# SmartPort

## Background

PSA Halifax has purchased the Fairview Cove container facility and now owns both the Fairview Cove and Atlantic Hub container terminals in Halifax, bringing our port closer together than a few others. There is presently only one terminal operator, one railroad operator, and one port authority at the Halifax Port. This adjustment will aid Halifax's transformation into a One Port City and provide new opportunities for our community.

## Problem Statement

Participants in this Data Challenge will be asked to think of novel ways to improve port efficiency and sustainability, as well as to help us better understand and explain the benefits of being a single container terminal operator port. Through this Challenge, we are inviting students from post-secondary institutions across Atlantic Canada to use ocean data to investigate how we might drive urban port sustainability.

In this document, we propose various ways Machine Learning, Reinforcement Learning and Data Visualization can be utilized with publicly available data to solve multiple problems. But our focus with SmartPort will be addressing **Challenge Stream #2 Theme: On the Terminal:**

*What efficiencies can be realized on terminals? What new opportunities are created through having one terminal operator, one railroad operator, and one port authority?*

## Solution Background

Maritime logistics decision-making frequently incorporates external, changeable factors that are essentially random, making preparing and recognizing well-considered actions more difficult. This emphasizes the significance of accurate forecasts while making business decisions in the face of uncertainty. Forecasts can reach unprecedented levels of accuracy and predictability for business-relevant influencing elements using machine learning-based predictive analytics methodologies. The method finds patterns and correlations in historical data and uses them to forecast future developments or events. The range and accuracy of information supplied to decision-makers daily can be expanded in this way. Furthermore, time-series projections, such as demand and freight volume forecasts, arrival time forecasts, and remaining lifetime estimations, allow for better control of operational uncertainty.

## How Machine Learning Can Help?

Machine learning model predictions can be used to speed up computation by replacing some particularly time-consuming activities of conventional metaheuristic and simulation approaches. Artificial neural networks, for example, can be used to choose scheduling rules in real-time based on the present state of the system. In the case of a yard crane or vehicle scheduling problem, this may mean that a machine learning model selects the appropriate priority rule (e.g., based on waiting time or minimum distance) to choose which container to load/unload or transport next. Furthermore, instead of running a simulation, machine learning can be used to tune hyperparameters of (meta-)heuristics or estimate system performance measures for various operational strategies. Computer vision in conjunction with ML can be used to analyze container state and safety. This ensures the containers are in suitable condition for loading and transport, saving a great deal of time, labour and effort compared to doing this task manually. Advanced forecasting techniques can be used to predict truck arrival and departure times. This allows truckers and trucking companies to make better dispatching and routing decisions. Also prepares terminals to plan equipment and people depending on the predicted workload.

We can monitor data from various ship sensors to predict optimal ship maintenance times using algorithms. These algorithms may even help in developing complex strategies for everyone to use. A one-port system is extremely beneficial to all these algorithms since there will be a larger amount of uniform data available, and every container will be able to adopt the strategies outlined, significantly increasing the overall productivity of the ports. A model can be used to control the various processes and decision support systems of the entire terminal. This can be like a supermodel, running on top of various other models.

There could be a model to predict the availability and demand for empty containers. There could be a model to predict container dwell times on the terminal, utilising dwell data (Refer to data folder). For all these models, we can supplement the traditional mathematical algorithms with machine learning models for predicting precise parameters, which essentially provides the algorithms with better data. An example of this would be running an ML model over a large amount of past routing, weather, and hydrodynamic data to learn the pattern between environmental conditions and optimal ship routes. The model can then use the traditional routing algorithms to optimize for either travel time, fuel consumption, or emissions. Use AIS data (Refer to data folder) to predict ship arrival and departure time over 72 hours. This data can be used in the overall optimization problem.

## How Reinforcement Learning Can Help?

Reinforcement learning can be a viable strategy for dealing with very complicated real-world problems when even a combination of optimization or control engineering methods with machine learning algorithms reaches its limits. Maritime routing logistics involve complex problems with sequential and recurrent decisions that need experimenting. Reinforcement learning is a great model for this kind of scenario. (e.g. assignment of containers to terminal equipment and adjusting ship routes). Reinforcement learning is very good for nautical decision support due to the changing environment.

Deep reinforcement learning has the potential to revolutionize AI and is a step toward developing autonomous systems that have a higher level grasp of the visual environment. Deep learning is currently allowing reinforcement learning to scale to previously unsolvable issues, such as learning to play video games directly from pixels. Deep reinforcement learning techniques are also used in robotics, allowing robot control strategies to be learnt directly from real-world video inputs.

Diagram

Description automatically generated

Figure Reinforcement learning (source: https://www.inwinstack.com/blog-en/blog\_ai-en/6262/)

Aside from aided navigation and autonomous cars, process control on container terminals and in ports is another interesting application of reinforcement learning. The types of possible use cases that can be evaluated using the criteria listed above are vastly different. Early research suggests that reinforcement learning can be used to optimize a ship's stowage strategy by automatically distributing containers to slots, reducing reshuffling and yard crane shifts.

Routing decisions can also be aided by reinforcement-learning approaches. The routing of automated guided vehicles in a guide-path network is an intriguing example. The algorithm considers traffic congestion at intersections and bidirectional path segments to discover the shortest-time route on the terminal rather than the shortest-distance route for each delivery. Experiments for this use case show that, when compared to standard methods that focus on shortest-distance routes, travel times can be successfully decreased.

Another potential application is yard crane scheduling, in which a reinforcement learning system specifies the sequence of drayage trucks served by a crane to minimize waiting time. The reinforcement learning agent's decisions in this scenario determine which truck to serve next, based on factors such as distances to the crane and current waiting periods.

In the theoretical computer science and operations research (OR) communities, the Traveling Salesperson Problem (TSP) is one of the most popular NP-hard combinatorial problems. "What is the shortest possible route that visits each city exactly once and returns to the origin city, given a list of cities and the distances between each pair of towns?" it asks. In our case, it could be rephrased as “What is the optimal way for an incoming vessel to onloading and offloading to minimize the on port time?” TSP has been solved by Deep Learning. TSP is useful in a variety of fields, including logistics, planning, and scheduling. A model could be trained from the publicly available data and utilised. The deep learning architecture for tackling the Traveling Salesperson Problem can be designed in a variety of ways. We could utilise a GNN to encode input nodes into dense feature vectors, and then use the Attention mechanism as a decoder to generate ordered nodes in an autoregressive manner.

## How Data Visualization Can Help?

We can utilize data visualization to gain insight into the massive volumes of data. We will profit from being able to spot new patterns and faults in the data. Understanding these patterns will allow us to focus on domains that represent red flags or slow progress. With the help of visualizing the data acquired by the watercraft entering the ports, it is possible to evaluate the estimated power consumption by these vehicles which can eventually help to develop an appropriate course of action for detecting operations requiring unnecessary high consumption.

## Introducing SmartPort

Smart ports help in evolving into futuristic ports by providing the following:

1. Managing ships reception across ports dynamically for faster servicing
2. Smart signals about delays in onloading/offloading to avoid wait times
3. Auto accommodates services depending on the urgency and readiness
4. Acts based on trucks and rail times to make the best use of onloading and offloading cargo
5. Reduction in CO2 emissions owing to lesser wait times
6. Faster processing of Cargo can save a lot of labour costs
7. Faster processing of Cargo can save a lot of fuel costs
8. Automatic guidance to trucks incoming and outgoing
9. Automatic guidance to ships' incoming and outgoing
10. Automatic guidance to rails incoming and outgoing

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