Auction Settings and Performance of Electronic Marketplaces for Truckload Transportation Services

Miguel Andres Figliozzi
University of Sydney
Institute of Transport Studies (C37)
Faculty of Economics and Business
Sydney, NSW 2006 Australia
miguel@its.usyd.edu.au

Hani S. Mahmassani
University of Maryland, College Park
Department of Civil & Environmental Engineering
Martin Hall, College Park, MD 20742
masmah@umd.edu

and

Patrick Jaillet
Massachusetts Institute of Technology
Department of Civil & Environmental Engineering
Cambridge, MA 02139-4307
jaillet@MIT.EDU

August 1, 2004

Submitted for presentation at the 84rd Annual Meeting of the Transportation Research Board, and publication in Transportation Research Record

Number of words: 5179 + 1500

Auction Settings and Performance of Electronic Marketplaces for Truckload Transportation Services

Miguel A. Figliozzi, Hani S. Mahmassani and Patrick Jaillet

Abstract

This paper compares the performance of different sequential auction settings for the procurement of truckload services. In this environment, demands arrive randomly over time and are described by pick up, delivery locations and hard time-windows. Upon demand arrival, carriers compete for the loads. Different auction and information disclosure settings are studied. Learning methodologies are discussed and analyzed. Simulation results are presented.

KEYWORDS: Freight Transportation, Carrier Management Strategies, Carrier Profitability, Information Technology, Bidding Strategies, Electronic Commerce, Auctions.

INTRODUCTION

Recent research in auction and marketplace design highlights the importance of auction rules on bidders and market performance (1 and 2). The principal focus of this research is to compare and evaluate the impact of distinct auction rules on the performance of a transportation marketplace. This investigation focuses on the dynamic procurement of truckload pickup-and-delivery services in a sequential auction transportation marketplace; this marketplace is denoted TLPM which stands for truckload procurement marketplace.

The motivation for this work arises from the growth of network business-to-business forecasts (3). This growth is partly supported by the increasing use of private exchanges, where a company or group of companies invites selected suppliers to interact in a real time marketplace, compete, and provide the required services. In the logistics sector, shippers have also set up private exchanges, which they use for confidential communications with their carriers, for example, DuPont has a logistic web portal to manage all inbound and outbound freight movements across all transportation modes (4). These exchanges allow for freight visibility as well as for consolidation and optimization opportunities (5). On the supply side, carriers have begun to offer more internet based services, particularly the larger motor carriers (6).

Carriers participating in a TLPM face complex interrelated decision problems. Two distinct problems stand out (a) profit maximization problem (chose best pricing or bidding policy) and (b) cost minimization problem (operate the fleet in the most efficient manner). Sequential auctions are notoriously complex problems; furthermore, no equilibrium solution exists when there are several auctions (three or more) and multi-unit demand bidders (7). Therefore, in this work carriers are assumed boundedly rational. In addition, due to the inherent complexity, it is assumed that TLPM carriers make not attempt to acquire or use knowledge about competitors' explicit decision (bidding) processes. Carriers solely learn about the distribution of past market prices or the relationships between realized profits and bids. Previous work has already dealt with the importance of dynamic vehicle routing technology and cost estimation in a TLPM (8).

The goal of this paper is not to find the “optimal” rules or procedures that lead to the best possible bidding. Rather, the goal is to define and simulate plausible bounded rational procedures and behaviors of carriers competing in a TLPM. Three different auction formats are compared using simulation experiments: second price auctions, first price auctions with minimum information disclosure, and first price auctions with maximum information disclosure.

The paper is organized as follows: the next section describes the marketplace framework and operation. Learning in a TLPM is discussed in the third section. Section four describes the utilized learning mechanisms. Section five describes the simulation framework. The experimental results are analyzed and discussed in section six, followed by concluding comments in the final section.

MARKET DESCRIPTION

The TLPM enables the sale of cargo capacity based mainly on price, yet still satisfies customer level of service demands. The specific focus of the study is the reverse auction format, where shippers post loads and carriers compete over them (bidding). The auctions operate in real time and transaction volumes and prices reflect the status of demand and supply. A framework to study transportation marketplaces is presented by Figliozzi, Mahmassani, and Jaillet (9).

The market is comprised of shippers that independently call for shipment procurement auctions, and carriers, that participate in them (we assume that the probability of two auctions being called at the same time is zero). Auctions are performed one at a time as shipments arrive to the auction market. Shippers generate a stream of shipments, with corresponding attributes, according to predetermined probability distribution functions. A shipment attribute is its reservation price, or maximum amount that the shipper is willing to pay for the transportation service. It is assumed that an auction announcement, bidding, and resolution take place in real time, thereby precluding the option of bidding on two auctions simultaneously.

In the TLPM there are n carriers competing, a carrier is denoted by $i \in \Im$ where $\Im = \{1, 2, ..., n\}$ is the set of all carriers. Let the shipment/auction arrival/announcement epochs be $\{t_1, t_2, ..., t_N\}$ such that $t_i < t_{i+1}$. 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. There is a one to one correspondence between each t_j and s_j (i.e. for each t_j there is just one s_j). Arrival times and shipments are not known in advance. The arrival instants $\{t_1, t_2, ..., t_N\}$ follow some general arrival process. Furthermore, arrival times and shipments are assumed to come from a probability space (Ω, F, 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 $\omega_j = \{t_j, s_j\}$.

In an auction for shipment s_j, each carrier $i \in \Im$ simultaneously bids a monetary amount $b_j^i \in R$ (every carrier must participate in each action, i.e. submit a bid). A set of bids $b_j^{\Im} = \{b_j^1, ..., b_j^n\}$ generates publicly observed information y_j. Under maximum information disclosure, all bids are revealed after the auction, this is $y_j = b_j^{\Im}$. Under minimum information disclosure, no bids are revealed after the auction, this is $y_j = \{\}$. Each carrier is solely informed about his bidding outcome: successful or unsuccessful.

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 by carrier $i \in \Im$) and V_j^i (set of vehicles in the fleet of carrier i, vehicle status updated to time t_j). The estimated cost of serving shipment s_j by carrier $i \in \Im$ of type z_j^i is denoted $\mathrm{c}^i(s_j, z_j^i)$. 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 π_j^i be the profit obtained by carrier i (if this carrier wins) for shipment s_j, then $\pi_j^i = b_j^i - c^i[s_j, \theta_j^i]$.

LEARNING IN A TLPM

In an auction context, learning methods seek good bidding strategies by approximating the behavior of competitors. Most learning methods assume that competitors' bidding behavior is stable. This assumed bidding stability is akin to believing that all competitors are in a strategic equilibrium.

Walliser (10) 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 processes. An eductive process requires knowledge about competitors' behavior (agents simulate competitors' behavior). Epistemic and behavioral learning are similar to fictitious play and reinforcement learning respectively (fully described in the next section). 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 work studies the two intermediate types of learning. Eductive-like type of play requires carriers to have almost unbounded computational power and expertise. On the other hand, evolutionary model players seem too simplistic: they have no memory, and simply 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 unskilled. They are merely limited in the strategies they can implement. It is assumed that carriers would like to implement the strategy (regardless of its complexity) that ensured higher profits, but they are restricted by their cognitive and informational (which give rise to bounded rationality).

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

Normal operating ratios in the TL industry range from 0.90 to 0.95 (11). It is expected that operating ratios in a TLPM would not radically differ from that 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, in response to 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 is quite common (12).

LEARNING MECHANISMS

In reinforcement learning 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.

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:

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

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

The first equation applies to first price auctions while the second equation 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:

$$\varphi_j^i(mc_k) = (1-\lambda\,\pi_{j-1}^i(mc_k))\varphi_{j-1}^i(mc_k) + I_{j-1}^i(mc_k)\,\lambda\,\pi_{j-1}^i(mc_k) \qquad (3)$$

To use equation (3), 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 (13) 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 (14). Furthermore, in an auction context there is no learning when the auction is lost since $\pi_{j-1}^i(mc_k)=0 \quad \forall\, mc_k \in \mathrm{M}$ if $I_{j-1}^i = 0$.

Borgers and Sarin (15) 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_j^i and the effective profit is denoted $\tilde{\pi}_{j-1}^i(mc_k) = \pi_{j-1}^i(mc_k) - \rho_j^i \quad (4)$, then

$$\varphi^i_j(mc_k) = (1-\lambda\,\tilde{\pi}^i_{j-1}(mc_k))\varphi^i_{j-1}(mc_k) + I^i_{j-1}(mc_k)\,\lambda\,\tilde{\pi}^i_{j-1}(mc_k) \qquad (5)$$

When $\rho^i_j = 0$, the equation (5) provides the same probability updating equation as (3). 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 (4) 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 a minimum 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 $\overline{\pi}^i_j(m_k)$ that is equal to:

$$\overline{\pi}^i_j(m_k) = \frac{\sum_{t\in\{1,\ldots,j\}} \pi^i_t(s_t)\; I^i_t(m_k)}{\sum_{t\in\{1,\ldots,j\}} I^i_t(m_k)}$$

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

$$\overline{\rho}^i_j = \frac{\sum_{t\in\{1,\ldots,j\}} \pi^i_t(s_t)\; I^i_t}{j}$$

Therefore the average effective profit is defined as $\overline{\pi}^i_{j-1}(mc_k) = \overline{\pi}^i_{j-1}(mc_k) - \overline{\rho}^i_j$. Probabilities are therefore updated using equation (6).

$$\varphi^i_j(mc_k) = (1-\lambda\,\overline{\pi}^i_{j-1}(mc_k))\varphi^i_{j-1}(mc_k) + I^i_{j-1}(mc_k)\,\lambda\,\overline{\pi}^i_{j-1}(mc_k) \qquad (6)$$

With the latter formulation (6), 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.

Stimulus-response learning requires the least information and can be applied to both first and second price auctions. The probability updating equations (3), (3), and (6) 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 (5) is used it is also necessary to set the aspiration level. If equation (6) 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 his 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 that 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.

Fictitious play came about as an algorithm to look for Nash equilibrium in finite games of complete information (16). 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.

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 (in our experiments carriers estimate a normal distribution using on competitors' past bids). If a second price auction format is used in the TLPM, the carrier bids using:

$$b_j^{*i} \in \underset{b \in R}{\arg\max}\ E_{(\xi)}\{\ \xi - c^i(s_j, z_j^i)\}$$

If a first price auction format is used in the TLPM, the carriers bids using:

$$b_j^{*i} \in \underset{b \in R}{\arg\max}\ E_{(\xi)}\{\ (b - c^i(s_j, z_j^i)\}$$

SIMULATION FRAMEWORK

This paper studies truckload carriers that compete over a square area; the sides' lengths are equal to 1 unit of distance. For convenience, trucks travel at constant speed equal to one unit of distance per unit of time. Demands for truckload pickup-and-delivery arise over this area and over time. Origins and destinations of demands are uniformly distributed over the square area, so the average loaded distance for a request is 0.52 units of distance. All the arrivals are random; the arrival process follows a time Poisson process. The expected inter-arrival time is $E[T] = 1/(K\lambda)$, where λ is the demand request rate per vehicle and K is the total market fleet size. Roughly, the average service time for a shipment is 0.77 units of time (approximately $\lambda = 1.3$). The service time is broken down into 0.52 units of time corresponding to the average loaded distance, plus 0.25 units of time that approximate the average empty distance (average empty distance vary with arrival rates and time windows considered). Different Poisson arrival rates per truck per unit of time are simulated (ranging from 0.5 to 1.5). As a general guideline, these values correspond to situations where the carriers are:

- $\lambda = 0.5$ (uncongested)
- $\lambda = 1.0$ (congested)
- $\lambda = 1.5$ (extremely congested)

The shipments have hard time windows. In all cases, it is assumed that the earliest pickup time is the arriving time of the demand to the marketplace. The latest delivery time (LDT) is assumed to be:

LDT = arrival time + **2** x (shipment loaded distance + 0.25) + **2** x uniform (0.0, 1.0).

All the shipments have a reservation price distributed as uniform (1.42, 1.52). In all cases, reservation prices exceed the maximum marginal cost possible in the simulated area (≈1.41 units of distance). It is also assumed that all the vehicles and loads are compatible; no special equipment is required for specific loads. In all the simulations, two carriers are competing for the demands.

Multiple performance measures are used. The first is total profits, which equal the sum of all payments received by won auctions minus the empty distance incurred to serve all won shipments (it was already mentioned that shipment loaded distances are not included in the bids, loaded distances cancel out when computing profits). The second performance measure is number of auctions won or number of shipments served, an indicator of market share. The third is shippers' consumer surplus, which is the accumulated difference between reservation prices and prices paid. The fourth is total wealth generated that is equal to the accumulated difference between reservation price (of served shipments) and empty distance traveled.

Carriers fleet assignment and cost estimation is based on the static optimization based approach proposed by Yang, Jaillet and Mahmassani (17). This approach solves static snapshots of the dynamic vehicle routing problem with time windows using an exact mathematical programming formulation. As new load occurs, static snapshot problems are solved repeatedly, allowing for a complete reassignment of trucks to loads at each arrival instance.

The second price auction used in the TLPM operates as follows:

i. Each carrier submits a single bid
ii. The winner is the carrier with the lowest bid (which must be below the reservation price; otherwise the auction is declared vacant)
iii. The item (shipment) is awarded to the winner
iv. The winner is paid either the value of the second lowest bid or the reservation price, whichever is the lowest
v. The other carriers (not winners) do not win, pay, or receive anything

The same procedure applies to first price auctions but the winner is paid the value of the winning bid (only point iv changes).

ANALYSIS OF EXPERIMENTAL RESULTS

Figure 1 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 1 shows the relative performance of ARL and RL after 500 auctions. 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. 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 previously, this issue can be avoided using “averages” (ARL method). The carrier RL tends to price lower (it keeps probing low bidding coefficients longer) and therefore serves a higher number of shipments.

The next experiment compares the performance of reinforcement learning and fictitious play in first price auctions. 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 2 shows the relative performance of Fictitious Play (FP) and ARL after 500 auctions. The ARL player has the same characteristics as the ARL player utilized for Figure 1. The FP carrier divides the possible competitors’ bids in fifteen intervals (from 0.0 to 1.5 in intervals of width 0.1) and starts with a uniform probability distribution over them.

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 use fictitious play or a similar bidding strategy, particularly since the complexity of FP (myopic) and ARL are not too different.

In second price auctions fictitious play coincides with marginal cost bidding (regardless of the price distribution, the expected profit is always optimized with marginal cost bidding). RL or ARL do not perform better than FP in the simulated experiments.

The next experiment compares the performance of different sequential auction settings from carriers and shippers’ points of view. 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 amongst all 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 auctions.

Figure 3 illustrates the profits obtained by carriers. FP carriers obtain higher profits than ARL carriers across the board. FP carriers use the obtained price information to their advantage. The highest carrier profit levels take place with the second price auctions. These results do not alter or contradict theoretical results. With asymmetric cost distribution functions, Maskin and Riley (18) show that there is no revenue ordering between independent value first and second price auctions.

Figure 4 illustrates the consumer surplus obtained with the three auction types. Clearly, first price auction with reinforcement learning (minimum information disclosed) benefit shippers. Unsurprisingly, figure 4 is almost the reverse image of figure 3. Figure 5 shows the number of shipments served with each auction setting. As expected, with second price auctions more shipments are served. Even in asymmetric auctions, it is still a weakly dominant strategy for a bidder to bid his value in a second price auction (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 higher cost carrier can underbid a lower cost carrier with a positive probability.

Figure 6 shows the wealth generated with each auction setting. In second price auctions more wealth is generated across the board. Marginal cost bidding is the most "price efficient" mechanism of the tested auction settings. As the arrival rate increases, the gap in total wealth generated tends to close up (figure 6). Consistently with previous results, 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 were 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.

CONCLUSIONS

A sequential auction framework was used to compare distinct sequential auction settings. Reinforcement learning and fictitious play, two learning mechanisms adequate for TLPM settings, are introduced and analyzed.

Computational experiments indicate that auction setting and information disclosure affect the TLPM performance. 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 generates more wealth and more shipments served than first price auctions. The results illustrate that under critical arrival rate there is no incentive to use bidding factors (no deviations from static marginal cost bidding).

ACKNOWLEDGMENTS

This study was supported by a grant from the National Science Foundation, Program: NSF 00-42, Award Number: CMS-0085691.

REFERENCES

1. Klemperer P., What really matters in auction design, Journal of Economic Perspectives, V16, N1, 2002
2. Roth A., Ockenfels A., Last minute bidding and the rules of second price auctions: evidence from eBay and Amazon auctions on the internet, American Economic Review, V92, N4, 2002.
3. Mullaney T., Green H., Arndt M., Hof R., Himelstein L., “The E-BIZ Surprise”, Business Week Magazine, May 2003
4. Gilligan E., DuPont takes a global view, The Journal of Commerce, Feb. 16-22, 2004, Accessed June 2004, website: www.joc.com
5. Cooke J., For your eyes only, Logistics Management Magazine, July 1st 2002, Accessed June 2004, website: http://www.manufacturing.net/lm/index.asp?layout=articlePrint&articleID=CA232464
6. Ellinger A., Lynch D., Andzulis J., Smith R., B-to-B E-Commerce: a content analytical assessment of motor carriers websites, Journal of Business Logistics, V24, N1, pp. 199-220, 2003
7. Krishna, V., Auction Theory, Academic Press, San Diego, USA, 2002
8. Figliozzi M., Mahmassani H., and Jaillet P., Competitive Performance of Dynamic Vehicle Routing Technologies using Sequential Auctions, forthcoming in *Transportation Research Records*.

9. Figliozzi M., Mahmassani H., and Jaillet P., "A Framework for the study of Carrier Strategies in an Auction Based Transportation Marketplace", forthcoming in *Transportation Research Records*.
10. Walliser B, A spectrum of equilibration processes in game theory, Journal of Evolutionary Economics, V.8, N.1, pp. 67-87., 1998
11. TCA, 2002, Truckload Carrier Association web site, http://www.truckload.org/infocenter/TCAdocs/info_08_02_02.htm Accessed December 16th, 2004
12. Paarsh H., Deciding between Common and Private Value Paradigms in Empirical Models of Auctions, Journal of Econometrics, N15, pp 191-215, 1991
13. Narendra K., Thatcher M., Learning Automata: a survey. IEEE Transactions on Systems, Man, and Cybernetics, N4, pp. 889-899, 1974
14. Fudenberg D., Levine D., The Theory of Learning in Games, MIT Press, Cambridge Massachusetts, 1998.
15. Borges T., Sarin T., Naïve reinforcement learning with endogenous aspirations, Mimeo, University College of London, 1996
16. Brown G., 1951, Iterative Solutions of games by fictitious play. In Activity Analysis of Production and Allocation, ed. by Koopmans T., Wiley. New York.
17. Maskin E., Riley J., Asymmetric Auctions, Review of Economic Studies, V67, pp 413-438, 2000
18. Yang, J., Jaillet, P., Mahmassani, H. S. (1999) "On-Line Algorithms for Truck Fleet Assignment and Scheduling under Real-Time Information," Transportation Research Record 1667

List of Figures

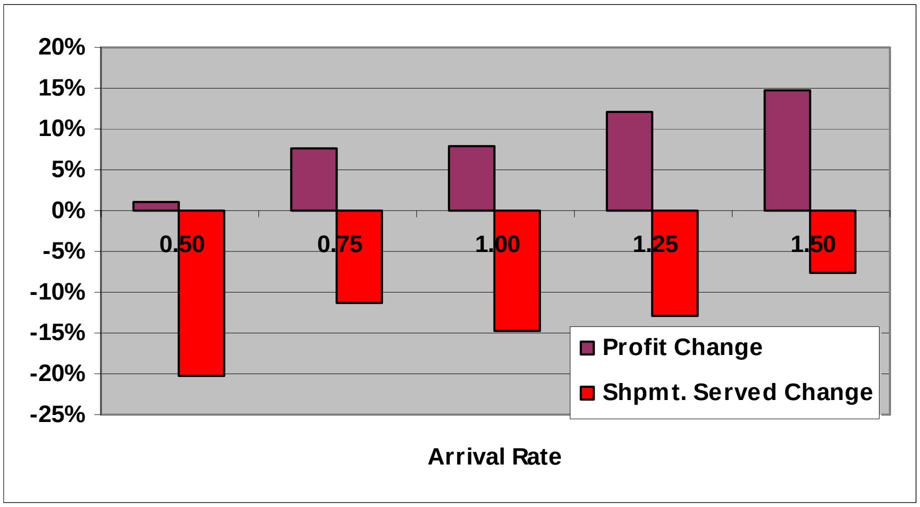

Figure 1. ARL vs. RL (RL performance as a base)

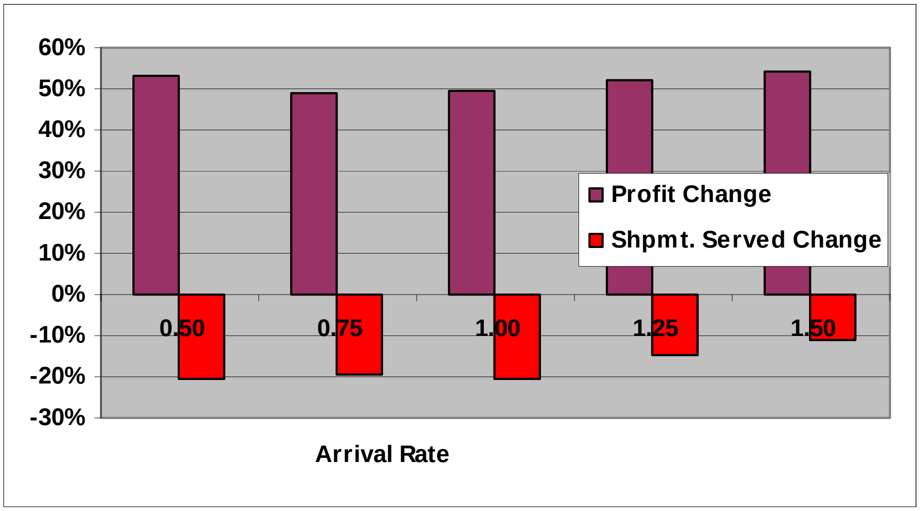

Figure 2 ARL vs. FP (RL performance as a base)

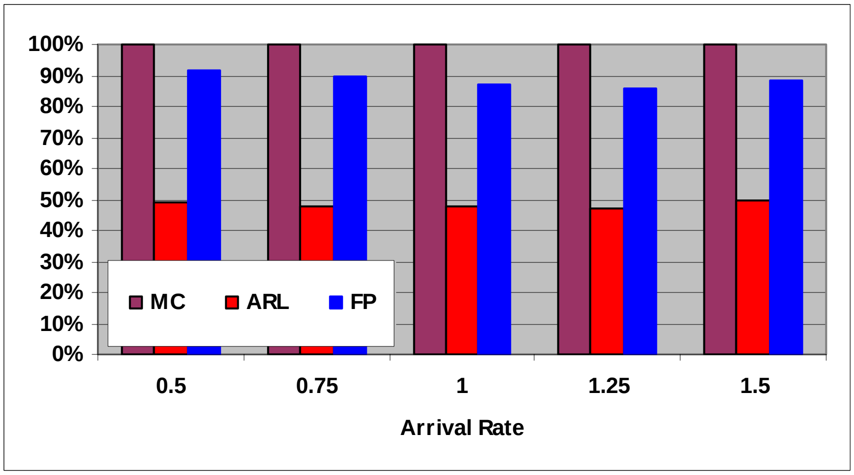

Figure 3 Carriers' Profit level (Second Price Auction MC as base)

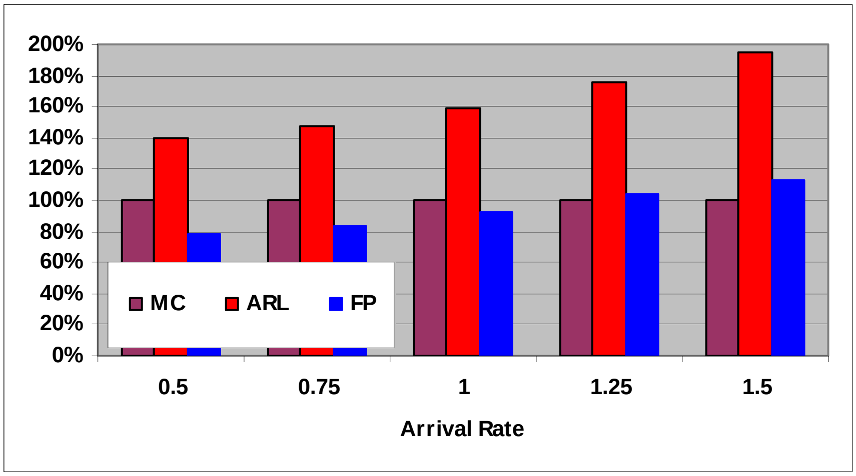

Figure 4 Consumer Surplus level (Second Price Auction MC as base)

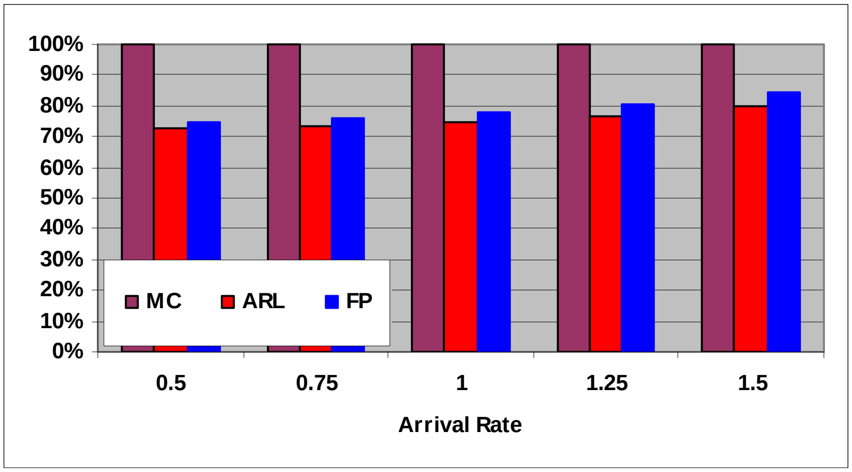

Figure 5 Number of Shipments Served (Second Price Auction MC as base)

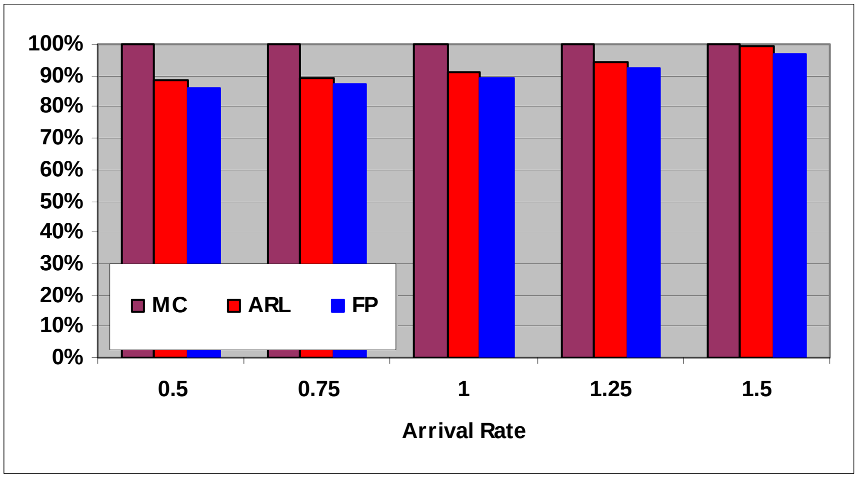

Figure 6 Total Wealth Generated (Second Price Auction MC as base)