QUANTUM COMPUTING AND MACHINE LEARNING FOR EFFICIENCY OF MARITIME CONTAINER PORT OPERATIONS

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Sidney Jennings

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On my honor as a University student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments.

ADVISOR
James Lambert, Department of Engineering Systems and Environment

Quantum Computing and Machine Learning for Efficiency of Maritime Container Port Operations

Ibrahim H. Hamdy[1], Maxwell J. St. John[1], Sidney W. Jennings[1], Tiago R. Magalhaes[1], James H. Roberts[1], Thomas L. Polmateer[1], Mark C. Manasco[2], Joi Y. Williams[3], Daniel C. Hendrickson[4], Timothy L. Eddy[1], *M.IEEE*, Davis C. Loose[1], *M.IEEE*, Mashrur Chowdhury[5], *SM.IEEE,* James H. Lambert[1], *F.IEEE*
[1]Department of Engineering Systems and the Environment, University of Virginia, Charlottesville, VA, USA
[2]Commonwealth Center for Advanced Logistics Systems, Petersburg, VA, USA
[3]Virginia State University, Petersburg, VA, USA
[4]Port of Virginia, Norfolk, VA, USA
[5]Clemson University, Clemson, SC, USA
ihh3fz@virginia.edu, mjs3pf@virginia.edu, swj8zv@virginia.edu, trm9wb@virginia.edu, jhr9yp@virginia.edu, polmateer@virginia.edu, mark.manasco@ccals.com, jywilliams@vsu.edu, dhendrickson@portofvirginia.com, tle7pa@virginia.edu, dcl6d@virginia.edu, lambert@virginia.edu

***Abstract*—Maritime container ports are experiencing a variety of challenges, including the pandemic and other stressors, that are altering perspectives on efficiency, risk, and resilience. This study reviews new methods of operations optimization that serve major goals of logistics systems: Increasing energy and time efficiencies and reducing emissions and congestion. Several computational methods will be assessed, including quantum computing, neural networks, and operations heuristics. The methods are compared by potential for increased efficiencies, including the increase in container volumes, reduction of dwell times, reduction of container moves, utilization of demand forecasts, and decreases in emissions. The results suggest opportunities for reinforcement learning to improve the scheduling of container transactions across transportation modes, including maritime, truck, rail, crane, and barge.**

Keywords—Neural networks, logistics systems, reinforcement learning, energy, emissions, container allocation, shipping container, systems resilience, network optimization

I. Motivation

McLean and Becker found that 93% of port executives do not understand the impending issue of climate change and how it can affect the daily operations [1]. Additionally, climate change and related policy and social movements are cited as the most potentially disruptive scenario for future port operations [2]. Many international ports have pledged to reduce carbon emissions to net zero by 2040. It is critical that the proposed solutions address the environmental issues at hand. Therefore, the solutions proposed must be in accordance with furthering the ability of ports to meet these goals.

Another motivation for this paper is the development of quantum computing. The advent of quantum computing has long been awaited for its potential to solve NP-hard problems in exponentially faster time than classical computers [3]. The technology is rapidly developing with quantum annealing machines increasing qubit counts at a pace similar to Moore's law for classical computing transistor counts [4]. Gate based quantum computers are also experiencing significant growth with IBM's announcement of a 127-qubit machine [5]. While researchers ultimately hope to create quantum machines capable of brute forcing combinatorial optimization problems (COPs) and mixed integer programming problems (MIPs), machines on a nearer horizon have potential in machine learning for training models in the square root of time that a classical computer takes, allowing for robust models and faster solutions [6].

Additionally, machine learning has experienced rapid growth and has undergone a renaissance over the last decade. A variety of machine learning techniques have been applied to port optimization problems including genetic algorithms and reinforcement learning. Reinforcement learning has made breakthroughs in complex decision optimization with new algorithms going beyond rigidly defined MIPs into continuous state spaces [7]. In preparation for increased computing performance of quantum neural networks, reinforcement learning models will enable ports to benefit from the capabilities of quantum computing.

Dwell time analysis focuses on the length of time a container is sitting in a container stack waiting to be picked up. Dwell time, typically measured in days, is impacted by numerous container and port variables. By exploring the relationship between these variables, dwell time predictions can be made for every container waiting in the container stacks. Accurate dwell time modeling will minimize the reshuffling of containers in the container stack and increase the throughput of containers through the port. If every container has a predicted dwell time, the container stack can be organized by placing containers that are about to be picked up in easily accessible locations, while keeping containers with longer dwell times out of the way. Three dwell time prediction methods are discussed and evaluated: Neural networks, ordinal regression, and decision trees.

The sorting and optimization of the container stack is a constantly changing problem that adjusts with every move within the stack. The paper will illustrate the evaluation of seven heuristics to determine the best practice for container placement within a stack. The seven methods were evaluated on a scale model of the stack, and will help the port determine the best way to move containers within the stack. Each heuristic evaluates based upon the current situation of the stack. Therefore, the container placement is based upon the containers underneath the proposed location or those containers neighboring the desired locations. These evaluation methods will aid the port in how to group containers within the stack for easier means of retrieval.

II. Purpose and Scope

First, the port infrastructure around the world is lagging behind the current leading technology due to transition costs and the aversion towards changing daily practices. The implementation of new technologies such as neural networks and quantum computing provide the means to achieve new levels of optimization across ports. The purpose of the optimization is twofold: increase throughout at the port and decrease emissions from port operations.

The intention behind research into areas of improvement at the port through the use of new technology is to allow for more goods to enter and exit the port as well as create a port more resistant to delays. The current state of the port system is behind schedule as a result of new surges in product demand and decreased supply from the producers. The potential solutions illustrated in the paper will attempt to provide more robust solutions so the delays currently occurring will be mitigated in the future.

The factor of port efficiency will be predominantly focused on areas this effort has found to be potential locations for increased throughput. The first area is the container stack in which all inbound and outbound containers are held prior to their next movement. Due to this factor, any increase in efficiency at the container stack will allow for all other areas of the port to see an improvement as well. For example, if containers enter and exit the stack at a faster rate, ships can be loaded more efficiently as well as trucks and trains can receive containers and depart more often.

The next area of focus is the scheduling of container volume. With a better estimate of incoming containers, the port can better allocate resources to the correct areas. For example, if a large volume of containers is to be delivered during a particular day, the yard crews can be scheduled to be on the ship side. The same applies to the scheduling of trucks to the container stack under the scenario of a large number of companies requesting their containers in a similar time frame.

The container volume analysis will also be taken a step farther to determine average time spent in the stack based upon the contents inside. If the container composition is known, it can be used to better predict exit times from the container stack.

III. Background

A. Pandemic and Other Stressors

COVID-19 has had a significant impact on port operations around the globe. While the effects of this pandemic have lessened in the United States, they will continue to fluctuate over time. A recent study simulates how aggravated COVID-19, weakened COVID-19, and baseline COVID-19 scenarios affect ports' operations in different stages of the pandemic [8]. In all three scenarios, cargo transportation was significantly hindered by the effects of COVID-19. Ports play an essential role in cargo transportation across the globe and will continue to be negatively impacted by COVID-19. All three scenarios provide relevant analysis, as the impact of the COVID-19 pandemic can significantly vary from country to country.

Unfortunately, COVID-19 will continue to have a negative impact on ports worldwide. The effects of COVID-19 on port operations will fluctuate in severity from month to month depending on the state of the pandemic. The emergence of COVID-19 has permanently altered port operations, with these operations likely never fully returning to their pre-pandemic state. The monumental impact of the pandemic on ports limits the effectiveness of studies and operational strategies devised prior to the pandemic. The pandemic has caused and will continue to create shipping delays, staff shortages, and container backlog at ports. With the arrival of containers often impacted by the speed of operations at other connected ports, significant delays can have a cascading effect on port operations across an entire region. Pre-pandemic research and operations need to be revamped or completely overhauled to better adapt to the impacts of COVID-19.

B. Maritime Port Disruptions

Wendler-Bosco and Nicholson explore the issue of port disruption and congestion with a focus on how it can be improved upon through port resilience and intermodal transportation resilience efforts [9]. In the same paper, the authors develop a stakeholder perspective analysis in order to better understand and therefore promote stakeholder needs as related to the consequences of maritime port disruptions.

Saeed et al. further investigate delays and congestion at shipping ports through an application of transaction cost analysis [10]. Mainly, this framework is applied to investigate strategies that port management can develop in order to mitigate delays and make operations more efficient. The study outlines three characteristics of transaction cost analysis that are relevant in reducing disruptions, these being asset specificity, frequency, and uncertainty. Specifically, frequency and uncertainty relate to events that directly affect port congestion, whereas asset specificity relates to the investments needed to carry out optimization measures. Upon these considerations, several testable propositions are identified in order to identify a management mode that should be selected by stakeholders to better mitigate port congestion.

Other research, such as that carried out by Neagoe et al., focus on the impact of port congestion on emission rates [11]. The increase in port backlogs in 2021 has resulted in the accumulation of diesel-powered ships along coasts and greater wait times for cargo trucks waiting to pick up containers. This densification of polluters has led to greater emissions and noticeable increases in pollution. With this in mind, Neagoe et al. seek to optimize port operations through the use of discrete event simulation in order to reduce port traffic and, therefore, pollution.

These studies emphasize the relevance of operational strains on maritime ports and the importance of systems to reduce such delays and resulting emissions. Further significance of this problem is evidenced in the series of reports on port delays due to increased operational strains, as well as the resulting increase in pollution. Berger, O'Neal, Goodman, and Fickling describe the importance of port congestion to society [12][13][14][15].

IV. Technical Approach

A. Dwell Time and the Container Stacking Problem

A recent effort used an Artificial Neural Network to predict the dwell time of containers [16]. The neural network had ten input variables, which can be seen in Table I below.

TABLE I. SAMPLE OF VARIABLES FROM NEURAL NETWORKS IN MODELING DWELL TIMES AT MARITIME CONTAINER PORTS. ADAPTED FROM [16]

Index	Variable
v.01	Container size (20ft, 40ft)
v.02	Container status (full, empty)
v.03	Container type (reefer, general cargo, hazardous)
v.04	Commodity
v.05	Exact date of arrival and departure from the vessel
v.06	Exact date of customs inspection (if performed)
v.07	Ocean carrier
v.08	Ocean carrier's assigned vessel
v.09	Ocean carrier's port of origin
v.10	Exact date of truck departing from the gates of the terminal

The model was built by iteratively adding variables to the model. Table II shows the order in which the variables were added.

TABLE II. VARIABLES ADDED EACH ITERATION IN MODELING OF DWELL TIMES AT MARITIME CONTAINER PORTS. ADAPTED FROM [16]

Iteration	Variable
i.01	Container type and size variables
i.02	Added customs inspection variable
i.03	Added month of discharge variable
i.04	Added day of discharge variable
i.05	Added vessel port of origin
i.06	Added types of cargo variables

The model was relatively successful, with the sixth and final iteration of the model classifying the dwell time of containers with an accuracy of sixty-five percent. Despite the accuracy, the study has numerous drawbacks. Most importantly, the study was completed in 2016, a few years before the port industry was significantly impacted by COVID-19. A second group attempted to predict dwell time more recently in 2021 using Ordinal Regression and Decision Trees [17]. The new model used similar variables as the previous study, with the addition of weather and container clustering variables. However, the models were trained on data prior to the pandemic, making its results similarly outdated.

Future implementations of dwell time modeling using more recent data would help improve port efficiency. The new models can use some of the same variables from the previous implementations while also accounting for variables more relevant today, such as COVID-19 information. Additionally, modeling the distribution of dwell times for a specific container will provide more insights. Modeling the distribution of dwell times can find the mean and variance of the predicted dwell times, as well as calculate probabilities of a container being picked up in a certain timeframe.

B. Hybrid Quantum-Classical Computing Methods

Both quantum computing and reinforcement learning aim to outperform heuristics in combinatorial optimization problems. However, the proposed technologies do not always perform well for models set to realistic scale expected of a port. Quantum based optimization of mixed integer programming problems is estimated to see results once machines exceed 100 gate-based qubits [4].

Until quantum computers advance enough to solve problems on their own, hybrid quantum-classical methods exist that could harness the power of quantum and develop the field. Quantum algorithms such as simulated annealing can optimize MIPs while running on classical hardware, which has applications for ports such as optimization of quay crane assignment to berths [3]. Additionally, quantum has applications in deep reinforcement learning. Results vary, but quantum reinforcement learning typically fails outright when faced with a large state space [18]. However, for smaller state problems, quantum learning has been shown to both converge on solutions faster and maintain the solution in future episodes more consistently than classical computers [6].

In order to reduce state spaces to something feasible for quantum reinforcement learning, hybrid models can combine reinforcement learning and quantum computing with traditional heuristics. In ports, the initial stacking of incoming shipping containers, remarshalling, and retrieval are typically governed by heuristics [19]. Heuristics such as blocking degree in conjunction with reinforcement learning have been shown to optimize the total number of container moves between stacking and retrieval [20]. Additionally, reinforcement learning has been shown effective in generation of hyper-heuristics for combinatorial optimization problems with uncertainties, which accurately describes many of the problems dealt with by ports [21]. Hyper-heuristics allow for selection of one of many problem solvers depending on the changing state space, so the best model can be constantly switched out [22]. As quantum computing grows into a more robust and capable technology, hybrid methods will allow for realistic applications and smoother transitions into full quantum solutions.

C. Emerging Methods for the Container Stacking Problem

A study by Hammed Bisira and Adbellah Salhi was tasked to find new ways to place containers within a stack to minimize the total reshuffles [23]. The authors developed and tested seven heuristics to determine the best method for placing containers.

The methods were tested on four sample container stacks. Each consisting of six columns of containers and varying maximum heights of each. The first iteration was six columns, max height of two, and nine total containers (6-2-9). The next was six columns, max height of three, and 13 total containers (6-3-13). The next was six columns, max height of four, and 17 total containers (6-4-17). The next was six columns, max height of five, and 21 total containers (6-5-21).

TABLE III. CONTAINER STACKING HEURISTICS FOR MARITIME PORTS. ADAPTED FROM [23]

Heuristic	Container Stacking Method
H1	Simplest Container Location
H2	Place in a stack that block the least containers underneath
R1	Move to a stack blocking the least number of containers
LPH1	Place on top of the least priority container
LPH2	Place on top of the least two priority containers
LPH3	Place on top of the least three priority containers
LPH4	Place on top of the least four priority containers

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Upon completion of testing, the study found the following results for each of the test scenarios. LPH2 performed the worst for small test sets; however, all results were extremely similar in CPU time and average number of reshuffles.

LPH2 performs the best on average. LPH2 has a lower number of reshuffles and CPU times as the size of the container stack increases. It places a container in a stack with the least two prioritized containers under the desired location. This heuristic is the best selection for ports, because most of the ports around the world utilize container stacks larger than those tested in the study.

D. Time Series Analysis for Predicting Container Volume and Allocation

Container volume forecasting aims to use time series analysis to predict incoming and outgoing containers on a monthly or annual scale. Accurate forecasting allows a port to better prepare for periods of intense operations through optimal allocation of resources. Such optimized resource allocation allows not only for improved operations, but also for decreased emissions. This said, by combining advanced time series methods and recurrent neural networks, models such as autoregressive integrated moving average (ARIMA), long-short term memory (LSTM), and bidirectional long-short term memory (BLSTM) may be applied to generate accurate forecasts of container volume at ports.

A December 2019 study by Gao et al. applies this concept to an unnamed Chinese port in order to test the accuracy of such recurrent neural network time series models and their effect on container yard management, container allocation and throughput, and, ultimately, port operations [24]. The methodology of this study consists of the use of historic port shipment data, primarily composed of incoming container dates and volume between 2013 and 2017, to build such forecasting models. Equipped with the necessary data, the first step in building the time series models is to clean the data by detecting and treating outliers, both through deletion or replacement with mean values, and then normalizing the dataset with values between 0 and 1, mainly for the convenience of data processing.

Having prepared the data, the study applies Python and the TensorFlow framework to implement the LSTM time series model. The result is a time series graph with months on the x-axis and daily container volumes in twenty-foot equivalent units (TEU) on the y-axis. For comparison purposes, the actual container volume observed throughout the forecasted period is also displayed in the graph, and results show significant pairing between the two functions, assuring the accuracy of the time series model.

With the benefits of forecasting container volume and with the Gao et al. study in mind, similar methods can be applied to the ports. Having data regarding incoming container volume for all years between 2012 and 2021, it is possible to apply similar methods to create a time series analysis of future container volumes. To improve upon the previous study, current work on forecasting container volume would be focused on using R programming to create a similar time series as done by Gao et al. but also including ARIMA and BLSTM methods, along with LSTM, to allow for comparisons. Comparing such time series models and results will enable this effort to deduce optimal use case scenarios for each model and improve upon current container volume forecasting system.

E. Reinforcement Learning and the Container Stacking Problem

For optimizing port container stacking for space and movement efficiency, a machine learning algorithm called MuZero was utilized to analyze the stacking problem and approximate optimal solutions [7]. First, a simulation of container stacking was constructed in Python. This simulation included shipping containers labeled with a unique identifier, a "stack" data structure that used a crane to store and move containers at certain addresses in a three-dimensional array, and a set of instructions for which a crane would need to carry out. This set included two types of instructions: adding containers onto the stack and removing containers from the stack. The model was then given control of the crane, and could move any container, load and unload the crane, etc. The model would then train by attempting to complete as many of the instructions as possible within 500 operations. Each instruction completed would earn the model 10 reward. After 500 operations or after all instructions were completed, the simulation would end and the algorithm would use the results gathered from the simulation to learn, which would help it perform better in future simulations.

This simulation was run on a virtual stack of size 5x5x5, randomly populated with computer-generated containers. Instructions were then generated by either selecting one of the randomly generated containers as one that needs to be removed or by generating a new container and marking it as needed to be added to the stack. This original stack layout and instruction set were then stored and used to reset the simulation at the beginning of each training step.

Fig. 1. shows the preliminary results of the simulation when asked to retrieve five containers. Fig 2. reflects the number of container reshuffles required per simulation.

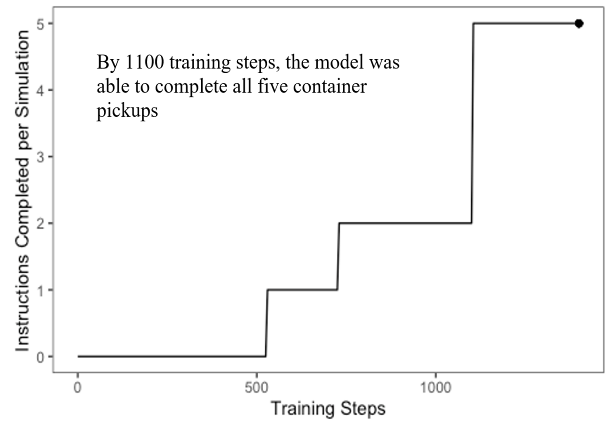

Fig. 1. Container retrievals completed per simulation versus the number of training steps completed

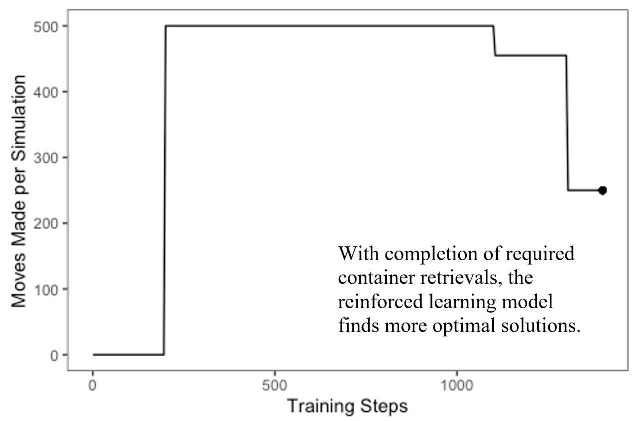

Fig. 2. Container moves per simulation versus training steps

The increasing instruction completion and decreasing unnecessary container moves demonstrate proof of concept. These results were produced on a consumer grade computer and reflect hardware limitations. For context, many implementations of the same algorithm reach maximum performance around 1,000,000 training steps, but we were limited to under 2000 [7]. Future steps involve running this simulation on more advanced processing units.

V. Conclusion

The results of the study above reflect promising future steps for the use of emerging computing methods, including reinforcement learning, to model the container stacks at ports across the world. The effort also located potential areas across the entire port system that can be optimized using emerging computing methods. The features highlighted in this paper provide a promising outlook for future implementation. The review and related experiments suggest that new computing technologies might improve and meet the goals of increasing energy and time efficiencies and reducing emissions and congestion.

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