Final Coursework

CASA0011: Agent-based Modelling for Spatial Systems

Centre for Advanced Spatial Analysis

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1099 words

Modeling Port Behavior: An agent-based approach

Introduction

As "points of convergence between two geographical domains of freight circulation" (Rodrigue 2017), ports represent critical points embedded in the global transportation system. They serve as entry points to sovereign territories and hinterland markets; the efficacy and efficiency of port operations affect commercial, public sector and environmental domains.

In an effort to better understand the dynamics of maritime shipping networks and their interactions with origin and destination markets of the goods they transport, we developed an agent-based model of the full "port performance continuum" (i.e. value chain) (Rodrigue 2017), including maritime, terminal and hinterland operations.

Literature Review

Despite the technique's suitability to the system of analysis, very few agent-based models of maritime transport systems have been developed; in 2013 "the first computational model that simulates deep sea shipping down to the level of individual vessels" was developed to study maritime piracy's impact on shipping patterns (Vanek). Cavalcante (2013) modeled the "complexities of actual freight markets"; Okada (2015) investigated the approach's potential to understanding emergent dynamics of smart supply chain networks, of particular relevance as the shipping industry adopts connected sensor technology (Xu 2014). Brax (2013) investigated maritime surveillance and Shieh (2012) applied a game-theoretic approach to scheduling coast guard patrols to improve port security.

Research Questions

How do variations in shipping fleet size affect ship wait times, a measure of system efficiency? How do variations in terrestrial transport capacity affect port container storage facility usage?

Methodology

We developed an agent-based model in NetLogo (Wilensky 1999) simulating an expanse of sea connecting four monofunctionnal container ports and associated hinterland markets (Rodrigue 2017). Markets both produced and consumed twenty-foot equivalent units of physical goods (Eurostat 2010). An abstracted terrestrial transport system representing a road and rail freight network transferred goods between markets and ports.

Homogeneous "ship" agents transported twenty-foot equivalent unit (TEU) quantities of containers between ports, awaiting berth availability upon arrival, then unloading and re-loading their cargo based on port processing rates and ship container capacity.

Model iterations represent one hour. Travel and logistics processes roughly mirror real-world rates (Teodorović 2017, Rodrigue 2017, Bureau of Transportation Services 2016), though ship travel speeds were scaled down proportionately to world size.

Network dynamics represent an immensely sophisticated logistics and transportation system; the real-world complexity of scheduling agent behavior was necessarily reduced in our middle range model. Destination ports for freshly-loaded ships were set at the moment of departure, usually to the port with the smallest container stockpile.

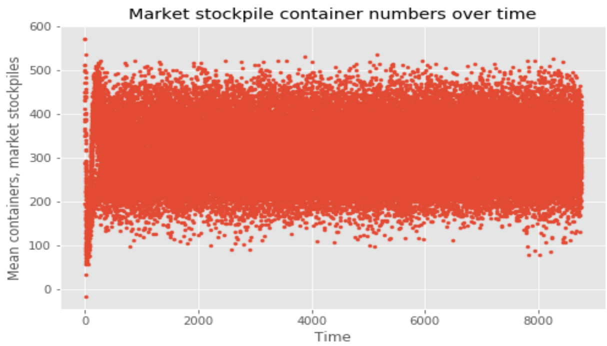
Stochasticity introduced into the model served to imitate uncertainty and randomness in the real world. Simulating price responses to over- and undersupply of products and subsequent consumption (OpenStax 2016), hinterland market supply and demand adjusts in response to accumulation of containers for import and export; the stochasticity in actual volumes produced and consumed by each market each tick nods to uncertainty in market dynamics.

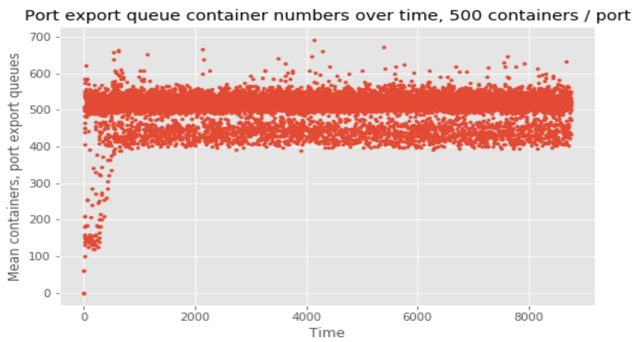
For our analysis we performed a parameter sweep across values representing the independent variables addressed by our research question. Data was captured at each tick or after each model run, as appropriate. Simulations were run for 8760 ticks, equivalent to one year.

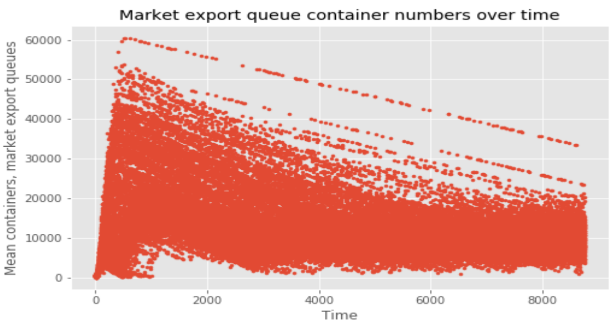
Results

Warm-up

Inspection of three plots depicting each of average number of containers stored in market export queues, market stockpiles, and port container export yards plotted over time suggests that this model's warm-up period lasted approximately 500 - 1000 ticks.







Effects of fleet size on wait times

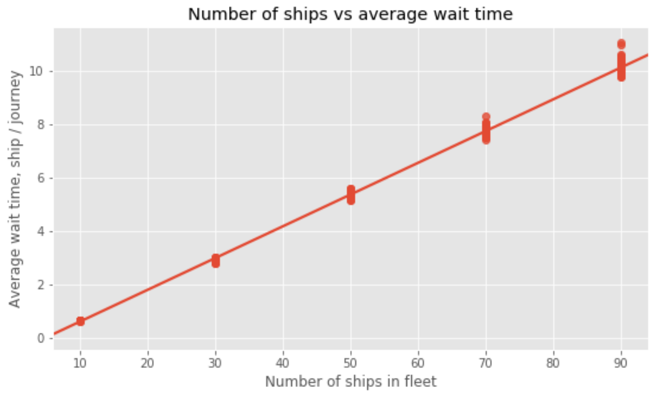
Based on data collected from a parameter sweep ranging from 10 to 90 ships in the simulation environment, we assessed the effect of fleet numbers on wait times. Based on an alpha value of 0.01, we performed a simple linear regression regression analysis to predict the average wait time experienced by ships based on the number of ships in the system.

The calculations resulted in a significant linear regression equation,

$$f(x) = 0.1186\ x - 0.5451$$

$$(p < 0.01, \text{R-squared} = 0.998)$$

Each increase of 0.1186 ships was associated with an increased average wait time per ship by 1 tick per journey. This linear relationship can be attributed to constancy in the other determining factor: number of berths per port and port unloading rates. We interpret the small observed variability in wait times at each fleet size to be due to stochasticity in destination port

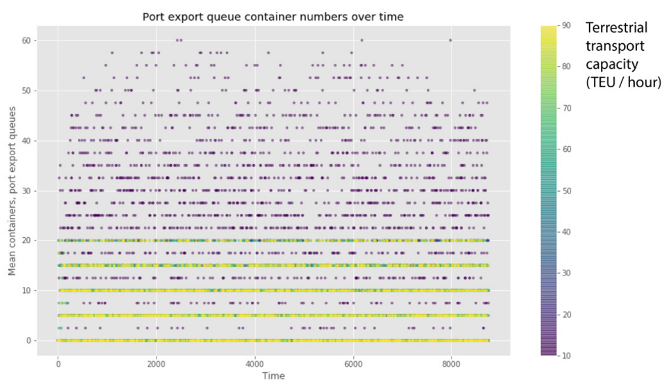


selection: by chance, some ships selected ports with more or fewer inbound ships, affecting wait times.

Effects of terrestrial transport capacities on port storage facility usage

The vast majority of port container yard capacity was consumed by containers for export in all simulations. This is likely due to the disparity between port berth processing rates and terrestrial transport rates; ships were unloaded more slowly than containers were delivered from hinterland markets.

Figures depicting port container yard usage reveal that container yards reach capacity more quickly as terrestrial transport rates increase. At lower terrestrial transport rates equilibrium is reached when export yards contain proportionally slightly lower levels compared to import yards. Once yards are full proportional volumes do not appear to change.



Discussion

The source of a system's complexity is not always apparent; in abstracting complex systems to their key attributes for modeling we risk failing to include a crucial component. This modeling effort captured a few of the characteristics of a maritime transport network, but much additional development and validation is required to be able to draw conclusions applicable to real world systems.

Further Analysis

Future iterations of this model will implement heterogeneous agents: variability in ships, ports and markets, as exists in reality. We also intend to implement mechanisms to measure operating costs (Seedah 2013), making the model results more relevant to shipping and logistics firms. Finally, we would like to explore the simulation of events such as disruptions of physical and informational architecture logistics systems rely on, such as the 2017 NotPetya ransomware attacks (Greenberg 2018).

Conclusion

Developing a facsimile agent-based model of the Earth's surface, including the maritime and terrestrial domains and their interface, could be of immense value to governments and commercial entities, but would be enormously complex. Our model includes a simplified effort to acknowledge market dynamics and comes nowhere near comprehensively modeling of environmental, human and technological factors. The harm that could be mitigated, and efficiency gained, by successfully modeling various events or policy interventions makes continued research into this field a worthwhile effort.

Properly developed and - crucially - validated agent-based models could be used to generate data to train machine learning algorithms designed, for example, to optimized smart supply chain networks (Okada 2015). Enormous efficiencies in the global transportation system might be found by training algorithms to optimize logistics systems governed by smart and Ricardian contracts (Gupta 2018).

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