Competitive Performance Assessment of Dynamic Vehicle Routing Technologies Using Sequential Auctions

Miguel Andres Figliozzi
The University of Sydney
The Institute of Transport Studies
Faculty of Economics & Business
Sydney, NSW 2006
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@wam.umd.edu

and

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

August 1, 2003

Submitted for presentation at the 83rd Annual Meeting of the Transportation Research Board, and publication in Transportation Research Record

Competitive Performance Assessment of Dynamic Vehicle Routing Technologies Using Sequential Auctions

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

Abstract

This paper compares technologies for a dynamic truckload pickup and delivery problem in a competitive environment using sequential auctions. 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 in a second price auction. Four fleet assignment technologies with different degrees of sophistication are tested using simulations. The technologies differ in how they deal with the combinatorial and stochastic elements of the online problem. A one-step look-ahead dynamic vehicle routing technology which tries to estimate the impact of current decisions on serving future loads (not yet arrived) is introduced. The performance of each technology is analyzed in relation to different demand characteristics.

KEYWORDS: Freight Transportation, Online Vehicle Routing Problem, Carrier Management Strategies, Carrier Profitability, Information Technology, Electronic Commerce, Auctions

Word count: 5500

INTRODUCTION

The principal focus of this research is to compare and evaluate the performance of dynamic vehicle routing (DVR) technologies in a competitive environment. This investigation covers the truckload pickup-and-delivery problem, entailing the dynamic operation of trucking fleets that provide service to a general pattern of stochastic time-sensitive customer loads. The research uses an innovative approach, comparing DVR technologies in a marketplace environment; each arriving load triggers an auction where carriers compete with each other to win the right of servicing the load.

On the demand side, the motivation for this work is two-fold. The growing demand for customer-responsive, made-to-order manufacturing is increasing the time-sensitivity of customer demands. This trend is shifting the logistics and transportation process from one that relies on long planned lead times to real time operations. The operation of Dell Computers in Texas exemplifies this trend.

The explosive growth in B2B electronic commerce, which is changing the way business is conducted, motivates the usage of marketplaces. A specific example of these changes is 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. Private exchanges are growing. A report published in mid 2002 estimated that as of June 2003, 15 percent of all Fortune 2000 companies would have set up private exchanges (1). Furthermore, the same source indicated that an additional 28 percent of all Fortune 2000 companies planed to implement one by the end of 2003. These market changes have produced a recent shift away from fixed pricing and toward flexible pricing. The typical dynamic pricing mechanisms are auctions, where prices and allocations are based on bids.

On the supply side, the use of different DVR technologies reflects the asymmetric nature of competition. Even though carriers may compete in the same market, 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 (2). This research presents the results of simulation experiments performed to test different DVR technologies. These technologies can be reduced to algorithms when simulated, however they are herein referred to as “technologies” as their real life implementation requires much more than implementing an algorithm. Implementation may require upgrades in communication and decision support systems, software, computational power, trained personnel, as well as understanding of the nature and complexity of the DVR problem.

The paper is organized as follows: the next section describes the marketplace framework and operation. Previous related work to the dynamic vehicle routing problem is discussed in the third section. Section four describes different DVR technologies simulated in this paper. Section five describes the simulation framework developed to illustrate and evaluate technologies through numerical experiments. The experimental results are analyzed and discussed in section six, followed by concluding comments in the final section.

MARKET DESCRIPTION

This paper focuses on the performance of different DVR technologies in sequential auction transportation marketplaces. The marketplace 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 (3).

The market is comprised of shippers that independently call for shipment procurement auctions, and carriers, that participate in them (we assume that the likelihood 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.

The auction type used is the second price or Vickrey auction. The second price auction for one load 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 void)
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

A powerful characteristic of (one item) Vickrey auctions is that the optimal strategy is simply to bid the true cost of serving the shipment. In economic terminology, this property is called a *truth revealing mechanism*. Furthermore, this paper assumes that the mechanism implemented in the marketplace for the *sequence* of bids is truth revealing at each bidding instance. This powerful assumption is necessary because the objective of the paper is to compare different DVR technologies. Bidding strategies therefore are reduced to marginal cost bidding, removing any strategic or speculative element from the results obtained. The reader interested in the latter, might refer to Krishna's work (4) for a general treatment of auctions and to Figliozzi, Mahmassani and Jaillet (5) for an analysis of carrier bidding and behavior in transportation auctions.

FORMULATIONS AND SOLUTIONS OF THE DVR PROBLEM

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, Jaillet, and Odoni (6) 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, Mahmassani and Jaillet (7-9) 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, Jaillet and Mahmassani (10,11) 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, Kim, and Jaillet (12-14) 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 (15-18). Gendreau et al. (19) and Ichoua et. al. (20) use tabu search to solve a DVR problem with soft time windows. Gendreau et al. (19) 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. (21) study the DVR problem with different degrees of dynamism (defined as the percentage of demands that carriers typically do not know in advance).

DVR TECHNOLOGIES

Carriers have to keep in mind the marginal cost for each transaction, especially in a sequential auction that implements a truth revealing mechanism. The loaded distance is not included in the marginal 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.

In real time situations, this is an increasingly 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. This paper presents four levels of DVR technologies. These technologies are presented in an order that shows an increasing level of sophistication.

1. 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" simply as the additional empty distance incurred when appending "s" 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. Nonetheless, it provides a useful benchmark against which to compare the performance of more complex and computationally demanding technologies.
2. Static Truck Optimal (STO): this carrier optimizes the static vehicle routing problem at the *truck* level. If the carrier has just one truck, it estimates the marginal cost of an arriving shipment "s" as the additional empty distance incurred when *inserting* or appending "s" to the current route. If the carrier has more than one truck, the marginal cost is the cost of the truck with the lowest inserting or appending 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 (i.e. ignoring the future but with real time information) truck driver can achieve.
3. Static Fleet Optimal (SFO): this carrier optimizes the static vehicle routing problem at the *fleet* level. If the carrier has just one truck, the technology is equivalent to the previous case. If the carrier has more than one truck, the marginal cost is the increment in empty distance that results from *adding* "s" to the *total pool of trucks and loads* yet to be serviced. If the problem where static, this technology would

provide the optimal cost. Again, like the two 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 (10, 11). STO is a special case of the general SFO formulation.

4. One step Look ahead Fleet Optimal (1LFO): as the previous carrier, this carrier optimizes the static vehicle routing problem the fleet level. This provides the *static marginal cost* (*smc*) for adding "s". However, this carrier also knows the distribution of load arrivals over time and their spatial distribution (this paper does not discuss how the carrier has acquired this information). Hence, the carrier can simulate whether and how much winning "s" affects the marginal cost of serving the next arriving load; this is the *dynamic marginal cost* (*dmc*) of serving "s". Unlike previous types, this carrier takes into account the stochasticity of the problem to estimate the static cost of serving "s" and the effect on the marginal cost of serving the next arriving shipment ("one step look ahead"). This technology roughly stands for what a fleet dispatcher with real time information and knowledge of future (yet unrealized probabilistic demands) can do. However, 1LFO is not an "optimal" technology, rather it is a heuristic that tries to estimate how serving "s" affects the cost of serving the next shipment.

   Defining:

   L, the set of loads (won bids) yet to be serviced by the carrier when "s" arrives

   c:L? $\Re$, a function that given a set of loads and current fleet deployment return the minimal empty distance required to serve all the loads included in L

   S = { $s_1, \ldots, s_n$ }, simulated set of *n* loads. Each of these loads represents a realization of the next unknown arriving load (immediately after "s") using probability distribution functions that the shippers use to generate loads.

   Then:

   $smc(s) = c(L + s) - c(L)$

   $dmc(s) = S_i\,[\,c(L + s + s_i) - c(L + s_i)\,]\ / n \qquad s_i \in S$

Using (1LFO) technology, the marginal cost used to bid is the average between *smc* (s) and *dmc* (s). The average is taken to "correct" the static estimation of the static marginal cost (*smc*) taking into account the impact of serving "s" on the next bid.

Three cases are possible:

a) *smc* (s) < *dmc* (s) : serving the arriving demand leads to a fleet deployment that causes a higher *dmc* (relative to the current *smc*), therefore the bid is increased

b) *smc* (s) > *dmc* (s) : serving the arriving demand leads to a fleet deployment that causes a lower *dmc* (relative to the current *smc*), therefore the bid is decreased

c) *smc* (s) = *dmc* (s) : serving the arriving demand leads to a fleet deployment that do not affect the value of *dmc* (relative to the current *smc*), therefore the bid is equal to *smc* (s)

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 *as if* they can always 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" 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."

SIMULATION FRAMEWORK

This paper studies truckload carriers that compete over a square geographic region. It is assumed that the length of the square sides is 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 distances vary with arrival rates and time windows considered). Three different Poisson arrival rates per truck per unit of time are simulated:

- $\lambda = 0.5$ (uncongested)
- $\lambda = 1.0$ (congested)
- $\lambda = 2.0$ (extremely congested)

The shipments have hard time windows. Three different time windows are simulated. In all cases, it is assumed that the earliest pickup time is the arriving time of the demand to the marketplace. The latest delivery times (LDT), in an order that reflects increasing "slackness", are the following:

LDT1 = arrival time + **1** x (shipment loaded distance + 0.25) + **1** x uniform (0.0, 1.0)
LDT2 = arrival time + **2** x (shipment loaded distance + 0.25) + **2** x uniform (0.0, 1.0)
LDT3 = arrival time + **4** x (shipment loaded distance + 0.25) + **4** x uniform (0.0, 1.0)

The respective time windows are respectively called TW1, TW2, and TW3. The first type of time windows (TW1) provides hardly enough flexibility of scheduling. The opposite can be said about the last type (TW3). 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 (therefore highest bid) in the simulated area ($\approx$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, four carriers are competing for the demands. Out of the four carriers, three compete using the Base or Naïve technology, the other carrier uses one of the more sophisticated technologies.

Multiple performance measures are used to evaluate the various technologies. 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 the carrier's average empty distance or the average distance from the destination of one load to the origin of the next load served. Average empty distance is a measure of the scheduling efficiency of the DVR technology. The fourth performance measure is average shipment (served) loaded distance.

ANALYSIS OF EXPERIMENTAL RESULTS

Figure 1 compares the absolute performance of STO and SFO technologies. The graphs in the two columns have comparables scales to facilitate visual comparisons. The results correspond to a marketplace with four carriers, three of them naïve and one more sophisticated (either STO or SFO). Each carrier has a fleet of two trucks. Figure 1 shows how SFO outperforms STO in number of won bids and average empty distance, for the most part with wider time windows and slightly congested arrival rates. With wide time windows (TW4) and congestion (AR=8) SFO outperforms STO in all four performance measures.

From a competitive point of view, it is essential to see their relative performance with respect to naïve carriers. Figure 2 compares the relative performance of STO and SFO against the naïve carriers. As expected, sophisticated technologies outperform the naïve one in general. However, relative performance critically depends on the arrival rate and time windows that characterize the demand. Shorter time windows have clearly a negative effect on profit performance. The first type of time windows (TW1) is so short that provides few opportunities to improve schedules. The plots of won bids and profits look like flat lines. As time windows get larger, there are more opportunities for swapping loads service orders and swapping loads among trucks. For wider time windows, plotting won bids vs. arrival rates bring about a concave looking curve.

Under low arrival rates, optimal formulations have few shipments to work with. Under very high arrival rates, all the carriers' fleets are fully utilized irrespectively of their intrinsic technology or efficiency. Therefore there is an "optimal" arrival rate that maximizes the competitiveness of static optimization techniques.

Average loaded distance is included as a performance measure because it reveals the working of the "optimal" static technologies. The MIP formulations manage to join together a larger number of short loaded distance shipments. As shipments arrive one at a time, the likelihood of a small shipment to "fit" into the existing routes does increase as its loaded distance decreases. In this paper, marketplace setting reservation prices are independent of shipments' loaded distances. A different marketplace, where shipment reservation prices strongly depend on loaded distances, would surely exhibit a different profit performance for the sophisticated technologies, though won bids, loaded distances, and empty distance could remain by and large unchanged.

Figures 3 and 4 depict similar graphics, but illustrating the absolute and relative competitiveness of technologies SFO and 1LFO. The knowledge about the stochastic nature of the demand makes an obvious difference in the number of won bids (see figure 4). Averaging *smc* and *dmc* seem to more accurately reflect the "true" marginal cost of serving a shipment. However, the relative performance of 1LFO decreases with increasing arrival rates. Under very high arrival rates (ar = 32 in figures 3 and 4) the respective performances of SFO and 1LFO are comparable. This seems to suggest that at high arrival rates, $smc \approx dmc$.

Figures 5 illustrates the results of a SFO type carrier competing against three STO carriers. The graphs on the left represent the absolute performance of the SFO carrier, the graphs on the right represent the relative performance of the SFO carrier against the STO carriers. The same patterns discussed above regarding figures 1 and 2 hold here. Optimization at the fleet level is more competitive at moderately congested conditions and wider time windows. However, unlike the previous case, the average loaded distance does not vary as much except for the case of high arrival rate and wide time windows.

CONCLUSIONS

A sequential auction framework was used to compare the competitiveness of different DVR technologies. The technologies were evaluated under different demand conditions. It was shown that under severely constrained DVR problems the performance gains obtained with sophisticated technologies are scarce. Major performance gains are obtained under moderately congested conditions as well as ample time windows.

The proposed methodology to test DVR technologies seems adequate to evaluate competitive performance, especially in logistics and transportation problems embedded in dynamic stochastic environments or supporting e-commerce marketplaces and activities. The paper also introduced a DVR strategy that assumes knowledge about the shipment arrival and other characteristics distributions. Simulation results show that this new strategy outperforms myopic ones, particularly in uncongested marketplaces. However, further research is needed to fully tap on the competitive edge provided by knowledge about the stochastic nature of future demand arrivals.

ACKNOWLEDGMENTS

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

REFERENCES

1. Hoffman W., Keedy J., and Roberts K., "The Unexpected Return of B2B", The McKinsey Quarterly, 2002, N3.
   http://www.mckinseyquarterly.com/article_abstract.asp?ar=1210&L2=24&L3=47
2. Regan, A.C., and T. F. Golob (1999) "Freight Operators' Perceptions of Congestion Problems and the Application of Advanced Technologies: Results from a 1998 Survey of 1200 Companies Operating in California". Transportation Journal, Volume 38, Number 3 pp. 57-67.
3. 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*.
4. Krishna, V, Auction Theory, Academic Press, 2002.
5. Figliozzi, M.A., Mahmassani, H.S. and Jaillet, P. (2003) Modeling Carrier Behavior in Sequential Auction Transportation Markets, paper presented at the 10th International Conference on Travel Behavior Research, Lucerne, August 2003.
6. Powell, W.B., Jaillet, P. and Odoni, A. (1995), "Stochastic and Dynamic Networks and Routing", in Ball, M.O., T.L. Magnanti, C.L. Monma. And G.L. Nemhauser (eds), Handbook in Operations Research and Management Science, Vol. 8, Network Routing, Elsevier, Amsterdam, pp. 141-296.
7. Regan, A.C., H.S. Mahmassani and P. Jaillet (1996), Dynamic decision making for commercial fleet operations using real-time information, Transportation Research Record 1537, pp. 91-97.

8. Regan, A.C., H.S. Mahmassani and P. Jaillet (1996), Dynamic dispatching strategies under real-time information for carrier fleet management, in J.B. Lesort (ed), Transportation and Traffic Theory, Pergamon, pp. 737-756.
9. Regan, A.C., H.S. Mahmassani and P. Jaillet (1998), Evaluation of dynamic fleet management systems: a simulation framework, Transportation Research Record 1645, pp. 176-184. .
10. 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
11. Yang, J., Jaillet, P., Mahmassani, H. S. (2002) "Real Time Multi-Vehicle Truckload Pick-Up and Delivery Problem", forthcoming Transportation Science.
12. Mahmassani, HS; Kim, Y; Jaillet, P, Local Optimization Approaches To Solve Dynamic Commercial Fleet Management Problems, Transportation Research Record1733, pp 71-79, August 2000
13. Kim, Y; Mahmassani, HS; Jaillet, P, Local Optimization Approaches To Solve Dynamic Commercial Fleet Management Problems, Transportation Research Record1733, pp 71-79, August 2000
14. Kim, Y; Mahmassani, HS; Jaillet, P, Dynamic Truckload Truck Routing And Scheduling In Oversaturated Demand Situations, Transportation Research Record1783, August 2002
15. Powell, W. B., A Stochastic Formulation of the Dynamic Vehicle Allocation Problem, Transportation Science, Vol 20, pp 117-129, 1986

16. Powell, W.B.(1987), "An operational planning model for the dynamic vehicle allocation problem with uncertain demands", Transportation Research-B, Vol 21B, No 3, pp. 217-232.
17. Powell, W.B. (1996), "A Stochastic Formulation of the Dynamic Assignment Problem, with an application to Truckload motor carriers", Transportation Science, Vol. 30, No. 3, pp. 195-218.
18. Powell, W.B., Towns, M. T., and Marar, A. "On the Value of Optimal Myopic Solution for Dynamic Routing and Scheduling Problems in the Presence of User Noncompliance." Transportation Science 34.1 (2000): 50-66.
19. Gendreau M., Guertin F., Potvin J., Taillard E., Parallel Tabu Search for Real-Time Vehicle Routing and Dispatching. Transportation Science 33, 1999
20. Ichoua, S., Gendreau, M., Potvin, J-Y. "Diversion Issues in Real-Time Vehicle Dispatching." Transportation Science 34.4 (2000): 426-438.
21. Larsen, A., Madsen O., Salomon M., "Partially Dynamic Vehicle Routing – Models and Algorithms". Journal of Operational Research Society 53: 637-646, 2002

List of Figures

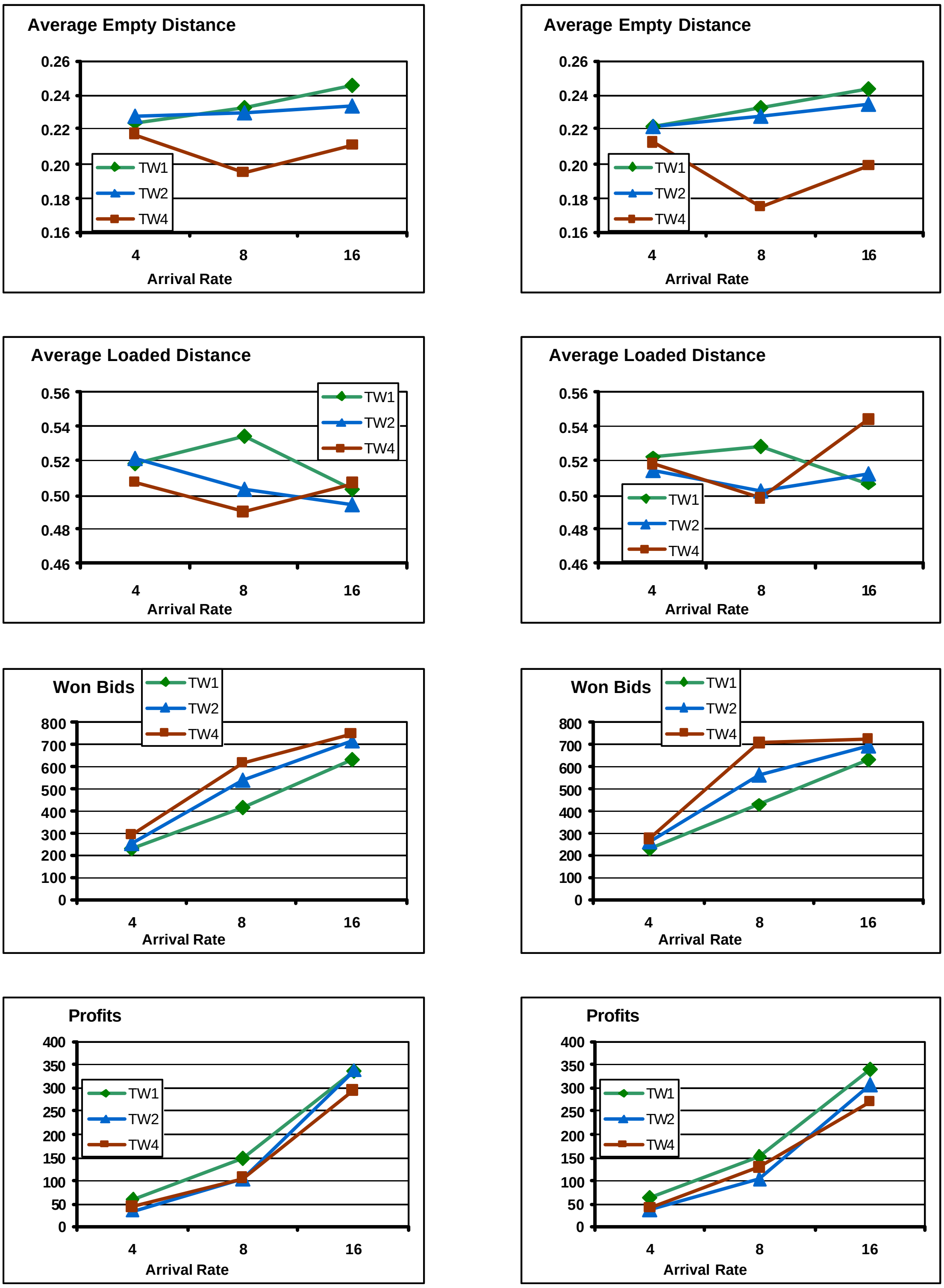

Figure 1
Comparing STO (left) and SFO (right) Performance against Naïve Carriers

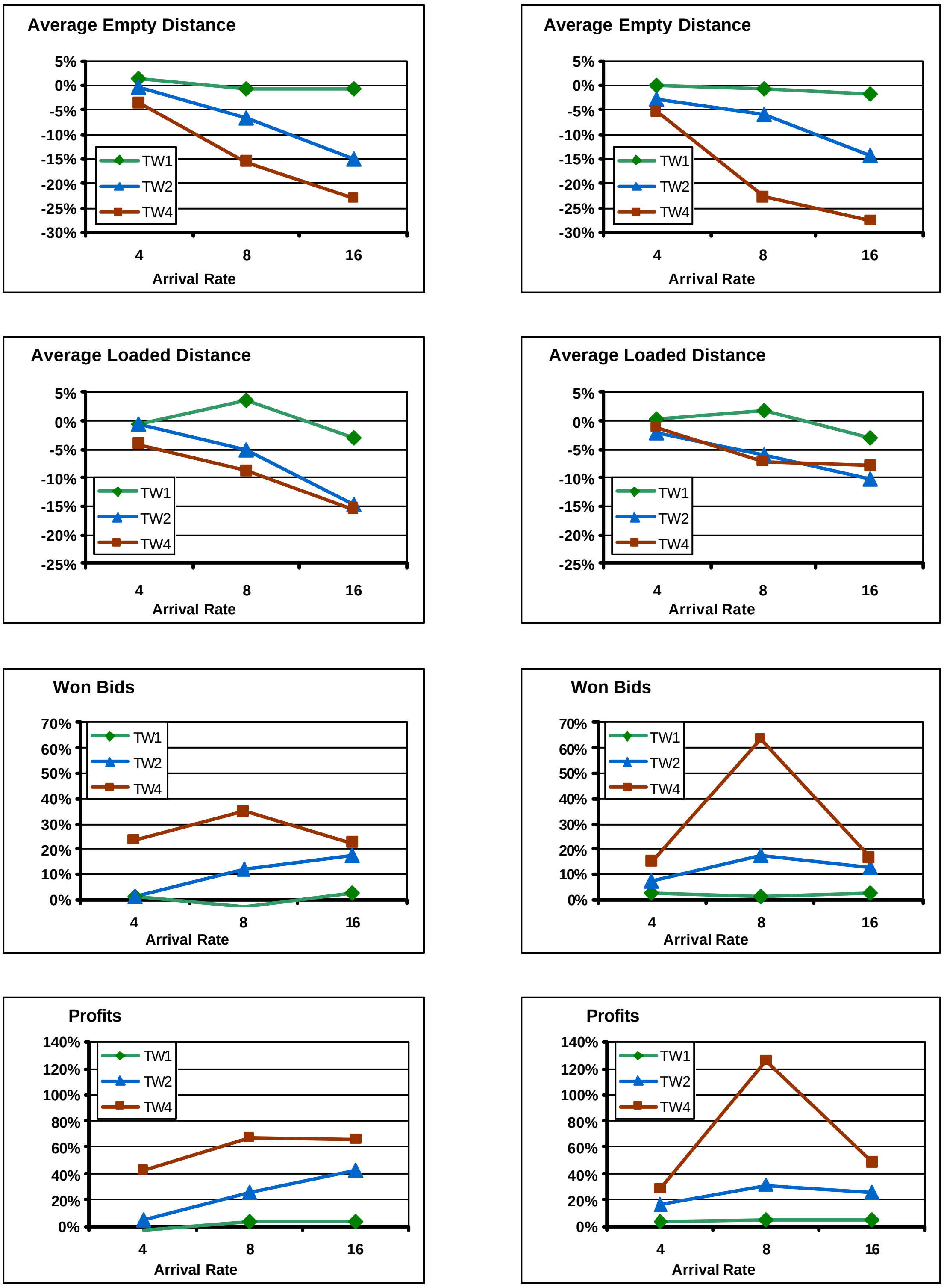

Figure 2
Comparing STO (left) and SFO (right)
% Change over Naïve Carriers

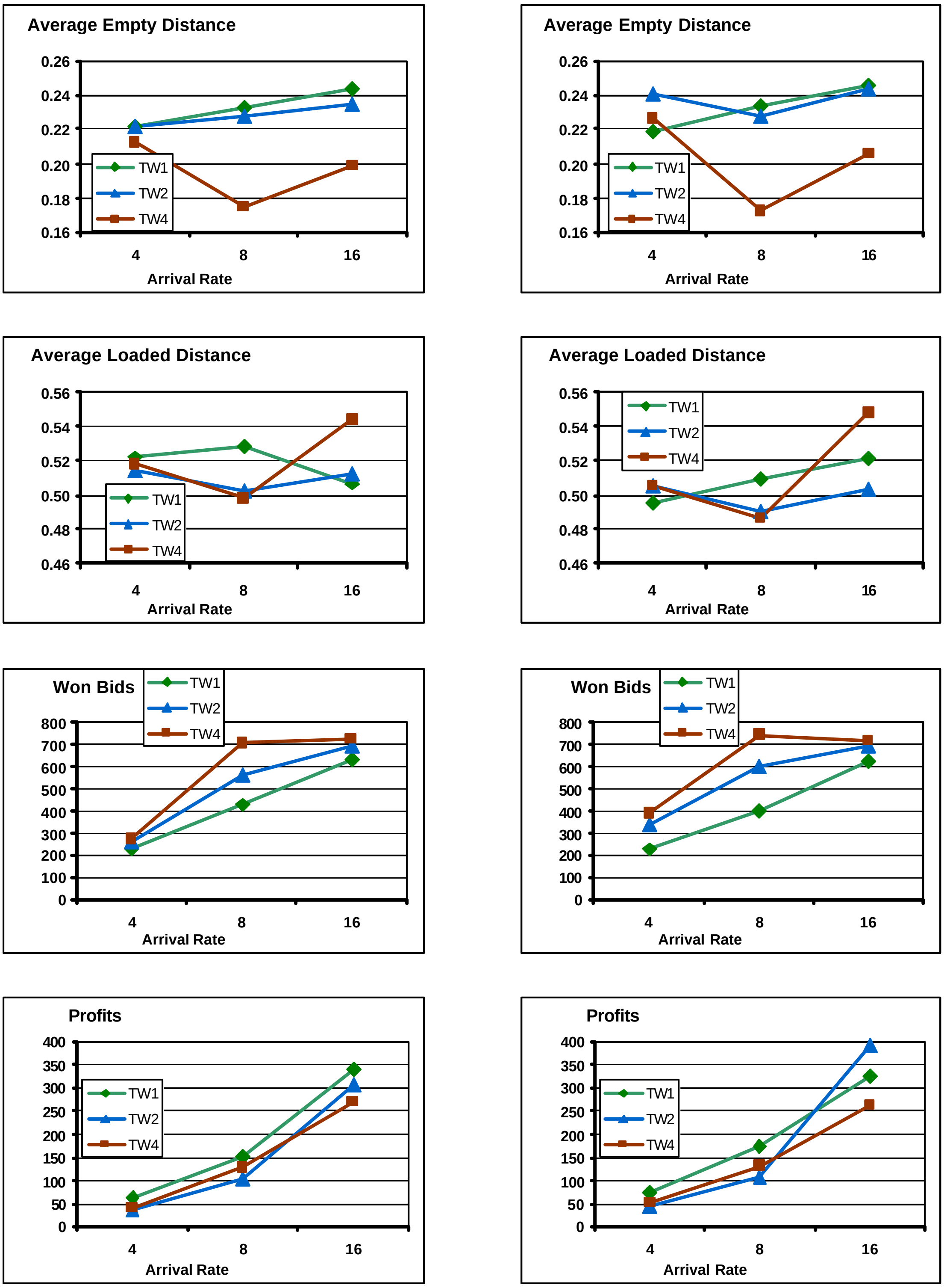

Figure 3
Comparing SFO (left) and 1LFO (right) Performance against Naïve Carriers

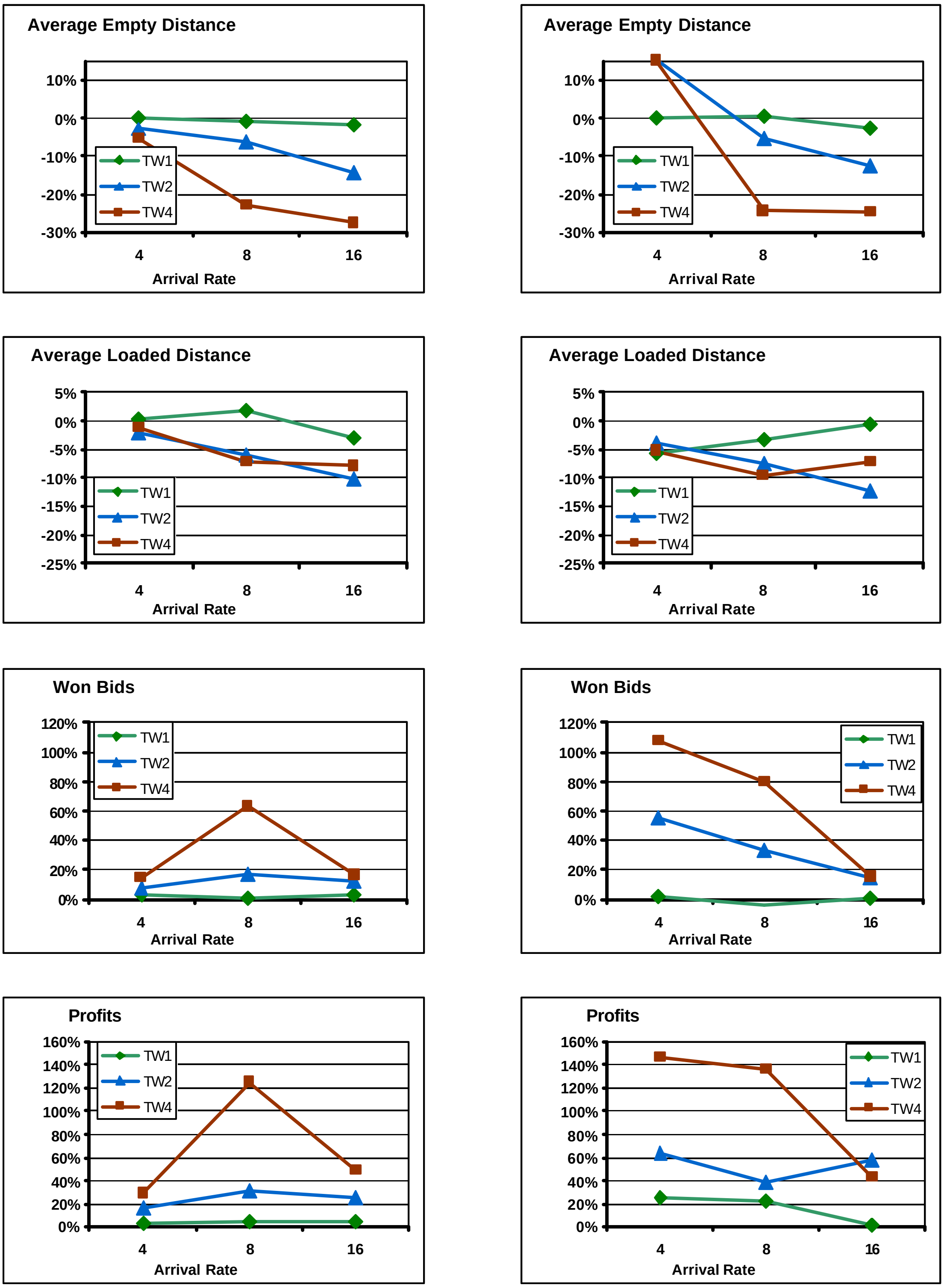

Figure 4
Comparing SFO (left) and 1LFO (right)
% Change over Naïve Carriers

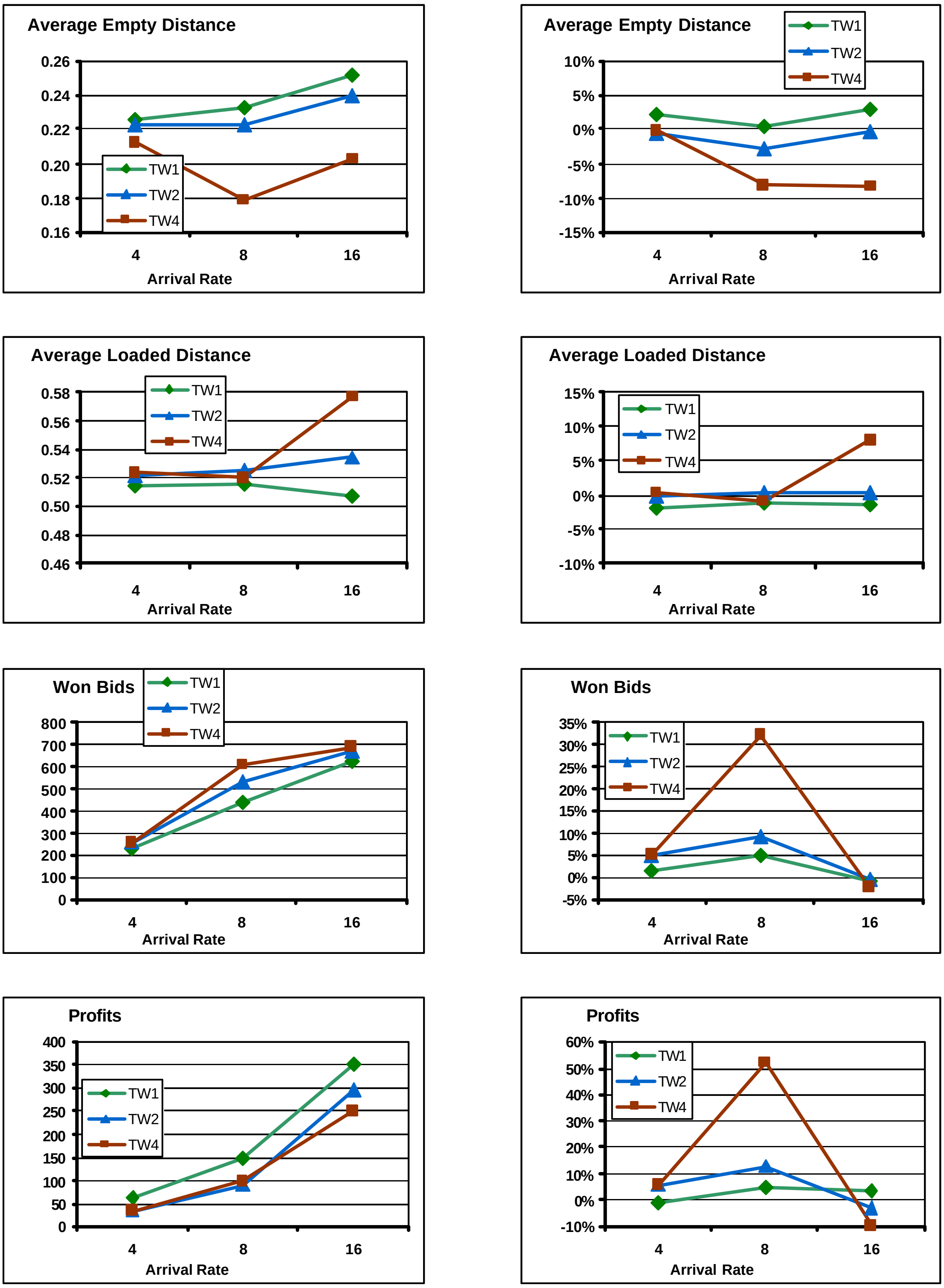

Figure 5
Comparing SFO and STO
SFO absolute values (left) and SFO % change over STO Carriers (right)