Markets of Logistics Services: The Role of Actors' Behavior to Enhance Performance

Nicola Bellantuono[1], Gregory E. Kersten[2], and Pierpaolo Pontrandolfo[1]

[1]Department of Mechanics, Mathematics and Management, Politecnico di Bari, Bari, Italy.
[2] InterNeg Research Centre, Concordia University, Montreal, Canada.

Abstract

In real markets of logistics services, actors make independent decisions to pursue their own objectives, neglecting the need for maximizing performance of the market as a whole. The aim of this paper is to assess the inefficiency of such logistics markets and define policies to improve system-wide performance, taking into account each actor's behavior. A simulation model of a logistics marketplace is thus defined, wherein the transportation needs of a number of shippers have to be matched with the capacities of several carriers. The model is used to assess the players' behavior and system performance in a decentralized logistics market. The analysis shows the extent to which certain features of the market affect inefficiency stressing the room for improvement. Based on simulation results, several recommendations are given, aimed at influencing the actors' autonomous decision making. We discuss how the recommendations' efficacy is impacted by behavioral issues.

Keywords: logistics market, coordination, performance evaluation.

Acknowledgments: The publication of the InterNeg Research Papers has been supported by the Natural Sciences and Engineering Research Council, the Social Sciences and Humanities Research Council, and the J. Molson School of Business, Concordia University.

1. Introduction

In supply chains (SCs) that are managed in a decentralized fashion, actors autonomously make decisions by defining the logistics policies (mostly dealing with inventory management) that maximize their own utilities, regardless of the system-wide efficiency. Research has shown that decentralized SCs prove inefficient (Cachon and Zipkin, 1999; Cooper *et al.*, 1997; Frohlich and Westbrook, 2001; Vickery *et al.* 2003). Several real SCs are not centrally managed, and in particular, logistics services are often exchanged through pure markets, wherein decisions are made under a totally decentralized fashion (Ağralı *et al.*, 2008).

Centralized management, which is consistent with the optimization of the SC as a whole, is based on hypotheses that are barely realistic. It postulates the existence of an actor (also referred to below as a decision maker) who: (i) owns all the relevant information along the chain, (ii) is able to define policies, which are optimal under a system-wide perspective, and (iii) has the bargaining power to make the other actors behave in accordance with such policies.

In reality, actors usually have little access to information about other SC stages (Corbett and Tang, 1999) and are affected by bounded rationality (Simon, 1982; Rubinstein 1998), which prevents them from identifying a true globally optimal policy (Su, 2008). Furthermore, the opportunistic behavior of all the parties makes it difficult to put into practice the optimal global policy, even if identified (Lee and Whang, 1999; Nyaga *et al.*, 2010).

Thus, it is very common that SCs operate in a decentralized fashion: all actors act as decision makers and, based on partial information, define and adopt policies that they consider effective for the SC stage.

In logistics and transportation, decentralization is more frequent than in manufacturing processes. Recently, manufacturers increasingly entrust the logistics functions of their operations to third-party logistics providers (3PLs), who provide one or more specialized services on behalf of their customers. The variety of logistics services and specialization of their providers, coupled with the need for a higher integration in the supply chain, resulted in the appearance of fourth-party logistics providers (4PLs), i.e. integrators capable of delivering complete solutions, from the strategic design of the logistics network to the day-by-day operational issues (Yao, 2010). The emergence of 3PLs and 4PLs has determined a growing coordination among the different logistics services. However this is not enough to guarantee an adequate SC coordination, in particular at the interface between logistics providers and manufacturing companies, or, generally speaking, between carriers and shippers, where a shipper is either a manufacturing company or a company that demands logistics services on behalf of third parties.

Specific additional problems of logistics are associated with the nature of services. They are indeed intangible, heterogeneous, perishable, their production is inseparable from their consumption (Zeithaml *et al.*, 1985), and often requires customization. All such features usually make it difficult to measure specifications and performances of services (Fitzsimmons *et al.*, 1998). In particular, logistics services are affected by additional sources of complexity and widely range from basic to advanced services (Andersson and Norrman, 2002; Giannoccaro *et al.* 2009). Moreover, services in some cases are procured as a bundle (Schoenherr and Mabert, 2008). This results in the need to consider several attributes beside price for managing logistics services procurement, i.e. lead time, time flexibility, occurrence of delays and associated penalties, etc.

Based on the above assumption that centralized decision making is neither common in reality nor easy to implement), this paper discusses ways to enhance SC coordination, with emphasis on logistics markets, in the context of decentralized decision making processes. We propose the concept of the "organized market of logistics services". This concept is mainly based on managing information which the actors receive in order to counterbalance the lack of a single centralized decision maker. One possible way to achieve this is the adoption of schemes such as supply contracts (Tsay *et al.*, 1999; Tang, 2006), which are mechanisms based on incentives coordinating transactions among two or more SC actors.

As the proposed approach is based on information management and leverages on autonomous decisions (and related actions) by the SC actors, it turns out that behavioral issues are the key. In fact, once decisions and actions are identified and coherent incentive schemes designed, the actual implementation of actions relies on issues such as understanding the rules to share costs, benefits, and risk, reciprocal trust (Cummings and Bromiley 1996; Zaheer *et al.*, 1998) and perception of opportunism (Williamson, 1985; Rousseau *et al.*, 1998; Brown *et al.*, 2000).

The specific aims of this paper are (i) to assess the inefficiency associated with decentralized decision making approach in a logistics services market and (ii) to suggest recommendations that guide actors in their decision making, in order to "organize the market". Such actions leverage on a suitable information management, based on the assumption that more effective decisions stem from better information management.

With respect to the first objective, we define a stylized simulation model of logistics services as a marketplace wherein the transportation needs of a number of shippers can be matched with the capacities of several carriers. On the supply side, each carrier is characterized by capacity, cost structure, and pricing strategy. On the demand side, each request for transportation (which is posted by a shipper) is defined by the quantity to be moved and the route (in turn specified by the points of origin and destination). All the shipments are assumed to be made at the same time.

We use simulation in order to determine the allocation of transportation requests to carriers. Because the actors make autonomous decisions, the allocation solution is likely to be inefficient, i.e. there are other solutions with lower total transportation costs for shippers and/or higher margins for carriers.

To assess inefficiency, we developed two heuristics. In the first heuristic decisions are based on the minimization of every price a shipper pays to the carriers and the maximization of each carrier margin. In the second heuristic the criterion of these actors describes global rather than local prices and margins. That is, every shipper and carrier selects solutions that lower total costs. Note that the second heuristic moves the process from local towards global optimization.

Based on the simulation results, we assessed the potential for performance improvement in markets of logistics services, prepared guidelines to pursue such an improvement in real systems characterized by decentralized decision making, and argue for the need for research on the behavioral issues related to logistics procurement.

The paper is organized as follows. Section 2 introduces the simulation model of the logistics market, discusses the two heuristics utilized to simulate the (decentralized) decision making process by which transportation requests are assigned to carriers, and presents performance measures to evaluate the solution to the transportation problem. In Section 3, we discuss simulation results, which lead us Section 4 in which we propose recommendations regarding the organization of logistics markets. In Section 5, we point out some limitations of our study, derive the main managerial implications, and suggest avenues for future research.

2. The simulation model

We define a logistics market as a marketplace wherein several companies interact to provide or acquire logistics services. Modeling a real-life logistics market is not trivial due to the number and the variety of involved actors, the complex relationships among them, and the features of the logistics service, which, in turn, require exchange of information other than the price to complement the offer; for instance, information may include technical service specifications such as quality and load assurance and special price schemes that rule delays, rush rates and early reservations.

The logistics market may also be modeled in a simplified way. We consider two different sets of actors: m shippers ($i = 1, \ldots, m$), each requesting one transportation service, and n carriers ($j = 1, \ldots, n$) who are able to provide those services. The problem lies in allocating each transportation request to a carrier. Carriers are heterogeneous in terms of costs structures and price strategies, and have a finite capacity K_j.

Each transportation consists of moving a quantity q_i of a good along its route, namely from an origin to a destination, and repositioning the vehicle to the point of origin once the delivery has been completed. The length of the i-th transportation route is calculated as Euclidean distance:

$$d_i = \sqrt{\left(x_{Ai} - x_{Bi}\right)^2 + \left(y_{Ai} - y_{Bi}\right)^2}\ , \tag{1}$$

wherein (x_{Ai}, y_{Ai}) and (x_{Bi}, y_{Bi}) are the coordinates of the origin and the destination, respectively.

We assume that all the shipments occur at the same time, therefore, each vehicle can be used along one path only. However, in order to account for the possible transportation of goods on vehicles returning to their points of origin we allow their use in both directions.

For the carriers' cost structures, the transportation cost (c_{ij}) sustained by the j-th carrier for the transportation service i depends on his per-mileage cost per unit of shipment (u_j) and is affected by two forms of economies of scale, which make the transportation cost increase in distance (i.e. path length) and in quantity less than proportionally. The existence of fixed costs per shipments (e.g., loading and unloading costs) explains the occurrence of the economies of scale associated with distance, whereas a cost per payload, which is lesser for large vehicles than for small ones, results in economies of scale associated with quantity. Both kinds of economies of scale follow a power function, with exponents α_j for distance and β_j for quantity ($0 < \alpha_j \leq 1$; $0 < \beta_j \leq 1$).

Thus the cost that the j-th carrier would sustain to provide the i-th service is:

$$c_{ij} = u_j d_i^{\alpha_j} q_i^{\beta_j} . \qquad (2)$$

The cost of providing the service may be affected by savings resulting from putting together transportation requests and allocating them to the same carrier as well as from the similarities of the requests. Similarities mostly are associated with transportation optimization. Even though this issue is out of scope, we note here about two forms of similarities in transportation:

- *similarity for consolidation* occurs when two or more shipments along the same route (i.e., with the same origin and the same destination) are provided by the same carrier; the carrier benefits from the economies of scale associated with quantity;
- *similarity for repositioning* occurs when two or more shipments along opposite routes (i.e., whose origins and destinations are reversed) are provided by the same carrier; the carrier avoids the cost of repositioning the vehicle to the origin after its usage.

It is assumed that carriers adopt a price strategy based on a mark-up policy. In default of similarities, the price p_{ij} that the carrier j asks for the transportation i is equal to the corresponding cost, increased by the mark-up factor $\gamma_j > 0$, which is peculiar to each carrier j:

$$p_{ij} = (1+\gamma_j)c_{ij} . \qquad (3)$$

If any similarity exists, the carriers can exploit it and reduce the price they offer by a discount factor:

$$p_{ij} = (\gamma_j + \delta_j)u_j d_i^{\alpha_j} q_i^{\beta_j} + (1-\delta_j)c_{ij} , \qquad (4)$$

where $0 \leq \delta_j \leq 1$.

If $\delta_j = 1$, then the carrier receives all the savings because of the transportation similarity (see above). If however, $\delta_j = 0$, then the price is such that the carrier gets the same margin that he would achieve in the absence of similarities. In this case the shipper gets all the savings.

2.1 Heuristics

To match the shippers' transportation needs with the carriers' transportation capacity, two heuristics are proposed. Heuristic 1 emulates the decision making behavior adopted in a marketplace, wherein actors do not collaborate to optimize the system-wide performance and do not share all information. This heuristic aims at providing a realistic solution in which each actor tends to pursue his or her own goals; specifically, the carriers' goal is maximizing the margin and the shippers' goal is minimizing the cost. Heuristic 2, used as a benchmark, is designed assuming that actors collaborate by sharing information so as to increase the system-wide efficiency; the latter is measured in terms of the sum of carriers' costs, that is the costs sustained by the system as a whole, assumed as a black box. In both heuristics, the actors choose their counterpart through a sequential approach.

Note that neither of the two heuristics is useful in itself; instead they are used here with the purpose of assessing the inefficiency of logistics markets in which both carriers and shippers make decisions independently and with no consideration of any form of collaboration. In other words, the heuristics do not intend to provide a near-optimal solution but rather attempt to: (i) emulate real life behaviors, (ii) identify inefficiencies and (iii) indicate potential improvements.

Heuristics 1

This heuristic refers to the case of lack of collaboration among the actors and consists of five steps:

1. *Request for quotation (RfQ).* In this step, each shipper, whose transportation request needs to be allocated, issues a RfQ communicating the service details (quantity, origin, and destination) to all carriers.
2. *Bidding.* All carriers, whose capacity has not yet been allocated, calculate the costs that they would sustain for each transportation request. The cost c_{ij} is primarily based on the quantity to be shipped, the transportation distance, and the carrier's cost structure. Specifically, the carrier takes into account possible similarities between each request and the transportations that they have confirmed in previous steps, if any. The cost is computed as follows:

   $$c_{ij} = u_j d_i^{\alpha_j} \left[\max\left(q_i + QC_{ij}; QR_{ij}\right)^{\beta_j} - \max\left(QC_{ij}; QR_{ij}\right)^{\beta_j} \right], \tag{5}$$

   where QC_{ij} and QR_{ij} denote the quantities similar for consolidation and for repositioning, respectively. Note that for $QC_{ij} = QR_{ij} = 0$, Equation (2) holds.

   Once the cost of the transportation request has been calculated, the carriers define the price through Equation (4) and post their offers to the shippers.

3. *Offers selection*. Each shipper evaluates all the offers received by the carriers and selects the one at the lowest price. Then, she reserves a certain capacity of the carrier.
4. *Reservations acknowledgement.* Carriers who have received at least one reservation calculate again the costs by taking into account similarities both with the requests confirmed at the previous steps and with the reservations received at this step, the latter being denoted as SC_{ij} and SR_{ij}:

   $$c_{ij} = u_j d_i^{\alpha_j} \left[\max\left(q_i + QC_{ij} + SC_{ij}; QR_{ij} + SR_{ij}\right)^{\beta_j} - \max\left(QC_{ij}, QR_{ij}\right)^{\beta_j}; 0 \right] \cdot \\ \cdot \left[\frac{\max\left(q_i + SC_{ij} - SR_{ij}; 0\right) + \frac{1}{2}\min\left(q_i + SC_{ij}; SR_{ij}\right)}{\max\left(q_i + SC_{ij}; SR_{ij}\right)} \right] \frac{q_i}{q_i + SC_{ij}} . \tag{6}$$

   Note that for $SC_{ij} = SR_{ij} = 0$, Equation (5) holds.

   Since all shippers emit their reservation concurrently, it may happen that a carrier receives requests exceeding his transportation capacity. Therefore, carriers may select which reservations to confirm: to do so, they compute the margin of each reservation and confirm the reservations in a descending order of margin, until their capacity is completely allocated. Exceeding reservations, if any, are rejected.

5. *Iteration.* Steps 1 to 4 are repeated until all the requests are allocated to a carrier or all the carriers use up their transportation capacity.

Heuristics 2

In this heuristic, a mutual collaboration exists among actors, and decisions aim at minimizing the system-wide costs. This heuristic includes 5 steps: steps 1, 2, and 5 are the same as in Heuristic 1, while the third and the fourth steps differ as described next:

1. *Request for quotation (RfQ).* The same as Heuristic 1.
2. *Bidding.* The same as Heuristics1.
3. *Offers selection.* Each shipper evaluates the offers received by the carriers and selects the offer at the lowest cost (for Heuristics 1 the selection criterion is the price). Then, she reserves certain capacity of the carrier.
4. *Reservation acknowledgement.* Carriers who have received at least one reservation calculate again the costs to provide the services by using Equation (6). Then, they compute the margin of each reservation and confirm the reservations according to an ascending order of cost, until their transportation capacity is completely allocated (for Heuristics 1 the criterion that carriers adopt to confirm reservations is the margin). Exceeding reservations, if any, are rejected.
5. *Iteration.* The same as Heuristic 1.

2.2 Performance measures

Three performance measures intended to assess performance of the shippers, the carriers, and the system as a whole are defined below.

Given that the goal of each shipper is to find a carrier that provides transportation service at the lowest price, the aggregate shippers' performance is measured as follows:

$$P = \sum_{i=1}^{m} \sum_{j=1}^{n} \overline{p}_{ij} \, , \tag{7}$$

where, if the service i is provided by the carrier j, $\overline{p}_{ij}$ is the price at which the reservation is confirmed; otherwise, $\overline{p}_{ij} = 0$.

The goal of carriers is to maximize their margin (calculated as the difference between price and cost). Therefore, the aggregate carriers' performance is defined as:

$$Y = \sum_{j=1}^{n} \sum_{i=1}^{m} \left(\overline{p}_{ij} - \overline{c}_{ij} \right), \tag{8}$$

where, if carrier j provides the transportation i, $\overline{p}_{ij}$ and $\overline{c}_{ij}$ are the prices at which carrier j confirms that reservation and the cost he sustains to provide it; otherwise, $\overline{p}_{ij} = \overline{c}_{ij} = 0$.

In a system-wide perspective, the goal is to satisfy all the transportation requests in the most efficient way, i.e., at the minimum cost. Therefore, the system-wide performance is:

$$C = \sum_{j=1}^{n} \sum_{i=1}^{m} \overline{c}_{ij} = Y - P \, . \tag{9}$$

The performances of both heuristics are compared by adopting properly designed competition penalties. As for the system-wide performance, we use:

$$CP_C = \frac{C_1 - C_2}{C_2} \, , \tag{10}$$

where the indexes $\cdot_1$ and $\cdot_2$ refer to Heuristics 1 and 2, respectively. Similarly, the competition penalties used to compare the shippers' and the carriers' performance, are defined as follows:

$$CP_P = \frac{P_1 - P_2}{P_2}, \tag{11}$$

$$CP_Y = \frac{Y_1 - Y_2}{Y_2}. \tag{12}$$

If $CP_C > 0$, then $C_1 > C_2$. Thus Heuristic 1 underperforms Heuristic 2 in the system-wide performance. Similarly, if $CP_P > 0$, then $P_1 > P_2$, thus Heuristic 1 underperforms Heuristic 2 in the shippers' performance. Conversely, $CP_Y > 0$ means that $Y_1 > Y_2$, i.e., Heuristic 1 outperforms Heuristic 2 in the carriers' performance.

3. Simulation results

A numerical analysis is provided to assess the inefficiency of Heuristic 1 in several scenarios. In all of them we assume $m = 100$ shippers, each requesting one transportation. For all transportation requests the quantity to be moved is equal to one, whereas the route may differ in terms of paths and direction. M paths are generated by drawing at random a couple of points in a 100×100 square. Then, to each transportation request we assign (i) a specific path by drawing at random from M paths, and (ii) the path direction. The higher the M value, the higher the probability that the transportation requests are dissimilar.

Table 1. Values of the variables characterizing the carriers.

Variable	Distribution	Mean	Standard deviation
u_j	normal	100	20
α_j	normal	0.70	0.10
β_j	normal	0.09	0.03
γ_j	normal	2.00	0.20; 0.50
δ_j	deterministic	0.30; 0.70	–

A number of carriers n are available to satisfy the transportation requests. Each carrier is characterized by the per-mileage cost per unit of shipment u_j, the parameters governing the intensity of the economies of scale (α_j and β_j), the mark-up factor γ_j, and the price discount factor δ_j. The values of u_j, α_j, β_j, and γ_j are randomly assigned according to a normal distribution, while δ_j is deterministic and equal to δ for all carriers (Table 1).

A real logistics market characterized by the existence of a few large logistics providers that serve many different routes corresponds to the scenarios characterized by a low n and a high M. The real cases of a logistics market where the shippers' demand is satisfied by a high number of owner-drivers is modeled by n = 10. The scenarios with asymmetric distribution of the capacity of the carriers resemble the logistics markets characterized by the presence of both large and small logistics providers.

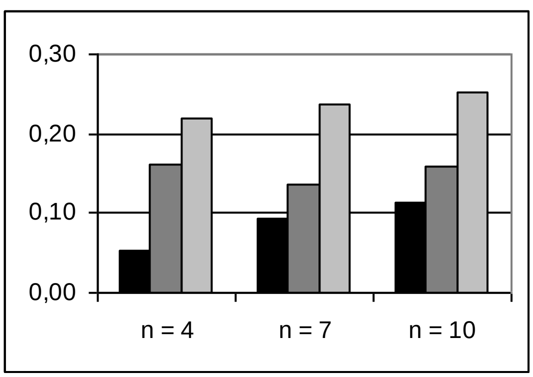
Table 2. Simulation results for the scenarios with symmetric distribution of the capacity among carriers.

Scenario				**Performance**		
n	M	δ	$\sigma(\gamma)$	CP_C	CP_Y	CP_P
4	10	0.3	0.2	0.0535	0.2064	0.1718
4	10	0.3	0.5	0.0724	0.2246	0.1901
4	10	0.7	0.2	0.1161	0.2537	0.2242
4	10	0.7	0.5	0.0964	0.2307	0.2020
4	30	0.3	0.2	0.1601	0.2610	0.2354
4	30	0.3	0.5	0.1351	0.2249	0.2022
4	30	0.7	0.2	0.1497	0.2448	0.2216
4	30	0.7	0.5	0.1258	0.2248	0.2005
4	100	0.3	0.2	0.2187	0.2031	0.2074
4	100	0.3	0.5	0.2384	0.2160	0.2223
4	100	0.7	0.2	0.2272	0.2157	0.2188
4	100	0.7	0.5	0.2048	0.2039	0.2041
7	10	0.3	0.2	0.0942	0.2281	0.1975
7	10	0.3	0.5	0.0970	0.2196	0.1915
7	10	0.7	0.2	0.0992	0.2081	0.1846
7	10	0.7	0.5	0.1120	0.2157	0.1932
7	30	0.3	0.2	0.1355	0.2077	0.1895
7	30	0.3	0.5	0.1289	0.1983	0.1807
7	30	0.7	0.2	0.1430	0.2044	0.1895
7	30	0.7	0.5	0.1706	0.2240	0.2111
7	100	0.3	0.2	0.2382	0.2069	0.2156
7	100	0.3	0.5	0.2438	0.2024	0.2140
7	100	0.7	0.2	0.2396	0.2139	0.2209
7	100	0.7	0.5	0.2297	0.1993	0.2076
10	10	0.3	0.2	0.1143	0.1951	0.1764
10	10	0.3	0.5	0.1190	0,1843	0.1692
10	10	0.7	0.2	0.1434	0.2071	0.1932
10	10	0.7	0.5	0.1379	0.1935	0.1813
10	30	0.3	0.2	0.1587	0.2135	0.1996
10	30	0.3	0.5	0.1559	0.1999	0.1887
10	30	0.7	0.2	0.1799	0.2085	0.2016
10	30	0.7	0.5	0.1809	0.1901	0.1879
10	100	0.3	0.2	0.2516	0.2168	0.2265
10	100	0.3	0.5	0.2405	0.1932	0.2064
10	100	0.7	0.2	0.2262	0.1933	0.2023
10	100	0.7	0.5	0.2259	0.1780	0.1911

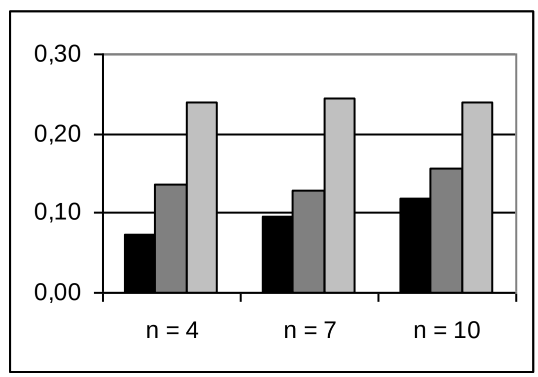
Table 3. Simulation results for the scenarios with asymmetric distribution of the capacity among carriers.

Scenario				Performance		
n	***M***	***δ***	***σ(γ)***	CP_C	CP_Y	CP_P
7	10	0.3	0.2	0.1022	0.2062	0.1828
7	10	0.3	0.5	0.1173	0.2196	0.1966
7	10	0.7	0.2	0.1268	0.2232	0.2025
7	10	0.7	0.5	0.1272	0.2292	0.2072
7	30	0.3	0.2	0.1560	0.2185	0.2028
7	30	0.3	0.5	0.1606	0.2208	0.2057
7	30	0.7	0.2	0.1951	0.2361	0.2262
7	30	0.7	0.5	0.1519	0.1853	0.1773
7	100	0.3	0.2	0.2429	0.2099	0.2191
7	100	0.3	0.5	0.2136	0.1826	0.1913
7	100	0.7	0.2	0.2223	0.1950	0.2024
7	100	0.7	0.5	0.2366	0.1894	0.2022

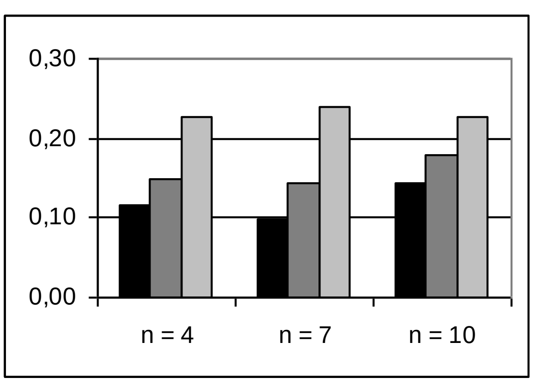
In each scenario, results represent the average of 1000 replications. Table 2 shows results for the scenarios in which the capacity is equally distributed among the carriers. Table 3 illustrates/provides finding obtained from asymmetric distribution of the capacity.



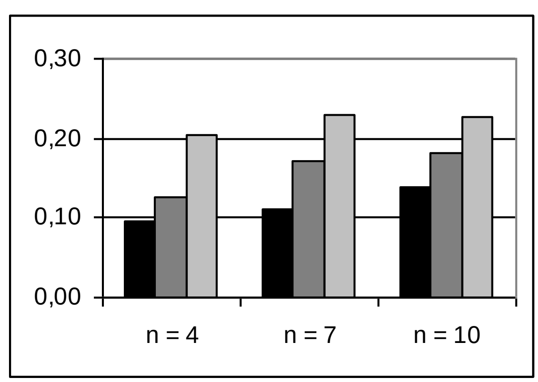
(a)



(b)



(c)



(d)

Figure 1. CP_C values for (a) $\delta = 0.3$ and $\sigma(\gamma) = 0.2$; (b) $\delta = 0.3$ and $\sigma(\gamma) = 0.5$; (c) $\delta = 0.7$ and $\sigma(\gamma) = 0.2$; (d) $\delta = 0.7$ and $\sigma(\gamma) = 0.5$.

As we expected, in all scenarios Heuristic 1 provides lower system-wide performance than Heuristic 2 ($CP_C > 0$). Moreover, in all scenarios both CP_P and CP_Y are positive, which means that Heuristic 2 determines lower aggregate performance of the carriers and higher aggregate performance of the shippers than Heuristic 1. Thus, the system as a whole benefits from the collaboration among the actors, but the resulting benefits are gained solely by the shippers. For this reason, the carriers have no interest in adopting a collaborative behavior aimed at optimizing the system-wide performance. To motivate the carriers to collaborate, a contract with a clause, specifying their share of benefits obtained from collaboration, could be prepared.

Even in the case of asymmetric distribution of the capacity, Heuristic 1 underperforms Heuristic 2 at the expense of the shippers' performance. As M increases, the CP_C value rises.

Figure 1 shows how the value of CP_C is affected by both n and M given the values of δ and $\sigma(\gamma)$. In particular, as M increases, the system-wide inefficiency of Heuristic 1 strongly rises in all the cases (Figure 1a-d) and it increases in n in most of cases. A Student's t-test confirms that all differences are statistically significant ($\alpha = 0.05$). Moreover, findings show that CP_C is not affected by δ and $\sigma(\gamma)$. In fact, the Student's t-test indicates that the null hypothesis cannot be rejected with $\alpha = 0.05$.

To assess the influence of the asymmetry in capacity distribution among carriers, the scenarios in which $n = 7$ with the capacity equally distributed are compared with those in which $n = 7$ with the capacity asymmetrically shared.

Table 4 reports the percent increases in CP_C moving from the symmetric (S) to asymmetric (A) capacity distribution. The higher this percent value, the higher the inefficiency of Heuristics 1 in the asymmetric case compared with the symmetric case. Data shows that if the similarity among paths is high (M = 10 or 30), the relative inefficiency of Heuristics 1 is on average higher with an asymmetric distribution of the capacity among carriers, whereas if the transportation paths are different (M = 100), it is higher when the capacity is equally shared.

Table 4. Percent increase in CP_C moving from the symmetric (S) to asymmetric (A) capacity distribution.

	δ = 0.3		**δ = 0.5**		**mean**
	$\sigma(\gamma)$ = 0.2	**$\sigma(\gamma)$ = 0.5**	**$\sigma(\gamma)$ = 0.2**	**$\sigma(\gamma)$ = 0.5**	
M = 10	8,49%	20,93%	27,82%	13,57%	17,70%
M = 30	15,13%	24,59%	36,43%	-10,96%	16,30%
M = 100	1,97%	-12,39%	-7,22%	3,00%	-3,66%

Note: the percent increase is calculated as $[CP_C^{(A)} - CP_C^{(S)}] / CP_C^{(S)}$.

4. Organizing the market

As mentioned in the Introduction, in most real cases the procurement of transportation services occurs through the market as a coordination mechanism. Recent trends – specialization of logistics providers and, in particular, the emergence of integrators, 3PLs and 4PLs respectively – seem not enough to exploit the opportunities to improve transportation service while reducing the related costs: the performance of transportation is indeed still poor (Gorick, 2006; Ergun *et al.* 2007).

The adoption of a coordination mechanism different from the market and characterized by a higher centralization of decision making (e.g., hierarchy) is barely realistic, due to the fragmentation of the transportation sector and the lack of a clear process owner. Acknowledging this, we claim that some improvement could be achieved by "organizing the market". To this aim, we have introduced a simulation model (Section 2) and assessed the potential for such improvements under different scenarios and different ways of organizing logistics markets.

It is crucial then to specify what "organizing the market" is, and how this can be actually implemented (and in turn reflected in the proposed model). Rather than modifying the organizational structure, which, to sum up, concerns the design of the allocation of decision rights and the related communication links, we propose influencing the decision making process and give three recommendations.

The recommendations aim at improving the match between supply and demand in logistics markets. The information exchange and the actors' decisions should be improved, so as to diminish the information processing effort and, at the same time, increase the decision effectiveness of both every actor and the system as a whole. We propose the following:

1. *Select*. Help actors to focus on data or potential transaction, which are more relevant (and might be overlooked due to excess of information coupled with bounded rationality);
2. *Enrich*. Complement the data formally exchanged in the potential transactions with other relevant information;
3. *Modify*. Change the terms of the potential transactions to make them more efficient and beneficial to both parties.

In the following we provide examples for each recommendation and relate them to the model proposed in Section 2.

With respect to recommendation 1, it is possible to select information by: (i) identifying similar transportation requests and push carriers or shippers to jointly examine them, when formulating or selecting the offers; and (ii) grouping requests consistent with offers (e.g., requests characterized by low quantity uncertainty that fit with transportation contracts involving advanced reservation).

With respect to recommendation 2, information can be enriched by complementing the transportation price with data such as the existence of some flexibility on the pick-up or delivery dates.

With respect to recommendation 3, modifying information means changing the terms of the potential transactions (e.g., contract clauses) to make certain transactions preferable as compared to others, due to their higher system utility, while at the same time making sure that neither party decreases utility, should he/she agrees on such transactions.

To explain the value of "organizing" activities mentioned above, we may consider an actor (e.g., an intermediating agency) responsible for these activities. This actor uses economic incentives in order to direct both carriers and shippers. The actor's recommendations lead to increase of the system's efficiency. The incentives include transferring a portion of the savings achieved from the increased efficiency to the shippers and carriers. The incentive scheme suggested above takes into account that decisions cannot be forced on SC actors. The scheme, therefore, conforms to the following two principles (Tsay et al., 1999; Bahinipati *et al.*, 2009):

1. *Channel coordination*, i.e., system performance has to increase compared with the "not-organized" market;
2. *Win-win condition*, i.e., every actor has to be convinced that the organization does not disadvantage her in any way.

Principle 1 ensures that there is the possibility to promote behaviors by SC actors, which are virtuous under a system-wide perspective. In fact, the whole system performance improvement means that the proverbial pie is available to be shared by the participants in the logistics market. Principle 2 deals with the criteria determining how to cut that pie to the satisfaction of every participant.

We believe that conforming to these principles requires that both rational and behavioral issues are taken into account. Decision making problems are usually modeled based on variables related to rationality, such as availability of perfect information, nature of information (e.g., private vs. public), utility functions (e.g., the risk aversion of decision makers). Such variables are relatively easy to be dealt with, however they are likely to be not adequate to describe real problems and to identify actual solutions. They need to be complemented by other variables, those that can model behaviors. Models should take into account aspects such as trust, perception of opportunism by the counterpart, expectation for building a relationship, etc. especially for systems within which decisions are made by several independent actors, who own information related to each respective local environment. What one might expect based only on rational variables may be contradicted due to the influence of behavioral variables.

5. Conclusions

Most of real logistics services are exchanged through pure market mechanisms where decisions are made in a totally decentralized fashion For instance, in transportation markets, carriers and shippers make independent decisions in order to pursue their own objectives, neglecting the need for maximizing the performance of the market as a whole. This is mostly due to the lack of conditions that would allow decisions to be centralized and results in significant inefficiencies for the market as a whole.

To assess such inefficiencies we conducted a simulation study on a simplified model of a marketplace, wherein shippers and carriers interact to provide or acquire logistics services. We developed a heuristics simulating the players' behaviors and compared performance against a benchmark. Results show that, (1) inefficiency increases with the diversity in the routes, the number of carriers, and the asymmetric distribution of the capacity of the carriers (the negative impact of the latter is emphasized for low diversity among routes); (2) the system-wide performance seems not to be affected by (i) a carrier pricing strategy aimed at pursuing consolidation (through discounts for similar routes) and (ii) a higher variance in the mark-up factor used by carriers to set prices.

To achieve performance improvements of logistics markets, one should acknowledge the allocation of decision rights as given in reality. In particular, when the decision making process is decentralized, global optimization models are likely to prove ineffective. In this paper we suggested to "organize the market", i.e., to influence the decision making process, in order to enhance coordination among the SC actors. To this aim we give recommendations aimed at increasing the decision making process' effectiveness. The recommendations are of three types: *select*, *enrich*, and *modify* information exchanged by actors. It is worthwhile to stress that such recommendations conform to channel coordination and win-win conditions, which jointly assure that a potential improvement exists and every party can benefit from it.

We argued that to effectively organize the market, in addition to the variables related to rationality, behavioral issues should be taken into account. They are indeed critical in contexts where several actors interact and make independent decisions. Behavioral issues relate to subjective social perceptions and expectations regarding oneself, the counterpart, and the context in which the transaction occurs, and are affected by the actors' bounded rationality.

We believe that the adoption of the proposed recommendations can positively impact the performance of logistics markets, by actually achieving the potential improvement assessed through the proposed simulation study. Subsequent studies will attempt to identify concrete actions required for the recommendations' implementation as well as analyze the impact of behavioral aspects on the implementation.

Acknowledgements

This work has been supported by Regione Puglia (APQ PS025) and the Engineering Faculty in Taranto of the Politecnico di Bari.

References

Ağralı S., B. Tan, F. Karaesmen (2008). Modeling and analysis of an auction-based logistics market. European Journal of Operational Research 191, 272-294.

Andersson, D., A. Norrman (2002). Procurement of logistics services – a minutes work or a multi-year project. *European Journal of Purchasing and Supply Management* 8, 3-14.

Bahinipati, B.K., A. Kanda, S.G. Deshmukh (2009). Coordinated supply management: review, insights, and limitations. *International Journal of Logistics Research and Applications* 12(6), 407-422.

Brown, J.R., C.S. Dev, D.J. Lee (2000). Managing Marketing Channel Opportunism: The Efficacy of Alternative Governance Mechanisms. *The Journal of Marketing* 64(2), 51-65

Cachon G.P., P.H. Zipkin (1999). Competitive and cooperative inventory policies in a two-stage supply chain. *Management Science* 45(7), 936-953.

Cooper M.C., D.M. Lambert, J.D. Pagh (1997). Supply chain management: more than a new name for logistics. International Journal of Logistics Management 8(2), 1-14.

Corbett C.J., C.S. Tang (1999). Designing supply contracts: contract type and information asymmetry. In: S. Tayur, R. Ganeshan, M. Magazine (eds.). *Quantitative Models for Supply Chain Management*. Kluwer Academic Publishers, London, UK, 269-297.

Cummings, L.L., P. Bromiley (1996). The organizational trust inventory (OTI): development and validation. In: Kramer, R.M., Tyler, T. (eds.), *Trust in Organizations: Frontiers of Theory and Research*, pp.302-330. Sage, Thousand Oaks, CA.

Ergun O., G. Kuyzu, M. Salvelsbergh (2007). Reducing truckload transportation costs through collaboration. *Transportation Science* 41(2), 206-221.

Fitzsimmons J.A., J. Noh, E. Thies (1998). Purchasing business services. *Journal of Business & Industrial Marketing* 13(4-5), 370-380.

Frohlich M.T., R. Westbrook (2001). Arcs of integration: an international study of supply chain strategies. *Journal of Operations Management* 19, 185-210.

Giannoccaro I., R. Moramarco, P. Pontrandolfo (2009). E-procurement of logistics services: the impact of the service attributes on the exchange mechanism. *20th International Conference on Production Research*, 2-6 August 2009, Shanghai, China.

Gorick J. (2006). Running on empty? *Logistics & Transport Focus* 8(10), 25-26.

Lee H., S. Whang (1999). Decentralized multi-echelon supply chains: incentives and information. *Management Science* 45(5), 633-639.

Nyaga, G.N., J.M. Whipple, D.F. Lynch (2010). Examining supply chain relationships: Do buyer and supplier perspectives on collaborative relationships differ? *Journal of Operations Management* 28(2), 101-114.

Rousseau, D.M., S.B. Sitkin, R.S. Burt, C. Camerer (1998). Not So Different After All: A cross-Discipline View of Trust. *Academy of Management Review* 23(7), 393-404.

Rubinstein A. (1998). *Modeling bounded rationality*. The MIT Press, Cambridge, MA, USA.

Schoenherr T., V.A. Mabert (2008). The use of bundling in B2B online reverse auctions. *Journal of Operations Management* 26(1), 81-95.

Simon H.E. (1982). *Models of bounded rationality*, The MIT Press, Cambridge, MA, USA.

Su X. (2008). Bounded Rationality in Newsvendor Models. *Manufacturing & Service Operations Management* 10(4), 566-589.

Tang C.S. (2006). Perspectives in supply chain risk management. *International Journal of Production Economics* 103(2), 451-488.

Tsay A.A., S. Nahmias, N. Agrawal (1999). Modeling supply chain contracts: a review. In: S. Tayur, R. Ganeshan, M. Magazine (eds.). *Quantitative models for supply chain management*. Kluwer Academic Publisher, Norwell, MA, USA, 299-336.

Vickery S.K., J. Jayaram, C. Drodge, R. Calantone (2003). The effects of an integrative supply chain strategy on customer service and financial performance: an analysis of direct versus indirect relationships. Journal of Operations Management 21(5), 523-539.

Williamson, O.E. (1985). *The Economic Institutions of Capitalism*. The Free Press, New York.

Yao J. (2010). Decision optimization analysis on supply chain resource integration in fourth party logistics. *Journal of Manufacturing Systems* 29(4), 121–129.

Zaheer, A., B. McEvily, V. Perrone (1998), Does trust matter? Exploring the effects of interorganizational and interpersonal trust on performance. *Organization Science* 9(2), 141-159.

Zeithaml V.A., A. Parasuraman, L.L. Berry (1985). Problems and strategies in services marketing. *Journal of Marketing* 49(2), 33-46.