COMPETITIVE NETWORK DESIGN IN SHORT-SEA LINER MARKETS USING AGENT-BASED GAME-THEORETIC MODELS

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Abstract: The industry of short-sea passenger shipping transportation is regarded as a growing market of increased competition. One of the most essential problems for the competitors (liners) is the design of their service system strategy. In the current study, an agent-based simulation framework is presented in order to simulate the behaviour of each competing shipping company, combined with a parallel co-evolutionary genetic algorithm able to solve complex game theoretic problems of competition.

Key Words: Deregulated transportation markets, competitive network design, agent-based simulation, co-evolutionary strategies.

1. INTRODUCTION

The industry of short-sea passenger shipping transportation is regarded as a growing market of increased competition. In Greece, after the introduction of deregulation in 2004, the privilege of "cabotage" was abolished and new shipping companies are gradually entering the market. One of the most essential problems for the competitors (liners) is the design of their service system strategy (network). The significance of the competitive network design problem reflects on applications to other competitive transportation markets, like those of bus companies and airlines. The design of services and their associated costs primarily concerns the allocation of the resources (ships) to the alternative markets (shipping lines), as well as the size (capacity) of ships, frequency of services, operating speed and determination of fares. The design and the pricing strategy set by each firm individually are affected by the choices of its competitors in the relevant market.

The procedure of designing transportation systems has been recognized as a multiple hierarchical levels decision making process (Fisk, 1986). The most typical situation of such a procedure concerns an authority playing the role of the designer who attempts to optimize the system performance by introducing alternative strategies in the network and taking into account the responses of users (Magnanti and Wong, 1984). The determination of these alternative strategies constitutes the Network Design Problem (NDP), which usually refer to network link capacity expansions, alternative traffic control schemes, pricing of the system use or combinations of all the above (see Côté *et. al*, 2003). The NDP in transportation systems is typically formulated and analyzed as a two stage leader-follower Stackelberg game of complete information, where at the upper level the designer imposes alternative strategies to optimize the system performance, by taking into account the response of users, who they are seeking to optimize their objectives at the lower level. The NDP is typically formulated as a bi-level programming problem, which facilitates the solution of Stackelberg games.

The case of network design by more than one authority adds to the complexity of the traditional problem, especially in the case where the alternative authorities do not act synergistically (van Zuylen and Taale, 2004) and when the alternative authorities act competitively. This is due to the nature of problems of competition that are usually modelled as non-cooperative games where the solutions (if any and if tractable) are based on the equilibrium assumption (see section 3). Although the literature on the classic form of the NDP is large, existing studies on the competitive NDP (C-NDP) are limited and mostly restricted in airline competition.

Specifically, Hansen (1990) examined the airline competition over the U.S. domestic air transportation system as an *n*-player non-cooperative game, in order to determine the Level-of-Service (LoS), in terms of the service frequency, of each airline connection. More recently, Wei and Hansen (2006) extended the previous model to determine the airline capacity and frequency per Origin-Destination (OD) pair, but their results were found to be tractable only for the case of duopolies. Friesz *et. al* (2005) studied the case of fare competition in an oligopolistic transportation service network within an evolutionary game theoretic framework, by using a Differential Variational Inequality formulation. Such a formulation based on optimal control is suitable only for cases of continuous variables, since the specific solution procedure involves mappings between Hilbert spaces. Lederer (1993) presented a model of firm competition that captures the interaction among provided capacity, fare and consumer choices. The existence and uniqueness conditions of the C-NDP with pricing were found to hold only for some restrictive cases.

The C-NDP process is modelled in this study as a *n*-agent non-cooperative game. This game-theoretic approach allows representing the behaviour of each shipping company (agent) in the alternative markets and determining its best strategy through finding a *Nash equilibrium* in the system design. In the current game theoretic setup, each company is competing for demand in order to maximize its profits by allocating capacity (vessels) to different lines. The design process determines the LoS, in terms of frequency of service for each line and vessel type, and the fare for each trip, by taking into account the travellers’ responses to the resulting system design. The agent-based logic enables the simulation of the responses of each firm to the competitors’ choices and makes possible to obtain a stable solution using co-evolution strategies. These strategies are implemented within a population-based parallel evolutionary algorithm for the solution of all combinatorial sub-problems of the optimal design of the services offered by each agent.

Section 2 presents a model of the short-sea liner market organization, accompanied with a model for estimating the market share for each company, based on its network design plan and the subsequent reaction of customers to the alternative strategies. Section 3 provides a description of the agent-based simulation framework introduced here for addressing the game theoretic setup of the C-NDP. Section 4 describes a method based on co-evolutionary strategies for estimating the optimum strategy of each agent. Section 5 demonstrates the applicability of the proposed methodology through employing an abstract but realistic example which refers to the competition between the short-sea liners from the port of Piraeus to the main island complexes of the Aegean Sea in Greece. Section 6 summarizes and concludes.

2. AN ORGANIZATION MODEL OF THE COASTAL-LINER MARKET

2.1 Modeling the performance of passenger shipping companies

The market of short-sea shipping liners is a very complex system of interrelationships among its various components. The main partners of this system are the customers (passengers and truck load shippers) and the carriers (shipping companies). In the multi-component environment of deregulated transportation markets, such as those of the EU, where shipping companies are competing for profit maximization, optimum strategies are sought at both the long-range and the tactical planning horizon. An efficient organizational model of the system can allow identifying optimal strategies by each shipping company. In the current section, such a model is presented on a cross-disciplinary basis which shares different concepts from industrial organization, spatial economics, game theory, pricing theory and consumer demand theory, in combination with techniques of operations research.

The specific organizational model follows the fundamental assumptions of the Arrow and Dedreu (1954) model of general equilibrium of competitive economies. In the context of transportation systems, the current model assumes that passengers (customers) are perfectly informed about the available alternative trip plans, and that shipping companies (producers) are *'profit maximizers'* over their available technological possibilities and *'price-setters'* to their provided services. This model leads to market clearance in which an equilibrium tending relationship of demand and supply can be observed. Moreover, it is assumed that the decisions of companies are made in a *'rational'* manner, which implies that their choices seek to maximize their benefits, and that they take into account their competitors' strategies, forming a so-called *n-person game* of interests.

The current model can be applied to highly competitive cases, allowing to the companies both product differentiation and price discrimination as alternatives in their strategy set, which reflects a completely deregulated market. The complete form of the sea transportation service market is composed of all the sub-markets of coastal lines servicing a region. Although the formation of routes for servicing a certain region is of great importance, since it could potentially give advantage among the competitors, the current study considers the routes forming the lines as fixed.

Each company offers a set of alternative service possibilities in each sub-market. These possibilities are differentiated at the provided LoS and the price for each alternative. In this study, the LoS is expressed in terms of the service frequency and travel time, although other variables, like the age of the vessel and the accuracy on the timetable, could be used. The capacity allocation for each shipping company in each sub-market concerns two components, i.e. the service frequency and the capacity of each vessel. Also, the total network design for each company considers here the pricing strategy for each trip, in each sub-market. Finally, it is assumed that passengers make their trip choices after the determination of the vessel type, service frequency and prices by each company. The next paragraph describes the notation used in the coastal-liner market organization model of the present study.

Notation:

D_{ij} : Total demand for coastal line (sub-market or O-D pair) $i-j$

T : Total study horizon

A : Shipping company $A \in \Im$

k : Vessel type

$d_{ij,t}^{Akvf}$: Market share preferring shipping company's A vessel type k for coastal line (sub-market or O-D pair) $i-j$, operating with a service frequency v and having a service price f for the period t.

$p_{ij,t}^{Akvf}$: Number of passengers using shipping company's A vessel type k, for coastal line (sub-market or O-D pair) $i-j$, operating with a service frequency v and having a service price f for the period t.

$v_{ij,t}^{Ak}$: Trip frequency of shipping company's A vessel type k, operating in the coastal line (sub-market or O-D pair) $i-j$, for the period t

$f_{ij,t}^{Ak}$: One-way passenger trip fare set by shipping company A for vessel type k, operating in the coastal line (sub-market or O-D pair) $i-j$, for the period t

$c_{ij,t}^{k}$: Total cost of vessel type k, operating in the coastal line (sub-market or O-D pair) $i-j$, for the period t

n^{k} : Capacity of vessel type k

$n_{ij,t}^{Ak}$: Available capacity of company's A vessel type k operating in the coastal line (sub-market or O-D pair) $i-j$, for the period t

C_t^A : Operating cost of shipping company A for the period t

R_t^A : Revenues of shipping company A for the period t

G_t^A : Profit of shipping company A for the period t

The model of coastal-liner market organization can be formulated as a simultaneous multiple-objective function optimization, which has the following form:

$$\max G_T^A(k,v,f),\ \forall A \in \Im \tag{1}$$

It should be noted that the specific formulation differs from the formulation of multi-objective mathematical programming problems. This is because in the cases of multi-objective problems an overall optimization of a synthetic objective function is attempted, while in the current setup each function is optimized with respect to the performance of the other objective functions, where each objective function involves unilaterally used control variables. Since the performance of all objective functions is interrelated and subject to the performance of each other, this leads to a highly complex and non-convex optimization problem. The following section provides the definition of the profit of each company, which signifies the interrelated nature of each objective function of the proposed market organization model.

The estimation of the daily profit of each company initially requires calculating the cost of its service system. This is based on the following equation:

$$C_T^A = \sum_t \sum_{ij} \sum_k \left(v_{ij,t}^{Ak} c_{ij,t}^{k} + m_{ij,t}^{Ak,v} \left(E^k + v_{ij,t}^{Ak} w H^k \right) \right) \tag{2}$$

Equation (2) implies that the total cost encountered by company A is the summation of the number of trips per O-D pair and vessel type multiplied by the unit operating cost of those trips, plus the fixed cost component. The latter component is given by the sum of the fixed cost E^k and vessels crew cost, which is composed of the frequency-weighted product of the average crew salary per trip, w, and the crew size H^k servicing vessel type k, multiplied by the number of vessels of each type, $m_{ij,t}^{Ak,v}$, necessary to provide trip frequency v, where $m_{ij,t}^{Ak,v} = v_{ij,t}^{Ak} / v_{0-ij}^{k}$, with v_{0-ij}^{k} being an integer representing the maximum daily number of trips between $i-j$ which can be offered by vessel type k. The operating cost per O-D pair is calculated as follows:

$$c_{ij,t}^{k} = a\,q\,S_{ij}\,\frac{u^2}{u_o^3} \tag{3}$$

where a is the fuel consumption for vessel base speed u_o, u is the vessel operating speed, q is the fuel cost and S_{ij} is the total trip length between $i-j$. Finally, the daily fixed cost is calculated by equation (4):

$$E^k = \frac{K^k}{L}\left(\frac{r_o(1+r_o)^n}{(1+r_o)^n - 1} + r_1 + r_2\right) \tag{4}$$

where K^k is the acquisition cost of vessel type k, L is the annual number of operating days, r_o is the annual loan rate, n is the vessel payback period in years, while $K^k r_1$ and $K^k r_2$ are the insurance cost and the other operational costs (personnel, port tariffs, marketing, etc), in terms of the total vessel capital.

On the other hand, the estimation of the daily revenues of each company can be given through the following equation:

$$R_T^A = \sum_t \sum_{ij} \sum_k p_{ij,t}^{Ak}\, f_{ij,t}^{Ak}\,, \tag{5}$$

which states that the revenues of each company A is the summation of the number of passengers per O-D pair and vessel type multiplied by the fare paid for each type of provided service (type of vessel). The number of passengers using an alternative option cannot exceed its *available capacity* $n_{ij,t}^{Ak}$ (product availability), which is defined as the frequency of an alternative service multiplied by the vessel capacity:

$$n_{ij,t}^{Ak} = v_{ij,t}^{Ak}\, n^k \tag{6}$$

Thus, the number of passengers preferring shipping company's A vessel type k is taken to be either the product of total demand with the market share of the specific service, if this is less or equal to the available capacity, or the available capacity:

$$p_{ij,t}^{Akvf} = D_{ij}\, d_{ij,t}^{Akvf}\,, \quad \text{if } D_{ij}\, d_{ij,t}^{Akvf} < n_{ij,t}^{Ak} \tag{7a}$$

$$p_{ij,t}^{Akvf} = n^k\,, \qquad \text{if } D_{ij}\, d_{ij,t}^{Akvf} \geq n_{ij,t}^{Ak} \tag{7b}$$

Then, it is straightforward to estimate the profits for each company as follows:

$$G_T^A = R_T^A - C_T^A \tag{8}$$

Equation (8) indicates that, although the cost of each company is based on its strategies, the revenues are based on the market share of each provided service, which is subject to the choices made by the other companies operating in each line. Subsection 2.1 presents a sub-model which enables the estimation of the response of passengers to the available alternative options, by taking into account the prevailing competitive market conditions as formed by all companies participating in the market.

2.2 The market share sub-model

The market share model used in this study relies on the assumption that passengers take decisions based on bounded rationality. In particular, the model assumes that passengers' perception error follows the Gumbel distribution, which is modelled following the multinomial logit logic (Ben-Akiva and Lerman, 1985). The present model has an iterative logic for estimating the passengers for each trip connecting an O-D pair, in order to take into account the available capacity constraints $n_{ij,t}^{Ak}$ of each alternative. These alternatives refer to the vessel type, in terms of its operating speed (and thus travel time), the service frequency and the fare for each setting. The market share of each service is estimated by:

$$d_{ij,t}^{Akvf} = \exp\left(U_{ij,t}^{Akvf}\right) \Big/ \sum_A \exp\left(U_{ij,t}^{Akvf}\right) \tag{9}$$

where $U_{ij,t}^{Akvf}$ is the utility function of an alternative service of company A in the coastal line (sub-market or O-D pair) i, j, of vessel type k, operating with a service frequency v and having a service price f for the period t.

In models of logit logic an essential role relies on the definition of the utility function. In the current study, such a function is adopted which enables the incorporation of both LoS and fare, as well as particularities observed in the coastal-liner markets. The utility function has the following form:

$$U_{ij,t}^{Akvf} = a_1 f_{ij,t}^{Ak} + a_2 \ln\left(v_{ij,t}^{Ak}\right) + a_3 V^k + U_{ij,t}^{A} \tag{10}$$

where V^k stands for the selection (group) variable of vessel type k and $U_{ij,t}^{A}$ stands for a constant reflecting the passengers preferences for company A, on line ij. In equation (10), the service frequency of the company's A vessel type k on line ij is expressed in a logarithmic form. This is because $v_{ij,t}^{Ak}$ is an attribute reflecting the *'size'* of an alternative and the logarithmic form is appropriate for representing such variables (Ben-Akiva and Lerman, 1985). The above model combines all different attributes of all competitors in each sub-market, leading to the formation of the interplay among the strategies of each competitor. Namely, the attractiveness of an alternative is subject to the choices of all other competitors participating in the market.

The estimation of the number of passengers preferring a specific vessel in each sub-market follows an iterative correction procedure, so that take into account the capacity of each alternative. The following algorithmic steps describe this iterative procedure, wherein the passengers (consumers) make choices among alternative transportation services (products) of limited capacity (availability):

Step 1: *Calculation of the utilities for each available alternative option*
Step 2: *Initial assignment of the market share per available alternative option and transformation to the number of passengers*

DO UNTIL market clears OR no further capacity is available

Step 3: *Check for excess demand for every alternative option*
Step 4: *Exclusion of fully booked trips and formation of a new available choice set*
Step 5: *Assignment of the excess demand to the available alternatives*

3. SIMULATION AND ESTIMATION OF SHORT-SEA LINER COMPETITION

3.1 Agent-based simulation of passenger shipping companies

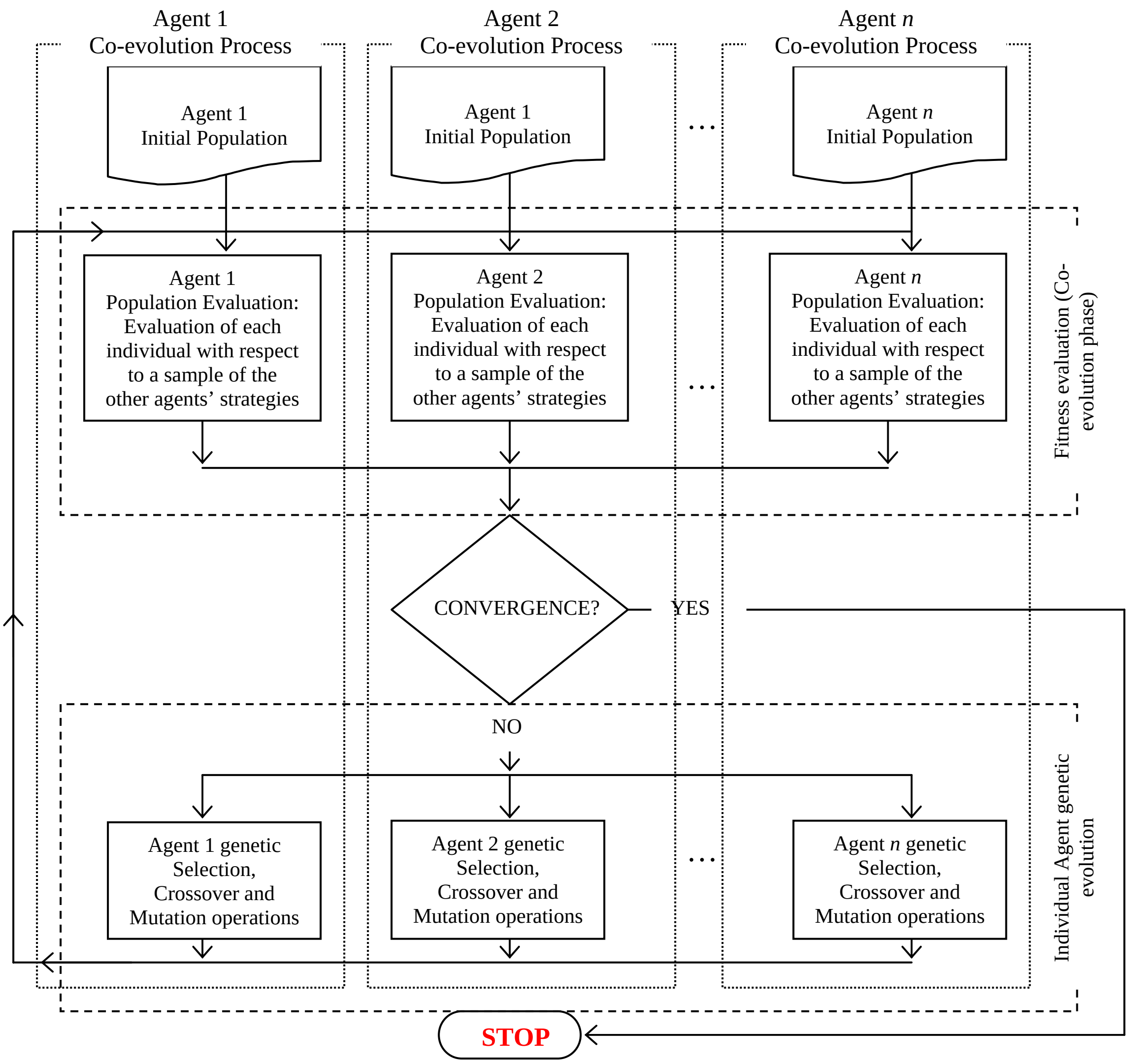
In order to identify optimal strategies in complex problems where multiple decisions are engaged into an environment of interrelations, as in the present case of coastal-liner competition, classical optimization methods cannot be useful. Hence, the current study adopts a decentralized optimization structure in order to address the problem of the C-NDP in the coastal-liner market. The present method is based on the structure of autonomous Intelligent Agents Simulation (IAS) or Agent-Based Simulation (ABS), which have been used to address similar complex decentralized optimization problems. In the recent years, the concept of decentralized decision-making structure is preferred to address complex problems of interrelated situations. ABS is a framework utilizing concepts of the Artificial Intelligence for modelling complex hyper-systems, which it simulates the behaviour of distributed sub-systems when they interact with each other. Applications of the ABS framework can be identified in advanced control strategies, complex biological systems and population dynamics (Weiss, 1999).

The current study addresses the problem of competitive network design in the deregulated sea passenger market by simulating the behaviour of each company as an intelligent agent. Each intelligent agent (shipping company) attempts to optimize its performance (maximize profits) in relation to the behaviour of all others agents. The present evolutionary game theoretic setup utilizes concepts of population dynamics and Evolutionary Stable Strategies (ESSs), as they were first introduced by Maynard Smith (1982). In every phase of the evolution, the search space of the choices of each agent is explored through a population-based evolutionary algorithm. The specific evolutionary algorithm, which is presented in the next subsection (3.2), which is used to identify the optimum responses of each agent, has a co-evolution structure, since the performance of every agent relies on the strategies employed by all other agents.

3.2 Co-evolutionary methods for solving competitive games

Genetic Algorithms (GAs) are population-based stochastic approximation methods for approaching optimality on the basis of Darwinian laws of natural evolution (Holland, 1975). Each individual of the population is a coded (typically binary) representation of a candidate solution of the problem at hand, which refers to as chromosome. Then, a mechanism of evolution of an initial population replicating biological systems is adopted in order to gradually approach optimal (or satisfactory sub-optimal) solutions. The mechanism of genetic evolution is based on three fundamental genetic operations, i.e., selection, crossover and mutation. At the selection phase, a stochastic selection of the most prosperous individuals of the population is made, according to the performance of each candidate solution, which results in an intermediate population fulfilling the most prominent law of evolution, termed as the *'surviving of the fittest'*. At the crossover phase, random paired individuals of the intermediate population exchange genetic information, in terms of parts of their chromosomes, so that form a new population of genetically improved candidate solutions. Finally, at the mutation phase, small random parts of the chromosome are altered in order to prevent early convergence to a final local-optimal solution.

Figure 1: The process of genetic co-evolution of the multi-agent system



Standard GAs have been successfully implemented into the optimization of highly complex single and multi-objective problems. However, the standard formulation of

GAs cannot be implemented in the C-NDP, since its formulation concerns the simultaneous optimization of several multiple-objective functions interrelated with each other in a competitive manner. Thus, a modification of the standard GA is made, utilizing parallel GAs with co-evolving populations, which are able to address this complex game-theoretic problem.

Since the first co-evolutionary algorithm presented in early 90s by Hillis (1990), a blossom in the applications of such algorithms has been observed in the recent years (Rosin and Belew 1997, De Jong and Pollack 2004, Bongard and Lipson 2005, Jin and Tsang 2005). The present co-evolutionary algorithm is based on the mechanics of mutual evolution of all agents participating in the game. Every participating agent searches for optimal strategies using a modified GA in the performance evaluation phase. This phase differs from that of the standard GA, since each candidate solution is tested against a sample of the other agent strategies, in order to investigate its performance with respect to possible responses of the other agents (see Figure 1). In this case, each agent attempts to evolve by identifying Evolutionary Stable Strategies (ESSs) in a competitive environment.

Each chromosome of the population of each autonomous agent contains all the necessary information (coded in binary numbering system), in terms of the complete network setting, i.e. the frequency of each vessel type and fare for each trip for all sub-markets. At the co-evolutionary phase, where the performance of each individual of the population of agents is evaluated, the performance of every chromosome is taken as the average performance over a sample of strategies from the populations of the other agents. In the current setup, the sample size is composed of combinations of 50% of all the other agents' population. For instance, assuming a case where 3 agents are competing using a population size of 100 individuals, at the evaluation phase the performance of each individual is taken to be the average of 50×50=2500 evaluations. By using this co-evolutionary pattern, a population-based evolutionary game-theoretic process of competing agents is formed, since the performance of each agent is optimized by taking into account the strategies of the all other agents.

4. APPLICATION OF THE METHOD

The present model of sea transportation market organization and competitive network design is applied into an abstract but realistic case, which corresponds to the market of the short-sea passenger transportation network in the complex of Aegean islands. The abstraction concerns the application of the model to a selected set of the 'busiest' ferry lines operating in the Aegean Sea, based on the study of Spathi (2005). These lines connect the islands with the hinterland of Greece via the port of Piraeus. The selection set is composed of 9 lines, as they are shown in Figure 2, namely the line connecting Piraeus with North-Eastern Aegean islands (Chios-Lesvos), three lines connecting Piraeus with the Cyclades islands (Paros-Naxos-Ios-Santorini, Syros-Tinos-Mykonos, Kythnos-Serifos-Sifnos-Milos), the line connecting Piraeus with Dodekanisos (Kos-Rhodes) and, finally, four lines connecting Piraeus with Crete (Chania, Rethimnon, Herakleio, Ag. Nikolaos).

After the abolition of the privilege of 'cabotage' in the Greek sea passenger transportation in 2004, the market of short-sea liners experienced an increased mobility, since the shipping companies changed their structure through exhibiting a trend in merging and creating larger fleets in an attempt to form economies of scale and, hence, strengthen their position in the new competition regime. In the current study, the competitive network design game is played among three major agents (shipping companies), which compete for dominance over the market of short-sea passenger transportation in the Aegean islands.

Figure 2: Overview of the modeled short-sea Aegean island market

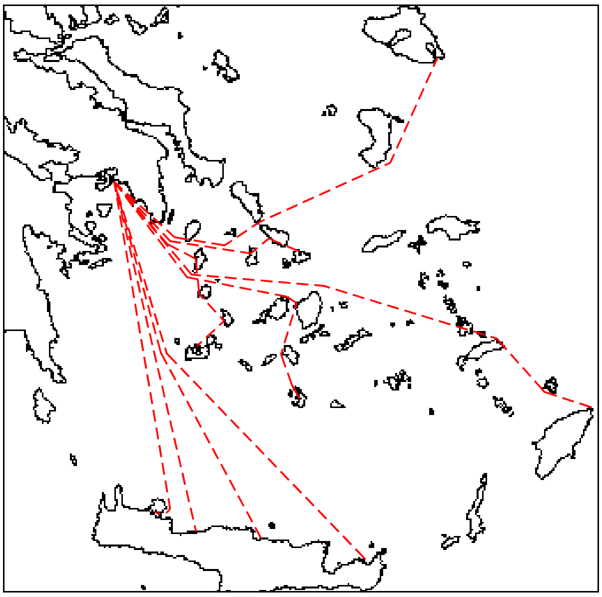


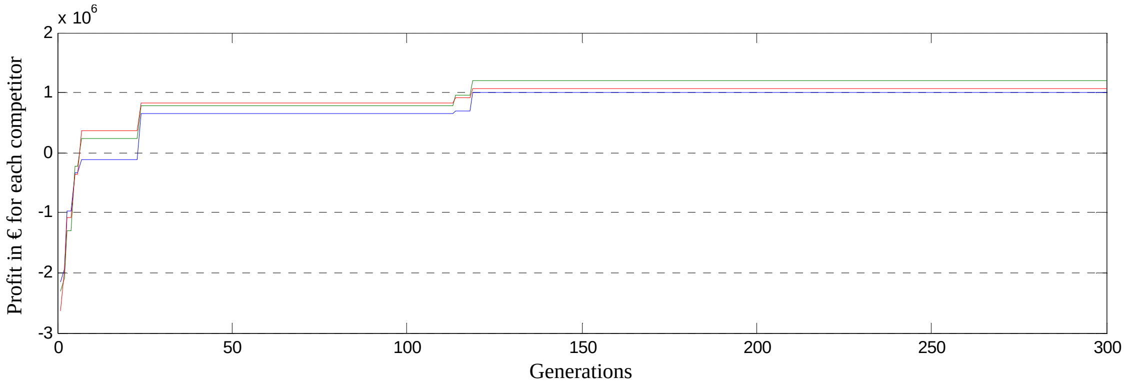
Table 1: Data used in the case study application

	Vessel Type A	Vessel Type B	Vessel Type C	
Vessel Type Capacity (Passengers)	1500	2200	700	
Vessel Type Speed (Knots)	20	20	32	
Piraeus to:	Daily Vessel Total Cost (€) per line and vessel type			Daily one-way demand per line (Passengers)
Chios-Lesvos	48.200,00	63.900,00	63.900,00	1500
Paros-Naxos-Ios-Santorini	43.500,00	59.200,00	59.200,00	2000
Syros-Tinos-Mykonos	45.700,00	61.400,00	61.400,00	2000
Kythnos-Serifos-Sifnos-Milos	43.300,00	59.000,00	59.000,00	800
Kos-Rhodes	51.880,00	67.600,00	67.600,00	3000
Chania	46.200,00	61.900,00	61.900,00	3500
Rethimnon	46.200,00	61.900,00	61.900,00	2500
Herakleio	47.100,00	62.850,00	62.850,00	3500
Ag. Nikolaos	47.100,00	62.850,00	62.850,00	2500

As it was mentioned previously, the control variables of each agent concern the provision of services in terms of the vessel type, service frequency per vessel type and fare structure per trip and vessel type, for every sub-market. Table 1 presents the data used for the analysis of the sea transportation market competition in this case study. It should be mentioned that the total vessel daily cost is calculated by assuming that all vessels are *new-buildings* and are operating for 11 months per year. Also, the cost for obtaining vessel type A is 70.000.000 €, and vessel type B and C is 100.000.000 €, while the shipping companies use a rather short payback period of 7 years. Moreover, the profit model considers only revenues earned from passenger fares, while revenues obtained from other sources have been omitted (car and truck loads, other passenger services, etc). Finally, despite that in the lines of Crete there is a strong preference of passengers to use specific shipping companies and the fact that the model allows capturing such peculiarities (see section 2.1), the current analysis ignores such preferences in order to test the model performance.

The co-evolutionary genetic algorithm of each agent utilizes a population of 50 candidate solutions. The sample size used for the performance evaluation of each individual is composed of the combinations of the individuals from the 50% of the other two agent populations (randomly chosen), yielding a number of 25×25=625 evaluations per individual. The algorithm was found to typically converge after 150 generations to an ESS. In the current setup, the agents are competing against each other using the same available alternatives to form their strategies, which imply that the market is expected to be equivalently sliced among the three competitors. This expectation is confirmed by the results of the algorithm (see Figure 3).

Figure 3: Diagram of the algorithm convergence



Although the market appears to converge to an ESS, no uniqueness conditions for the current setup are available. Thus, multiple equilibria solutions could be potentially found for the specific game. Nevertheless, several assumptions regarding equilibrium selection can be adopted here in order to narrow the number of stable solutions, including the reputation of each shipping company or other long-run market relationships.

5. CONCLUSIONS

This paper described the development and application of a new model of passenger short-sea liner market organization, which allows capturing complex interrelationships among the various market participants. An agent-based simulation framework has been adopted in order to simulate the behaviour of each competing shipping company. This framework is combined with a parallel co-evolutionary genetic algorithm to allow the determination of the optimal strategies of each agent. A case study which refers to the Greek passenger coastal-liner market in the Aegean Sea was considered to examine the model performance. The application results show the ability of the model to identify Evolutionary Stable Strategies (ESSs) for each agent in the specific deregulated market. The study outcomes can provide useful insight into the profit-maximizing design of the services offered by the shipping companies. They can also facilitate the evaluation and prediction of the impact of potential changes in the short-sea liner competition on the cost of service provision and the response of passengers. Such changes can include the introduction of new regulatory measures and pricing regimes, the appearance of conflicts and/or merging behaviour among shipping companies, and the emergence of oligopolistic market conditions.

6. REFERENCES

Adler, N., and K. Smilowitz [2006]. Hub-and-Spoke network alliances and mergers: Price-location competition in airline industry. *Transp. Res.* B, Vol. 41, No. 4, pp. 394-409.

Arrow, K.J. and Debreu, G. [1954]. Existence of an Equilibrium for a Competitive Economy. *Econometrica*, Vol. 22, pp. 265-290.

Ben-Akiva, M., and S. Lerman [1985]. *Discrete Choice Analysis: Theory and Application to Travel Demand*. MIT Press, Cambridge, MA.

Bongard, J., and H. Lipson [2005]. Nonlinear system identification using co-evolution of models and tests. *IEEE Transact. on Evol. Comp*, Vol. 9, No.4.

Côté J-P., Marcotte P. and Savard G. [2003], A bilevel modelling approach to pricing and fare optimization in the airline industry. *J. of Rev. and Pric. Manag.*, Vol. 2, pp. 23–36.

De Jong, E. D. and J. B. Pollack [2004]. Ideal evaluation from co-evolution. *Evol. Comput.*, Vol. 12, No. 2, pp. 159–192.

Fisk, S.C. [1986] A conceptual framework for optimal transportation systems planning with integrated supply and demand models. Transp. Sci. 20, pp. 37-47

Friesz, T.L., R. Mookherjee, and M. Rigdon [2005]. An evolutionary game-theoretic model of network revenue management in oligopolistic competition. *J. of Rev. and Pric. Manag.*, Vol. 4, No 2, pp. 156-173.

Hansen, M. [1990]. Airline competition in a hub-dominated environment: an application of non-cooperative game theory. *Transp. Res.* B, Vol. 24. No. 1, pp. 27-43.

Hillis, W. D. [1990]. Coevolving parasites improve simulated evolution as an optimization procedure. *Physica* D, Vol. 42, pp. 228–234.

Holland, J.H. [1975]. *Adaptation in Natural and Artificial Systems*. 2nd Ed., MIT Press, Cambridge, MA.

Jin, N. and E. Tsang [2005]. Co-evolutionary strategies for an alternating-offer bargaining problem. *IEEE 2005 Symp. Comp. Intel. and Games*, G. Kendall and S. Lucas and, Eds., 2005, pp. 211-217.

Lederer, P.J. [1993]. A competitive network design problem with pricing. *Transp. Sci.* Vol 27, No. 1, pp. 25-38.

Magnanti, T.L., and R.T. Wong [1984]. Network Design and Transportation Planning: Models and Algorithms. *Transp. Sci*. Vol. 18, pp 1-55.

Maynard Smith, J. [1982] *Evolution and the Theory of Games.* Cambridge University Press, Cambridge, UK.

Rosin, C. D. and R. K. Belew [1997]. New methods for competitive co-evolution. *Evol. Comput.*, Vol. 5, No. 1, pp. 1–29, 1997.

Spathi, S. [2005]. Comparing air and sea passenger transportation in domestic lines: Econometric estimation of demand, *Studies* Book Series, No. 62, Centre of Planning and Economic Research, Athens, Greece.

Van Zuylen, H.J., and H, Taale, [2004]. Urban networks with ring roads: a two-level, three player game. 83rd Transportation Research Board Annual Meeting Proceedings CD-ROM.

Wei, W., and M. Hansen [2006]. Airlines' competition in aircraft size and service frequency in duopoly markets. *Transp. Res.* E, in press.

Weiss, G. ed. [1999]. *Multiagent Systems. A modern approach to distributed intelligence.* The MIT Press, Cambridge, MA.