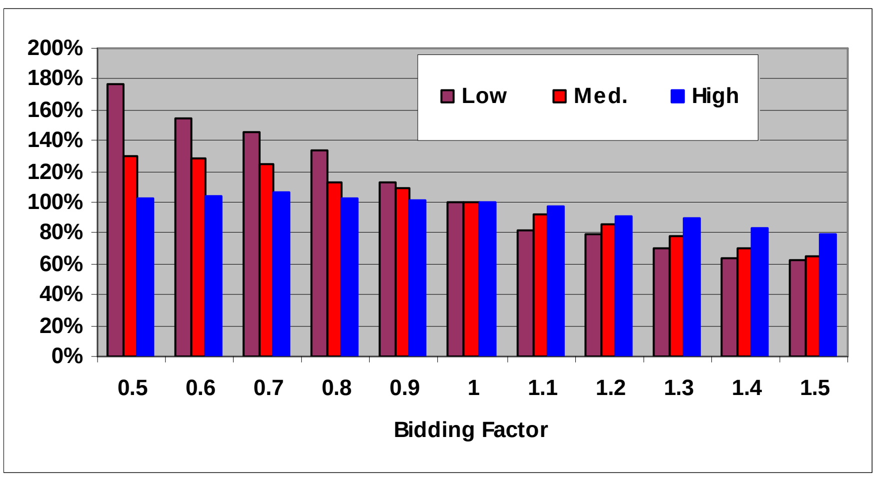

Figure 23 Shipments Served by BF carrier

A possible explanation to the results of Figure 22 may be obtained by analyzing how profits are generated. Total profits can be expressed as the average profit obtained per shipment multiplied by the number of shipments served. Figures 23 and 24 show the impact of bidding factors on number of shipments served and average shipment served profit respectively. Again, the number of shipments served and average profit used as reference are those of a BF carrier when the bidding factor is equal to 1.0.

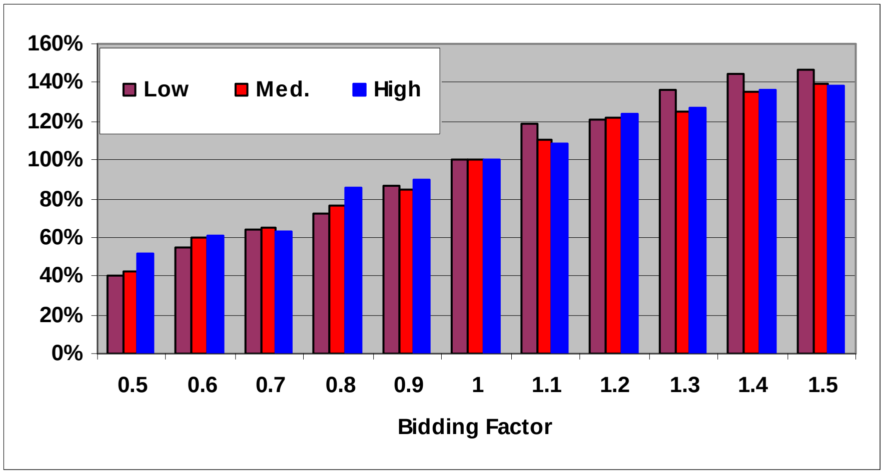

Figure 24 Average Profit per Shipment Won for a BF Carrier

It is clear from Figures 23 and 24 that, as expected, higher bidding factors increase the average profit per shipment won but decreases the number of shipments won. Vice versa, lower bidding factors decrease the average profit per shipment won but increases the number of shipments won. There are clearly two opposing forces at work when the bidding factor changes; this fact helps to explain the concave shape of the profit curve in Figure 22.

At this point, it has not yet been explained why the low arrival rate "optimal" bidding factor is around 1.0 (marginal cost case), while the "optimal" bidding factors are shifted to the right for higher arrival rates. The answer to this matter lies in the relation between profit elasticity and shipment served volume elasticity. To understand why profit elasticity and shipment served volume elasticity changes with the arrival rate is necessary to introduce Figures 25 and 26. Figure 25 and 26 illustrate the different fleet utilization rates of carriers MC and BF respectively. Fleet utilization rate is defined as the average vehicle utilization. Vehicle utilization is defined as the percentage of the time a vehicle is moving (i.e. not idle).

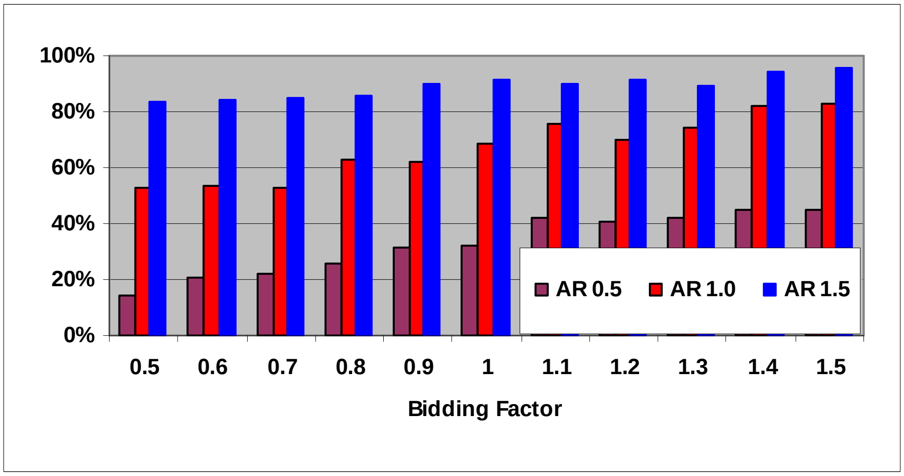

Figure 25 Fleet Utilization (MC Carrier)

With low arrival rates the utilization of the MC carrier is low (around 35% if the BF carrier uses a bidding factor equal to 1.0 - see Figure 25). Therefore when carrier BF increases his prices (utilizing higher bidding factors) carrier MC gains a significant percentage of the demand. This explains why in Figure 26 there is such an abrupt drop in demand (from 100 to 80%) when carrier BF moves from a bidding factor of 1.0 to 1.1. With higher arrival rates the fleet utilization of carrier MC is higher (at or over 70% - see Figure 25) and at very high utilization rates it is more difficult to accommodate or to inexpensively add new shipments. As fleet utilization grows the capacity to serve new shipments decreases, therefore on average the opportunity costs of serving additional shipments starts to be significant. Figure 26 is the reverse mirror image of Figure 25. With high arrival rates carrier BF can rise prices substantially and still have a high fleet utilization; the increase in profits prevails over the decrease in shipments served.

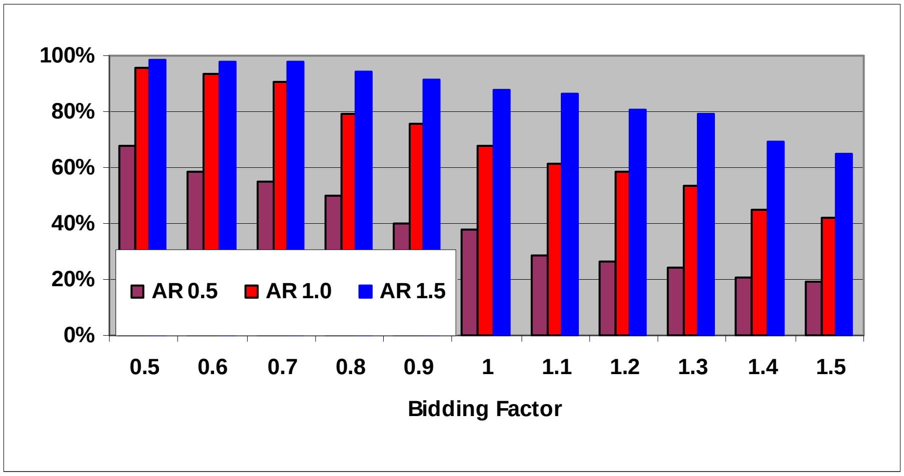

Figure 26 Fleet Utilization (BF Carrier)

The explanation provided is plausible but not definitive. However, similar phenomena as the ones observed in Figures 22, 23, 24, 25, and 26 have been widely recognized in the economics-industrial organization literature. The incentives to increase prices as remaining market capacity decreases are contemplated in price-capacity oligopoly models. For example, in the Edgeworth-Bertrand model of competition, pricing is at marginal cost levels when demand is low, however prices increase after a critical capacity utilization threshold is surpassed (Martin, 1993). Similar intuition was obtained from Benoit and Krishna (2001) model of capacity constrained auctions, with limited capacity it is advantageous to speculate (this model was analyzed in chapter 2 section 2.6). Even in fleet management, the idea of filtering out shipments or similarly increasing the "admission" price of shipments under very high arrival rate conditions has been previously used (though not in a competitive environment). The Kim, Mahmassani, and Jaillet (2002) study indicates that a fleet dispatcher under very high arrival rates (over capacity) is better off filtering out some demands (not being too close to capacity).

Similar results are also found when carriers use other technologies such as the naïve or 1FOOC. Figure 27 shows the profit changes when both carriers use naive technologies. Even when carriers have different technologies, similar results can be expected. Figure 28 shows the profit changes for the BF carrier using naïve technology against a MC carrier using SFO technology.

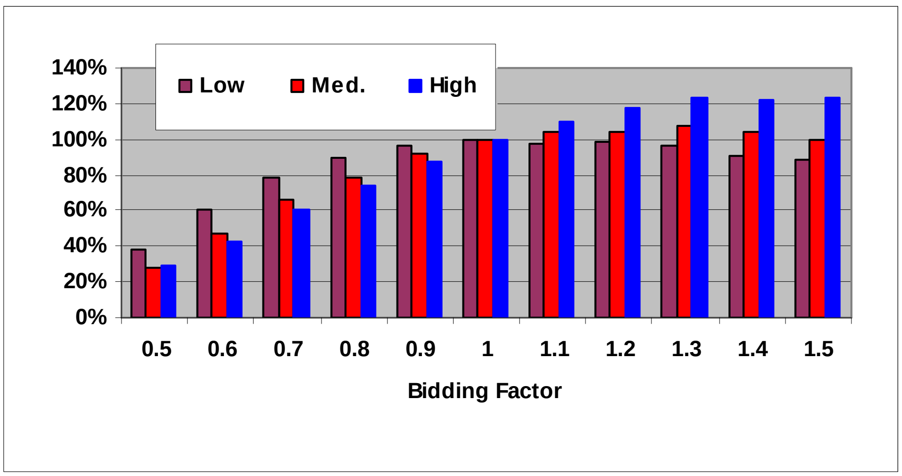

Figure 27 Profit Level for a BF Carrier (both carrier use naïve technology)

The question that motivated these simulations was: in a TLPM second price auction environment can carriers be better off by using bidding factors? The answer is yes, but only at high arrival rates. This answer provides additional insights into the applicability of auction analysis to online algorithms/technologies. The results confirm the notion that DVR technological leadership can be better exploited under low to moderate arrival rate conditions, where there is no incentive to adopt bidding factors that are not one. If there is an incentive to adopt bidding factors that are higher than one, there is an incentive to restrain capacity or to increase prices (profits are increased without increasing fleet management efficiency). As reflected by the results of chapter 4, as the arrival rate grows the advantage of being more efficient decreases; in general, scarcity exposes the incompetent while abundance hides inefficiencies.

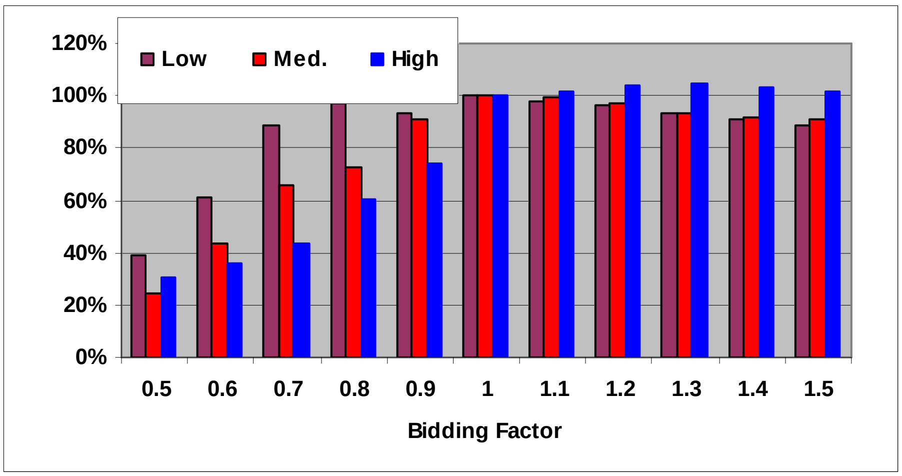

Figure 28 Profit Level for a BF Carrier (SFO vs. naïve technology)

6.7. Learning Methods Performance

This section addresses the issue of learning performance of the two learning methods presented in this chapter. The previous section shows that bidding factors can be used to increase carriers' profits in TLPM second price auctions with high arrival rates. Reinforcement learning could be used to "learn" which bidding factors produce a higher profits on average; as the auction results accumulates the most profitable bidding factors continuously increase their probability of being used. With low arrival rates, there is nothing to learn but the fact that marginal cost bidding (bidding factor 1.0) is the best alternative.

Learning can be expensive though. For example, in a second price auction the longer it takes a bidder to learn that underbidding (bidding below his marginal costs) is not a good strategy, the more the bidder loses potential profits. The importance of the right learning coefficient then becomes evident. If the learning coefficient λ is too small learning is too slow; if λ is too big it may lock the learning algorithm in an undesirable bidding factor too quickly. Another important element is the number of alternatives that the learning algorithm must choose from; as a general rule, the more the alternatives the smaller the λ.

The speed of reinforcement learning can be quite slow in an auction setting like TLPM. The "optimal" bidding factor can be used and there is still roughly a 50% chance of losing (assuming two bidders with equal fleets and technologies). If the "optimal" bidding factor loses two or three times its chances of being played again may reduce considerably which hinders convergence to the "optimal" or even convergence at all. As discussed in section 6.3, this issue can be avoided using "averages" (ARL method).

Figure 29 illustrates the relative performance of Average Reinforcement Learning (ARL) and Reinforcement Learning (RL) in a first price auction. Both learning methods select a bidding factor among 11 different possibilities, ranging from 1.0 to 2.0 in intervals of 0.1. The learning factor is $\lambda = 0.10$. Figure 29 shows the relative performance of ARL and RL after 500 auctions.

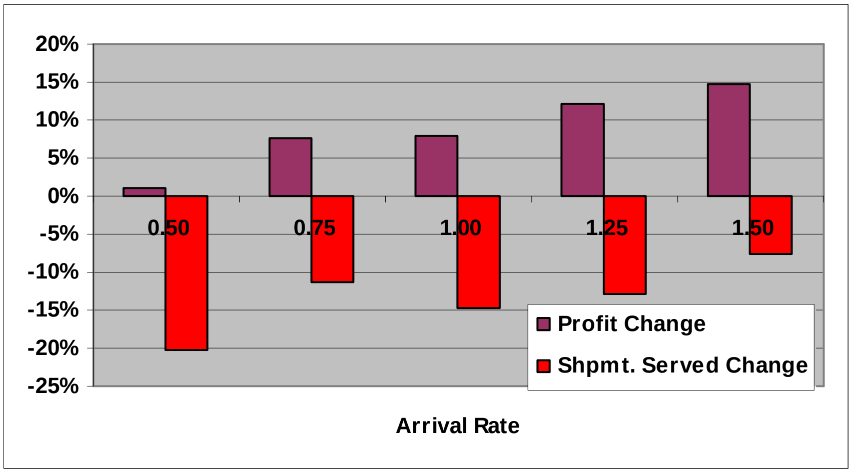

Figure 29 ARL vs. RL (RL performance base of comparison)

It is clear that RLA obtains higher profits as the arrival rate increases. RL has a poorer performance because it cannot converge steadily to the "optimal" coefficient due to the reasons mentioned in the previous paragraph. The carrier RL tends to price lower (it keeps probing low bidding coefficients longer) and therefore serves a higher number of shipments. As shown in the previous section, as arrival rates increase after a critical point, a carrier can charge higher prices regardless of what the competitor is doing.

In first price auctions reinforcement learning and fictitious play can be used. The latter uses more information than the former. Therefore, it is expected that a carrier using fictitious play must outperform a carrier using reinforcement learning. Figure 30 shows the relative performance of Fictitious Play (FP) and ARL after 500 auctions. The ARL player is the same as in Figure 29. The FP carrier divides the possible competitors' bids in 15 intervals (from 0.0 to 1.5 in intervals of width 0.1) and start with a uniform probability distribution over them.

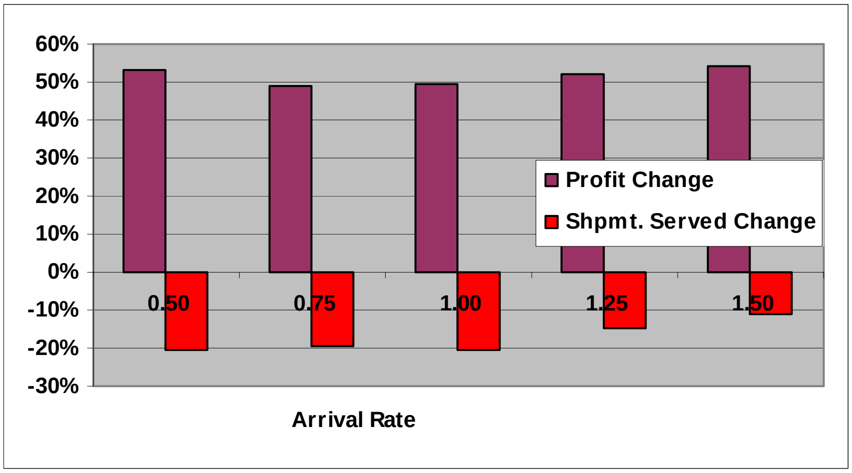

Figure 30 ARL vs. FP (RL performance base of comparison)

Clearly the FP carrier obtains higher profits across the board. The usage of a competitor past bidding data to obtain the bid that maximizes expected profits clearly pays off. In this case carrier ARL tends to bid less and serve more shipments, again, the difference diminished as the arrival rate increase. In the TLPM context even a simple static optimization provides better results than a search based on reinforcement learning. Not surprisingly, more information and optimization lead to better results. Therefore, if there is maximum information disclosure, carriers will choose to play fictitious play or a similar bidding strategy, especially since the complexity of FP (myopic) and ARL are not too different.

6.8. Comparing Auction Settings

This section describes computational results obtained from TLPM competition with different sequential auction settings. Within the competitive no-knowledge assumptions stated at the beginning of the chapter, three basic auction settings are compared: second price auction with marginal cost bidding, first price auction with reinforcement learning, and first price auction with fictitious play.

Four different measures are used to compare the auction environments: carriers' profits, consumer surplus, number of shipments served, and total wealth generated. To facilitate comparisons in all the four graphs that are presented subsequently, second price auctions with marginal cost bidding are used as the standard to measure up the two types of first price auction. All two carriers use SFO technologies.

Figure 31 illustrates the profits obtained by carriers. After the results of the previous section, it is not surprising that FP carriers obtain higher profits than ARL carriers. FP carriers use the obtained price information to their advantage. The highest carrier profit levels takes place with the second price auctions. These results do not alter or contradict theoretical results. With asymmetric cost distribution functions, Maskin and Riley (2002) show that there is not revenue ordering between independent value first and second price auctions.

Figure 32 illustrates the consumer surplus obtained with the three auction types. Clearly, first price auction with reinforcement learning (minimum information disclosed) benefit shippers. Unsurprisingly, Figure 32 is almost the reverse image of Figure 31.

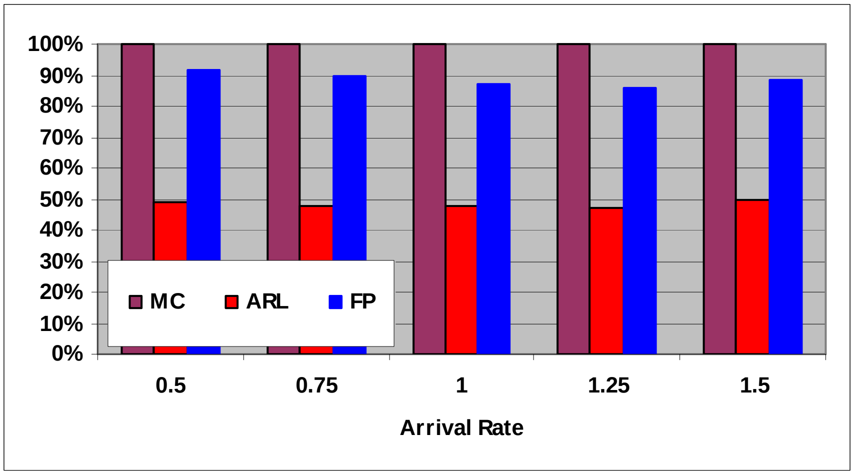

Figure 31 Carriers' Profit level (Second Price Auction MC as base)

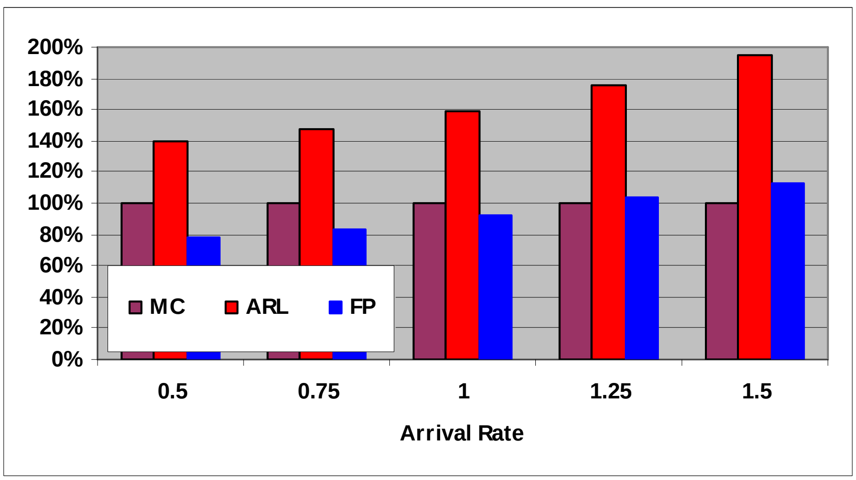

Figure 32 Consumer Surplus level (Second Price Auction MC as base)

Figure 33 shows the number of shipments served with each auction setting. As expected, with second price auctions more shipments get served. Even in asymmetric auctions, it is still a weakly dominant strategy for a bidder to bid his value in a second price auction – recall that this property of one-item second price auction is independent of the competitors' valuations. Therefore, in the second price auction the shipment goes to the carrier with the lowest cost.

In contrast, with ARL there is a positive probability that there are inefficient assignments since a higher cost competitor can use a bidding coefficient that results in a lower bid. Similarly with FP carriers, if the price functions are different (which is very likely since each carrier models the competitors' prices), a lower cost carrier can be underbid by a higher cost carrier with a positive probability. The results of Figures 32 and 33 are similar to the insights provided by the reverse auction model with elastic demand (chapter 2, section 4.6), where introducing higher price uncertainty decreases prices (carriers' profits) but also decreases the probability of completing a potentially feasible transaction (number of shipments served).

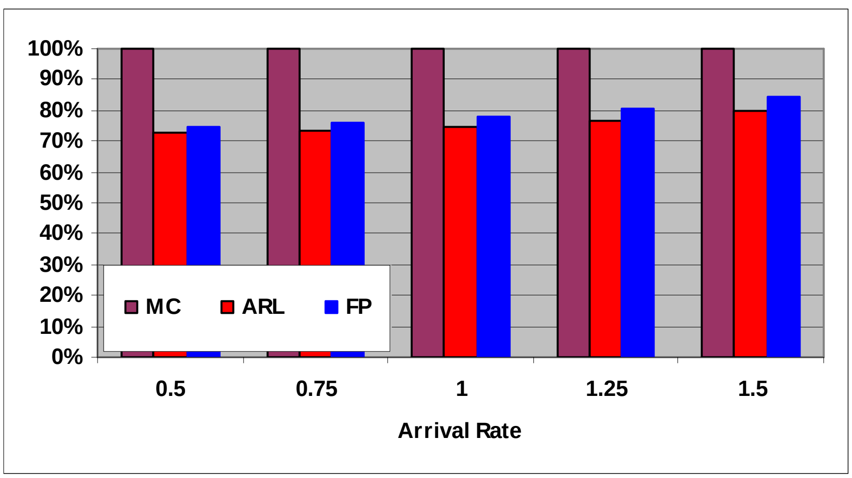

Figure 33 Number of Shipments Served (Second Price Auction MC as base)

Figure 34 shows the wealth generated with each auction setting. Predictably, with second price auctions more wealth is generated. It was already mentioned in chapter 3 that marginal cost bidding is a "price efficient" mechanism. As the arrival rate increases the gap in total wealth generated tends to close up (Figure 34). Consistently, the lowest wealth generated corresponds to the case with FP bidders.

Summarizing, under the current TLPM setting, carriers, shippers, and a social planner would each select a different auction setting. Carriers would like to choose a second price auction. If first price auction are used, carriers would like to have maximum information disclosure. More information allows players to maximize profits, though total wealth generated is the lowest. Shippers would like to choose a first price auction with minimum information disclosure; more uncertainty about winning leads carriers to offer lower prices. However, the uncertainty leads to a reduction in the number of shipments served. Finally, from society viewpoint the most efficient system is the second price auction. More shipments are served and more wealth is generated.

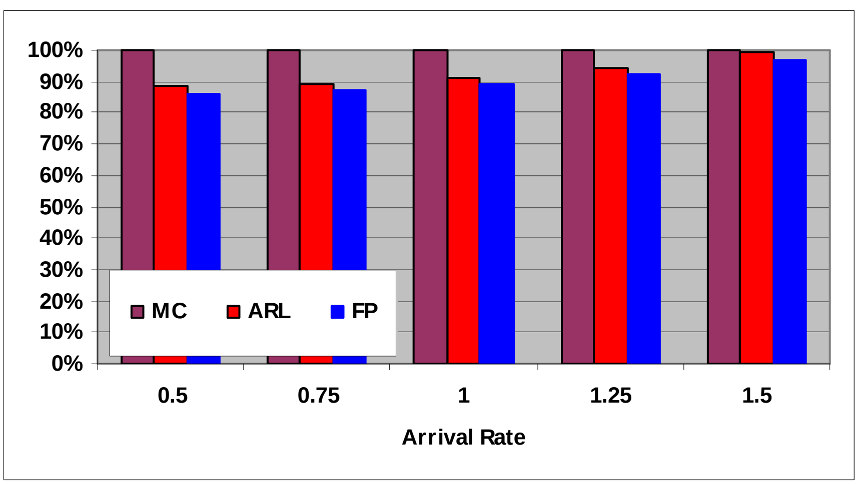

Figure 34 Total Wealth Generated (Second Price Auction MC as base)

6.8.1. Auction Settings and DVR Technology Benefits

The final set of experiments looks at how auction settings impact the competitive edge that a more sophisticated DVR can provide. Figure 35 illustrates the profit improvement of a carrier using a SFO technology over a carrier using the naïve technology. As expected, the second price auction better rewards a lower cost carrier. Again, this can be attributed to the lack of speculation about prices, which removes unnecessary speculation about competitors. This type of result also validates experimentally the second price auction as the best methodology (chosen in chapter 4) for auction analysis of algorithms.

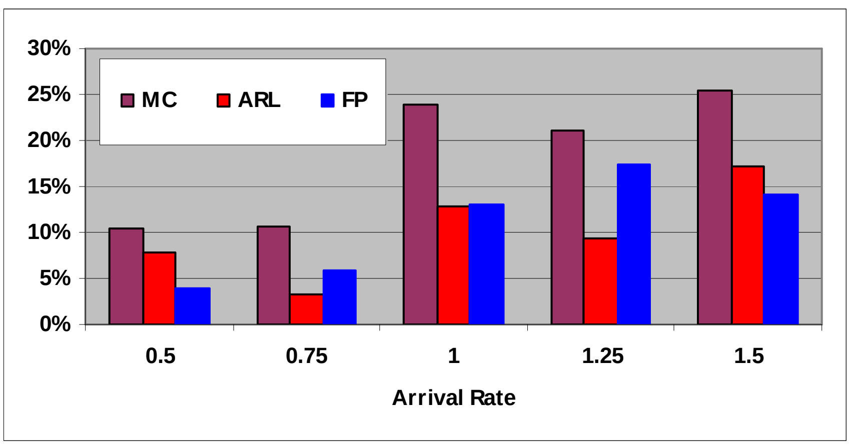

Figure 35 Impact of Auction Type and Technology upgrading on Profits

6.9. Summary

Chapter 6 studied the bidding behavior of carriers in a competitive setting where carriers are unable to use causal models of competitors' behaviors. Reinforcement learning and fictitious play, two learning methodologies for this type auction setting and assumptions are introduced and analyzed, as well as carrier learning and behavioral assumptions. Simulation of different bidding and fleet management strategies was utilized to evaluate the performance of different auction settings.

Computational experiments indicate that auction setting and information disclosure matters. Maximum information disclosure allows carriers to maximize profits at the expense of shippers' consumer surplus; minimum information disclosure allows shippers to maximize consumer surplus but at the expense of lowering the number of shipments served. Marginal bidding in second price auctions remains the most efficient incentive compatible auction mechanism, producing more wealth and more shipments served than first price auctions. It is demonstrated that under critical arrival rate there is no incentive to use bidding factors (no deviations from static marginal cost bidding). Furthermore, second price auction TLPM is the mechanism that provides the highest reward to carriers with more sophisticated DVR technology.

Chapter 7: Contributions, Extensions, and Future Research

In this concluding chapter, the first section summarizes the main findings and contributions. The second section articulates the limitations and opportunities for future research.

This research establishes a new type of problem environment in the area of Transportation Science and Operations Research, the TLPM (truckload procurement market), within which several specific problems are defined and formulated. Throughout the chapters, effort is made to properly position this new problem environment relative to the existing body of research. One salient characteristic of this research is that it uses sequential auctions to model an ongoing transportation market; therefore the problem is characterized as essentially dynamic. Market competition is used to study carriers' technologies and decision making processes. In a broad sense, this research is about the decision making complexity that carriers face in a competitive market, where decisions involve not only the management of the fleet but also the pricing of provided services

*7.1. **Contributions***

The original contributions of this research are intertwined and distributed throughout the chapters. For clearer understanding and exposition, the contributions are grouped into three areas of research. In decreasing order of generality, the areas are: auctions, transportation marketplaces, and dynamic vehicle routing and pricing.

7.1.1. Auctions

This research uses sequential auctions in a novel environment with a novel commodity (TL services). Previous work in auctions is limited to homogenous or heterogeneous objects which are characterized by cost or value (and arrival time in some on-line auctions). The TLPM object traded in that market is characterized along multiple dimensions, such as arrival time, time windows, origin, destination, etc. Furthermore, bidders (carriers) do not know the real cost of servicing them. Calculating the optimal bid (or even the service cost) involves complex optimization problems that are beyond the usual capability of ordinary carriers. The characterization and comparison of the TLPM model in relation to standard auction models is performed in chapter 2.

The TLPM problem is formulated as an incomplete multi-stage game under imperfect information in chapter 3. The complexity of solution assuming rational bidders is discussed. Furthermore, chapter 5 analyzes the complexity of TLPM bidding for first and second price auctions. It is concluded that second price auctions are not only equal or less computationally burdensome but also that in second price auction environments carriers have less incentive to utilize their scarce computational resources in estimating their competitors' bids. In addition, it is shown in chapter 6 that a second price auction TLPM is the mechanism that provides the highest reward to carriers with more sophisticated DVR technology. It is also the most efficient mechanism.

The contribution to the characterization of auctions is two-fold. First, a considerably richer environment and auction object is considered. Second, the usual assumptions of the archetypical rational bidder are relaxed, resulting in more realistic assumptions that help bridge theory-practice gaps in complex environments; auction theory must not be just about idealized models but should also be useful for practice and policy making.

7.1.2. Transportation Marketplaces

Dynamic aspects are explicitly included in the TLPM problem environment, which fundamentally distinguishes this work from contributions in the area of combinatorial auctions for transportation (limited to a static approach). At the same time, fleet management operational aspects are fully incorporated, which sets this research apart relative to general procurement studies or to the analysis of shipper-carrier relationships. Therefore, characterizing activities of the TLPM as a bi-level allocation problem, using prices/bids to allocate shipments among carriers and costs to allocate shipments to trucks, constitutes a contribution to the study of transportation marketplaces.

Chapter 5 characterizes the competitive behavior of carriers as the result of carriers' technology and their bounded rationality (intrinsic elements), auction rules, and the strategic setting (extrinsic elements). Chapter 6 circumscribes competition to a setting in which carriers are unable to discover or use competitors' private information. The emphasis is on "learning" good bidding strategies based on previous experience and market prices.

The contribution of chapters 5 and 6 is to provide an alternative framework to traditional models of behavior, equilibrium, decision-making, and analysis for transportation carriers. Decision making and behavior are defined as an expression of the goals, and bounded rationality of the carrier as the type of pricing/bidding/fleet management problem that the carrier is able to tackle. Table 2 coupled with the appropriate learning mechanisms (for example reinforcement learning and fictitious play when aplicable) embody the approach to carrier behavior proposed in this research.

The computational results of chapter 6 indicate the importance of market and auction design in the performance of the TL market. Computational experiments indicate that auction setting and information disclosure affect the performance of the marketplace. Maximum information disclosure allows carriers to maximize profit at the expense of shippers' consumer surplus; minimum information disclosure allows shippers to maximize consumer surplus but at the expense of lowering the number of shipments served. Chapter 6 also studies the influence of learning (fictitious play and reinforcement learning) on market performance and technological asymmetries.

Finally, a significant contribution is the quantification of the potential gains to carriers and shippers of service procurement through real time transportation markets. The economies of density, volume, and scope of transportation have long been articulated, though largely based on static settings. Computational experiments performed in chapter 4 show that the proposed usage of sequential second price auctions could provide a new tool to quantify the advantages of real-time competitive markets (as in wealth creation). The flexibility of the method allows the incorporation of new elements such as the effect of time windows, which were not considered in previous economic static analysis of transportation systems.

It is also shown in chapter 4 that economics of market integration are also incentive compatible, which may lead to resale markets for carrier companies that handle only private contracts. The advent and diffusion of information and communication technologies give rise to real opportunities for wealth generation in real time exchange. Economies of integration also have the benefit of keeping carriers' decision problem complexity bounded to the same original level and (as already mentioned) incentive compatibility – assuming the market is truth revealing.

7.1.3. Dynamic Vehicle Routing and Pricing

The performance evaluation of dynamic vehicle routing technologies is problematic. The existing evaluation paradigm (competitive analysis) does not possess all the desired characteristics of an evaluation tool, especially in a marketplace, as discussed in chapter 4. This research proposes a new methodology, auction analysis, to evaluate dynamic vehicle routing technologies. The methodology is particularly suitable when the technology is applied in a marketplace. Moreover, the methodology has adequate theoretical properties. Acceptance/rejection and minimal cost routing problems are special cases of auction analysis. In addition, the methodology fits nicely in the bounded rationality framework presented in chapter 5. In light of the experimental results of chapter 6, the values obtained with auction analysis can be considered adequate for sequential second price auctions and an upper bound for first price auctions (under no-knowledge assumptions)

The steps of a rational decision making process are applied to fleet management technologies and pricing problems in chapter 5. These steps can be applied to dissect the sophistication of dynamic vehicle routing technologies. A new technology that better evaluates the consequences of current fleet and bidding decisions on future auctions is presented in chapter 4 (1FOOC technology). This technology outperforms static approaches and uses simulation to determine the profit impact of serving a shipment in the next auctions; these impacts can be interpreted as the opportunity costs (positive or negative) of serving a shipment.

Chapter 5 links carriers' technology, decision making, computational resources, bounded rationality, and problem selection to a family of pricing/fleet management problems. Furthermore, by assuming no-knowledge about the competition's private values or bounded rationality, a TLPM automaton can represent the behavior, learning, and problem solving abilities of a carrier. As expressed in chapter 6, behavior with this level of sophistication can be expected in transportation marketplaces, though levels of sophistication may vary with the resources of the company. However, complexity levels the competitive playing field since it grows exponentially with problem size (number of trucks, shipments, competitors)

7.2. Limitations, Extensions, and Future Research Directions

This research presents a comprehensive study of the TLPM problem environment. However, as in any new problem, many important research avenues remain open. Balancing the breadth and depth of the topics covered in this research, the TLPM model considered is streamlined to its essential features and the treatment of TLPM issues are limited to the associated fundamental questions. Selected suggestions for future research are presented herein. First, suggestions that expand the scope of the studied TLPM are presented; second, suggestions that deepen our knowledge in some selected topics are presented. Last, some reflections about general directions for future research are presented.

7.2.1. Limitations

A key assumption made in the TLPM study was the sequential treatment of one-item auctions. It is clear that the complementary effects of two or more shipments are explicitly ignored in the auction design, even though the effects of complementary shipments may be indirectly present in some strategies (i.e. the 1FOOC strategy). If two or more shipments are bundled together, the new marketplace leads to the appealing concept of *online-combinatorial auctions*. This new type of sequential auction may present a new array of incentive compatibility issues for carriers and shippers, pricing issues, and trade-offs among bundle size, complexity, and the real time information arrival rate.

The role of shippers is fairly limited. In this research, shippers do not use the information revealed by the sequential auctions to set reservation prices, nor do they try to maximize their profits (no learning or attempt to manipulate the market). What could the impact of shipper speculation on the transportation marketplace be?

Even though carriers and shippers are always assumed to be profit maximizers, the impact of explicitly gaming (cheating) the system is not analyzed (e.g.. shilling, the use of fake players by the carriers or shippers). How vulnerable are the presented sequential auction mechanisms to cheating or collusion?

7.2.2. Extensions

A possible extension is the development of more sophisticated dynamic vehicle routing technologies. It was already mentioned that the 1FOOC technology might be improved by extending the look-ahead depth (two or more auctions ahead) or evaluating a larger set of fleet deployments. Both approaches would be challenging. Extending the look-ahead increases the complexity of the problem considerably. The development of efficient heuristics or approximate approaches, and the evaluation of deeper look-ahead advantages are natural extensions. On the other hand, it is equally challenging to develop methodologies that select alternative fleet deployments which favorably position the carrier for the upcoming auctions.

The learning mechanisms proposed in chapter 6 are standard and well accepted. Reinforcement learning was adapted to the TLPM environment; a new method using average profit data improved the carrier's performance. It is still an open challenge to improve on those learning mechanisms without substantially increasing the complexity of the learning problem. Knowledge acquisition about competitors appears to substantially increase the complexity of the problem. It may be worth exploring straightforward methods of knowledge acquisition and usage problems, as well as the trade-offs between knowledge acquisition and market performance. Pattern recognition techniques may provide an effective learning tool without compromising too many computational resources.

The properties and characteristics of the proposed auction analysis of algorithms could be further evaluated and analyzed, possibly extending the concept to other online problems. From the technological standpoint, what is the impact of information availability, competition, and market settings on encouraging technological development and adoption in a competitive marketplace?

7.2.3. Future Research Directions

Previous research ideas dealt with applications, limitations, and extensions of the core TLPM framework and associated problems. In an increasingly changing technological world, exploring issues that are likely to impact society and the economy is valuable. The next paragraphs deal with the general direction of future research, which are loosely based on this research work as well as on contemporaneous trends.

As information and communication technologies become ubiquitous, the low cost of up-to-date information may enable economic agents (both human and automaton agents) to be better informed about their environment. As the number of connections and agents in the system increases, it is expected that the rate of information arrival, events, and complexity will increase. At the same time, the concepts of static conditions and "full" optimization become less relevant. On the other hand, avoiding information overload and dealing effectively with complexity seem more relevant than ever before.

An increasingly interconnected world, where decision makers deal with information overload and scarce resources (time, attention, and knowledge), requires the systematic incorporation of behavioral constraints in optimization problems. The application of operations research techniques and methods to complex transportation problems will have to deal increasingly with agents' limitations and behavioral aspects.

As behavioral constraints are incorporated in optimization problems, the type of problem to solve (i.e. problem types as in Table 2) may itself become a decision dimension. Closer collaboration between operations research and behavioral sciences seems inevitable.

Appendix A: Online Matching Services

List of online matching services (March 2001). Source:

www.landlinemag.com/Archives/2001/Mar2001/Your_Money/load_boards.html

www.expediteloads.com

www.dat.com

www.cargolinx.com

www.LoadScout.com

www.efreightservices.com

www.getloaded.com

www.truckwebusa.com

www.besttransport.com

www.truckit.com

www.freightlist.com

www.loadlinkonline.com

www.truckloadfreight.com

www.transportation.com

www.directfreight.com

www.internettruckstop.com

www.itruckers.com

www.drivernet.com

www.carrierpoint.com

www.nettrans.com

www.BeBrokerFree.com

www.loglink.net

www.americasloadsonline.com

www.backhaul.net

www.cargofinder.com

www.dventerprises.com

www.eFlatbed.com

www.freightmarket.com

www.ifs.net

www.internetlog.com

www.freight-terminal.com

www.i-t-n.com

www.truckstop.com

www.linklogi.com

www.loadline.net

www.loadmatch.com

www.loadsource.com

www.loadxchange.com

www.moversconnect.com

www.nte.net

www.routelink.com

www.loaddock.com

www.loadingzone.com

www.theroad.com

www.transerv.com

www.cargox.com

Appendix B: Acronyms

The format used in the alphabetical ordered list of acronyms is the following: acronym, description, page where first used, chapter.

1FOOC: one (1) Fleet Optimal Opportunity Cost, page 115, chapter 4

3PL: Third Party Logistics, page 4, chapter 1

ARL: Average Reinforcement Learning, page 207, chapter 6

BF: Bidding Factor carrier, page 200, chapter 6

DVR: Dynamic Vehicle Routing, page 82, chapter 4

EDI: Electronic Data Interchange, page 7, chapter 1

MC: Marginal Cost carrier, page 200, chapter 6

FP: Fictitious Play, page 208, chapter 6

ICT: Information and Communication Technologies, page 1, chapter 1

JIT: Just In Time, page 6, chapter 1

RL: Reinforcement Learning, page 207, chapter 6

SFO: Static Fleet Optimal, page 114, chapter 4

SIPV: Symmetric Independent Private Values, page 27, chapter 2

TL: Truck Load, page 3, chapter 1.

TLPM: Truck Load Procurement Market, page 3, chapter 1

TSP: Traveling Salesman Problem, page 89, chapter 4

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