Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 00 (2017) 000–000

Procedia Computer Science

www.elsevier.com/locate/procedia

The 6th International Workshop on Agent-based Mobility, Traffic and Transportation Models, Methodologies and Applications (ABMTrans 2017)

Modeling the Efficiency of a Port Community System as an Agent-based Process

Elnaz Irannezhad*, Mark Hickman, Carlo G. Prato

School of Civil Engineering, University of Queensland, Brisbane 4072, Australia

Abstract

We present an agent-based method which makes use of reinforcement learning in order to estimate the efficiency of a Port Community System. We have evaluated the method using two weeks of observations of import containers at the Port of Brisbane as a case study. Three scenarios are examined. The first scenario evaluates the observed container delivery by individual shipping lines and estimates the consignments allocated to the various road carriers based on optimizing the individual shipper's total logistics cost. The second scenario implies that, in the optimum case, all agents (shipping lines and road carriers) communicate and cooperate through a single portal. The objective of cooperation is in sharing vehicles and creating tours to deliver shipments to several importers in order to reduce total logistics costs, while physical and time window constraints are also considered. The third scenario allows for some agents to occasionally decide to act based on individual costs instead of total combined logistics costs. The results of this study indicate an increase in the efficiency of the whole logistics process through cooperation, and the study provides a prototype of a Port Community System to support logistics decisions.

Keywords: Multi-agent-based simulation; Port community system; Freight transport modeling; Freight agent-based modeling; Vehicle routing

1. Introduction

While billions of dollars are spent on infrastructure to move freight more efficiently, the complexity of the freight market and the lack of collaboration between the various agents in this market often lead to sub-optimal use of that

* Corresponding author. Tel.: +61-432-712-822.
E-mail address: e.irannezhad@uq.edu.au

1877-0509

infrastructure. Freight agents mostly aim for profitable and safe operations, and they share or interact with the same infrastructure. These agents include shippers, carriers, terminal operators, and logistics solution providers such as freight forwarders. Yet, due to data confidentiality and competition among freight actors, there is poor information sharing, contributing to the sub-optimal use of infrastructure.

Ports are the primary interface in the import-export industry and play an important role in driving economic growth. Currently, many port authorities play a minimalist role as a landlord, only providing the necessary infrastructure to shippers and carriers in the port. Individual freight agents (e.g. shipping lines) optimize their own logistics process while not coordinating with other shipping lines, which may result in more truck movements than necessary and incurring higher transport costs. In this context, freight agents may be aided by the exchange of information concerning road traffic conditions, real-time availability of drivers and carriers, and opportunities for bundling of shipments into fewer vehicles. In the literature, this information exchange has been called a "Port Community System (PCS)", formally defined as a holistic, geographically bounded information hub in a global supply chain that primarily serves the interest of a heterogeneous collective of port-related companies[1].

The PCS helps port authorities take the lead by providing a logistics solution to private actors, encouraging them to share information that may lead to lower logistics costs, to faster delivery/pickup in the import/export chain, and to higher customer satisfaction. Bringing all users together enhances the efficiency of the physical flow of freight, drives economic growth, and as a secondary result, assists in reducing externalities such as pollution, congestion, and land use impacts. For example, the PCS helps transport yards and container parks to predict and plan future shipments and helps carriers to better plan for their fleets. The benefits of the PCS have been seen in several examples (see Srour, van Oosterhout [1]), namely the Port of Rotterdam (Portbase), the Port of Hamburg (DIVA: Dynamic Information on Traffic Volumes), the Port of Antwerp (CCS Dakosy), the Port of Valencia, and the Port of Singapore (Portnet Trade Exchange).

The purpose of this study is to develop a multi-agent-based simulation model to examine an application of the PCS, allowing shipping lines to coordinate the delivery of import containers for shipment bundling and routing decisions. According to Malone and Crowston [2], coordination means managing the interdependencies among activities. Coordination here explicitly is defined as the ability to bundle shipments and to share vehicles for delivering containers to various destinations.

A multi-agent-based simulation consists of several agents who are interacting in an environment. This modeling technique captures the explicit decision making of various actors, representing their management of resource and time constraints and their reaction to various policies. Agent-based models have been adopted in several domains, such as the interactions of economic agents in financial markets (e.g., Xu and Chi [3], Bonabeau [4] and Taghawi-Nejad [5]), supply chain management for single firms, and the activities in fleet management including scheduling, dispatching or terminal management (e.g., Bouzid [6], Burckert, Funk [7], Henesey [8] and Dong and Li [9]). For freight transport systems, this approach seems very suitable to illustrate competition and interaction among agents. INTERLOG (Liedtke [10]) and TAPAS-Z ((Holmgren, Dahl [11]) are examples of agent-based freight transport models at the regional level.

In addition to simulating the current situation, agent-based methods can be applied to examine various policies by changing the environment and observing how agents behave in the new environment. For example, Taniguchi, Yamada [12] developed a multi-agent-based model (including shippers, carriers, and administrators) on a small test network to study the effects of road pricing on shippers' and carriers' strategies. Abdul-Mageed [13] examined a coordinated truck assignment system for five trucking companies, comparing direct competition with cooperation by sharing vehicles. Results showed that the coordinated assignment system improved the transport process in terms of decreasing the number of empty trips and the number of late arrivals.

This study examines the impacts of the PCS on an inland container transport system in which shipping lines learn whether to act individually or to cooperate in order to deliver import containers, while maintaining the objective to minimize logistics costs. The total logistics costs consider time-based and distance-based operational costs, the capacity and fixed cost of vehicles, the road network operating constraints for larger trucks, and the fixed time windows for importers. This study contributes to the literature by implementing a reinforcement learning algorithm in a joint routing and vehicle type decision-making process through the PCS. Accordingly, three scenarios have been tested. In the first scenario, the choices of vehicle type and delivery routing are optimized individually by shipping lines. In the second scenario, all deliveries are managed by the PCS. In the third scenario, each shipping line decides whether to cooperate with others through the PCS or to act individually. Shipping lines learn the optimal strategy through a Q-learning algorithm, which is a type of off-policy reinforcement learning method. In Q-learning, agent behaviors can be defined using a simulation system, allowing agents to perform independent actions but also to learn through experience to obtain specific objectives.

2. Methods

2.1. Model specification

A multi-agent-based system consists of agents and the environment where the agents are in interaction with each other. Each agent's actions follow predefined rules. Given the fragmentation of the container transport industry, a multitude of actors collaborate within a transport system, and significant time and budget are allocated to this interaction, as shown in Fig. 1.a. Some of the actors provide physical transport, located in either the port or the hinterland (e.g., stevedores, carrier companies, distribution centers, container parks), while others provide logistics services (e.g., freight forwarders, shippers).

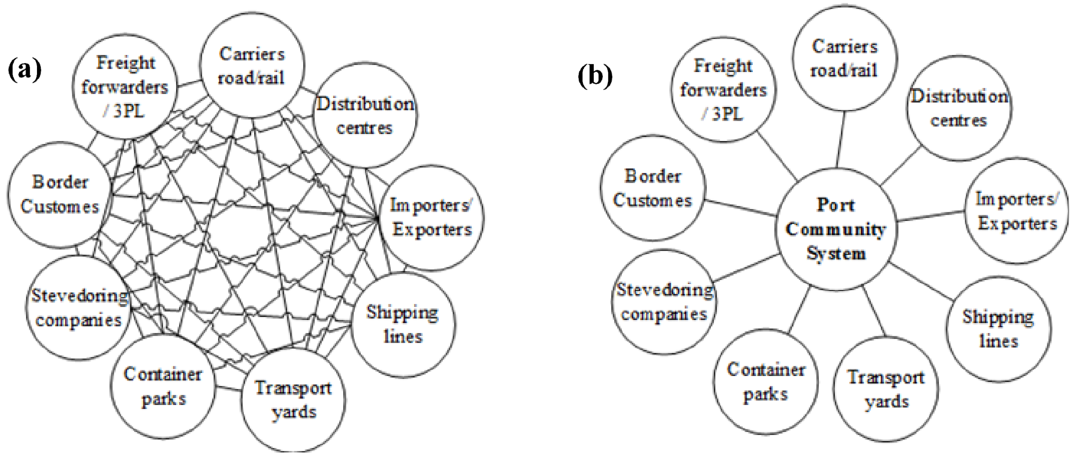

Fig. 1. Communication between individual port-related freight agents (a) without the PCS and (b) with the PCS

The agents in this model consist of importers, shipping lines, and road carriers. Importers/exporters, as the owners of shipments, have a given number of containers, the time-windows of delivery for those containers, and their origin/destination locations. There are two types of road freight vehicles, including semi-trailers and B-double trailers, which have different capacity and cost attributes. Shipping lines, as the main logistics providers, collect and distribute the import/export containers within the prerequisite time-windows and choose an optimum vehicle and route. The environment consists of discrete states of the freight market (shipments to be delivered daily) and a physical road network in which B-doubles are not allowed to operate on some road segments.

In the first scenario (the current situation, shown in Fig. 1.a.), the simulation outcome is achieved with individual shipping lines acting independently, while in the second scenario the simulation outcome is the result of full cooperation of all shipping lines to deliver their shipments through the PCS (shown in Fig.1.b). Notably, in the third scenario, in each of 50 discrete simulations (steps), each shipping line is given the opportunity to explore and exploit these two options (individual vs. cooperative delivery plans) for 14 days (with 1 day exhibiting 1 "state" of the environment) by learning through an off-policy reinforcement learning (RL) algorithm called Q-learning.

An RL algorithm is a computational method in which an agent is trained to take the optimal action through a learning process. The agent takes action based on a predefined policy, predicts a value for that action, experiences the actual outcome for every state (day), and then compares this prediction (expected) to the experience (observed). Q-learning is the most salient RL algorithm, and it is defined as[14]:

$$Q(s_t,a_t) \leftarrow Q(s_t,a_t) + \alpha\left[r_{t+1} + \gamma \max Q_a(s_{t+1},a) - Q(s_t,a_t)\right] \tag{1}$$

where:
$Q(s_t, a_t)$: Value of taking action a_t in state s_t.
r_{t+1}: Reward from the environment in step $t+1$.
α: The learning rate, a value between 0 and 1, where a higher value represents faster learning.
γ: The discount factor, a value between 0 and 1, where a smaller value represents a more short-sighted agent, with the extreme 0 standing for an agent who only considers the current rewards.
$max\ Q_a(s_{t+1},a)$: The maximum reward that is expected to be achieved in the following state, if action a is chosen.

In this model, the action-value function $Q(s_t,a_t)$ is defined as the savings in the total logistics cost for action a_t compared to other actions, where the logistics cost are a summation of the cost due to time-windows violations, the operational costs attributed to travel time and distance, and the fixed costs of a road carrier. Travel time and distance are determined based on the result of the optimum routing in every state s_t (the environment on day t), where the optimum routing is obtained from the solution to the "capacitated vehicle routing problem with time-windows" (CVRPTW). The CVRPTW model is a combinatorial optimization problem which determines the optimal set of routes for a fleet of vehicles to traverse in order to deliver containers to a given set of customers considering vehicle capacities, delivery time windows, driver work rules, and network constraints for some vehicles. Accordingly, the optimum vehicle type is chosen within the solution to the CVRPTW. The algorithm for solving the CVRPTW is as follows:

Step 1: Initialize $Q(s_0, a_0)$ for each agent (137 shipping lines), where a_0 = individual action, s_0 = all shipments to be delivered in first day, $Q(s_0, a_0)$ = savings in total transport cost for all shipments for the first day, comparing each shipping line acting independently to all shipping lines cooperating
Repeat for each episode (*50* simulations) until s_t is terminal:
Step 2: Initialize state s_t (s_t = 1..14 days)
Step 3: Choose a_t (independence or cooperation) using an action-taking policy. We use ε = 0.2 which means 20% of the actions involve a random action and 80% of the actions the optimum action is taken. The optimum action is the action which has delivered the highest Q-value in the last 5 episodes.
Step 4: Observe the next state (s_{t+1} = all shipments in next day) and associated savings in total logistics cost (r_{t+1}) resulting from action a_t
Step 5: Update action-value function by $Q(s_t,a_t) \leftarrow Q(s_t,a_t) + \alpha\left[r_{t+1} + \gamma \max Q_a(s_{t+1},a) - Q(s_t,a_t)\right]$ where $\alpha = 0.7$, $\gamma = 0.3$
Step 6: Move to the next state $s_t \leftarrow s_{t+1}$;

Fig. 2. Q-learning algorithm of shipping lines

Python code was developed to implement the algorithm, calling the geo-processing tools of ArcGIS to solve the CVRPTW. It should be noted that, since each shipping line decides individually which action to take, the predicted value of action **max** $Q_a(s_{t+1}, a)$ will not necessarily match what will be experienced in every episode (r_{t+1}).

2.2. Data

The case study focuses on container shipments entering the Port of Brisbane (Australia). The dataset was provided by the Port of Brisbane Import/Export Logistics Chain Study[15] and includes details of individual container movements: identification number, timestamps of arrival and departure, postcodes of origin and destination, weight of shipment, and size of container. This study focuses on the movements of full containers in import chains (1942 records) which are mainly destined into the suburbs of Brisbane. There are 137 agents (shipping lines) who delivered 1942 containers to 248 postcodes. The road network consists of 18,890 links and 22,700 nodes, from which only 5338 links allow B-doubles to operate.

3. Results

The principal measures of performance for the three scenarios, and the results, are shown in Table 1. The comparison between these measures confirms the benefits of cooperation through a PCS, in line with the literature[13]. The analysis of the results reveals that, in cooperation, the number of visits in each tour increases by using larger vehicles, while the total distance traveled and consequently the total logistics cost decrease.

Table 1. Results

	Scenario 1:	*Scenario 2:*	*Scenario 3: Q-learning result in 50^th^ episode*		
	Individual action	*Full cooperation*	Cooperating agents	Individual agents	Sum
Total logistics costs ($)	2,238,925	1,947,616	1,603,323	367,158	1,970,481
Time-based operating costs ($)	311,864	260,587	209,341	57,689	267,030
Distance-based operating costs ($)	1,926,725	1,686,863	1,393,836	309,390	1,703,226
Number of trips by B-doubles	253	591	466	40	506
Number of trips by semi-trailers	1,174	747	550	296	846
Total number of trips	1,427	1,338	1016	336	1,352
Total travel time (hr)	3,448	2,929	2,406	558	2,964
Total distance (km)	159,343	135,222	111,143	25,770	136,913

Figure 2 indicates the Q-value function for ten major shipping lines (expressed by their name's acronym) who operate through the Port of Brisbane. Interestingly, the savings in logistics costs in cooperation are generally higher for shipping lines who have fewer shipments to deliver, while cooperation sometimes imposes a higher logistics cost upon the major shipping lines. This is why some shipping lines would prefer individual action over cooperation in the proposed RL algorithm, and leads to less total improvement compared to the full cooperation approach.

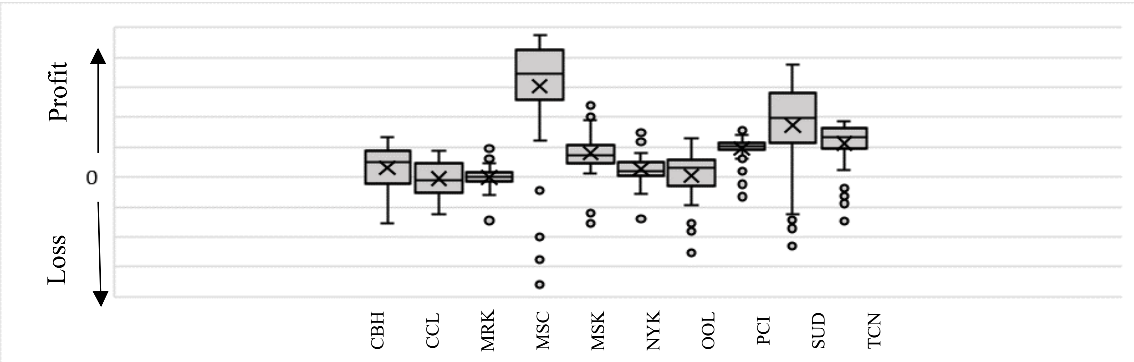

Fig. 2. Q-values for top ten shipping lines during 50 episodes (α = 0.7, γ =0.3, ε=0.2)

4. Discussion and conclusions

This paper provides insight into the benefits of adopting the PCS for private actors in terms of increasing efficiency, profit, and infrastructure utilization. The agent-based model developed in this study is based on the notion that freight markets are not usually in a stable equilibrium, as simplistically assumed in traditional modeling approaches[16], because agents are highly heterogeneous and should have a degree of freedom to choose non-optimum actions. The results prove that the cooperation between shipping lines in sharing vehicles through the PCS can decrease the total travel distance and total logistics cost as well as improve the vehicle utilization. Further avenues for research are foreseen based on the limitations of this study:

- Postcodes were the only information about the container destinations, and we assumed the same destinations for all containers sharing the same postcode.

- Travel time is assumed to be a function of only distance, while in reality it is a function of traffic volumes that vary dynamically by time of day.
- There is no information on time windows (working hours of agents and/or desirable receiving time for specific containers), nor of the costs of time window violations or late delivery. Thus, in this study, time windows for customers were assumed to be the observed destination timestamp plus or minus a 30 min threshold.
- The parameters used in the Q-learning algorithm should be chosen (or calibrated) based on the actual agent behavior. Calibration and sensitivity analysis for the parameter values (alpha, gamma, and epsilon) will be included in the future studies.

There are also a number of additional strategies to consider with the PCS. First, by taking into account the empty container and export chain, we can better plan to balance the empty and full container movements by having more efficient container movement in the hinterland. Second, by adding the truck mass restrictions on the road network, and also the dynamic travel time of links, routing will better match reality. Third, the probability of choosing each action (ε) can be obtained through developing a discrete choice model, using parameters from previous studies, developing a sample case–study, or developing a game (e.g. SMUrFS[17]). Last, about half of the import containers were stored at transport yards for several hours or days. By including the costs of storage and handling at transport yards, the choice of using transport yards can also be modeled jointly with vehicle type and routing.

Acknowledgements

We are grateful for the data provided by Andrew Rankine from the Port of Brisbane Pty Ltd (PBPL), by Dr. Darrell Bowyer from Port of Brisbane Import/Export Logistics Chain Study team, and by Dr. Peggy Schrobback from the University of Queensland.

References

1. Srour, F. J.; van Oosterhout, M.; van Baalen, P.; Zuidwijk, R. Port community system implementation: Lessons learned from international scan In *Proceedings of Conference Port community system implementation: Lessons learned from international scan*. TRB 87th Annual Meeting Compendium of Papers DVD; 2008.p. 16p.
2. Malone, T. W.; Crowston, K. The interdisciplinary study of coordination. *ACM Computing Surveys (CSUR)*. 1994; ***26***: 87-119.
3. Xu, C.; Chi, Z. Pattern-oriented agent-based modeling for financial market simulation. *International Symposium on Neural Networks.* 2007.p. 626-631.
4. Bonabeau, E. Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences*. 2002; ***99***: 7280-7287.
5. Taghawi-Nejad, D. Modelling the economy as an agent-based process: Abce, a modelling platform and formal language for ace. *Journal of Artificial Societies and Social Simulation*. 2013; ***16***: 1.
6. Bouzid, M. On-line transportation scheduling using spatio-temporal reasoning. *Temporal Representation and Reasoning, 2003 and Fourth International Conference on Temporal Logic Proceedings 10th International Symposium on.* 2003.p. 17-25.
7. Burckert, H.-J.; Funk, P.; Vierke, G. An intercompany dispatch support system for intermodal transport chains In *Proceedings of Conference An intercompany dispatch support system for intermodal transport chains*. IEEE; 2000.p. 10 pp. vol. 12.
8. Henesey, L. Multi-agent container terminal management. In *Blekinge Institute of Technology Doctoral Dissertation Series*. 2006.
9. Dong, J.-w.; Li, Y.-j. Agent-based design and organization of intermodal freight transportation systems. *Machine Learning and Cybernetics, 2003 International Conference on.* 2003*; 4*.p. 2269-2274.
10. Liedtke, G. Principles of micro-behavior commodity transport modeling. *Transport Res E-Log*. 2009; ***45***: 795-809.
11. Holmgren, J.; Dahl, M.; Davidsson, P.; Persson, J. A. Agent-based simulation of freight transport between geographical zones. *Procedia Computer Science*. 2013; ***19***: 829-834.
12. Taniguchi, E.; Yamada, T.; Okamoto, M. Multi-agent modelling for evaluating dynamic vehicle routing and scheduling systems. *Journal of the Eastern Asia Society for Transportation Studies*. 2007; ***7***: 933-948.
13. Abdul-Mageed, L. An Agent-based Approach for Improving the Performance of Distributed Business Processes in Maritime Port Community. In *Faculty of Science and Technology*. Research Theses Main Collection: University of Plymouth, 2012.
14. Watkins, C. J.; Dayan, P. Q-learning. *Machine learning*. 1992; ***8***: 279-292.
15. POB *Port of Brisbane_ Import/Export Logistics Chain Study*. 2013.
16. Friesz, T. L.; Holguín-Veras, J. Dynamic game-theoretic models of urban freight: formulation and solution approach. In *Methods and Models in Transport and Telecommunications*). Springer; 2005.p. 143-161.
17. Anand, N.; Meijer, D.; van Duin, J. H. R.; Tavasszy, L.; Meijer, S. A participatory simulation gaming framework for the validation of an agent based 5 model: the case of city logistics In *Proceedings of Conference A participatory simulation gaming framework for the validation of an agent based 5 model: the case of city logistics*. 2016.