Electrification of Utility Tractor Rigs at a Maritime Container Port

A Technical Report submitted to the Department of Systems Engineering

Presented to the Faculty of the School of Engineering and Applied Science

University of Virginia • Charlottesville, Virginia

In Partial Fulfillment of the Requirements for the Degree

Bachelor of Science, School of Engineering

Zack Goss

Spring, 2024

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

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Electrification of Utility Tractors at Maritime Container Ports

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Abstract— Maritime container ports use various technologies to achieve decarbonization including investing in electrification of vehicles and facilities. There is particular urgency to ensure that capital investments are consistent with future charging facilities and vehicles. Mathematical simulation has been used to predict and avoid disruption and surprises, including evolving requirements, organizations, contract negotiations, anomalous demands, supply chains, grid outages, workforce behaviors, commodity and service markets, obsolescence, regulation, and environmental protection. This study develops a simulation to explore the integration of electric vehicles into freight operations of a maritime container port. The simulation enables the comparison of alternative configurations and capacities of chargers on several time horizons. The effort optimizes performance indices for managers, users, and customers, including emissions, resource utilization, costs, and energy. The simulation addresses four performance metrics, thirty utility tractor rigs, three to fifteen chargers, ten to twenty drivers, five container stacks, and five rail sidings. The simulation describes daily, weekly, and annual schedules and use cases. The results guide \$3 billion in investment and suggest how particular business decisions are sensitive to the trajectory of investment in advanced technologies and their configurations.

Keywords: Systems evaluation, decarbonization, fleet vehicles, systems integration, optimization, mathematical simulation

I. MOTIVATION

Ports are advancing sustainability goals by replacing diesel-powered utility tractor rigs (UTRs) with their electric counterparts to reduce emissions while maintaining operational effectiveness [6-8, 10-11, 14-16, 20-21]. As ports face a variety of stressors and catastrophic events such as the 2024 collapse of the Francis Scott Key Bridge in Baltimore, Maryland, understanding how electric infrastructure will impact both the internal network resilience to surges in twenty-foot equivalent units (TEUs) and national maritime resilience will be key in deciding how much and in what order this infrastructure is put in place [1, 12-13, 17, 22]. This transition underscores the need for analysis of the

infrastructure necessary for electric UTRs. A goal of a particular port might be to achieve carbon neutrality by 2040.

II. PURPOSE AND SCOPE

This study aims to identify the optimal configuration for the Port of Virginia to successfully integrate electrically charged UTRs, particularly focusing on the port layout and amount of various technical equipment for this transition. By developing a simulation model and comparing it against various modified scenarios, the study aims to find efficient, economical, and environmentally beneficial configurations. The performance of the several configurations will be evaluated to recommend paths for the electrification of the port. This analysis assists in implementing and forecasting the long-term sustainability of port operations in transitioning to electric vehicles.

III. BACKGROUND

The electrification of port operations presents a considerable challenge given the current limitations of the electric grid's capacity and the costs associated with it [18-19]. As financial commitment falls heavily on the electric grid's implementation, the port must balance its investments wisely to maximize the success of electrification, especially ensuring port operations remain resilient in a variety of failure events. The recent Baltimore bridge container ship collision is an extreme but important real-world failure case that the Port of Virginia is currently handling, processing an increased flux of TEUs. This scenario is one of five that we tested to ensure that port operations remain resilient in unexpected events. The success and resilience of the simulation models will be measured through designated performance metrics [9, 23-24].

IV. TECHNICAL APPROACH

A. State Diagram Conceptualization



Figure 1. Logic diagram for charging of utility tractors at a maritime container port

To assist with the visualization of UTR operations, a State Diagram was constructed to display the states a UTR could be in: Driving with/without a TEU, picking up/dropping off a TEU, Idle (waiting for a TEU arrival or inactive), Charging, and Waiting to Charge (Figure 1). The decisions and conditions that affect when state transitions occur as well as what criteria trigger state transitions are labeled in the diagram. The rhombus-shaped blocks represent points in the state diagram where a binary condition affects the UTRs state transition. The square-shaped blocks represent the different UTR states previously listed. Lastly, the arrows represent the flow of transitions between different states. This diagram lacks transition rates and fails to provide any mathematical relationships between the states but is useful for planning UTR operations and comprehending simulation results derived later in this paper.

B. Vehicle State Diagram Conceptualization



Figure 2. Vehicle State and Transition Diagram for Electric UTRs at a Maritime Container Port

Figure 2 describes the several states of a UTR vehicle. This transition diagram provides insight to how the populations of the vehicle states evolve.

C. Mathematical Concepts

The following system of equations describes changes in the population of the several states of electric UTRs.

$$\frac{dS}{dt} = -\beta I \cdot \left(\frac{S}{N}\right)^{\mu} + \sigma R$$
$$\frac{dE}{dt} = \beta I \cdot \left(\frac{S}{N}\right)^{\mu} - \alpha E$$
$$\frac{dI}{dt} = \alpha E - \gamma I$$
$$\frac{dR}{dt} = \gamma I - \sigma R$$
$$\beta = R_0 \cdot \gamma$$
$$N = S + E + I + R$$

where *N* is the total population of UTRs, and *S*, *E*, *I*, and *R* are the proportion of *charging*, *idling*, *queuing*, and *operating* UTRs respectively. The coefficients in the model are as follows: $\beta = 11$, $\alpha = 1$, $\gamma = 0.05$, $\sigma = 0.14$.



Figure 3. Proportion of Electrified UTRs in the Several States over Nine Hours of Operations at a Maritime Container Port.

Table 1 describes formulas for determining the performance metrics used: TEU percentage delivered, average TEU time in system, UTR utilization rate, and UTR percentage time transporting TEUs [2].

| TABLE I. | Concepts | for Port | Electrification |
|----------|----------|----------|-----------------|
|----------|----------|----------|-----------------|

| Relationships | Variables | |
|--|---|--|
| $N_{TEUs} = \frac{24}{0.01 + (0.03*Random.Beta(5.26, 3.49))}$ | N _{TEUs} : Total number of TEUs arrived in 24 hours. (Beta distribution in hours) | |
| $U_{UTR} = \frac{T_{Active}}{T_{Total}}$ | U _{UTR} : UTR utilization rate. T _{Active} : UTR time operating. T _{Total} : Total time operating | |
| $A_{TEU} = \frac{\sum_{i}^{N} (T_{i,dep} - T_{i,arr})}{N_{TEU}}$ | A_{TEU} : TEU average number in system. T_{dep} : Time individual TEU is delivered. T_{ar} : Time TEU arrives. | |
| $D = 6.7 * T_{travel} * 60$ | D: UTR distance traveled. T _{travel} : UTR time spent driving | |
| $B = B_0 - 0.007\% * D$ | B: Battery percentage. B ₀ : Initial battery percentage. | |
| $T_{charge} = \frac{80\% - B}{5\%}$ | T _{charge} : Time to charge a UTR back to operating power | |

Table II provides a notional result of the simulation output based on the mathematical relationships described in Table I.

TABLE II. Notional Performance Metrics for UTR Electrification

| Scenario | UTR Utilization | TEU TransferRatio | Average TEU Time in System (minutes) | Average Number of TEUs in System |
|----------------|-----------------|----------------------|--|---|
| S ₀ | 90% | 96% | 15 | 50 |
| S_1 | 90% | 77% | 20 | 60 |
| S_2 | 90% | 90% | 25 | 70 |
| S_3 | 85% | 87% | 30 | 65 |
| S_4 | 95% | 96% | 10 | 45 |

D. Carbon Emissions Avoided

The assumptions to estimate carbon emissions avoided are as follows: The efficiency of the vehicles is 15 miles per gallon. The CO2 emissions are 8.89 x 10-3 metric tons/gal The number of vehicles on average running is 35. The vehicles move on average 1,000 miles in a year. The annual carbon emissions are $(M/E) \times CEG \times n$ where M = miles traveled, E = miles per gallon, CEG = CO_2 emitted per gallon, and n = number of vehicles [4].

E. Simulation Modeling

Figure 4 describes the simulation with five scenarios [5]. There is one baseline scenario that has all standard set parameters, while the four other scenarios aim to test the sensitivity of a specific parameter. The simulations represent a stack-to-rail connection at the port, in which UTRs pick up shipping containers from the stacks and drop them off at the railway, and vice versa.

| SØ.Base Scenario | S1. Only Four UTRs per stack | S2. Increased Arrivals | S3. 2x UTR Battery Loss | S4. 2x UTR Charge Rate |
|---------------------|--|------------------------------|--|---------------------------|
| - Crane1 UTR1 | BAL 1 | BA1.1.1 | Cranel 15.5 UTR16 | Crane1 1 5 5 1 4 |
| Cranes BAS | Crane1_1_UTR7 Crane1_1_2_UTR8 Crane1_1_4_UTR10 | Crane1_1_5_2 | Crane1_1_5_5_1_1 Crane1_1_5_5_1_1 Crane1_1_5_5_1_2 Crane1_1_5_5_1_3 | Crane1 1 5 5 1 8 UTR23 |

Figure 4. Mathematical Simulation of Electrification of Utility Tractors at Maritime Container Ports with Five Configurations

The entities entering and leaving the simulations through the sources and sinks are the TEU shipping containers. Each scenario contains ten sources and ten sinks. There are five cranes in each scenario that have a source producing TEUs, as well as a sink to leave TEUs at the rail sidings. There are five railway sources that produce TEUs from trains, along with five sinks along the railway to drop TEUs from the stacks. Each stack-to-rail connection is disconnected from all other stack-to-rail connections, meaning a UTR can only transport TEUs from the first stack to the first rail siding, etc...



Figure 5. Detail of a Stack-to-Rail Transport Unit in the Mathematical Simulation of UTR Electrification at Maritime Container Ports

In the base scenario, the TEUs enter the system at each source at an interarrival time of 0.01 + (0.03 * Random.Beta(5.26, 3.49)) hours [3]. The TEUs are transported by the UTRs from the sources to the corresponding sinks. The TEUs only move throughout the system once they are picked up by available UTRs. The UTRs are reserved by a "closest available" reservation system, meaning whichever unoccupied UTR is the smallest distance away from the TEU when it enters the system will transport it.

In the base scenario, six UTRs populate each of the five rail-to-stack connections, for a total of thirty UTRs. Each railto-stack connection has one charging station, represented by a transfer node. The charging station acts as the home node for the six UTRs. If there are no TEUs to pick up, or the UTR battery drops below 40%, the UTRs return to the charging station and recharge at a rate of 5% per minute. The UTRs lose battery proportionally to the distance traveled at a rate of 0.007% per meter traveled. The UTRs can also fail within the model to help simulate mechanical repairs and malfunctions. There is an uptime between failures of an Exp(6) hour distribution, and the time to repair a UTR is Exp(0.5) hour distribution.

The paths the UTRs run on are drawn to logical lengths. These lengths were made through assumptions and by taking averages of the distances between the stacks and the railway stations at the port. The distance between the charging station to the stacks and to the rail drop point are 0.1 miles. The distance between the stacks and the rail drop points are 0.4 miles. The UTRs themselves move at a speed of 15 miles per hour.

The simulation was exercised for eleven hours, which is a full workday with two shifts. The UTRs run from 7 a.m. to 12noon, are off shift for a one-hour lunch break, and then run again from 1 p.m. to 6 p.m. Table III and Table IV describe the base scenario S_0 parameter values, as well as the alternate scenarios S_1 - S_4 parameters.

TABLE III. Mathematical Simulation Scenario S_{0} Parameters for UTR $$\ensuremath{\mbox{Electrification}}$$

| Parameter | Base Value |
|-----------------------------------|---------------------------------------|
| Number of UTRs per stack | 6 |
| Interarrival time of TEUs (hours) | 0.01 + (0.03*Random.Beta(5.26, 3.49)) |
| UTR Battery Loss Rate | 0.007% per meter traveled |
| UTR Battery Charge Rate | 5% per minute at charging station |

TABLE IV. Mathematical Simulation Alternate Scenario Parameter Changes

| Scenario | Parameter Changed in the | Adjusted Value |
|----------|---------------------------|--|
| | Scenario | |
| S_1 | Number of UTRs per Stack | 4 |
| S_2 | Interarrival Time of TEUs | 4/3*(0.01 + (0.03 * Random.Beta(5.26, 3.49))) |
| S_3 | UTR Battery Loss Rate | 0.014% per meter traveled |
| S_4 | UTR Battery Charge Rate | 10% per minute at charging station |

V. RESULTS

A. Overview

Each of the five scenarios were run with ten replications. Table V describes the summary of performance.

TABLE V. Mathematical Simulation of UTR Electrification Sensitivity Analysis Results

| Scenario | UTR Utilization | TEU Successful Transfer Ratio | Average TEU Time in System (minutes) | Average Number of TEUs in System |
|----------------|--------------------|--|---|---|
| S_0 | 68% | 99% | 7 | 45 |
| \mathbf{S}_1 | 89% | 79% | 55 | 437 |
| S_2 | 84% | 83% | 49 | 465 |
| S_3 | 93% | 87% | 42 | 284 |
| S_4 | 52% | 99% | 2 | 14 |

The base scenario S_0 is viable. With an approximately 99% TEU transfer rate, a low TEU processing rate of 7.4 minutes, as well as a UTR utilization that provides high room for variability, S_0 is able to support electrification in port operations. However, it is important to test the sensitivity of these parameters and determine which aspects of the base simulation are the most crucial to ensuring high productivity and efficiency.

B. Reducing the Number of UTRs

In Scenario S_1 , the number of UTRs available at each stack was reduced from six to four, for a total reduction of UTRs from thirty to twenty in the system. UTR reduction did result in significant changes in the key performance metrics. While UTR utilization did expectedly increase by a significant margin (20%), system performance declined, as the lack of available transporters resulted in large queues and wait times. The average number of TEUs in the system increased tenfold, and the average TEU processing rate increased by nearly eight times the base scenario. These findings demonstrate the importance of having enough UTRs to meet system demand, or else port operations will suffer.

C. Increasing the Arrival Rate of TEUs

In scenario S_2 , the arrival rate of TEUs was multiplied by 4/3 to test the response to overloading or overscheduling of TEU shipments. Increasing the arrival rate of the TEUs led to a decrease in system performance and an increase in UTR utilization. However, the system was more sensitive to a decrease in UTRs rather than to an increase in arrival rates, as there was a higher percentage of transported TEUs (83% vs. 79%) and the TEUs had a smaller average time within the system.

D. Increasing the Rate of UTR Battery Loss

In scenario S_3 , the UTR battery loss rate was doubled, resulting in the highest UTR utilization of the 5 scenarios at 93%. This high utilization signals that these conditions represent the maximum intensity the UTRs could handle before collapsing. However, while the UTRs were nearing breakdown, the TEU processing rates and average TEUs in the system were more favorable than scenarios S_2 or S_3 . These findings signal that the system is significantly less sensitive to UTR battery life than it is to the size of the UTR fleet or the rate of TEU arrivals.

E. Increasing the Rate of UTR Charging

In scenario S₄, the charging rate of the battery was doubled, resulting in an improvement on all key performance metrics compared to the base scenario, as UTRs were able to perform at more efficient rates and keep up with system demands. Nearly all UTRs entering the system were transported immediately, and there were minimal queues or wait times involved with TEU processing. Overall, these findings demonstrate that ensuring adequate UTR fleet sizes and maximizing charging rates will result in the best system performance.

F. Percentage of UTR Time Transporting

The other metric analyzed on a per-UTR basis was the percentage of time the UTRs spent transporting TEUs. While overall average utilization was used for the summary statistics, this metric defines utilization as any time the UTRs are not idle, meaning charging and returning to charge are included as utilization. By analyzing the percentage of time a UTR is transporting, an understanding of specific UTR usage and charging-working time splits can be achieved. Figure 6 describes the UTR percentage of time transporting TEUs by scenario.



Figure 6. Percentage of Time that a UTR is Transferring a TEU for Each of Five Design Scenarios.

The notable difference in UTR utilization of time spent transferring TEUs is most affected by the UTR battery. S₄

represents doubling the battery charging rate, accounting for the highest transferring time of 62%. The scenario, S_3 , represents doubling the battery loss rate, accounting for the lowest transferring time of 38%. These results correlate with the UTR utilization rate for all five scenarios. Understanding the nature of port operations, it can be concluded that there is a linear relationship between the time UTR is operating and not charging vs. UTR transferring time rate. To increase UTR utilization as well as UTR transferring time, the port should minimize UTR charging time.

VI. CONCLUSION

This paper has described the mathematical modeling of several configurations of charging of UTRs at a maritime container port. The approach included characterizing the urgency of decarbonization, building a state transition model and system of equations representing port vehicles, creating concepts for quantifying the performance of chargers, and assembling a comprehensive mathematical simulation of 30 UTRs and 5 charging stations. With this, sensitivity of system performance to various design scenarios was explored. Future work should include analyzing several other factors that play a role in electrification such as economic and environmental impacts and additional economic opportunities that come with electrification such as entering a market for selling surplus electricity [25-29]. Workers take one-hour breaks for every five hours of work. With disruptions such as the recent Baltimore Bridge Collapse, workers might have to work with reduced breaks for a temporary period.

ACKNOWLEDGEMENT

This effort was supported in part by the Port of Virginia, the Commonwealth Center for Advanced Logistics Systems, and the National Science Foundation grant 1916760 "Phase I IUCRC University of Virginia: Center for Hardware and Embedded Systems Security and Trust (CHEST)."

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