Capacity Planning and Investment for Electrification of Maritime Container Ports

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Abstract—**Container ports face the decision of investment into a variety of emerging technologies, including electric vehicles, autonomous equipment, and hydrogen-based power. This research paper presents a simulation-based optimization study of a port using simulation software to reduce carbon emissions and improve efficiency of operations of a maritime container port. Through capacity planning and electrification modeling, the port was provided with recommendations that will be used for 3-5 year-out planning focused on decreasing emissions and improving energy utilization. Research focused on reduction of operational emissions, existing simulations of ports, and emerging technologies including electric vehicles, liquid natural gas, hydrogen power. The methodology included modeling smaller sections of the port through simulation software. Use cases were extended to various forms of equipment and vehicles.**

Carbon emissions were also represented. These models allowed for the simulation of the effect of the changes in equipment and observation of resulting financial and time costs. Recommendations for the number of chargers and the number of additional vehicles to be purchased were also discussed. Use cases also allowed for the identification of beneficial expansion into electric vehicles according to fuel times and maintenance requirements, with consideration of financial constraints. Preliminary results revealed positive potential, both environmentally and economically, in regard to the transition towards electrification of heavy-duty port machinery and away from diesel-powered equipment. The findings of this study highlight the prospect of using simulation-based optimization to improve the sustainability of operations of the maritime container port and to reduce their overall carbon footprint.

I. Motivation

With millions of tons of goods handled each year, ports are a significant center for global trade and business. Across international commerce and the global economy, ports stimulate surrounding local economies through increased trade and job opportunities. Subsequently, port operations give rise to substantial detrimental effects on their natural surroundings, entailing significant effects on the health of human beings, animals, and the purity of air and water reservoirs. Thus, there is a rising need to comprehend the environmental effects of port operations better and to create mitigation plans. Figure 1 describes an analysis of emissions at a maritime container port by both propane emissions and kWh usage at various terminals of the port.

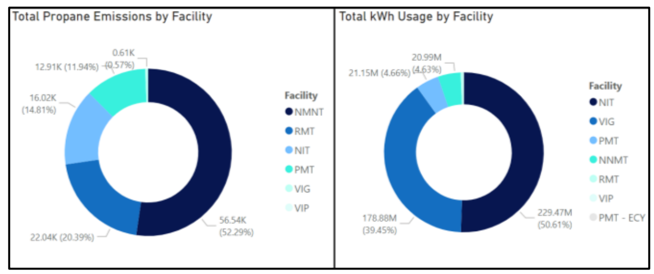

Fig. 1. Sample Analysis of Energy Factors at a Maritime Container Port

The complex dynamics of port operations can be represented using simulation models, which are also useful for predicting the possible effects of various scenarios [1, 13–18]. Researchers and stakeholders can learn more about how various variables, such as cargo volume, vessel traffic, and weather conditions, affect environmental effects of a port.

Simulation models can be used, for instance, to examine the efficacy of various techniques for lowering air pollution and greenhouse gas emissions, such as different modes of transportation or emission control technology. Moreover, simulation models can assist in locating potential environmental impact hotspots, such as locations with high levels of noise or water pollution, where focused mitigation efforts may be most successful.

Figure 2 describes several terminals of a maritime container port. Environmental awareness has led to new tasks in the management of port systems [2]. The negative effects of carbon emissions on public health emphasize the critical importance of reducing air pollutant concentrations. On an international scale, present-day initiatives include the “EU-funded H2Ports project” which was designed to accelerate the “port industry towards low-carbon/zero-emission and safe operative models” [3]. Such enterprises include testing and validating hydrogen-powered solutions, with inputs sourced from “customers, hydrogen producers, suppliers, etc.” [3]. Other state-of-the-art initiatives include the Proteus plan, which incorporates cold ironing, electric propulsion charging, multipurpose energy storage via "charging of electric vehicles within the port", and a refined "energy management system" [4].

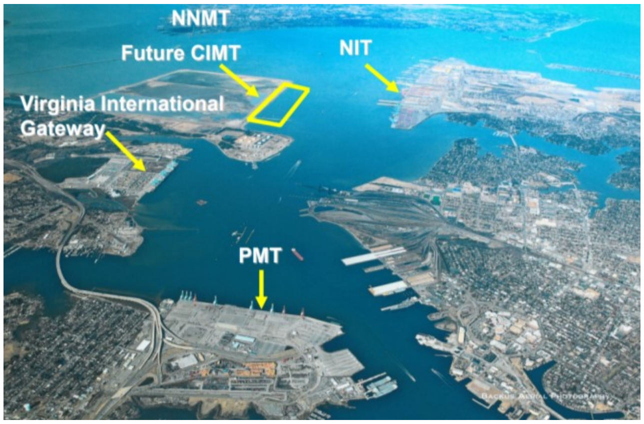

Fig. 2. Maritime Container Port That Benefits into the Future from Electrification and Conversion to Hydrogen Energy

II. Purpose and Scope

There is a global opportunity to reduce emissions from operations at maritime container ports [5]. The study will focus on modeling various scales of operation and comparing the variables of operational equipment and their effect metrics. This will involve an assessment of the current state of emissions and sustainability practices in the industry, as well as identifying opportunities for improvement through the use of systems engineering, stakeholder engagement, and innovative clean energy technology. The study will explore the different equipment and processes involved in port operations, including TEU (twenty-foot equivalent unit) throughput, equipment charging and fueling, and transportation to and from the port. By analyzing the environmental impact of these activities and identifying areas for improvement, the study aims to reduce the carbon footprint of maritime container ports and contribute to a more sustainable future. Future plans for expansion in terms of equipment inventory and expanded territory necessitate the need to understand streamlined port equipment operations and incite adequate capacity planning. While inventory expansion is beneficial to improved operations, increased fixed and variable costs entail the need to mitigate overinvestment.

III. Background

The electric grid capacity needed for electrification is two to three times greater than the current grid infrastructure [6]. It is crucial to prioritize the sustainable expansion of the electric grid by utilizing a combination of clean energy sources, while gradually decreasing the reliance on fossil fuels. Different energy sources have varying fixed costs and inefficiencies that are often unaccounted. Despite increasing usage, solar energy is currently the most costly and inconsistent in many regions due to periodical lack of sun. Looking into the future, all green energy costs are expected to fall, making mass electrification more economically feasible. 2027 estimates regard geothermal energy as the cheapest renewable energy source at that time, with price decreasing to around $22.04/MWh [7].

Currently, geothermal energy costs between $56-$93/MWh, so costs are decreasing quickly across the industry [8]. The cheapest clean energy source at the present time is wind, with a cost of $26-$50/MWh. However, this is only expected to decrease to an average of $29.90/MWh for onshore wind by 2027, while offshore wind platforms are predicted to be about four times more expensive than onshore [7].

IV. Technical Approach

A. Simulation Design of Utility Tractor Rig Model

Figure 3 describes the Utility Tractor Rig (UTR) simulation design that has one set of sources, two sets of servers, and one sink. The figure describes that the model has ten chargers. The berth that is modeled as the source begins at the five Rail Mounted Gantry (RMG) cranes, according to the distribution: 0.01 + Gamma(0.00356, 9.39) [9].

Following the berth, the RMGs transfer the TEUs to the container stacks, where the UTRs are in service to then transfer the TEUs onward. Once at the stacks, the UTRs process the TEUs with a distribution of Random.Exponential(15) minutes, with a rate of 4 moves/hour.

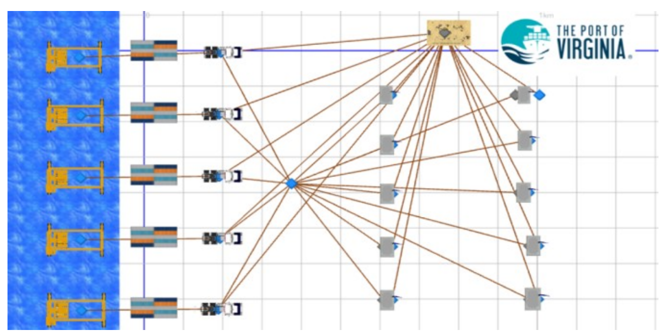

Fig. 3. Simulation for Electrification for Utility Tractor Rig at Maritime Container Port

The number of UTRs at each stack varies from 4-7, based on the number currently in service. The UTRs transfer the TEUs to a discharge location or are sent to the charging stations to replenish power. If sent to a charging station, the selected station is chosen based on the lowest current number of UTRs in the queue.

In the electrification model, the processing of UTRs occurs at a standard rate of Random.Exponential(80/22) minutes if sent to the charging stations, using the Orange EV UTR data [10]. The processing of UTRs occurs with a rate of Random.Exponential(3) minutes if sent to the hydrogen refueling stations, using data provided by the Toyota and Fenix UTR [11].

Fig. 4. Ship-to-Shore (STS) Cranes at a Maritime Container Port

B. Simulation Design of Rail Mounted Gantry Model

The RMG model is designed with a single source representing a ship, RMG cranes as servers, and container yard stacks as sinks. It is designed in isolation from other pieces of port equipment and their operations. The source connects to each server via a single one-way path that splits from a transfer node. Each server is connected to a sink by a single one-way path. At maximum, each container yard has two operational RMGs.

Thus, in the scenarios with three operational RMGs, there are two separate container yards. In the scenarios with six operational RMGs, there are three separate container yards. Figure 5 describes the simulation of six operational RMGs scenario.

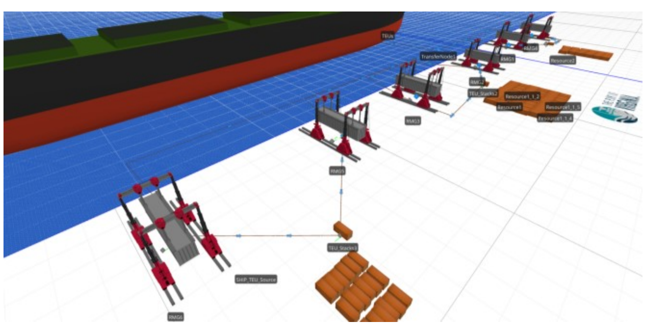

Fig.5. Simulation of Capacity and Throughput of Rail Mounted Gantry Cranes at Maritime Container Port

The processing rate used for each server is 0.01 + Gamma(0.00356, 9.39) Hours per Box and is based on distribution data from Hassan et al. [9]. The distribution was used for rubber-tire gantries (RTG) handling, and was thus adapted to RMGs in this simulation [9]. The processing rates for all operational RMGs is identical.

A first-in-first-out (FIFO) order was assumed and used for the entry ranking rule at the transfer node for transport of containers from the ship to the RMGs. It was assumed that there were no delays with transferring entities from RMGs to the yard stacks, so the transfer-in time to the stacks was 0 minutes.

Though RMGs operate bidirectionally to load and offload containers, this simulation focuses on the offloading process. Seen in Figure 4, ship-to-shore (STS) cranes are the first piece of equipment to offload containers from the sources and then pass these on to the RMGs; however, this simulation does not include STS processing nor STS servers. Simulations were conducted with an initial capacity of 30,000 entities at the source. All scenarios assume that each hour of operation has equal cost association. It was also assumed in all scenarios that no other disruptions occur, and that all shift changes and meal breaks do not run overtime nor experience delays.

Each piece of equipment was modeled in separation from one another; there was no joining of RMGs, utility trucks, and top picks into one integrative simulation.

For RMGs, there were three areas of particular interest: 1) How does an increase in the number of RMGs affect the average container time in the system? 2) How does an increase in the number of RMGs impact queue lengths at individual RMGs and 3) How does doubling RMGs in operation at a single berth from 3 to 6 impact both average container time in system and queue lengths in a 24-hour workday versus a 5-day workweek (composed of 5, 24-hour workdays)? The average values for the workweek represent the average value for an entire week, and not of a single 24-hour day within the week. Four sets of work schedules were created, and each set contained two scenarios of 3 vs. 6 RMGs in operation to produce a total of eight scenarios. Table I describes the influence of these scenarios.

TABLE I. SCENARIO DESCRIPTIONS AND NUMBER OF SERVERS OF RAIL MOUNTED GANTRY CRANES AT MARITIME CONTAINER PORT

Scenario	Description	Number of RMGs as Servers
1	2 shift switches at 6-7 AM and 6-7 PM; 2 meal breaks at 12-1 AM and 12-1 PM	3
2	2 shift switches at 6-7 AM and 6-7 PM; 2 meal breaks at 12-1 AM and 12-1 PM	6
3	2 shift switches at 6-7 AM and 6-7 PM; Staggered 1-hour meal breaks at 11 AM, 12 PM, and 1 PM	3
4	2 Shift switches at 6-7 AM and 6-7 PM; staggered 1-hour meal breaks at 11 AM, 12 PM, and 1 PM	6
5	Full automation with offline hours between 6-7 AM and 6-7 PM	3
6	Full automation with offline hours between 6-7 AM and 6-7 PM	6
7	2 faster shift switches at 6-6:30 AM and 6-6:30 PM; 2 meal breaks at 12-1 AM and 12-1 PM	3
8	2 faster shift switches at 6-6:30 AM and 6-6:30 PM; 2 meal breaks at 12-1 AM and 12-1 PM	6

C. Simulation Design of Electric Shuttle Carrier Model

The motivation for creating the electric vehicle model using simulation software is to provide a starting point for users who have specific knowledge of their electric shuttle carrier battery and the container arrival rate. The model serves as a baseline that can be adjusted to fit specific conditions, allowing users to determine the optimal number of shuttle trucks required to operate the system efficiently.

The model serves as a valuable tool for users to build upon and refine to achieve outcomes suited for their specific needs. Additionally, the versatility of the model makes it a resource for researchers and industry professionals looking to optimize the performance of electric shuttle trucks at maritime container ports [15]. The Electric Shuttle Carrier model incorporates an interarrival rate of containers into the system with a distribution of 0.01 + Random.Gamma(0.00356, 9.39) [9]. A FIFO order was assumed for the processing of the TEUs. The simulation model is designed with the ability to incorporate additional shuttle trucks should there be a need. This enables the simulation to provide an accurate representation of the system's performance at different conditions such as one, five, or ten shuttle carriers. The *Electric Vehicle SimBit* [12] was utilized for this model as it enables the user to simulate the charging and discharging of electric vehicles in the model.

Furthermore, it allows the user to specify the battery capacity and the charge rate of the electric vehicle, as well as the power output of the charging station. This SimBit can be utilized in the electric vehicle model to simulate the charging and discharging of the shuttle trucks' batteries, providing valuable data on their performance and energy usage. The SimBit also enables the user to set a charging threshold, allowing the shuttle trucks to automatically charge when their battery level falls below a specified level. This feature is particularly useful in the electric vehicle model, where the shuttle trucks' batteries need to be charged to keep the system running efficiently.

The model includes the ability to visualize the shuttle trucks carrying containers to the stack yard and going to charge when their battery level falls below 20%. Figure 6 describes the movement of containers and the shuttle trucks across the system. It enables users to identify any bottlenecks or inefficiencies in the system and make adjustments accordingly.

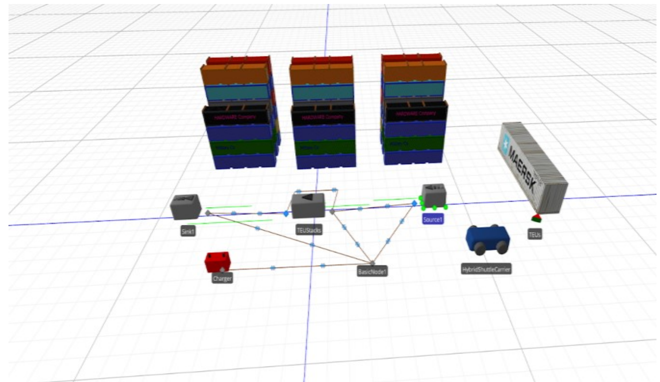

Fig. 6. Simulation of Electric Shuttle Carriers at Maritime Container Port

D. Simulation Design of Hydrogen Top Pick Model

Figure 7 describes that the simulation consists of a single source, six total servers and one sink.

The TEUs were assigned an interarrival time according to the distribution 0.01 + (0.03*Random.Beta(5.26, 3.49)) TEUs per hour. TEUs are then transferred to the stacks at the dock. The Top Picks then transport the TEUs from the stacks to the discharge location according to the distribution Random.Uniform(2, 2).

Once a Hydrogen Top Pick runs low on fuel, it is directed to one of two available fuel stations for refueling. The fuel station refuels the Top Picks according to the distribution Random.Uniform(15, 15). The Top Picks then return to the dock and continue processing TEUs to the discharge location. Top Picks refuel at 10% remaining fuel percentage.

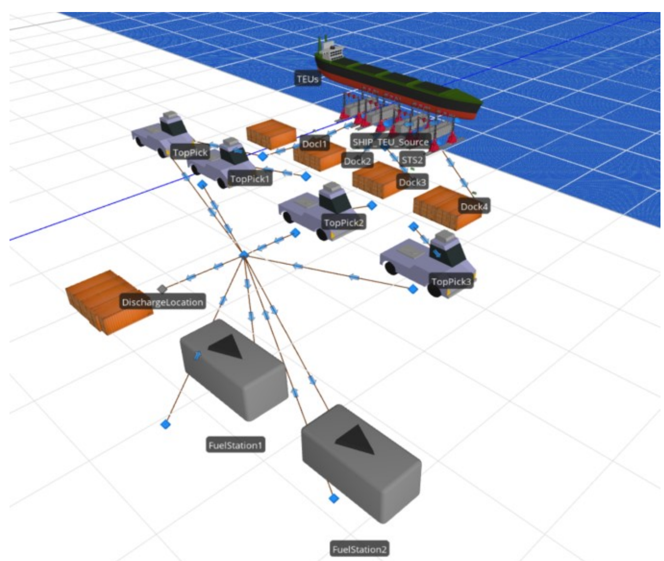

Fig. 7. Simulation of Hydrogen Fueled Top Picks at Maritime Container Port

V. Results

A. Results of UTR Model

The first simulation models the UTR system with hydrogen fuel stations. Three separate use cases are run, each containing a different number of fuel stations (ranging from 1-3). Table II describes an overview of the data collected from the simulations.

Table II. Hydrogen Utility Tractor Rig Model at Maritime Container Port

Number of Fuel Stations	Number In Fuel Queue	Time in Fuel Queue (Minutes)
1	0.0047	0.29
2	0.0002	0.05
3	0.0009	0.0103

From the model, it can be concluded that there is minimal difference among the fuel stations. Due to the fact that the UTRs are able to be refilled at such a fast rate (mean of 3 minutes), there is no need to allocate additional expenditures towards extra fuel stations. As such, one fuel station is the optimal number if hydrogen UTRs are to be put in use.

The next set of simulations are run using the electric powered UTR model. These simulations differ in the number of charging stations, ranging from 6-10, and the number of UTRs currently in service, ranging from 21-35. Table III describes the data collected from the model with 21 UTRs in use. When 21 UTRs are in use, 10 chargers are the preferred amount to implement when accounting for efficiency. The average number in the charging queue for 10 chargers is 23% lower than the next best option, and the average time in the charging queue is 18% faster than the next best option. Table IV describes the electric powered UTR model with 28 UTRs in use.

Table III. Electric Utility Tractor Rig model at Maritime Container Port (21 UTRs)

Number of Charging Stations	Number In Charging Queue	Time in Charging Queue (Hours)
6	2.30	4.41
7	1.95	3.82
8	1.45	3.23
9	1.31	3.30
10	1.01	2.72

Table IV. Electric Utility Tractor Rig Model at Maritime Container Port (28 UTRs)

Number of Charging Stations	Number In Charging Queue	Time in Charging Queue (Hours)
6	3.32	4.73
7	2.41	4.07
8	1.91	3.67
9	1.12	2.72
10	0.96	2.33

When 28 UTRs are in use, 10 chargers are the preferred amount to implement to maximize efficiency. The average number in the charging queue for 10 chargers is 14% lower than the next best option, and the average time in the charging queue is 14% faster than the next best option. Table V describes the electric powered UTR model with 35 UTRs in use.

Table V. Electric Utility Tractor Rig Model at Maritime Container Port (35 UTRs)

Number of Charging Stations	Number in Charging Queue	Time in Charging Queue (Hours)
6	2.45	3.60
7	2.30	4.16
8	1.99	3.86
9	1.26	3.14
10	0.95	2.82

When 35 UTRs are in use, 10 chargers are preferred when accounting for efficiency. The average number in the charging queue for 10 chargers is 25% lower than the next best option, and the average time in the charging queue is 10% faster than the next best option.

B. Results of Hydrogen Top Pick Model

The Hydrogen Top Pick model uses one, two, and three charging stations within the system. Table VI describes the average TEU time in the system, number of Top Picks in the fuel queue, and the total time in the fuel queue for each of the three scenarios.

Table VI. Results for Hydrogen Fueled Top Pick Model at Maritime Container Port

Number of Fuel Stations	Average TEU Time in System (Hours)	Number in Fuel Queue	Time in Fuel Queue (Minutes)
1	0.923	0.0387	0.538
2	0.896	0.00491	0.0114
3	1.456	0.00096	0.0038

In the first scenario, the average TEU time in the system is approximately 0.9 hours with each Top Pick waiting an average of 0.5 minutes to begin hydrogen fueling. The second scenario with two fuel stations improves performance on all three calculated metrics. In this scenario, the total TEU time in the system falls to its minimum along with the other two metrics.

This output data shows that the time that machinery waits to be fueled for reuse decreases by 97.8% when an additional fuel station is added. When three hydrogen fuel stations are added, the average TEU time in the system increases by over 60%. Using two fuel stations might be preferred. Utilization of hydrogen fuel stations was also analyzed. It was found that in a system with one fuel station, the station has an average long-run utilization of 5.4%.

For systems with two and three fuel stations, the average long-run utilization of the fuel stations is 8% and 5.7% respectively. This further reinforces the conclusion that implementation of two fuel stations may be preferred as low utilization may indicate that the system is overstaffed or that there are inefficiencies in the handling process.

VI. Conclusions

Future work will verify and validate server processing rates and refine the several assumptions descried above. Varying simulation run times will be explored to accommodate planning on a five-year horizon. Additionally, scenarios should be elaborated to include the bidirectionality of RMG frameworks, and container loading operations can be simulated. The effort will perform integration of different types of port equipment, cranes, and railway as well as semi-automated pieces of equipment.

Acknowledgment

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References

[1] I. Chatterjee, G. Cho, "Port Container Terminal Quay Crane Allocation Based on Simulation and Machine Learning Method," Sensors and Materials, vol. 34, no. 2, pp. 843-853, 2022.

[2] Y. Yu, R. Sun, Y. Sun, J. Wu, and W. Zhu, "China's Port Carbon Emission Reduction: A Study of Emission-Driven Factors," *Atmosphere*, vol. 13, no. 4, p. 550, Mar. 2022.

[3] "CORDIS | European Commission," *Europa.eu*, 2023. [Online]. Available: https://cordis.europa.eu/project/id/826339

[4] D. V. Lyridis, J. M. Prousalidis, A.-M. Lekka, V. Georgiou, L. Nakos, "Holistic Energy Transformation of Ports," *IEEE Electrification Magazine*, Mar. 2023.

[5] N. L. Densberger, K. Bachkar, "Towards accelerating the adoption of zero emissions cargo handling technologies in California ports: Lessons learned from the case of the Ports of Los Angeles and Long Beach," *Journal of Cleaner Production* 347 (2022) 131255.

[6] "The Rewiring America Newsletter," *Rewiring America*. [Online]. Available: https://www.rewiringamerica.org/newsletter/electrification-wont-break-the-grid-it-will-make-it-smarter

[7] Estimated levelized capital costs of electricity for new power plants in the United States with operation start in 2027, by energy source (in U.S. dollars per megawatt hour) [Graph], EIA, March 3, 2022. [Online]. Available: https://www.statista.com/statistics/194327/estimated-levelized-capital-cost-of-energy-generation-in-the-us/

[8] Estimated unsubsidized levelized costs of energy generation in the United States in 2021, by technology (in U.S. dollars per megawatt hour) [Graph], Lazard, October 28, 2021. [Online]. Available: https://www.statista.com/statistics/493797/estimated-levelized-cost-of-energy-generation-in-the-us-by-technology/

[9] R. Hassan, R. O. S. Gurning, D. W. Handani, "Analysis of the Container Dwell Time at Container Terminal by Using Simulation Modelling," *International Journal of Marine Engineering Innovation and Research*, vol. 5(1), pp. 34-43, Mar. 2020.

[10] L. Brasfield, "Orange EV Making Electrification Work: A Yard Truck Case Study," Transportation & Innovation Expo. [Online]. Available: https://wicleancities.org/wp-content/uploads/2019/05/Larry-Brasfield-Orange-EV.pdf

[11] "*Toyota and Fenix Demonstrate First Hydrogen Fuel Cell Electric UTR*," Toyota USA Newsroom, April 14, 2021. [Online]. Available: https://pressroom.toyota.com/toyota-and-fenix-demonstrate-first-hydrogen-fuel-cell-electric-utr/

[12] Simulation software Simio. Official website, available from:https://www.simio.com/software/simulation-software.php

[13] P. Alikhani, L. B. Tjernberg, L. Astner and P. Donnerstal, "Forecasting the Electrical Demand at the Port of Gävle Container Terminal," *2021 IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe)*, Espoo, Finland, 2021, pp. 1-6, doi: 10.1109/ISGTEurope52324.2021.9640170.

[14] I. Sarantakos et al., "Digitalization for Port Decarbonization: Decarbonization of key energy processes at the Port of Tyne," in IEEE Electrification Magazine, vol. 11, no. 1, pp. 61-72, March 2023, doi: 10.1109/MELE.2022.3233114.

[15] N. Tashakor, J. Kacetl, D. Keshavarzi and S. Goetz, "Topology, Analysis, and Modulation Strategy of a Fully Controlled Modular Reconfigurable DC Battery Pack with Interconnected Output Ports for Electric Vehicles," in IEEE Transactions on Transportation Electrification, doi: 10.1109/TTE.2023.3263775.

[16] I. H. Hamdy et al., "Quantum Computing and Machine Learning for Efficiency of Maritime Container Port Operations," 2022 Systems and Information Engineering Design Symposium (SIEDS), Charlottesville, VA, USA, 2022, pp. 369-374, doi: 10.1109/SIEDS55548.2022.9799399.

[17] C. G. Gacek et al., "Managing Operational and Environmental Risks in the Strategic Plan of a Maritime Container Port," 2021 Systems and Information Engineering Design Symposium (SIEDS), Charlottesville, VA, USA, 2021, pp. 1-6, doi: 10.1109/SIEDS52267.2021.9483787.

[18] D. Bosich, M. Chiandone, M. D. Feste and G. Sulligoi, "Cold Ironing Integration in City Port Distribution Grids: Sustainable electrification of port infrastructures between technical and economic constraints," in IEEE Electrification Magazine, vol. 11, no. 1, pp. 52-60, March 2023, doi: 10.1109/MELE.2022.3232965.